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# Space disaggregation in models of route and mode choice: method and application to the Paris area

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UNIVERSITE PARIS-EST  
Ecole Doctorale Ville Transports et Territoires  
Laboratoire Ville Mobilité Transport

THESE DE DOCTORAT  
Spécialité Transport

# Space Disaggregation in Models of Route and Mode Choice: Method and Application to the Paris Area

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le 18/01/2013

sous la direction de Fabien Leurent

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# List of French Abbreviations

- IAU-IdF: Ile-de-France Development and Urban Planning Institute  
*“Institut d'Aménagement et d'Urbanisme de la Région Île-de-France”*
- IGN: National Geographic Institute  
*“Institut Géographique National”*
- INSEE: National Institute of Statistics and Economic Studies  
*“Institut National de la Statistique et des Etudes Economiques”*
- DRIEA-IF: State’s Department for Regional and Interregional Infrastructure Planning of Ile-de-France  
*“Direction Régionale et Interdépartementale de l'Équipement et de l'Aménagement d'Île-de-France”*
- LAURE: Law on Air Quality and the Rational Use of Energy  
*“Loi sur l’Air et l’Utilisation Rationnelle de l’Énergie”*
- PDU: Urban Mobility Plan  
*“Plan de Déplacements Urbains”*
- PDUIF: Ile-de-France Urban Mobility Plan  
*“Plan de Déplacements Urbains d’Île-de-France”*
- RATP: Autonomous Operator of Parisian Transports  
*“Régie Autonome des Transports Parisiens”*
- SNCF: French National Railway Corporation  
*“Société Nationale des Chemins de fer Français”*
- STIF: Ile-de-France Public Transport Executive  
*“Syndicat des Transports d’Île-de-France”*
-

# Abstract

Spatial representation of modeling area in travel demand models has changed little over the course of last several decades. In this regard, the state-of-the-art still widely relies on the same centroid-connector system that has been used in classic models. In this approach continuum bidimensional space is lumped on centroids. It is an aggregate approach which ignores the physical variability linked to the scatteredness of disaggregate residence- and activity-places over the *local* space. Consequently the modeling performance in explaining route and mode choice behavior degrades at local scales: In route choice, disaggregate location influences the propensity between a distant interchange to a highway, or a nearby road. In mode choice, feeder service to public transportations influences the auto vs. transit modal share.

We propose a disaggregate approach for spatial representation. Based on a zoning system, a stochastic disaggregate representation is used to characterize the space within a traffic analysis zone. For each zone, anchor-points are defined as the network nodes that are used for accessing to the network from within the local space. An itinerary between a pair of zones is then considered as a chain of *legs* composed of two terminal legs, corresponding to the intrazonal route sections, and one main leg between two anchor points. The route choice problem is transformed to a joint choice of a pair of anchor points. The vector of random terminal travel times is Multivariate Normal resulting in a Multinomial Probit model of choice of a pair of anchor points.

To extend to the *multimodal* context, a transit composite mode is defined as a chain of access, main, and egress *modal legs*, and transit platforms are considered as anchor points connecting the feeder legs to the main line-haul leg. A Multinomial Logit mode choice model is estimated based on the 2001 Paris Household Travel Survey for the auto mode and the composite transit modes. It is joined with the two Multinomial Probit models corresponding to the choice of anchor points. The result is a joint model of mode and station choice with a disaggregate representation of the local space.

**Keywords:** mode choice, space disaggregation, route choice, station choice, stochastic traffic assignment, multimodal network, spatial representation.

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# Résumé

## Désagrégation de l'espace dans les modèles de choix d'itinéraire et de mode : Méthode et application à la région Ile-de-France

La représentation spatiale de l'aire de modélisation dans les modèles de la demande de transports a peu changé au cours des dernières décennies. A cet égard, l'état-de-l'art repose encore largement sur le système de centroïde-connecteur qui est utilisée dans les modèles classiques. Elle est une approche agrégée qui ignore la variabilité physique liée à la dispersion des lieux désagrégés de résidence et d'activité dans l'espace *local*. En conséquence, le pouvoir explicatif des modèles quant aux comportements de choix d'itinéraire et de mode demeure limité à l'échelle locale : Par exemple, la localisation désagrégée influence sur le choix entre une autoroute dont l'échangeur est éloigné, et un autre itinéraire non-autoroutier. Egalement, le rabattement terminal influence sur le partage modal auto vs. transports en commun.

Nous présentons une approche désagrégée pour la représentation spatiale. Dans un découpage zonal, l'espace à l'intérieur d'une zone est représenté de manière désagrégée stochastique. Pour chaque zone, les points d'ancrage sont définis relative aux nœuds du réseau qui peuvent être utilisés pour accéder au réseau. Un itinéraire entre une paire de zones est ensuite considéré comme une chaîne, composée de deux trajets terminaux, correspondants aux sections intrazonales de l'itinéraire, et d'un trajet principal correspondant à la section entre deux points d'ancrage. En conséquence, le modèle de choix d'itinéraire est transformé à un modèle de choix conjoint d'une paire de point d'ancrage. Le vecteur des temps aléatoires terminaux est Normal Multidimensionnel donnant lieu à un modèle Probit de choix conjoint de points d'ancrage.

Pour étendre au cadre *multimodal*, un mode collectif composite est défini comme une chaîne composée des trois *trajets modaux* d'accès, principal, et de sortie, et les stations sont considérées comme les points d'ancrage, connectant les trajets de rabattement au trajet principal. Un modèle Logit Multinominal de choix de mode est estimé à partir de l'Enquête Globale de Transport de 2001 pour le mode auto et le faisceau des modes collectifs composites, et est combiné avec les deux modèles Probit correspondants au choix des stations.

**Mots clés:** choix modal, désagrégation de l'espace, choix d'itinéraire, choix de station, affectation stochastique, réseau multimodal, représentation spatiale.

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---

# Executive Summary

## 1. Introduction

The present dissertation contributes to the literature of travel mode choice modeling. Its aim is to ameliorate mode choice modeling by improving model spatial representation in order to better account for local disaggregate situations in modeling travelers' mode choice behavior in multimodal urban transportation networks.

We assume that an itinerary can be represented as a chain of one main section and two terminal sections, one at the origin side, i.e., the access section, and one at the destination side, i.e., the egress section. Each section corresponds to a modal leg, i.e., a section of the itinerary with a mode associated to it. The choice of the travel mode is modeled as a three-stage problem where each stage corresponds to a section of the itinerary. We introduce the concept of anchor point and define it as the physical node where traveler leaves the local space and enters the main transportation network. Terminal sections are articulated to the main section at anchor points. In highway network, anchor points are high capacity network nodes that provide access to the network from inside the traffic analysis zone. In transit networks, anchor points correspond to the main transit platforms.

The model representation of space is continuous, allowing for a disaggregate representation of trip-ends within space. Therefore, time of travel between the traffic analysis zone and a given anchor point, at origin or destination, is a random variable. The vector of terminal travel times is specified by a Multivariate Normal distribution.

In total, two sources of variability are addressed: The first source is “behavioral” corresponding to the variability in the mode choice behavior, due to unobserved behavioral factors. The second source is “physical” and deals with the variability of terminal travel times, due to the scatteredness of disaggregate trip-ends within space. Therefore, for any given pair of origin-destination zones, the model is capable of evaluating the probability of the joint choice of a composite travel mode (i.e., a particular chain of access,

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main, and egress modes) and a pair of anchor points, one at origin and one at destination.

The mode choice model is estimated on the 2001 Paris Household Travel Survey. We focus on work trips made by car-owning commuters who are the only worker of their household. Focusing on this particular demand segment allows: (1) ignoring complexities due to intra-household interactions, and (2) making sure that all of commuters have the liberty to use the auto mode. On the supply side, we use three different networks to reconstruct a fully detailed representation of the Parisian transportation networks. The Ile-de-France highway and transit networks are reconstructed using data from DRIEA, describing the transportation supply of the region as of 2008. Street level networks are reconstructed from IGN's BD TOPO<sup>®</sup> database. These detailed data are required to realistically represent disaggregate terminal trip sections.

This abstract follows the general plan of the dissertation and highlights the main assumptions and conclusions of each part.

## 2. Transportation Demand Modeling Paradigms

The domain of demand modeling has been witnessing continuous progress, in the course of the last few decades. From direct demand and classic trip-based models to the state-of-the-art activity-base models, different modeling aspects have been improved and founded on more consistent and robust theoretical grounds.

Inventing a multi-step system for representing the decision-making process has been an important step forward in model system design. It allowed analysts to break from regression-like descriptive models of mobility, such as direct demand models, and to devise a conceptual framework where “different-in-nature” aspects of decision are structured in a consistent manner and dealt with in specialized modeling steps. Even though the identification of these steps, their sequential hierarchy and interdependence relationships, have been always subject to discussion, the very idea of viewing the human decision process as a system of interdependent components which deal with different decision aspects, offered a more synergic and prolific approach to modeling travel behavior. The incorporation of the random utility framework in the modeling of microeconomic choice behavior should also be considered as another major leap. The random utility theory provided a solid theoretical basis for modeling microeconomic decision-making behavior, and by doing so, it also characterized a category of models.

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## 2.1. Travel Demand Representation

From the point of view of the microeconomic choice behavior, the representation of the travel demand in the model has been approached from two complementary angles:

On one hand, efforts have been concentrated on giving a better account of traveler's mobility during the modeling period (a working day, for instance), and to respond to the question of what describes the mobility: Is it about a number of independent trips between various origins and destinations? Is it about a number of independent tours composed of successive trips between two consecutive visits to home? Or is it actually an agenda of scheduled activities that should be undertaken within a limited amount of time and spatial range? Travel analysis and forecast by a trip-based approach is just another name for regression. Instead, we need to recognize underlying factors that have led to the *status quo* and try to understand what those factors will lead to in the future. In trip-based models, travel decisions are all supposed to be decided at single-trip level. On the contrary, tour-based models consider trips and travel decisions related to each other, and activity-based models represent travel demand as being derived from the need to participate in activities distributed in time and space.

On the other hand, efforts have been concentrated on preserving the heterogeneity among travelers and households as decision-making units, and the variability of their individual attributes and physical situations. Classic models treat individuals and households as well as time and space, as aggregates. Individuals are treated as groups traveling between traffic analysis zones; model account of space is based on centroid-based representations, and time periods represent only peak and off-peak hours. The explanatory power of the models depends largely on their capacity to account for the variability of attributes and decision-making situations among travelers.

Modeling paradigms from the trip-based models up to the tour- and activity-based models have mainly concentrated on the behavioral aspects. They shift their emphasis from the single trip, by recognizing superior structures of mobility such as travel tour or daily activity schedule. In addition, models have been able, to the best of their ability, to preserve variability in the demand, using demand segmentation techniques and random coefficient models. Though, the model account of the space has been mainly based on a centroid-connector system associated with a zoning system.

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## 2.2. Demand segmentation

The decision to make a trip, from its genesis at home, where the need to move first takes form at the beginning of the day (afterwards the motivation for moving again is mandatory at least for returning to home), down to the subsequent aspects such as destination, mode, hour, ... is conditioned by who the traveler is (demand segment) and what the traveler wants to do (travel purpose). This is because factors such as social and professional status, income, age and household composition condition needs and eventually the travel behavior as a derived demand. Therefore there is no way to treat different people together in one common aggregate and hope to obtain traceable explanatory relationships between observed travel behaviors and observable attributes and situations that condition them.

In more elaborate terms, the random utility framework is useful for explaining decisions that are made in the same behavioral mindset. In other words, once the traveler is in the time-minimizing mindset, for going to work for example, the random utility framework explains (and evaluates) the propensity towards alternatives that offer lesser travel times. Instead, the random utility framework leads to erroneous interpretations when it is applied to compare decisions made in two different mindsets. Let us compare a commuter – reasoning on a time-minimizing basis – with a traveler driving for leisure. The former rides to make a great time whilst the latter is having a great time and does not necessarily mean to minimize his/her travel time, as it is no longer a priority. The same is true with a grocery shopper to whom getting the least travel time is not the first priority; instead, he/she prefers to bring a vehicle to carry the weight of purchased goods even if a faster public transportation alternative is available. As another example, a young traveler may prefer to ride a fast but overcrowded public transportation service rather than to drive an automobile, whilst an elderly may prefer to drive his own car and spare himself the burden of an uncomfortable ride in public transportations. These examples are to illustrate the fact that the explanatory power of a model depends entirely on identifying and isolating different reasoning contexts.

## 2.3. Disaggregate Representation of Space

Residence- or activity-places are not located on zone centroids. Instead, they are all scattered over space, i.e., trip-ends are distributed over space. Except for the walk mode, transportation modes are not immediately available to travelers. As regards the auto mode, a traveler needs to access to a vehicle at origin, then egress from it once arrived to destination. The vehicle may be parked on street, in a parking lot, or on a private parking place. As regards

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public transportations, the traveler has to access a transit platform nearby the departure point in order to board a public transportation service, and has to alight at a destination transit station and continue the end of the trip until the arrival point. Different individuals based on their relative distance to transportation networks experience different situations of choice and different levels of accessibility. This has important implications in terms of mode choice behavior and requires a disaggregate representation of trip-ends in space. This is yet another source of variability in the demand, which requires to be addressed properly.

Identification of travelers' mode choice set is another important task, which is influenced by traveler's vehicle ownership status as well as the local situations in space at origin and destination. As regards the former, members of a non-motorized household do not have the possibility to use the auto driver mode. As regards the latter, for instance, travelers living nearby a bus stop have the liberty to choose a bus service either for their entire travel or for accessing a transit platform; whereas those living outside the catchment area of the bus stop find the bus mode unavailable. Similarly, the accessibility to transit platforms by walk depends on the distance. In this respect, an aggregate centroid-based spatial representation causes erroneous representation of mode choice sets and eventually leads to a behaviorally inconsistent model as "not choosing" is not the same behavior as "not being able to choose".

In this work, the main objective is to address the disaggregate representation of space in a mode choice model. A fully disaggregate representation of decision-making units, individuals and households, in space requires huge amounts of resources both in terms of simulation power and empirical databases. Therefore, we propose a stochastic representation of travelers in space to account for scatteredness of trip-ends at origin and destination zones. We approach the problem in two steps: First, we develop a stochastic spatial representation framework and study its implications in the case of traffic assignment to a monomodal network. Then we introduce multimodality, and incorporate the variability due to the scatteredness of trip-ends, in modeling the travel mode choice behavior.

### 3. Trip-end Disaggregation in Monomodal Networks

We start by introducing the concept of "anchor point": it is a network node with a distinctively high traffic capacity, which provides the connection between the local network of streets within a traffic analysis zone, and the regional network of highways and major urban axes. It is the node, which drains the intrazonal traffic and injects it to the regional network, and

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reciprocally provides access to the intrazonal network from major axes and highways. Each zone may correspond to a number of anchor points based on its geometry and the configuration of the highway network. In addition, an anchor point might be shared by a number of adjacent zones. Every trip, from a departure point within the origin zone to an arrival point within the destination zone, is necessarily composed of three sections, including: the access section from the departure point to one of the origin anchor points, the main section from the chosen origin anchor point to one of the destination anchor points, and the egress section from the chosen destination anchor point to the final arrival point.

We suggest that because every interzonal trip is supposed to end up eventually passing from a pair of anchor points (one at origin, one at destination), the route choice problem can be reduced to the choice of a pair of anchor points. In other words, once the two anchor points are chosen, the entire interzonal itinerary is also uniquely determined. We proceed in two steps:

Firstly, an idealized network is used to illustrate the concept. We consider a rectilinear network composed of two superposed rectilinear meshes: a fine mesh to represent local streets, and a coarse mesh to represent highways. Fine and coarse meshes are connected to each other at crossways of the coarse mesh. We define a zoning system such that zone boundaries are defined by the coarse mesh. Each zone therefore is a rectangle, meshed with a fine network of streets. Each zone is represented by four anchor points corresponding to the four vertices of the rectangle. Trip-ends are supposed to be distributed uniformly over space. We suggest studying the route choice problem for the idealized network. First, the equivalent version of the problem is considered and solved to obtain exact probabilities of choosing an anchor point from within a traffic analysis zone. Then, it is shown that the exact disaggregate solution is equivalent to a stochastic solution where interzonal travel times follow a multivariate trapezoidal distribution with a corresponding covariance structure.

Secondly, we generalize by approximating the exact intrazonal distribution with a Multivariate Normal distribution, which leads to a Multinomial Probit anchor-pair choice model. The consequent Multinomial Probit model is solved using Clark's algorithm (Clark, 1961)<sup>1</sup> allowing for the development of an operational traffic assignment model with a disaggregate representation of trip-ends. The model is used for the assignment of peak-hour origin-

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<sup>1</sup> Clark, C. E. (1961). The greatest of a finite set of random variables. *Operations Research* 9(2):145–162.

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destination traffic matrix to the highway network of the Greater Paris Region. Several statistical indicators are defined in order to analyze results, aggregated according to a macro zoning system of the Parisian region.

This is a mathematical assignment model, which solves the shortest path problem over a graph with non-centripetal vertices. Daganzo (1980a<sup>2</sup>, 1980b<sup>3</sup>) is the first to have studied the stochastic disaggregate representation of trip-ends for traffic assignment to a monomodal network and Sheffi and Trexler (1980)<sup>4</sup> have checked the accuracy of his algorithm. Our treatment of the subject shows a real application of the model and paves the way towards our main objective which is the study of mode choice in a multimodal network with disaggregate representation of trip-ends.

## 4. Trip-end Disaggregation in Multimodal Networks

In the final part of the dissertation, we study the mode choice problem with a disaggregate representation of travelers in space. The aim is to extend the monomodal stochastic assignment concept to the multimodal context. We consider two sets of modes: an auto driver mode including car and motorbike, and the bundle of transit modes including all itineraries that use a public transportation service.

### 4.1. Multimodal Itinerary Abstraction

Private modes such as auto or motorbike are generally considered as being immediately accessible modes of transportation. This is not quite true: at origin as well as destination, the vehicle may be parked at a dedicated parking place, on the street or in a nearby parking lot. Therefore an auto driver has to access to his personal vehicle at origin by walk before being able to use it, and has to egress from it again by walk once he/she arrives at destination. Analogously, in public transportations the traveler has to access a transit platform in order to board a public transportation service and egress from one once he/she alights. Therefore, a transit itinerary also consists of a succession of access, main, and egress sections. Only this time each section can have a

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<sup>2</sup> Daganzo, C. F. (1980a). An equilibrium algorithm for the spatial aggregation problem of traffic assignment. *Transportation Research B* 14(3):221–228.

<sup>3</sup> Daganzo, C. F. (1980b). Network representation, continuum approximations and a solution to the spatial aggregation problem of traffic assignment. *Transportation Research B* 14(3):229–239.

<sup>4</sup> Sheffi, Y., Trexler, R. (1980). A note on the accuracy of the continuum approximation spatial aggregation algorithm of traffic assignment. *Transportation Science* 14(4):306–323.

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different mode. Such an itinerary is called multimodal. The notion of multimodality applies commonly to both private and public transportation modes. In a multimodal framework, we try to account for different trip stages, explicitly.

In order to be able to address such issues in a comprehensive way, it is necessary to elaborate an appropriate system of representation. In the case of the auto mode, the multimodal representation requires modeling (explicitly or implicitly) the choice of a parking place. Such a model introduces additional parameters involved in finding a parking place, and allows accounting for tradeoffs between, for instance, a paid but closer and a free but further parking place. In the case of public modes, the multimodal representation should explicitly account for the terminal sections of the trip as well as the line-haul chain of public modes between the access and egress transit platforms.

Our ultimate aim is to acquire a deeper insight into the mode choice behavior of travelers by looking to the ways in which the local space conditions traveler's perception of mode alternatives. From the mode choice modeling point of view, the choice of the main transportation mode should be understood within the whole sequence of legs that constitute together a multimodal itinerary. In other words, we recognize that the travel mode choice is not decided at only one instant, but that the choice of the main mode is conditional upon a number of mode choice decisions, which occur "physically" at transfer points between legs. This enables us to account explicitly for the physical factors that influence the mode choice behavior of the individual, which has been classically left out of the scope of the models. We suggest that this approach leads to a more conceptually consistent and econometrically explanatory model. Here we assume that the auto mode is an immediately accessible mode. As for the transit itineraries, we represent them in three legs: an access leg from the departure point to the first transit station, a main transit chain between the first and the last transit stations, and an egress leg from the last station to the arrival point. Our purpose is to develop a consistent modeling framework in which the stochastic disaggregate spatial representation of the local space, on one hand, and the behavioral aspects underlying the formation of multimodal itineraries, on the other hand, are combined.

In the literature, the study of multimodal transit itineraries and access to transit services has been addressed as feeder mode only or access station only choice problems, and also as a joint feeder mode and access station choice problem. However, models have mainly focused only on the articulation

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between transit feeder and main sections, and a true modeling of mode choice for disaggregate multimodal urban systems, has rarely been tackled:

Liou and Talvitie (1974)<sup>5</sup> study the joint feeder mode and access station choice for work trips in Chicago. Three alternative feeder modes are walk, auto and bus. The auto mode is considered as always available. The walk mode is considered available if the walking time does not exceed 20 min. Bus is considered available if the traveler is within half a mile from a bus route. For the station choice set, alternatives stations are chosen usually near the stated chosen station.

Kastrenakes (1988)<sup>6</sup> develops a station choice model for New Jersey regional transit system to predict the way the distribution of the transit demand responds to a change in transit access conditions.

Bovy and Hoogendoorn-Lanser (2005)<sup>7</sup> develop a joint feeder mode and access station choice model as a part of their study of the influences of multimodal trip attributes on the competitiveness of interurban multimodal train alternatives. They consider the interurban train as the main travel mode and combine the feeder mode and access station choices into a single multimodal route choice problem.

Fan et al. (1993)<sup>8</sup> study feeder mode and access station choice for work trips in the Greater Toronto Area. Transit service in the area is provided by two transit systems: the commuter rail network with walk, auto and transit feeder modes and the subway system with auto feeder mode.

Debrezion et al. (2009)<sup>9</sup> develop a joint feeder mode and transit station choice model in the Netherlands based on data from Dutch Railway Company customer satisfaction survey. As for feeder mode identification, all four feeder modes are considered to be available all over the postcode area. As for transit station identification, in each postcode area the three most frequently accessed transit stations are considered. The choice of a departure station is dependent

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<sup>5</sup> Liou, P. S., Talvitie, A. P. (1974). Disaggregate access mode and station choice models for rail trips. *Transportation Research Record* 526:42–65.

<sup>6</sup> Kastrenakes, C. R. (1988). Development of a rail station choice model for NJ TRANSIT. *Transportation Research Record* 1162:16–21.

<sup>7</sup> Bovy, P. H. L., Hoogendoorn-Lanser, S. (2005). Modelling route choice behaviour in multimodal transport networks. *Transportation* 32(4):341–368.

<sup>8</sup> Fan, K.-S., Miller, E. J., Badoe, D. (1993). Modeling rail access mode and station choice. *Transportation Research Record* 1413:49–59.

<sup>9</sup> Debrezion, G., Pels, E., Rietveld, P. (2009). Modelling the joint access mode and railway station choice. *Transportation Research Part E* 45(1):270–283.

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on three factors: the accessibility of the station, the level of transportation service accessible from the station, and the availability of accessory facilities offered at the station.

## 4.2. Space Disaggregation in Mode Choice Modeling

Sheffi and Daganzo (1980)<sup>10</sup> study the equilibrium on a hypernetwork, where mode legs and route links can be represented together as hyperlinks. They consider a basic road network, connected to the origin and destination centroids by a number of access links. Links in the basic network are characterized by deterministic impedances. Impedance of an access link, on the other hand, is characterized as the sum of an average value and an unobserved additive disturbance, which varies from individual to individual according to a Multivariate Normal distribution. They work out the equilibrium state for such a hypernetwork. Their model takes into account only one level of randomness, which can be employed to account for either the variability due to the stochastic spatial disaggregation, or the variability due to the disturbance terms in the composition of modal utility functions. Our model however requires both.

According to our setting, disaggregate mode choice modeling in a multimodal context is subject to several levels of complexity: First, in a multimodal network, there are different available modes and by each mode, there are a number of routes between the departure and arrival points. Second, how to abstract and represent a multimodal transit itinerary is an important modeling decision, which directly influences model performance, especially in a complex and hierarchical transit network such as the Parisian public transportations. Some of the main decisions include:

- How to identify basic modes and decide, for instance: Whether Metro and Tramway are two different modes or can be regrouped as one single mode? Whether Bus functions as a feeder for Metro and Train, or as an independent public mode fed by walk? ...
- How to represent transit itineraries and identify legs, and decide: Whether a new leg corresponds to a change of service at a transit station (physical junction) or to a change of mode regardless of physical coordinates (modal junction)? ...
- How to account for order in the transit chain. For instance, is “Metro-Train” different from “Train-Metro”? ...

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<sup>10</sup> Sheffi, Y., Daganzo, C. F. (1980). Computation of equilibrium over transportation networks: The case of disaggregate demand models. *Transportation Science* 14(2):155–173.

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After identifying the main transit modes, we combine the main transit section with access and egress legs to obtain the complete multimodal itinerary. We consider two different Multimodal Path Enumeration Schemes. In the first Multimodal Path Enumeration Scheme (MPES-I), we identify three access feeder modes: auto, bike, and walk, giving access to the 7 main transit modes. The only egress feeder mode is walk. This gives rise to 21 potential composite mode alternatives. The 22nd alternative is the auto mode.

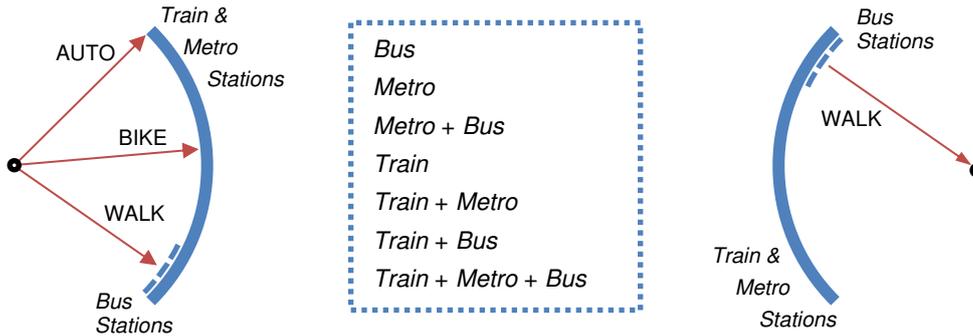


Figure ii. Multimodal Path Enumeration Scheme I (MPES-I).

For each commuter a simulation model provides level-of-service characteristics for all of the 22 alternatives between disaggregate departure and arrival points. In the next step, we eliminate unobserved combinations, i.e., combinations such as Bus with auto access that are not observed in the survey dataset. The final mode choice set includes a maximum number of 14 effective modes in total, including the auto mode. Results are used to estimate Multimodal Logit and Nested Logit discrete choice models.

Although the first multimodal path enumeration scheme leads to satisfactory model estimations, it is not convenient for application to a stochastic disaggregate spatial representation. This is mainly related to the choice of anchor points. With bus stops being explicitly included, there will potentially be a large number of transit platforms that can be identified as anchor points in each zone. Therefore, we propose a second Multimodal Path Enumeration Scheme (MPES-II) where local Bus is also identified as a feeder mode. In other words, itineraries composed of a walk access to a local Bus service followed by a transfer to a nearby Metro/Train service are represented as a Bus access to a Metro/Train transit platform. In this way, only Metro and Train stations need to be represented explicitly and the number of potential anchor points decreases dramatically. MPES-II includes four access feeder modes: auto, bike, walk, and bus, giving access to the 7 main transit modes, followed by two egress feeder modes are: walk and bus. This gives rise to 56 potential composite mode alternatives. The 57th mode is the auto mode.

For each pair of departure and arrival points a simulation model provides level-of-service characteristics for all of the 57 alternatives. All unobserved combinations are eliminated from the dataset. The final mode choice set includes a maximum number of 23 effective modes in total, including the auto mode. Results are used to estimate Multinomial Logit and Nested Logit models.

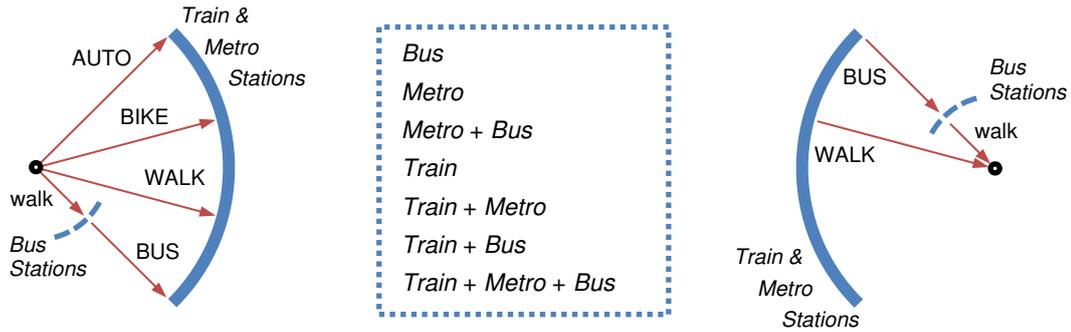


Figure iii. Multimodal Path Enumeration Scheme II (MPES-II).

The second specification is then associated with a stochastic disaggregate representation of space. We consider that travel times on the access and egress legs of the trip are random variables following a Multivariate Normal distribution. With a total number of  $\bar{g}$  pairs of anchor points, a  $\bar{g}$ -rank covariance matrix reflects the spatial configuration of origin-destination zones and anchor points. Then we consider the covariance structure of the additive disturbance terms in the modal utility functions. With a total number of  $\bar{m}$  modes, a  $\bar{m}$ -rank matrix reflects the covariance structure of the mode choice model. Then we combine the spatial covariance matrix with the modal covariance matrix in a  $\bar{m} \times \bar{g}$ -rank covariance matrix which leads to a Multinomial Probit model of joint mode and route (pair of anchor points) choice. This model can be solved using Gaussian approximation method (Clark's method).

## 5. Conclusion

This work addresses the vast domain of transportation demand modeling and particularly the mode choice problem. Its aim is to improve the mode choice modeling and proceeds through a systemic analysis of the process of mode choice decision-making. We propose a new approach to mode choice modeling within a stochastic disaggregate representation of space. Accounting for variability among disaggregate physical locations in space using a stochastic spatial disaggregate representation, is somehow analogous to using random

coefficients and mixed models to account for variability of individual attributes among travelers. First we concentrate on developing a model for traffic assignment to a monomodal network with stochastic disaggregate representation of trip-ends in space. The model is successfully applied to the highway network of Ile-de-France. Then we undertake the development of a stochastic model of trip-end disaggregation for traffic assignment to a multimodal network. A systematic analysis of the different aspects of traveling in a multimodal transportation network sheds light on a number of major points and raises important questions. A consistent modeling methodology is proposed and its application is demonstrated to an origin-destination pair of zones. Inherent complexities of the public transportation system in the Paris area require that modeling settings are further investigated. Especially, given the inherent unbalance between the catchment radiuses of the feeder modes, optimal identification of anchor points needs to be studied with care. However, the methodology can be applied to regions with simpler public transportation systems, straightforwardly.

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# Introduction

## 1. Context

Transportation demand modeling is the art of transforming knowledge in retrospect of mobility behavior, to knowledge in prospect. Its aim is to understand different aspects of the mobility behavior of individuals through observing mobility patterns and incorporating them into relevant theoretical frameworks. Purposeful movement in space, known as trip, has many different aspects such as time, mode, itinerary and destination. These aspects require assigning proper resources. This is the subject of transportation planning. Demand modeling assists transportation planning by studying parameters and mechanisms that influence travel behavior so that policies can be aimed more effectively and comprehensively.

The behavior of individual agents in their choice of travel mode has been for long considered as the central subject of transportation planning. Nearly all aspects of urban transportation policy making are related to the way trip makers choose between different transportation modes for attending their activities. Planners have promoted the public transportation over private modes, mainly because public transportations have been considered as being more economic, environment friendly, and accessible to all social classes; properties which made them more affordable. Therefore, one major issue in nearly all urban transportation planning strategies has always been to promote a shift towards public modes. Transport modeling constitutes the engineering device, which enables planners to evaluate such strategies quantitatively. The pertinence of the results produced by such models is crucial for the policy making where small shifts in numbers may entail dramatic differences in terms of cost and time.

### 1.1. Demand Modeling Paradigms

Modern transportation modeling is now about half a century old. Travel demand models aim to emulate the outcome of different interacting entities that have an effect on transportation as one sector of urban economics and to establish static or dynamic demand-supply equilibrium. In this regard, on the

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demand side, different modeling paradigms have been developed, which has been aggregate or disaggregate, trip-based or tour/activity-based. The classical trip-based modeling constitutes probably the most classic modeling paradigm, which despite its many drawbacks, continues to remain the main modeling tool for many metropolitan planning organizations. Its endurance and long lasting legacy should be mostly attributed to its systemic and conceptually coherent structure (baptized as four-stage structure) as well as its wide availability of technology and survey data requirements. In the classic aggregate trip-based paradigm, modeling of the travel demand from its genesis at origin until the arrival at destination, is divided into four stages, namely trip generation, trip distribution, mode choice, and traffic assignment. Disaggregate trip-based paradigm has made a great leap forward by introducing new concepts to the classic aggregate paradigm such as demand segmentation, joint choice of mode and destination, hierarchical choice structures, etc.

Trip-based demand modeling remains as the main modeling tool for many metropolitan planning organizations. However, despite its relatively successful role in many planning contexts and effective improvements that it has received, the trip-based demand modeling paradigm is limited by the very hypothesis on which it is founded. One of the major shortcomings of the trip-based modeling paradigm is the choice of “trip” as the fundamental mobility unit. It is considered that travel related decisions are made per trip so that there is no dependence between different trips that one makes during a home-to-home travel episode. This hypothesis could be sustained if the structure of travel episodes is simple enough so that it can be reduced to a two-leg round trip. However the emergence of new life styles have clearly established a need for gaining a better insight on the way travelers reorganize their trips into more complex travel patterns. New approaches should aim at understanding the way individuals respond to ever-increasing demands of economic society under spatial and temporal constraints. Tour-based modeling paradigm offers a new modeling framework by recognizing the tour (i.e. a chain of trips between two successive “home” activities) as the basic element of travel, and activity-based modeling paradigm enhances it by recognizing the constraint daily (or weekly) time budget within which activities should be scheduled.

## 1.2. Traffic Assignment to a Network

The urban transportation supply is represented by a mathematical model of highway and transit networks. The travel demand, once evaluated in the demand modeling stage, is assigned to the transportation networks. The highway and transit network assignment produces traffic volumes on network

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links and level-of-service characteristics, such as travel times, for different routes, at the demand-supply equilibrium state. Assignment models are generally formulated as route choice problems in which different effects are cast into one generalized travel cost (time) and the traveler tends to choose among the alternative routes the one offering the least generalized cost. The economic basis for the network demand-supply equilibrium is known to be established by Wardrop (1952) as what is known as Wardrop's first and second principles, at the early 1950s; theoretical grounds for the highway assignment problem and the formulation of route choice algorithms was worked out towards the end of the same decade by Beckmann et al. (1956) and Dijkstra (1959) (Correa and Stier-Moses, 2011). In transit assignment, the route choice algorithm must deal with extra complexities related to the discrete nature of transit services. It requires incorporating mission frequencies or scheduled time tables, as well as wait and connection times. It has been formulated as an optimization problem to which Spiess and Florian (1989), for instance, suggested a linear programming approach.

Although, the state-of-practice of the demand assignment modeling is still mostly based on those pioneering works, research has been directed towards further exploration of the different underlying hypothesis. In traffic assignment, recent works have been pursued in two major directions. The first line of research deals with fundamental aspects of the network equilibrium (existence and uniqueness) for different generalized cost function forms, in which the travel cost of a link can be as sophisticated as a multivariate non-symmetric nonlinear function of all network traffic volumes; this direction leads to more realistic estimations of travel costs for different origin-destination routes. The second line of research deals with the demand assignment as a route choice problem and aims to understand how travelers perceive route costs and choose among available route alternatives. The problem is approached from two different angles. Firstly, the route alternatives on a traffic or transit network are usually highly inter-correlated; this suggests that the simplest discrete choice framework is not nearly adequate to address the full extents of the traveler's choice behavior and more elaborate models must be employed to deal with complex covariance structures (Cascetta et al., 1996, Ben-Akiva and Bierlaire, 1999). Secondly, the perception of the route travel cost is subject to uncertainties induced from different sources. This suggests that the model must allow and account for variability in the characteristics of the network elements and the attributes of the traveler (Dial, 1971, Maher, 1992, Maher and Hughes, 1997). In transit assignment, recent researches consider multimodal viable paths, capacity constraints, access to transit, etc.

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### 1.3. Zoning System: a Representation of Space

Spatial representation of the urban space is usually based on a discretization of the continuum space into traffic analysis zones. In the discrete urban space, each zone is associated with a centroid, which is usually its geometric center. Centroids are connected to the highway or transit network by a number of dummy links called connectors, which provides the connection between the intrazonal demand and the interzonal network. On the transportation demand side, this implies that the demand is represented in a lumped zone-to-zone way. On the transportation supply side, this implies that the intrazonal transportation network is poorly coded or even completely neglected and replaced by a fictive link which does not belong to the real network. Highway or transit networks are accessed from zone centroids and through connectors.

Unlike other modeling aspects, mentioned earlier in this introduction, the model representation of space by a centroid-connector system has not changed during last several decades. Theoretical developments aimed at providing a continuum representation of space have been carried out (Daganzo, 1980a, 1980b), but seldom incorporated in a consistent modeling framework.

## 2. Problem Statement

Firstly, although the centroid-based system has proven an effective modeling approach at *regional* scale, and has withstood the test of time, it is inadequate as it ignores the physical variability due to the scatteredness of residence- and activity-places over *local* space. As a result, the performance of the models degrades in explaining travel behavior at local scales. One practical solution to the problem is to remesh and refine large traffic analysis zones locally where required. Nevertheless this solution is inefficient, because the spatial variability is still being ignored though at a smaller scale, and inconsistent, because connectivity between trip-ends and the network is established using dummy links known as connectors that are not part of the real network.

Secondly, with an aggregate spatial representation, the precision of mode choice sets is limited. This is especially important for transit modes. In suburbs, intrazonal bus is primarily used as a feeding mode for the regional train. Besides, travelers may prefer to walk to the transit station or use a bike or automobile. As a result, travelers' choice set differs depending on their intrazonal location. Those who are near the regional transit station may prefer to walk whereas those living further but at the proximity of a bus stop may take the bus or use a bike. Centroid-based model is inherently incapable of addressing such behaviors.

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Abundant research work has focused on improving the mode choice model specification, and the network assignment algorithms. However, the association between intrazonal demand and interzonal network, and its consequent effects on mode choice requires a combined framework to address the effect of disaggregate intrazonal location on (1) the perception of terminal travel time, and (2) the choice of access/egress feeder modes and formation of multimodal itineraries. In the literature of travel demand modeling, each of these two problems is addressed separately, but the combination of the both is rarely studied.

### 3. Objectives

We aim to ameliorate the mode choice modeling in the urban context. We particularly focus on three main objectives:

- Emphasizing on the place of the home-to-work demand segment and recognizing its structuring effect on travel patterns in Ile-de-France: we proceed using a tour-based approach and compare it to a trips-based one, so as to improve the representativeness of the model and to demonstrate the significant change in mobility patterns. A tour-based approach enables us to capture secondary purpose trips being chained within primary purpose tours.
- Improving spatial representation in the traffic assignment stage as well by recognizing the variability of intrazonal diffusion times and providing a disaggregate representation of terminal travel sections. We introduce a stochastic framework to account for the scatteredness of intrazonal locations.
- Econometric estimation of mode choice models in a multimodal framework with two categories of motorized modes (auto and transit), provided a stochastic disaggregate representation of space and an improved choice set identification.

### 4. Methodology

We address the stated objectives by a twofold physical and behavioral approach. On the physical side, we develop a stochastic framework for disaggregate representation of locations in space. This in turn improves the evaluation of level-of-service characteristics and provides a more consistent framework for representing the choice context in which the individual makes travel decisions. On the behavioral side, we adopt the random utility

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framework to analyze the mode choice behavior of travelers. We improve the mode choice modeling by:

- using an disaggregate representation of traveler’s local situation, which helps to identify local mode choice sets more accurately;
- adopting an explicit representation of modal access, main, and egress legs in complex multimodal itineraries, which helps to specify composite mode alternatives more consistently.

An extensive review of transportation demand modeling paradigms will provide a global vision on how the objectives of this dissertation are addressed in different demand modeling paradigms, and in the state-of-the-art. Subsequent literature reviews at the beginning of each chapter help to nourish the discussion and treatment of the subject.

Statistical analysis methods are employed to analyze data from the reference stated-preferences survey. Detailed GIS maps with street level precision are used for a satisfactory disaggregate treatment of trip-ends in space.

Extensive programming is carried out in different phases of this dissertation. In many occasions, especially for the implementation of numerical algorithms, direct programming is preferred, as it provides more efficiency, flexibility, repeatability, and control. Fortran 90/95 is used for the final implementation of numerical algorithms. MATLAB scripts are used in the predevelopment stage for testing and benchmarking. SAS scripts are used for statistical and econometric analysis. GISDK<sup>1</sup> scripts are used to implement GIS applications in TransCAD.

## 5. Outline

The dissertation is organized in three parts and eight chapters. The first part entitled “*Review of literature and analysis of mobility*” aims to give a wide snapshot of the transportation demand modeling. This part is concluded with an analysis of mobility in Ile-de-France.

Chapter 1 provides an extensive literature review of the travel demand modeling paradigms; from the classic aggregate four-step models up to the state-of-the-art disaggregate activity-based models. Main building blocks of the state-of-the-art demand modeling paradigms are discussed. We also study the more classic and conventional modeling paradigms for two reasons: (1) To understand the underlying motivations which have driven the evolution of the modeling paradigms over the last several decades. (2) Because classic

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<sup>1</sup> Caliper’s Geographic Information System Development Kit

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modeling paradigms are still being used in applied modeling. This study shows that new demand modeling paradigms have mostly been concerned with providing a better representation of the transportation demand. Demand segmentation in disaggregate models has increased the explanatory power of the models by dividing the transportation demand into “homogeneous” subcategories, in order to capture a greater portion of the total variability of the main explanatory variables in the model. Recognizing travel tour or chain of activities instead of single trip as the fundamental unit of travel in tour/activity-based models has improved models’ ability to comprehend travel patterns and choice behaviors robustly. However, in nearly all of these models, the representation of the modeling area has been based on a discrete zoning system. The zoning system is associated with a corresponding centripetal system of centroids that represent origins and destinations of all trips.

Chapter 2 focuses on the transportation models used in Ile-de-France and in other French metropolitan areas. This review aims to put in context the general literature review presented in the first chapter.

Chapter 3 provides an analysis of mobility in Ile-de-France according to the 2001 Paris Household Travel Survey. It completes the literature review of the first chapter, by providing an empirical basis for comparing trip-based and tour-based analysis of mobility patterns. It does a general observation of the different aspects of individual travels in terms of purpose, pattern and mode as well as duration and distance, and provides the empirical basis for demand segmentation. It emphasizes on the structuring effect of the work purpose on the daily activity program of individuals.

The second part entitled “*Disaggregation of trips-ends in a traffic assignment model*” develops a stochastic spatial framework allowing us to incorporate the variability due to the scatteredness of trip-ends in space in traffic assignment to a highway network. It consists of three chapters:

Chapter 4 lays out a stochastic framework for representing locations in a two-dimensional space, and explores statistical aspects of such a representation. We view all of the trips made within a modeling area, as one statistical population. Then we suggest that origin-destination pairs of zones constitute statistical classes that contain trips; a given trip belongs to the one origin-destination class that contains its departure-end at origin and its arrival-end at destination. In a disaggregate representation of space, variability of trip-end locations in space leads to the variability of level-of-service characteristics within each origin-destination class. We suppose that trip-ends are randomly distributed in space. As a result, a level-of-service characteristic such as travel time within a given origin-destination class is represented by a random

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variable which is characterized by a mean and a variance. The mean value corresponds to the time of travel between the two centroids of the origin-destination pair of zones. The variance captures the variability of trip-ends within the origin-destination class.

According to the law of total variance, the total variance of travel time within the population of all trips can be decomposed in terms of intra-class and interclass variances. In conventional models with an aggregate representation of space, travel time for all trips within a given origin-destination class is considered to be the same and equal to the time of travel between the two centroids of the origin and destination zones. This means that all intra-class information on disaggregate trip-end locations is lost. Therefore, in order to maximize the efficiency of a zoning system, one should try to minimize the intra-class portion of the total variance. This by the way defines a criterion for optimal zoning system design.

Chapter 5 develops a stochastic model for traffic assignment to a highway network based on the disaggregate representation of trip-ends. In this chapter, we first introduce the concept of “anchor point”. An anchor point is defined as a high capacity node that drains the intrazonal traffic demand and injects it to the highway network. It can be the point of intersection between two major highways or major avenues, or the end of a highway connected to a number of local streets. Then we assume that an itinerary can be decomposed into three legs: an access leg from the departure point to an anchor point at the zone of origin, a main leg between the origin anchor point and an anchor point at the zone of destination, and an egress leg from the destination anchor point to the arrival point. Therefore, the route choice problem is mathematically equivalent to the choice of a pair of anchor points, one at origin and one at destination.

We illustrate these concepts by studying an idealized two-level rectilinear network. The network is formed by superposing a coarse mesh of regional high-speed links over a fine mesh of local low-speed links. A regular rectangular zoning system is used where high-speed links define zone boundaries. Anchor points are placed at intersection points between high-speed links. It is assumed that departure and arrival points are uniformly distributed over the rectangular zones. A deterministic disaggregate solution for this idealized network is provided. Then, we aggregate by supposing that the travel times of access and egress legs are random variables. It is assumed that the vector of intrazonal travel times follow a Multivariate Normal distribution. Results from the deterministic and stochastic solutions are compared for the idealized network and found consistent. Then we develop a

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stochastic trip-end disaggregation assignment model for the general case of highway networks.

Chapter 6 reports results from the application of the stochastic assignment model to the Paris standard highway network.

The third part of the dissertation entitled “*Towards a disaggregate treatment of trip-ends in mode choice*” extends the stochastic trip-end disaggregation framework to a multimodal framework. It includes two chapters:

Chapter 7 studies the mode choice problem in by identifying the auto mode and the bundle of multimodal public transportation alternatives. We follow a typical itinerary from a disaggregate point of view and study its structure. The auto mode is identified as an immediately available mode. Public modes on the other hand are identified to be compositions of three modal legs: an access leg (from the departure point to a transit station), a main transit leg (from the access transit station near origin to an egress transit station near destination) and an egress leg (from the egress station to the arrival point). Each modal leg corresponds to a physical section of the itinerary associated with a mode. Therefore different mode chains can be formed by combining different available access, main and egress modes. For example, an Auto-Train-Walk mode corresponds to an itinerary where the traveler uses Auto to reach a transit station, which in turn gives access to a train service and walks from the alighting station to the final destination. We study observed transit mode chains according to the 2001 Paris Household Travel Survey and use the consequent analysis as a basis for specifying the mode choice model.

Two different identification schemes are proposed for the transit alternatives. In the first identification scheme, three access modes (walk, bike, auto) are combined with seven main transit composite modes, and only one egress mode (walk). In the second identification scheme, bus is also considered as a possible feeder mode. Four access modes (walk, bus, bike, auto) are combined with the same seven main transit composite modes, and two egress modes (walk, bus). Then the multimodal mode choice model is combined with the stochastic trip-end representation to obtain a stochastic model of trip-end disaggregation for traffic assignment to a multimodal network.

Chapter 8 reports an application to the Greater Paris area. It first reports simulation results for the two mode choice identification schemes. Then it reports estimation results of mode choice model specifications. At the end, it presents a limited application of the stochastic multimodal assignment model.

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# PART I

## Review of Literature and Analysis of Mobility

# Chapter 1: Transportation Demand Modeling: A State of the Art



## 1. Introduction

This chapter provides a review of different paradigms that have been introduced to travel demand modeling. We start by mostly conventional models, which are aggregate and descriptive, and develop our discussion towards more advanced transportation demand models and will briefly cover land use transport interaction models.

Classic trip-based demand models have been used and explored for a long period of time and are supported by a significant body of literature. Therefore, the concern of this dissertation is not to replace a textbook in providing exhaustive descriptions of these models in a historic context. Instead, we will try to provide a synthesis of conceptual developments of different demand modeling paradigms. This will serve as an overture towards the-state-of-the-art models, i.e., tour- and activity-based paradigms.

### 1.1. Direct Demand Models

Direct demand models constitute probably the most primitive of travel demand modeling paradigms. In these models, the estimation of demand volume, distribution of the demand in space, and choice of travel mode are combined in one single functional form. These models have been developed in the 1960s, and became obsolete during the 1970s and early 1980s, but they regained some attention during the 1990s (Ortúzar and Willumsen, 2001).

#### 1.1.1. Model Functional Form

One specification, for example, estimates demand as a multiplicative function of activity and socioeconomic variables for each pair of zones, giving the level-of-service characteristics of the modes serving them. The amount of travel between origin  $i$  and destination  $j$  by mode  $k$  is:

$$T_{ijk} = \phi Y_{ik} Z_{jk} \prod_m L_{ijm} \quad (1.1)$$

where,  $\phi$  is a scale parameter,  $Y$  and  $Z$  represent activity and socioeconomic variables of origin and destination zones, and  $L$  represents level of service attributes of available modes. One may choose population and income as explanatory attributes and travel time and cost as level-of-service characteristics and specify the above direct demand function in the following way (see, Ortúzar and Willumsen, 2001, pp. 211–215):

$$Y_{ik} = P_i^{\theta_{k1}} I_i^{\theta_{k2}} \quad (1.2)$$

$$Z_{jk} = P_j^{\theta_{k1}} I_j^{\theta_{k2}} \quad (1.3)$$

$$L_{ijm} = t_{ijm}^{\alpha_{km1}} c_{ijm}^{\alpha_{km2}} \quad (1.4)$$

Here, only one functional form dictates the entire decision-making process, which is probably too much to ask from one equation. This has two consequences:

On one hand, the model is hard to control. More recent conventional demand forecasting models are based on a rational separation of naturally independent tasks. Therefore trip generation, trip distribution, mode choice, etc. are recognized as independent tasks, which constitute different steps of a demand-forecasting model. These steps are assembled in a successive manner and feedbacks are sometimes provided to improve results of a preceding step based on outcomes of a succeeding step. This separation of tasks allows a better understanding of the role of each procedure and provides a better control over each step as well as the whole model system.

On the other hand, the functional form does not allow incorporating more than a few parameters, that is, whatever the functional form specification is, it is not feasible to incorporate more than two or three explanatory variables and level-of-service characteristics, meaningfully. This may limit the use of direct demand models to cases where a few variables are capable of sufficiently explaining observations. This is probably the reason why direct demand models are mostly used in inter-urban contexts.

Despite these shortcomings, the possibility to adopt arbitrary functional forms in direct demand models has been appreciated. Talvitie (1973) reports a successful implementation of a direct demand model for work trips in the Chicago Central Business District with auto, bus and rail as available modes. In this study, constraints are imposed to make sure that model obeys intuitive signs for direct- and cross-elasticities whilst “conventional models do not provide estimates on travel demand elasticities”. Wardman (1997) uses a direct demand model in an inter-urban context and considers different functional forms to analyze elasticity variations and to examine the interaction between rail, bus and car. Four functional forms have been used regarding their ability to examine two sources of elasticity variation: the competitive position and the level the variable takes. This research particularly points out that the performance of direct demand models in evaluating elasticities surpasses the conventional four-step models. Anderson

et al. (2006) report a successful use of a direct demand model in Anniston, Alabama based on demand segmentation and conclude that these models can be regarded as efficient as conventional four-step models in small urban communities, probably where data availability issues may limit the efficiency of the conventional modeling paradigm.

### 1.1.2. Summary on Direct Demand Models

In its core, direct demand modeling paradigm is nothing more than a set of regressions of a functional form that relate observed demand to explanatory parameters. Although this modeling approach probably was a successful debut to demand modeling, it has several major drawbacks.

Firstly, direct demand models are purely descriptive in the sense that they do not incorporate elements of individual decision-making behavior. Here, a functional form is estimated over a database of observations but it misses the behavioral point of view provided in random utility theory.

Secondly, as discussed in the preceding section, the fact that one functional form dictates everything deteriorates model transferability and makes difficult to adapt the model to various case scenarios, flexibly.

Thirdly, direct demand models do not explicitly account for space. In other words, the interaction between travel demand and space as the physical entity that contains both land use and transportation network is not explicitly accounted for. For example, Talvitie (1973) studies work trips between non-CBD and CBD areas in Chicago. In this typical study it is clear that no discretization of space is done, and for instance, non-CBD areas does not refer to a zone of which land use attributes and network accessibility characteristics can be estimated. As we have mentioned earlier, many applications of direct demand models are in inter-urban context where origin and destination zones refer to regions sometimes as big as an entire city.

Direct demand models have been able to outperform conventional four-step paradigm in some aspects. Further control over functional form is one of these advantages. However, direct demand modeling paradigm was ephemeral and was soon replaced by more efficient versions of the conventional approach. The task-specialized modular structure of four-step models provides more control over different modeling steps and at the same time allows ameliorating each step without interfering with other steps. Generally, this is not the case with direct demand models, where everything is tied up within one functional form and no direct control is possible over different modeling steps.

Nevertheless, direct demand models remain an attractive alternative, in particular, in areas where zones are large and far apart as is the case in inter-urban contexts. In addition, Ortúzar and Willumsen (2001) after [Timberlake, R. S. (1988). Traffic modeling techniques for the developing world: case studies. Transportation Research Record 1167:28-34] report that in developing countries direct demand models are better than conventional four-step approaches where, for example, car availability and income override significantly other eventual explanatory variables in determining mode choice.

## 1.2. Explicit Representation of Space

In transportation modeling, space is the entity that contains both land-use attributes and transportation network. Land-use attributes such as population, number of employment opportunities, number of services, etc. are considered having a global effect on the transportation demand. Transportation networks including highways and public transportation networks represent the transportation supply. Both land-use and network availability vary over space and a transportation model is effective to the extent that it is capable of taking into account these variations. A model's capability of explicitly representing variations of land-use attributes and level-of-service characteristics in space is one of the principal factors that determine the extent to which a transportation model is successful as an aide for transportation planning. Because, it is only by manipulating such elements that a transportation policy can expect to influence the behavior of rational traveler who responds only to changes that tend to increase his perceived utility.

Conventionally, model space is discretized into a finite number of traffic analysis zones. Such a discrete representation of space, allows for take into account of the variation of land-use attributes among zone. In addition, each zone represents its local travel demand and acts as a catchment area for network nodes that it contains. Designing a zoning system is however a subtle task because the size and the shape of the zone should be adapted to the area it represents. Especially sparse areas with non-uniform distribution of population and low density of transportation network should be treated carefully.

In a conventional four-step model, land-use attributes are mainly involved in trip generation step. Trip productions and absorptions per trip purpose are usually calculated based on these attributes. This is also feasible in previously introduced direct demand models as the general functional form allows a few land-use attributes to be incorporated. The representation of the

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transportation supply network is more crucial as it affects three subsequent steps. Trip distribution uses interzonal impedances which are calculated based on generalized travel times (or costs) provided by transportation networks. Mode choice step incorporates level-of-service characteristics provided by transportation network. Finally, assignment step is where transportation supply is represented in the most explicit way.

### 1.2.1. Discretization of Space

Urban geographical space is a continuum offering different opportunities in different locations. However for analysis purposes, it is often more convenient to use a discrete representation of space in which traffic analysis zones are considered as fundamental elements defining the spatial representation within the modeling system. Consequently, because characteristics of transportation demand and supply are lumped on zone centroids, the spatial precision of the model is limited by the size and the geography of zones. Reasons for this are in three different categories:

- Land-use data are often provided at precise spatial scales. However, several land units offering similar uses can be regrouped to major attraction centers such as business districts, shopping centers, natural and recreational spaces, etc. It is, depending upon the case, beyond system analyst's interest to study precise interactions inside, for example, a business district.
- Transportation networks are represented with a certain level of detailing. Although, it may look affordable to represent every public transportation mission, it is not feasible, either mechanically or computationally, to represent every single street in the road transportation network. Assuming that each traffic zone should contain at least one access/egress point to be appropriately connected, the transportation supply representation, limits the precision of model system spatial representation.
- Policies are made to be effective within administrative borders and decisions made at one district do not dictate actions in another. Analyst should be able to provide decision makers with information such as the number of daily trips in and out of the region, respective part of different trip purposes, and transportation mode choices.

These arguments not only explain the need for spatial discretization, they also imply criteria to fulfill in order to obtain a conceptually correct discrete spatial representation.

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Probably, the first decision to make concerns the spatial precision. If the individual needs, on one hand, and service opportunities, on the other hand, were distributed uniformly over space, there was no need to make any trip. In other words, trip generation is a direct result of the spatial heterogeneity of land-use attributes which motivates individuals to move across the land to satisfy their desires. Nevertheless, discretization via lumping attributes and characteristics on zone centroids tends to eliminate variations inside the zone and to replace them with zone-level averages. Therefore, the most important dilemma to which the analyst should respond is how to maintain the maximum of this heterogeneity in the discrete system.

The bigger is the zone size, the more would be the information loss. This is because in bigger zones averaging operator is applied over wider spans. Consequently, bigger zone sizes can be used in rural or less developed regions where less variation occur over long distances but in central zones where activities and service are dense one should decrease the scale. In statistic terms, to each zoning system can be attributed a variance threshold, defining the maximum level of admissible variation of different characteristics within each zone in the zoning system. Coarser zoning systems contain greater variances, and vice versa.

Try should be made in order to separate explicitly lands with fundamentally different uses. In other words, it is better to regroup lands that already demonstrate less variation. This will reduce the total variance within each zone and will promote specialized zones with distinct principal occupations.

A zone centroid should not necessarily be situated at the geometric center of the shape. It rather should be placed close to populated areas where activities take place. Figure 1.1 shows a case where geometric center of zone is located in some unoccupied lands. Clearly, a dense road network at the west side of the zone and a road passing through the east side are completely neglected. It is unrealistic to consider that transportation network will serve central rural areas instead of three nearby concentrations of built areas. Using long connectors to relate these built areas to the geometric centroid can entail very unrealistic end travel times. A better solution in such cases is either to scissor the original zone to several smaller zones or to define more centroids and locate them appropriately over built areas.

The level of precision of the transportation network also influences spatial discretization. Travel demand at origin zones enters the transportation network via access nodes to reach destination zones. Zone centroids are connected to the transportation network access and egress nodes via

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connectors to allow the lumped travel demand flow over the network. It is convenient to have at least a few network nodes inside each zone.

Finally administrative border should be respected in order to, first, distinguish between district where traffic policies and decision making priorities are different and, second, provide each district with proper statistics on which the administrations have an influence.

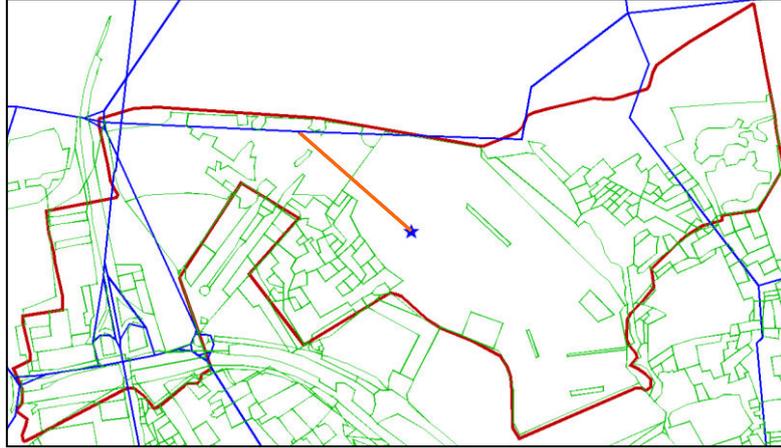


Figure 1.1. Distinct built area concentrations within a geographical zone.

### 1.2.2. Modeling Implications of Discrete Space

In aggregate modeling, lumping zonal travel demand on zone centroids means that the actual origin or destination location of trip is unknown. All travelers are supposed to depart from a centroid point and arrive at another one. Therefore, the model has no information about endpoint trajectories. This induces some level of uncertainty over basic trip characteristics such as travel time or travel distance. Although over long distances, this uncertainty may seem negligible, it becomes considerable over relatively short distances, which occupy an important portion of the total travel demand. In disaggregate modeling travel distances are calculated from point to point. That is, given exact origin and destination blocks, nearest network nodes at origin and destination are considered as access and egress nodes. Depending upon the resolution of the network, there will be a gap between recorded departure and arrival locations and actual network nodes. Let us consider a typical generalized cost function for a trip by car as follows:

$$GC_{od}^{auto} = C^{auto} + f_T t_{od} + f_C d_{od} + f_P C_p, t_p \quad (1.5)$$

where  $C^{auto}$  represents the constant cost of using an automobile (i.e. the amortized cost of acquiring an automobile),  $f_T t_{od}$  represents the generalized

cost of the net travel time,  $f_C d_{od}$  represents the vehicle consumption and depreciation costs as a function of travel distance, and  $f_P C_p, t_p$  represents the generalized cost due to parking, which consists of a constant parking cost and a monetary equivalent of parking place search time. Zoning introduces variations in travel time and travel distance:

$$f_T \cdot = \beta t \quad ; \quad t = \tau + \theta + \tau' \quad (1.6)$$

$$f_C \cdot = \gamma l \quad ; \quad l = \rho + \lambda + \rho' \quad (1.7)$$

Where  $\tau$  is the time between the departure point and network access node,  $\theta$  is the time of travel on the road network between access and egress nodes, and  $\tau'$  is the time between network egress node and the arrival point. Similarly,  $\rho$ ,  $\lambda$  and  $\rho'$  are access, main, and egress travel distances.

In aggregate model systems, all endpoints are located at centroids, as the model is considered unaware of the interior of zones. As a result, for all trips between a given origin-destination pair, travel times and distances are the same and equal to the centroid-to-centroid travel time and distance. In order to illustrate the loss of information due to the spatial aggregation we define three centroid-to-centroid distance categories and evaluate the variance of different components of the travel time. For each distances category four zone pairs with maximum number of observed trips have been chosen. Using observations from the 2001 Paris Household Travel Survey, we first evaluate the order of magnitude of the unknown end-point distance. Then we measure its variation within zone by calculating its variance and standard deviation. We use the standard zoning system and highway network for the Greater Paris area provided by DRIEA which is composed of 1277 (Figure 1.2).

In suburbs, the density of population and services is less than in the central areas. As a result, road networks become sparser and zone sizes increase. This should affect peripheral zones in two distinct ways: On one hand, bigger zone size and less number of network nodes means that distances between access/egress nodes and departure/arrival points are distributed over wider ranges; this should increase uncertainty at endpoints. On the other hand, as the number of available network access/egress nodes inside peripheral zones decreases, more trips will be connected to the same access/egress points and will take the same itinerary on the network; this should decrease the uncertainty due to the main section of itinerary.

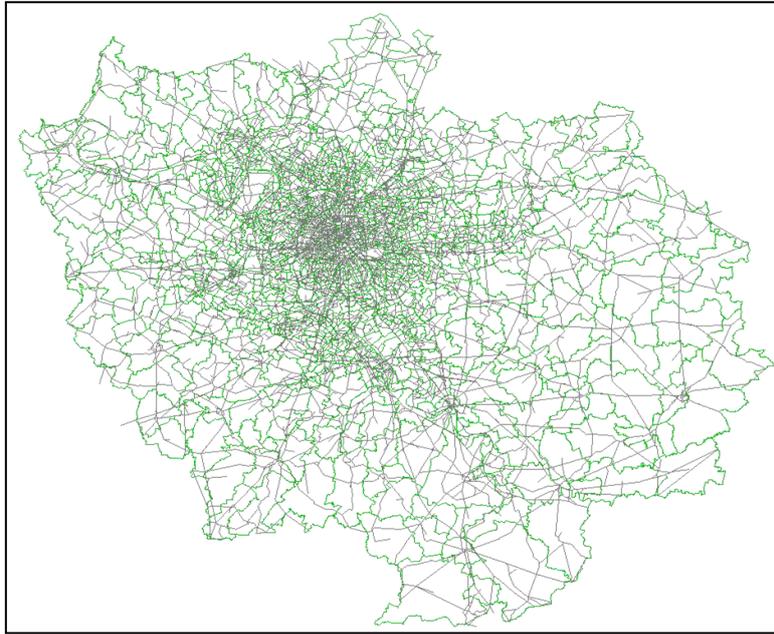
Two statistical indicators are defined to analyze results and to observe the two aforementioned trends: The first indicator measures the ratio of the total intrazonal variance to the total variance:

$$S_1 = \frac{\text{var } \rho + \text{var } \rho'}{\text{var } \rho + \text{var } \lambda + \text{var } \rho'} \quad (1.8)$$

The second indicator measures the ratio of the sum of the standard deviations of intrazonal distance at origin and destination to the characteristic interzonal distance:

$$S_2 = \frac{[\text{var } \rho]^{1/2} + [\text{var } \rho']^{1/2}}{L_c} \quad (1.9)$$

where  $L_c$  is the characteristic interzonal distance class. In this example, it will assume one of the following values: 2 Km, 5 Km or 15 Km.



**Figure 1.2. Road network and zoning system of the greater Paris region (DRIEA, 2008).**

Table 1.1 shows variances at endpoints and over the main section of itineraries used between two zones as well as the value of the two statistical indicators. According to these results, in average, the intrazonal variance is about 8% of the total variance over 2 Km distance class, and 10% over the 5 Km distance class, where zone sizes are relatively small and network is relatively dense. The ratio increases to about 35% for the 15 Km distance

class. On the other hand, the ratio between the standard deviation of the intra zonal distance and the characteristic distance shows a clear decrease over longer characteristic distances. The average of the  $I_2$  indicator varies from 25% for the 2 Km distance class to about 20% for the 5 Km and 15 Km distance classes. These indicate the relative loss of information due to spatial aggregation to the zone level.

**Table 1.1. Total variance components for different travel distance categories.**

Distance Category	Number of Observations	Zone Size (Km <sup>2</sup> )		End Section Variance (Km <sup>2</sup> )		Main Section Variance (Km <sup>2</sup> )		$S_1$	$S_2$
2 Km	9	3.58	1.47	0.185	0.102	0.96	23.0%	37.5%	
	8	1.14	1.28	0.033	0.029	1.85	3.2%	17.6%	
	14	2.08	1.23	0.001	0.069	0.81	8.0%	14.7%	
	9	1.07	3.65	0.160	0.059	3.25	6.3%	32.1%	
5 Km	13	1.77	5.14	0.097	0.339	3.85	10.2%	17.9%	
	14	5.14	1.77	0.085	0.190	3.28	7.7%	14.5%	
	8	9.28	7.08	0.244	0.310	4.57	10.8%	21.0%	
	10	7.08	9.28	0.288	0.359	4.82	11.8%	22.7%	
15 Km	9	73.4	61.5	3.178	0.204	13.36	20.2%	14.9%	
	21	61.5	27.9	0.572	9.644	3.42	74.9%	25.7%	
	11	9.42	44.3	3.442	0.326	15.36	19.7%	16.2%	
	10	44.3	48.3	1.720	5.695	14.11	34.4%	24.7%	

Variances shown in Table 1.1 are indeed uncertainties caused by space discretization. In disaggregate trip assignment, given a complete road network, variances for each trip are limited to errors generated at the endpoints as each trip is free to choose its “true itinerary” once the traveler accessed the network. In aggregate trip assignment, on the other hand, variances are much higher. This is because all direct itineraries are in fact mistaken by the centroid-to-centroid shortest path; therefore, the main section of the itinerary becomes uncertain itself.

## 2. Trip-Based Modeling: Aggregate Approach

The earliest travel demand models are trip-based. In this paradigm, there is independence between trips and the individual trip is considered as the basic element of modeling. The trip-based approach is generally implemented based

on a four-step structure. This structure is in effect a result from practice in the 1960s but has remained more or less unaltered despite major improvements in modeling techniques ever since (Ortúzar and Willumsen, 2001). The classic model is presented as a sequence of four sub-models: trip generation, trip distribution, mode split and trip assignment.

## 2.1. Model Structure

The four-step model is the primary applied tool for forecasting future demand and the performance of regional transportation systems. Initially developed for evaluating large-scale infrastructure projects, it is policy sensitive with regard to alternative arrangements of major capacity improvements. It has not been effectively applied for policies involving management and control of existing infrastructures, and for the evaluation of restrictive policies involving demand management.

The four-step framework posits trips as the fundamental unit of analysis, and then aggregates trips into generation ends and attraction ends. The temporal dimension enters in an ad-hoc fashion, typically introduced after trip distribution or mode choice where the production-attraction tables are factored to reflect observed distributions in defined periods. In most applications, equilibrium concepts are first introduced in the route choice step, with informal feedback to prior stages.

The sequence of submodels in a four-step model reflects an assumption about the order in which decisions involving different choice dimensions are made, and therefore about how these decisions influence each other. For instance, the structure described above and shown in Figure 1.3 implies that destination choice depends only on trip generation and the choice of the trip frequency, whereas mode choice depends on both destination and trip making frequency. In other words, the decision-maker first chooses the trip destination from among all the available zones, then the travel mode from among all modes available for the chosen destination. Clearly, other submodel hierarchies are also possible. For example, a traveler willing to make a grocery shopping is more likely to give priority to the choice of the automobile as transportation mode due to the considerable weight of goods that need to be transported. Any sequence should be carefully reviewed in the calibration phase and compared with reasonable alternatives, in order to determine the one that better matches observations (Cascetta, 2009).

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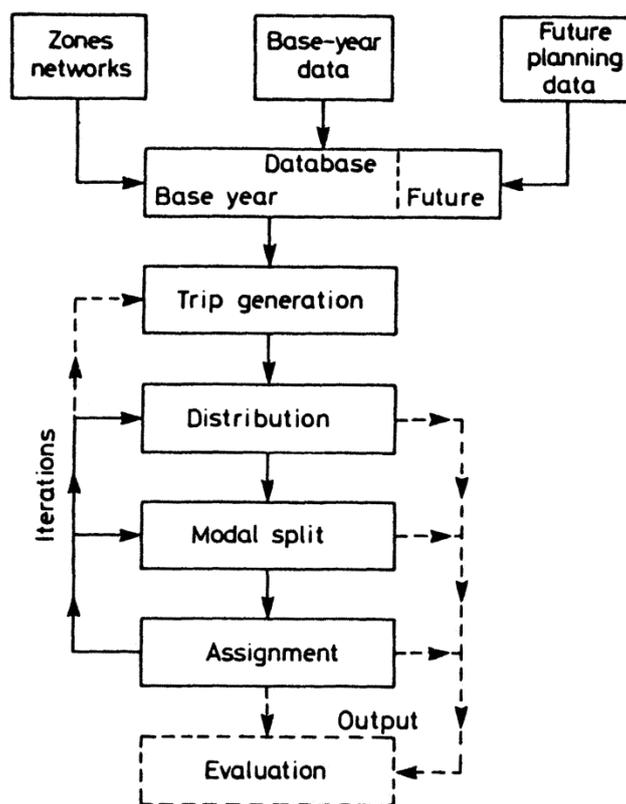


Figure 1.3. Classic four-step model structure (Ortúzar and Willumsen, 2001).

### 2.1.1. Trip Generation

The first step, trip generation, defines the intensity of travel demand (frequency by trip purpose). In this step, total number of trip production and attraction for each zone is estimated independently for each trip purpose as functions of land use and socio-demographic attributes.

With structural absence of feedback to this stage, overall travel demand remains fixed and essentially independent of the transportation system. The production and attraction ends of each trip are split and aggregated, and parameters are estimated via independent models. Generation essentially defines total travel in the region and the remaining steps are effectively share models.

### 2.1.2. Trip Distribution

In the second step, trip distribution, generated trips are distributed in proportion to the estimated attraction distribution and estimates of travel impedance (time or generalized cost) among zones, yielding trip tables of person-trip demand. In the aggregate trip-based models, the trip distribution is usually based on gravity models:

$$T_{ij} = \frac{E_i A_j}{l_{ij}^\beta} \quad (1.10)$$

where  $T_{ij}$  is the traffic from zone  $i$  to zone  $j$ ,  $E_i$  is the traffic emission from zone  $i$ ,  $A_j$  is the traffic attraction in zone  $j$ ,  $\beta$  is the model parameter to be estimated, and  $l_{ij}$  is an impedance measure. It is oftentimes the case that impedance measures are calculated based on auto travel times only. However, some recent models use advanced measures, such as the logsum of the utility of different available modes.

It is nearly always the case that after the application of the gravity model, and due to its rigid mathematical form, the sum of the flows that a zone emits or attracts does not match with the total emission and attraction volumes estimated in the trip generation step. In response to this problem, trip distribution models are also characterized as singly- or doubly-constrained. A distribution model is considered “constrained” if it makes sure that the sum of distributed flows at one or both of the emission and attraction ends are equal to the total emission and attraction volumes predicted by the trip generation step. They run iterative redistribution procedures that marginally modify original values and progressively improve the consistency between the generation and distribution steps.

### 2.1.3. Mode Choice

In the third step, mode choice, trip tables are essentially factored to reflect relative proportions of trips by alternative modes. The mode choice is often the only step of the model where random utility theory is employed to determine the choice of transportation mode. Each transportation mode is associated with a utility function mostly composed of level-of-service characteristics (e.g., travel time) and land-use attributes (e.g., number of parking places at destination zone). Personal attributes cannot be effectively incorporated due to the aggregate treatment of the transportation demand and lack of demand segmentation.

### 2.1.4. Trip Assignment

Trip assignment is the last step where road and public transportation demand are distributed over corresponding networks. Conventionally, the method used for trip assignment is all-or-nothing. This means that every link or public transport service is considered to have an infinite capacity so that demands from different origin-destinations passing over the same network link are

superposed. An implication of this algorithm is that where there exist two itineraries between origin and destination zones, the one with less travel time will be always more attractive, regardless to its actual traffic load.

In reality, one expects that the shortest itinerary gradually becomes less attractive due to congestion problems. Therefore, trip assignment models were developed to take into account the effect of capacity by actualizing link travel time as a function of traffic load and establish an “equilibrium” state. These developments were done predominantly for road transportation networks. Recent works are considering public transportation networks as well.

## 2.2. Summary on the Aggregate Trip-Based Modeling Paradigm

The weaknesses and limitations of trip-based models have been discussed by many authors. Domencich and McFadden (1975) present one of the relatively early critiques of the conventional trip-based paradigm. They mention that these models are non-behavioral and that they replicate the results of conditions existing at the time of the survey and provide little or no guidance to the effects on travel decisions of changes in travelers’ circumstances or in the transportation environment. Also they emphasis on the important issue that except for mode choice step, the models are basically not policy oriented, i.e., the effects of the variables which policy-makers are able to control are excluded from the trip generation and attraction functions and, at best, are applied in the trip distribution step, to a limited extend. Therefore, there is essentially no interaction between system performance and the choice of trip frequency or trip destination. Finally, they mention that these models are based on data representing zonal aggregates of trips and socioeconomic conditions. This obscures much of the information in the data, and together with the lack of a behavioral structure, makes the models very difficult to generalize from city to city.

Efforts have been made to make these models behavioral and policy responsive. Despite these efforts, the trip-based paradigm cannot break itself of its basic limitations due to the aggregate predictive tool at its very core. The basic argument is that people travel, not zones, and by averaging to the level of the zones, much of the information is lost and the aggregation bias is significant (Walker, 2005).

As McNally (2000) mentions, “... trying to infer underlying behavior from the observation of only trips is somewhat akin to trying to understand the behavior of an octopus by examining only the individual tentacles ...”. Travel is one of many attributes of an activity. In conventional trip-based approach,

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activity attributes such as the mode used and travel time consumed in accessing an activity are treated as travel attributes and are the focus of descriptive and predictive models, with most other activity attributes besides activity type being ignored.

### 3. Trip-Based Modeling: Disaggregate Approach

Since the 1970s, it was known that conventional aggregate demand models were subjected to increasing criticism due to their lack of responsiveness to many of issues in transportation planning and policymaking. As it was discussed in the last section, this was essentially because of the very nature of aggregation. The use of aggregate data implies an averaging over the individual decision-makers within the aggregation unit, i.e., traffic analysis zone, which in turn will result in a major loss of variability among individuals in the model representation. In addition, the use of aggregate models also increases the risk of what is called ecological fallacy which means the occurrence of non-causal correlation between variables (for more discussion, see Richards, 1974).

Disaggregate trip based paradigm follows the same general four-step procedure that has been studied in the preceding section but the way the demand is treated is fundamentally different. Whilst in the conventional aggregate models, demand is treated at the zone level, in disaggregate models demand is viewed as being composed of various population segments that show differences in their travel behavior. The idea is that individuals travel not zones therefore travel behavior should be modeled at individual's level. In this section, our goal is to understand what makes a trip-based model "disaggregate". Consistent theoretical base of disaggregate models, derived from the postulates of consumer rationality and utility maximization, has allowed them a claim to generality (Dunne, 1985). We will compare the two trip-based modeling paradigms, and will scrutinize the improvements that are applied to conventional model steps.

#### 3.1. Model Structure

Travel demand models should represent the decision to travel made by individuals with important demographic and policy sensitive explanatory variables. This recognition has led to a shift in the past couple of decades from aggregate modeling toward disaggregate modeling (Kim et al., 2009). Encompassing of policy-relevant variables in disaggregate models has provided them with a potentially more useful role in forecasting than descriptive aggregate models (Dunne, 1985).

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In the aggregate trip-based paradigm, trip generation step estimates global amounts of trip emissions and receptions between zones, therefore the level of geographic zone. On the contrary, disaggregate trip-based paradigm adopts a more individual oriented analysis unit, usually groups of individuals.

### 3.1.1. Demand segmentation

Demand segmentation refers to the process of constructing “homogeneous” groups of individuals with similar “critical” attributes. Critical attributes are those, which are regarded as having fundamental influences on travel behavior, such as car ownership, occupation, household size, age class, etc. For example, unemployed persons do not make work trips and individuals from households with young children are more likely to make escort trips (e.g., children pick up/drop off at school). These differences are all confound in conventional aggregate models so that, for example, unemployed population will contribute in estimating the amount of work trips.

Transportation demand models take advantage of the random utility theory to provide a robust basis for behavioral analysis by accounting for unobserved determinants influencing the behavior. However, the random utility theory is useful for explaining decisions that are made in the same behavioral mindset. In other words, once the traveler is in the time-minimizing mindset, for going to work for example, the random utility framework explains (and evaluates) the propensity towards alternative that offer lesser travel times. Instead, the random utility framework leads to erroneous interpretations if it is applied to compare decisions made in two different mindsets. Let us compare a commuter – reasoning on the same time-minimizing basis – with a traveler driving for leisure. The former rides to make a great time whilst the latter is having a great time and does not necessarily mean to minimize his/her travel time, as it is no longer a priority. The same is true with a grocery shopper to whom getting the least travel time is not a first priority; instead, he/she prefers to bring a vehicle to carry the weight of purchased goods. Also where a young traveler may prefer to ride a fast but overcrowded public transportation service over driving an automobile, an elderly may prefer to drive in his/her own car to spare himself the burden of such a ride. These examples are to illustrate the fact that the explanatory power of a model depends entirely on identifying and isolating different reasoning contexts. This is the main purpose of demand segmentation to make sure that decisions are being modeled within the same decision-making mindsets. Some of the attributes that are usually used in demand segmentation include: socio-professional category and travel purpose but also income, car ownership,

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household structure, family size, age class, residential density, and accessibility as well.

#### *3.1.1.1. Segment specific choice-set generation*

Choice set specification is probably one of the most important aspects of travel demand modeling. This is particularly important in mode choice modeling step. In fact, the whole idea of making a choice decision depends upon correct specification of the set of available alternatives. It is because a choice model should be applied only to individuals who have the liberty to make a choice, for choosing among alternatives that are available to them. Otherwise, the model is not behaviorally consistent as not choosing is not the same as not being able to choose. For example, a teenager will never use “car driver” travel mode due to legal constraints; an individual whose household does not have any car, is not likely to choose car driver travel mode, either. Therefore, variables such as car ownership or age class seem to be good candidates for being considered as critical variables for demand segmentation.

Albeit, aggregate models are partly capable of dealing with the issue of modal captivity using modified discrete choice models such as Dogit (Gaudry and Dagenais, 1979, Gaudry, 1980, Hensher, 1982) which in an aggregate way takes account of captive portions of the demand. However, they eventually subject all of the demand population to the same choice context that may result in highly biased results. Further, failing at correctly identifying the free-to-choose portion of the demand makes it impossible to explicitly assess effects of policies designed to persuade individuals to consider a modal shift in favor of public transportation (We will return to this subject in § 3.1.4).

### 3.1.2. Trip Generation

Disaggregation in trip generation step is mostly due to demand segmentation. Differentiating among classes of individuals allows taking into account important characteristics that may influence trip generation.

#### *3.1.2.1. Cross classification*

In aggregate demand models, trip generation consists of estimating the total or mean number of trips at zone or household level, per purpose and per daytime period, using (linear) regressions over variables such as car ownership, income, age, household size, occupation, etc. The aggregate nature of the model dictates that each variable should be first averaged over zonal demand population and then used in the regression equation to estimate aggregate trip generation of that zone. In disaggregate models, the use of

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demand segments allows estimating trip generations at demand segment level. The method is the same by using regressions over individual attributes. Demand segments are considered to contain relatively homogeneous individuals who generate similar number of trips. Therefore averaging over a demand segment will entail biases much smaller than that of aggregate models. Although this method, which is also known as cross classification or category analysis, makes a much more efficient use of data and provides much better predictions, but it still is based on the same descriptive approach of aggregate models. In other words, it does not model the trip making decision behavior of individuals but rather describes observations using regressions over several explanatory variables.

### *3.1.2.2. Trip making decision behavior*

The decision to make a trip can be regarded as a choice that individual makes only if it offers further utility than staying immobile at home. This provides a behavioral framework for disaggregate trip generation. Individual's utility of trip making can be expressed by a linear in parameter functional form and explanatory variables such as income, car ownership, age, household size, etc. Therefore, it is possible to use a binary, say logit, choice model to calculate the probability of making a trip over staying still. Daly (1997) proposes a "stop-go" trip generation model using a hierarchical structure that consists of nested binary choice models. At each level, the choice is whether to make further trips or to stop at the present number. Two important decisions are distinguished: the decision of making any trips at all and the decision of choosing "go" option at each subsequent stage. The distinction between these two decisions is because of the possibly strong difference in behavior between the choice to move at the first place, and the remaining choices to continue moving. This is because individuals who do not move at all can be categorically very different from others who make at least one trip. For example, the former category can comprise unemployed or disabled people whilst the latter category consists of people who, however demonstrating some difference in preferences, share mostly similar economic and demographic characteristics. This model is successfully implemented in ANTONIN-2 model for the Greater Paris Region (RAND Europe, 2006).

### *3.1.2.3. Explaining accessibility measures*

Conventionally, the trip generation is considered merely dependent upon economic and demographic characteristics of individuals and the performance of transportation network is not incorporated in estimating individual trip making rates. This assumption may be justified for trips with mandatory

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purposes as the need for trip making has little to do with the availability of convenient transportation services. On the other hand, high levels of transportation service make it more likely that individuals choose to participate in non-mandatory activities. Daly (1997) mentions that there is a clear political need to include in modeling the influence of accessibility on the total number of trips made.

In four-step structure, transportation network and level-of-service attributes normally get involved in trip distribution and mode choice steps. Therefore, efforts have been done to explore the possibility of defining an overall measure of zone accessibility to influence trip generation. One can consider the following equation as to give an overall measure of accessibility to all or a number of eventual destination zones departing from zone  $i$ .

$$A_i = \sum_j E_j \exp -\beta \cdot GC_{ij} \quad (1.11)$$

In this equation,  $GC_{ij}$  is generalized cost of travel between zone  $i$  and a given zone  $j$ ,  $\beta$  is the gravity model parameter, and  $E_j$  is a measure of attraction of zone  $j$ . However this procedure has seldom produced the expected results because the estimated parameters of the accessibility variables have either been non-significant or of the wrong sign (Ortúzar and Willumsen, 2001).

The theory of random utility maximization provides logsums as a consistent mean through which accessibility measures can affect trip-making decisions. Yao et al. (2008) use the following logsum expression to incorporate accessibility measures in trip generation:

$$A_i = \ln \sum_j \exp \left[ \frac{1}{N} \sum_n V_{jn} - V_{in} \right] \quad (1.12)$$

In this equation,  $N$  represent the number of individuals (or demand segments) in the zone  $i$ ,  $n$ , counts individuals (or demand segments), and  $j$  counts admissible destination zones. Accessibility measure  $A_i$  is then included in linear regression to estimate total number of trips departing from zone  $i$ .

The trip generation structure proposed by Daly (1997) provides a random utility compatible model, which allows accessibility measures to be encompassed through logsum terms, and therefore makes trip generation dependent on transportation level-of service attributes. For more discussion on logsum terms, see, Ortúzar and Willumsen (2001, § 6.5.1).

### 3.1.3. Trip Distribution

In trip distribution step, estimated trip generations are to be distributed among zones so that the total sum of incoming trips to each zone matches its estimated amount of trip attraction. In disaggregate trip distribution approach, unlike aggregate trip distribution, trip attractions are not fixed a priori. Instead, individuals explicitly choose destinations based on their attractiveness. For example, using a MNL model of individual destination choice behavior the following expression will determine the portion of total departing trips from zone  $i$ , named  $O_i$ , which is attracted to zone  $j$ :

$$T_{ij} = O_i \left[ \exp V_{ij} / \sum_k \exp V_{ik} \right] \quad (1.13)$$

In aggregate models the distribution is done using descriptive entropy maximizing methods based on inaccurate measures of accessibility (e.g., geographic distance), and a final redistribution process is included to ensure that total trip attraction estimates are met once all trip productions are distributed. Disaggregate trip distribution follows an individual-oriented behavioral approach, therefore provides major advantages over aggregate trip distribution. The issue of destination choice concerns only trips whose destination is not predetermined, that is trips with non-mandatory purposes. Mandatory purposes (basically, work and school) in general have predetermined destinations (in this case, workplace and school location), and therefore are excluded from disaggregate trip distribution process. Further, each purpose measures attractiveness of zones in a different way. Those zones that are appropriate for shopping purposes are not necessarily suitable for discretionary activities. Therefore, trip distribution should be purpose dependent.

To introduce accessibility measures in disaggregate trip distribution step, within the general framework of the random utility maximization theory, maximum expected utility of available travel modes to each destination is included in the calculation of the utility of that destination zone. We will discuss this in § 3.1.5.

### 3.1.4. Mode Choice

Disaggregate mode choice uses the random utility maximization framework to constructs complex combinations of modes and allows refining the mode structure to represent explicitly every possible transportation mode in relation with other modes. Aggregate models usually consider only auto and public

transportation modes. Non-motorized modes are almost always absent because interzonal distances are already long enough to make non-motorized travel infeasible. Aggregately modeling, it is not possible to distinguish between detailed sub-modes such as bus and metro as it depends mostly upon local accessibilities that are not visible at aggregate zone level. These problems are resolved in disaggregate mode choice models.

Disaggregate mode choice models use hierarchical choice structures to include a complete choice set comprising all available modes. Similar sub-modes, for example bus and metro, are arranged under one grouped mode, for example public transportation. Choice sets can differ among demand segments in order to account for modal captivities, correctly.

### 3.1.5. Joint Choice of Mode and Destination

One important issue is how to take into account accessibility measures in destination decision-making. A zone should be attractive to be chosen but it also should be accessible by the transportation network. This raises the question whether a rational individual will prefer a more attractive but less accessible zone or a less attractive but more accessible one. The answer to this question requires considering destination choice and mode choice as two facets of a simultaneous or, better stated, joint mode and destination choice. Hierarchical choice models are usually adopted to make joint mode/destination choices. Although, the hierarchical nature of these models does not provide simultaneity of decisions, it allows taking into account effects of inferior choice alternatives on the superior decision-making process using their expected maximum utility.

Thus, two specifications are possible depending upon whether the priority is given to mode choice or destination choice. If destination choice is to be made first, then maximum expected utility of available travel mode options subordinate to each zone will increase its utility, accordingly the odds that it be chosen. Reciprocally, if mode choice is to be made first, maximum expected utility of zones accessible by that mode will incorporate to increase its choice probability. In such cases, trip distribution and mode choice steps are integrated in one ensemble as joint mode/destination choice model.

Although it seems more plausible to give priority to destination choice decision making, it would be better if, for each non-mandatory travel purpose, both specifications are tested on observations and the one with higher likelihood is adopted. In the case where destination choice is decided prior to mode choice, maximum expected utility of those modes, which form the choice

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set of a destination alternative, in fact constitutes a trip-based measure of accessibility to that destination zone.

### 3.1.6. Trip Assignment

Trip assignment in disaggregate models has identical to that of aggregate models. This step is makes the choice of road itinerary which maximizes traveler's utility. The only difference is probably that in disaggregate trip assignment individuals (or demand segments) are free to make their own choices according to their individual preferences. This allows including attributes that are more diverse for itineraries.

Aggregate trip assignment always all the time gives significance to those level-of-service attributes, such as time and monetary cost, which have immediate economic returns. This is because collective rationale of human communities, in general, is thought to reason on economic basis. This may be adequate for regions where major congestion or other traffic-related problems are yet to be solved. In such cities, planners need to change overall network situation and policies focus on economic levers to affect major portions of travel demand. Therefore, aggregate models are adequate for capturing effects of such different scenario proposals. On the contrary, in regions with high levels of transportation service, usually minor modifications are made regarding specific segments of population. In addition, policies are designed on "non-economic" basis. For example, a road may be reconfigured in order to become more comfortable or less noisy, providing more social convenience, while still offering higher travel times or monetary costs. Disaggregate trip assignment, may be differentiated from aggregate trip assignment considering higher number of variables that it takes into account for each itinerary. It is generally more likely that such factors, if included in disaggregate trip assignment, can find some levels of significance.

## 3.2. Model Stability and Transferability

Aggregate view of demand does not take into account the internal structure of the demand. For example, number of individuals residing in a zone may be used as an explanatory variable that influences trip generation, without understanding how these individuals are distributed among households. For instance, the same total number of individuals with bigger households is likely to make more escort trips and less work trips and vice versa.

The issue of transferability regards the possibility of using a model, which is constructed and estimated upon observations of another region, to predict correctly the travel demand. In order to be transferable, a model should be

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able to capture fundamental elements of travel demand. For example, as explained above, a model, which only includes the number of individuals as explanatory variable, omitting the number of households, provides less transferability. Therefore, disaggregation generally ameliorates transferability because it allows looking into the demand from a more fundamental vantage point. However, it is not the only factor. It is also important to have a correct fundamental model of individual behavior. Disaggregate trip based modeling uses the same analytic basis of the trip-based paradigm so, in this regard, does not promise any advantage over aggregate trip based models.

### 3.3. Result Aggregation

There is no doubt that disaggregate modeling paradigm is highly superior to the conventional aggregate trip-based paradigm in capturing individual travel behavior. However, while it is desirable to estimate choice models at a disaggregate level, the use of these models in forecasting generally requires some level of aggregation. That is, planners and policy makers are not necessarily interested in detailed results at individual level. Instead, they are willing to make policies that affect groups of travelers, and therefore they need to evaluate policy effects at an aggregate level. Clearly, the unit of observation for aggregate models is closer to the unit of prediction than for the disaggregate models.

The most trivial method for aggregating over results produced by a disaggregate model system is direct enumeration. In this approach, every single individual is enumerated to calculate weighted average modal choice probabilities. This approach, although simple, does raise piratical problems, as it requires predicted values for each individual in the sample and therefore has rather extreme data requirements. As a result, simpler short-cut methods have been developed which provide more computational convenience with the price of admitting some level of aggregation over individual characteristics and explanatory variables across the sample.

The simplest of these methods is called the naïve approach, which uses the average sample values of the individual variables together with the disaggregate model coefficient estimates. This will however provide inaccurate predictions, as the average of a nonlinear function is not the same as the function evaluated at the average values (Dunne, 1985). To overcome this problem, a number of other approaches have been developed including the classification approach, the statistical differentials approach, and the density function approach (Watson and Westin, 1975, Dunne, 1985).

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The classification approach is somehow a generalization of the naïve approach. In this method, demand segmentation is used to divide prediction group into relatively homogeneous groups of individuals, or market segments, and then estimating the average probability based on the average probabilities over all of the market segments. It is hoped that this can provide homogeneity within the groups, allowing efficient and more accurate use of the naïve method upon the segments. The estimated probabilities for each segment can then be weighted and averaged.

The statistical differentials approach is based on the moments of the distribution of probabilities over the population. This can be done using a Taylor series expansion about the mean of the cumulative density function. Limiting the expansion up to the second-order term, this approach needs only the mean and variance of the linear combination of explanatory variables to estimate the probability, hence having limited information requirements. This approach is superior to the classification approach as it accounts for variations among individuals. Albeit there is still some information loss arising from the zonal aggregation implied by the use of the distribution moments, and the truncation of the expansion usually at the second-order term.

The density function approach attempts to represent the distribution of the variables across the population in terms of a frequency distribution, assuming usually a normal multivariate probability density function. For more discussion on the issue of result aggregation in disaggregate models, see Watson and Westin (1975), Dunne (1985), and Ortúzar and Willumsen (2001).

### 3.4. Surveying Requirements

In the fond, the purpose of a travel survey is to provide elements and fix base points to ensure a credible forecasting in time periods shorter than survey renovation itself. Short terms models does not consider the evolution of long-term characteristics because the survey will provide the real state of those variables in a “short” period of time. Richards (1974) states that “in model development we are essentially endeavoring to explain differences in observed behavior, thus the greater the variability in the data available, the greater the chances of explaining the differences”. That is, using a dataset, which does not provide adequate variability in a given characteristic, may erroneously lead to concluding that it is not relevant to the studied choice behavior. The use of aggregate data implies an averaging over the individual behavioral units within for example a traffic zone and such a procedure results in a major loss of variability. This is important as it has been shown that traffic zones are

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usually highly heterogeneous and even the variability within zones can be very much greater than that among zones.

Disaggregate models make much more efficient use of available data since the full variability data is retained. Consequently, fewer observations are required for model estimation. This allows applying them to situations, such as less-densely populated regions, where aggregate data may be difficult to gather. In addition, this makes disaggregate models very effective on monetary grounds, given the assumption that surveying and data collection costs may absorb significant portions of the budget in urban transportation studies. It is ultimately futile trying to provide excessively detailed data, whilst the precision will be eventually lost through result aggregation on the output side (Watson and Westin, 1975).

### 3.5. Summary on the Disaggregate Trip-Based Paradigm

Ignoring the fact that travel demand is derived from activity participation decisions in the trip based paradigm has led to inadequate specification of the interrelationships between travel and activity participation and scheduling, including activity linkages and interpersonal constraints. Ignoring the spatial and temporal interrelationship between all trips and activities comprising an individual's activity pattern has also degraded the predictive quality. Trip-based models are weak at representing the overall behavior as an outcome of a true choice process, and are generally unable to establish distinct choice alternatives available to the decision maker in a constrained environment that causes misspecification of individual choice sets (McNally and Rindt, 2007).

Trip-based models cannot incorporate disaggregate time-of-day travel decisions, which are especially important for predicting the effect of congestion relief policies. Typically, only two or three periods of the day are considered and the proportion of trips made in each period is treated as constant and not sensitive to traffic congestion or other factors. Prediction of the time-of-day for travel must necessarily be based upon the individual's time-space constraints and examined within the context of his/her daily activity schedule. Only in this fashion can a feasible set of schedule choices be constrained. It is by examining how different policies affect this choice set that the effect of congestion relief policies can be realistically studied.

## 4. Tour-/Activity-based Modeling

The usefulness of a model is largely dictated by its predictive ability. Classic four-step models have proven their usefulness in many policy contexts.

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Nevertheless, they are typically based on sets of restrictive assumptions, which consequently make it difficult for the classic paradigm to keep up with the upcoming trends and the increasing need for more realistic and precise predictions of the impact of policy decisions and to respond to new questions. On the other hand, with increasing involvement of sophisticated techniques and implication of more precise behavioral assumptions one should make sure that actual developments are not diverging from the reality underlying the individual mobility behavior. As Borgers et al. (1998) mention, this is not only a quantitative matter in the sense of predicative success; it may as well be a qualitative consideration in the sense that the actual decisions cannot be simulated with the model because it lacks the fundamental mechanism or variables that would reflect such behaviors.

Increasing flexibility in working hours, whether forced by changes in the economy or use of new technologies, influences timing of activities and introduces new daily activity patterns. Introducing new auto allocation schemes, changing transport mode ridership as an effect of congestion relief strategies, encouraging the use of mixed modes such as park-and-ride, shared car ownership or carpool, and improving traffic sustainability by means of road guidance systems, and more reliable and frequent public transportations, will all have significant effects on individual's travel decision-making behavior. In addition, people's attitude towards mobility may be influenced by the increasing social basis for the idea of a sustainable society, and this may have effects on travel mode choice and activity scheduling. This includes privileging public transportations over automobile, encouraging trip chaining instead of conducting several separate tours, or promoting in-home activities over out-of-home activities (Borgers et al., 1998, Bowman and Ben-Akiva, 2001).

Doherty (2003) point out that travel demand models are required to provide a realistic representation of the travel decision-making behavior, and to improve the ability to forecast travelers' complex responses to travel management strategies; responses which are more often in the form of activity rescheduling. For example, an individual who chains non-work stops with the commute, or pursues stops during the midday from work, is unlikely to switch to a new or improved transit service between home and workplace. Consequently, ignoring the joint nature of work mode and commute/midday stop decisions can lead to overly optimistic projections of the reduction in drive-alone mode share and peak period congestion due to transportation control measures (Bhat and Sardesai, 2006). This requires a new modeling paradigm that can incorporate different aspects of individuals' mobility behavior, and simulate the behavioral process that leads to a short run decision more realistically. The tour/activity-based modeling paradigm is based on the hypothesis that individual's daily

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trips are inter-dependent. For example, in households with more than one worker, combination of tasks, such as bringing children to school or day care on the way to work, is often necessary. This in turn is likely to promote a change in household's travel mode choice in favor of automobile being the only mode that offers the required flexibility. As another way of relieving the time pressure, the household members may decide to make multi-purpose, multi-stop trip chains rather than several independent trips and a realistic modeling paradigm should be able to take into account these socio-demographic factors.

In this regard, the four-step approach where the process of activity scheduling and task allocation is not addressed explicitly, presents fundamental shortcomings in a microsimulation context. Often the best one can do is to formulate additional assumptions, develop scenarios, and use these scenarios as input for the discrete choice models to predict likely mobility consequences. A fundamental approach however, would try to represent explicitly the full process of decision making providing in addition to traditional four-step approach, information about the timing and sequencing of choices, with respect to time and space constraints and also with respect to other members of the household. This does not necessarily imply that activity-based models outperform conventional four-step models in terms of their predictive success; this remains an empirical issue. In fact, in many practical studies until the late 1990s, the models used have been of the classical aggregate four-step form despite many criticisms about their inflexibility, inaccuracy and cost. One important reason for this persistence, apart from the familiarity, is that they offer a tool for the complete modeling process, from data collection through to the provision of forecasts of flows on links. This has not often been the case with disaggregate model approaches perhaps because the data necessary to make aggregate forecasts with them is not readily available (Ortúzar and Willumsen, 2001, p. 307). Nevertheless, activity-based models allow the analyst to predict the impact of particular trends, especially with regard to space and time; this is beyond the scope of the conventional modeling apparatus. For example, to predict the mobility consequences of the increasing work force participation of women, it is necessary to develop models that explicitly take resource allocation problems into account (Borgers et al., 1998).

The activity-based approach is not new. Many authors have attributed “the intellectual roots of activity analysis to fundamental contributions from Hägerstrand (1970), Chapin (1974), and Jones (1979) (see, Bowman, 2009, McNally and Rindt, 2007, Algers et al., 2005). The activity-based approach began as a natural evolution of research on human behavior, in general, and travel behavior, in particular. Early criticism of the performance of the four-

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step models did not serve as a major catalyst for activity-based research until the fundamental incompatibility of the four-step approach and the emerging policy directions was realized. Rather these criticisms placed significant focus on enhancing the four-step approach, primarily through the introduction of disaggregate models, which was an important step forward as they are often key components of activity-based approaches, and equilibrium assignment. The overall framework was maintained and effectively, institutionally reinforced (McNally and Rindt, 2007).

Bowman and Ben-Akiva (2001) summarize the most important elements of activity-based travel theory in two ideas: First, the demand for travel is derived from the demand for activities. Travel causes disutility (except for recreational activities), therefore is undertaken only when the net sum of the utility of activity and disutility of travel, exceeds the utility available from activities involving no travel. Second, individuals face spatial and temporal constraints, functioning in different locations at different points in time by experiencing the time and cost of movement between locations. They are also generally constrained to return to a home base for rest and personal maintenance. This can be presented in a more detailed fashion according to McNally and Rindt (2007):

- Travel is derived from the demand for activity participation;
- Sequence of patterns of behavior, and not individual trips, are the relevant unit of analysis;
- Household and other social structures influence travel and activity behavior;
- Spatial, temporal, transportation, and interpersonal interdependencies constrain both activity and travel behavior;
- Activity-based approaches reflect the scheduling of activities in time and space.

The terms “tour-based” and “activity-based” nowadays have sometimes assumed close meanings. However, one may use the term “activity-based” specifically for models, which consider a full-day context and take into account the connection among multiple tours taken in the same day.

The modeling of tour decisions provides an incremental improvement over trip-based model systems, incorporating an explicit representation of temporal-spatial constraints among activity stops within a tour. However, the tour-based approach lacks a connection among multiple tours taken in the same day, thereby fails to capture the effects of inter-tour temporal-spatial constraints. Broadening the model scope to include activity decisions spanning

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a day or longer periods is difficult because the variety of available schedules is immense and, despite the advances in activity-based travel theory, the factors underlying the decisions are still not well understood. Accordingly, many such models are developed as incomplete prototypes, and rely on exogenous forecasts of important dimensions of the activity and travel scheduling decisions, such as activity participation, location, and travel mode (Bowman and Ben-Akiva, 2001). In the following sections, we will develop the various aspects of the activity-based approach and their explicit or implicit consideration in applied models.

#### 4.1. Trip Chaining Behavior and Travel Tour Formation

Ye et al. (2007) study whether the people prefer to make individual trips or to organize their trips in complex tours. As individual and household resources such as time, income, auto ownership, etc. become rarer, the tendency to make more complex tours is likely to increase over time. This can have direct concrete implications on travel behavior. For example, traveler who needs to organize more trips in tours is more likely to use auto modes because of its flexibility. On the other hand, traveler whose household owns a car, may be more stimulated to make more complex tours thanks to increased flexibility of auto mode. The central question is that does mode choice influence the complexity of trip chaining patterns or does the complexity of trip chaining patterns influence mode choice? After examining three econometric models to study the causal relation between tour complexity and mode choice, based on the 2000 Swiss Travel Microcensus, Ye et al. (2007) find a number of interesting findings. For example, they find that demographic and socio-economic characteristics, tour's primary purpose, and time-of-day significantly influence mode choice and tour complexity. It is found also that individuals in larger households tend to make less complex tours as opposed to individuals living in smaller households, perhaps because household maintenance activities can be allocated to more persons. But above all, on the causal relationship between tour complexity and mode choice, their conclusion is that a sequential model system where individuals first make decisions about whether or not to make commute stops and then decide on commute mode choice represents the decision-making process of commuters well. Clearly this finding suggests that activity-based models should be formulated such that individual activity agendas and tours are formed first and then mode choices is determined based on the nature of the activity agenda or tour complexity.

Findings from several studies generally confirm that evening commutes are more likely to contain several trips than morning commutes. Bhat (1999) explores the evening stop-making in travel from workplace to home using a

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random coefficient heteroscedastic ordered response logit model for the 1990 San Francisco Bay Area Household Travel Survey. He finds that almost a third of all commuters made at least one stop during an evening commute during the weekday. In addition, he found that women are more likely to make stops than men are.

Employment status and having children are two other important factors underlying stop-making behavior. Unemployed males in no earner households without children tend to make less home-based tours. On the contrary, male with a job and children in single earner households have a higher than average number of daily home-based tours (Timmermans et al., 2003). Ye et al. (2007) also find that auto ownership is positively correlated with the tendency to make more complex tours. They report that the young and the elderly are less likely to pursue complex non-work tours possibly because they have fewer household obligations than those in the middle age groups.

Timmermans et al. (2003) study the tour complexity within a spatial context. They report that most of the spatial contexts effects were not significant on the number of trips chained in one tour. They note the evidence that people in suburban locations and people in urban locations with poor transport tend to chain more destinations in a single travel (in accordance with other finding that in suburban areas people are more auto dependent), however they find this relationship weak and not significant. They point out that people's daily activity organization and tour making behavior is driven by more powerful rules than the urban context: within a particular society, psychological principles seem more important in shaping activities than the specific characteristics of the urban structure and the transportation system, unless some major hard constraints are involved.

## 4.2. Tour-Based Versus Activity-Based

It is important to elicit the distinction between tour-based and activity-based demand modeling paradigms. These two together with trip-based paradigm represent three levels of travel behavior representation. In the trip-based approach, the focus was on individual trips being considered as the basis of analysis.

In tour-based paradigm, however, the focus is on establishing consistency among several trips chained in between two successive visits of the anchor point (being often the home or workplace). The tour-based paradigm, especially takes into account the reciprocal effects of trips on trip mode and destination choices. For example, a commuter who drives to work in the morning must use the auto mode for his return trip in the evening (it seems

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unreasonable that a commuter use auto mode to reach workplace and then return home by public transport). Therefore, travel mode of the return trip is forced and there is no choice to make. As another example, the commuter who needs to shop some grocery items at midday will choose the nearest shopping center to his workplace so destination choice for this midday shopping trip is also forced.

Activity-based demand modeling paradigm goes one step further and seeks for consistency between activities undertaken in a given period of time, usually one day (longer periods are still difficult to handle) (Bowman and Ben-Akiva, 2001). The activity-based paradigm should not be considered as a continuation to the tour-based paradigm as these two paradigms were developed rather independently. Activity-based models integrate the representation of activities and travel conducted by an individual, and in some cases by an entire household, over the course of an entire day (Bowman and Bradley, 2008). Figure 1.4 illustrates different representation of one same travel trip-, tour-, and activity-based paradigms.

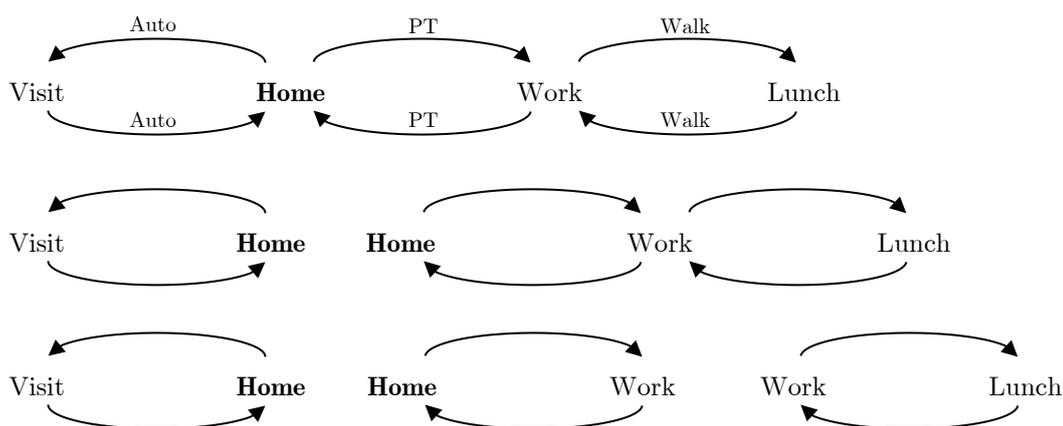


Figure 1.4. Travelling in activity- (top), tour- (middle), and trip-based (bottom) paradigms.

### 4.3. Activity Based Model Systems Structure

Activity based approach is not new. Many authors attribute its intellectual roots to Hägerstrand and his time-geography, and to Chapin and his emphasis on individuals' desires and the personal characteristics behind their engagement in different activities. Whereas Hägerstrand stressed various forms of constraints, Chapin's interest was more on opportunities and choices. The fundamental tenet of the activity-based approach is that travel decisions are driven by a collection of activities, which form an agenda for participation, and as such, cannot be analyzed on an individual trip basis. Thus, the choice process associated with any specific travel decision can be understood and

modeled only within the context of the entire agenda. The collection of activities and trips actually performed comprise an individual's activity pattern, and the decision processes, behavioral rules, and the environment in which they are valid, which together constrain the formation of these patterns, characterize complex travel behavior.

A household activity pattern respects an ensemble of individual member's patterns, which reflect the household activity program, the household transportation supply environment, and the constrained and interactive decision processes among these members. The household activity program, representative of the demand for activity participation within the household, is transformed through various activity demands and transportation supply allocation decisions into a set of individual activity programs, each an agenda for participation reflective of the constraints, which influence the choice process. The actual scheduling and implementation of the program is completed by the individual, producing the revealed behavior of the individual activity program.

Achieving "consistency" between modes for different trips on the same tour has been one of the major reasons for a wide acceptance of the tour-based modeling paradigm (Vovsha et al., 2008); Bowman and Bradley (2008) and Vovsha et al. (2005) explore this more in depth. A daily activity pattern can be viewed as one single complex outcome of purposeful human planning process and it would be more convenient to model simultaneously many components that have formed individual or household daily activity pattern. Although a person or household's entire day is so complex that, generally, a full simultaneous representation is not feasible, but simpler implementations are sometimes feasible where there is important complex correlation among component outcomes that can be correctly represented by a known and practical model structure. Bowman and Bradley (2008) call such a consistency is called "horizontal integration". For example, a horizontally integrated model identifies the most important on-tour activity purpose of the day, whether one or more stops is made before, during or after that activity on the same tour.

Apart from simple horizontally integrable features of daily activity planning process, it is too complex to understand all at once, the factors underlying human behavior and put them into a mathematical form. Modelers have been forced to break the entire process into pieces that can be implemented sequentially, and integrate them in an attempt to preserve important sequential relationships among them. This is what is called "vertical integration". Vovsha et al. (2005) distinguish between "downward integrity" and "upward integrity": Downward integrity means that all lower-level

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decisions in the model hierarchy are properly conditional upon the upper-level decisions. It is ensured by sequencing the model properly, tracking important variables from choice to choice in order to control the feasible scope left for each subsequent choice accurately, and by preventing conflicting choices for the same individual. Upward integrity means that when modeling upper-level choices the composite measure of quality of the lower-level choices available for each upper-level alternative is properly taken into account using, for example, logsums.

### 4.3.1. Intra-Household Interactions

The problem of group decision making at household level is at the core of the activity-based approach to travel demand modeling. Conventional travel demand models consider individual trip generated at the household level, i.e. they involve household level explanatory variables, without regard to which household members are making the trip. Numerous facets of intra-household interactions and group decision-making have important implications for modeling travel behavior. Household members allocate and distribute tasks and activities among each other and jointly participate in or undertake others. A parent may drop a child at school, a family may undertake a joint shopping or social recreation activity, or a household member may be tasked with running a household errand. Early activity-based models considered tours generated at the individual level using household characteristics as explanatory variables, but without explicit consideration of the presence of other household members on the tour or on the other activities undertaken by individual household members. The need for resource allocation modeling arises where common resources such as time or automobile, are accessible to several household members at the same time.

Bhat and Pendyala (2005), and Timmermans and Zhang (2009) provide reviews of the literature on intra-household interactions. The review by Bhat and Pendyala (2005) focuses on utility-based modeling approaches. On the econometric side, Srinivasan and Athuru (2005) use a nested mixed logit modeling framework investigate both within household and between household differences in the case of maintenance activities. Bradley and Vovsha (2005) model the joint choice of daily activity pattern types for all household members simultaneously in three slayers where, first the overall daily activity pattern type choice is considered, second joint activity and travel participation by household members in activity episodes is considered, and finally the generation and allocation of maintenance activities among household members is considered. Gliebe and Koppelman (2005) use a parallel constrained choice logit model for pairs of household decision-makers. They

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develop a structural discrete choice model that predicts the separate parallel choices of full-day tour patterns by both persons, subject to the higher level constraint, imposed by their joint selection of one of several spatial interaction patterns. Srinivasan and Bhat (2005) study the complexity associated with studying interactions between in-home and out-of-home activity engagement in the context of intra-household interactions and group decision-making, using a Seemingly Unrelated Regression equation for in-home maintenance activity participation and a joint mixed logit hazard duration model for out-of-home shopping activity.

Meister et al. (2005) apply a different approach using a sequential decision making process which iteratively narrows down the solution space by employing complex search heuristics (for instance, genetic algorithms). They apply their model to a three person household to demonstrate the capability of genetic algorithms to produce a complete household and individual daily activity schedule that accounts for intra-household interactions and group decision-making. Although, many of the qualitative results that these works point out seem trivial, their major contribution should mostly be providing quantitative frameworks and methodologies that can be used in activity-based model system to explicitly take into account intra-household interaction effects on traveler's tour/activity-based behavior.

The review by Timmermans and Zhang (2009) comprises a broader set of different methodologies and approaches. Feil et al. (2009) comment that econometric models bear the advantage that they are based upon a well-established statistical methodology and econometric theory, however they quickly become very complex and difficult to estimate and employ.

Bradley and Bowman (2006) and Bowman (2009) consider four key linkages across household members. The first of the key linkages regards the "day pattern type": if each person's full day activity pattern is classified into three main types – stay at home, go to work/school, or travel for some other purpose – then we see strong similarities between the patterns of members of the same household.

The second of the key linkages considers joint activities. A joint activity is the case where two or more household members travel together to and from an activity location, and participate in the same activity while at that activity location. In the lower level models such as mode and destination choice, it is best to model such cases as a single joint decision, rather than as independent decisions made by different people.

The third of the key linkages is when two or more household members travel together to/from a location, but do not necessarily participate in the same

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activity; this is also called an “escort trip”. The most common example is a parent driving a child to school and then either returning home (an escort tour) or else deriving on to work (an escort stop on a work tour). Because the escort trips are partly joint and partly independent, it can be very complex to explicitly link them across persons, so explicit modeling of escort linkage has not been done in any of the applied models or recommended for the models under design.

The last of the key linkages concerns maintenance activity allocations. Certain types of activities, such as grocery shopping, escorting, and other household maintenance chores, are allocated across members in a household, showing a negative correlation of frequencies and duration across household members within a day.

### 4.3.2. Short- and Long-Run Decision-Making

It is important to understand how short- and long-run decisions interact, and to incorporate modeling features, which allow integrating them within one unique model system. This is especially important when the travel demand forecast period spans over several years, because not taking account of the possibility that a household acquire a car or move to a nearer place to the workplace, results in unrealistic evaluation of future situation leading to erroneous policy making. Long-run decisions are key decisions that influence the spatial context of the household members or the long-term ability to travel, including residential location choice, employment location choice, and automobile purchases. Short-run decisions are those that are made day-to-day, such as activity participation, scheduling and mode choice. The key difference between short and long run decisions is that short run decisions involve a fixed set of resources and constraints whereas long run decisions act to change the current resources or constraints (Miller, 2005).

Traditionally hierarchic discrete choice structures have been employed to represent different levels of decision-making. More important (or longer-term) decisions are made at upper levels and they will condition less important (or shorter-term) decisions on lower levels of the decision tree. Following the same approach, efforts have been made on using hierarchic utility-based structures to integrate short-term and long-term decisions within one model system. Dissanayake and Morikawa (2010) applied a two level Nested Logit to study car ownership and mode choice in the city of Bangkok using a combined revealed/stated preference database. In their model at the upper level, the choice is made between car owning, motorcycle owning and no vehicle owning

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alternatives. Then for each case, mode choice decision is made from a proper choice set.

People are often unable (or at least very unwilling) to act at the margin. That is, in many situations people do not make continuous marginal adjustments to their state so as to maintain themselves at their optimal utility maximizing state (Miller, 2005). This is particularly the case with respect to large discrete choices such as residential location, auto ownership, etc. in which marginal adjustments are generally not possible due to significant monetary and psychic transaction costs that are involved in state changes. This weakens the basic assumption underlying the use of random utility hierarchic structures to study short- and long-run interactions.

Miller (2005) introduces the notion of “stress” depicting the potential motivation accumulated over time, which will trigger a long-run change once it exceeds a certain threshold value. Thus people will tend to remain in their current state (same house, same job, etc.) when stress is low. Different stress measures can be associated to different long-run stress generating sources. Then a “stress resolution mechanism” is needed to decide once a long-run decision is triggered. For example, once a child is born, the residential location stress resolution mechanism may decide between moving to another place or expanding current place’s floor-space. However, when several stress sources and stress resolution mechanisms are involved, it is not always easy to decide for a stress relief strategy. For example, birth of a child may also trigger a need for higher income, which will be responded by changing to a better paid job located at much further distance from home. This in turn causes a new stress, which may be relieved either by changing place of residence or by buying a car. Thus, on one hand, relief of one stress may trigger a cascade of responses, and on the other hand, decision should be made in order to decide among several stress relief strategies. Thus the concept of the stress manager is introduced as the object that manages different stresses and stress resolution mechanisms.

Roorda et al. (2009) follow the work by Miller (2005) and use it in an applied study of vehicle transactions and mode choice. They identify two possible sources of stress being the conflict between household members due to lack of vehicle, and the disutility that “losers” of conflicts experience due to a reduction in the quality of the mode of transportation. They point out the necessity of finding appropriate quantifiable measures of stress in each case, and the need to examine the relationship of other long run decisions such as residential and employment location choice, to vehicle transaction and mode choice decisions.

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Verhoeven et al. (2005) incorporate long-term decisions in a mode choice model using a Bayesian approach. Their principal idea is that an individual maintains his habits until a key event makes him to reconsider his transport choices. Choices are rarely done in isolation and different other decisions may trigger a change. In addition, the choice behavior often depends upon the choice context: conditions other than socio-demographic attributes and characteristics of alternatives influence the decision. Verhoeven et al. propose to model these complexities in a mode choice context using a Bayesian decision network. It is assumed that the choice of mode of transport is influenced by key events and critical incidents. A key event is defined as a major life event such as marriage, moving place, changing job or becoming 18 years (possibility of possession of driver's license), while a critical incident is an event with fundamental consequences such as a dismissal which can disrupt the rhythm of life.

### 4.3.3. Disaggregate Spatial Representation

Disaggregate spatial representation – sometimes referred to as microsimulation – provides a practical method to implement models at the level of the individual. The motivation is that aggregate demand is made up of decisions made by individuals, and therefore it is necessary to do behavioral modeling at the level of the individual. That is, one person is processed at a time, and then these individual decisions are summed up to produce summary statistics on the behavior (including the impacts of policies). It has long been recognized in transportation that there is great value in modeling transportation at the level of the individual (Walker, 2005).

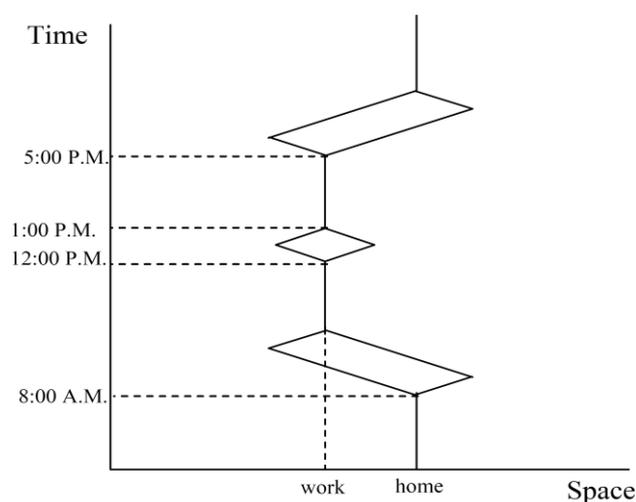
There has been much discussion in the research community on the disaggregate modeling of travel and activities. Advantages of microsimulation include the ability to tabulate impacts for subgroups of the population (for example, low income or elderly), the capability of explicitly modeling realistic travel behavior patterns such as trip chaining and activity scheduling, and the ability to better reflect heterogeneity in the demand (i.e., demand segmentation). Also important is that while aggregate applications have aggregation bias (error induced by applying the model based on average characteristics of the population), a microsimulation approach avoids such biases. However, with microsimulation there is simulation bias, which is not desirable too but has the advantage of having the possibility to estimate the magnitude of the error.

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#### 4.3.4. Activity Time–Space Constraints

Hägerstrand (1970) introduced three kinds of constraints on the activities that an individual can undertake: “capability constraints” which are biological constraints related to, for example, the need for eating and sleeping; “coupling constraints” which reflect that some activities such as a meeting require people to be at the same place at the same time; and “authority constraints” which are external institutional constraints set by various kinds of regulations such as opening hours of shops and working hours of businesses. This in combination with the location of the opportunities where different activities can be performed, and travel speed of available means of transport, determine the time-space prisms, inside which the individual has to act.

Let us consider a space-time reference. For a home-work trip, “home” corresponds to the point whose time coordinate is the earliest possible time by which the traveler can leave home, and “work” corresponds to the point whose time coordinate is the latest time by which the traveler must be at destination. Given traveler’s maximum possible travel speed, the travel will take place within a parallelogram known as Hägerstrand space-time prism (Figure 1.5).



**Figure 1.5. Hägerstrand prisms for a commuter during a day (Pendyala et al., 2006).**

In the activity-travel forecasting model system of Florida, Florida Activity Mobility Simulator or FAMOS, (Pendyala et al., 2006), prior to the simulation of activity-travel, a Prism-Constrained Activity Travel Simulator module identifies all prisms that govern the behavior of the individual. It then generates the activities and movements within each prism within the constraints posed by private transportation modes and operating hours of

public transportations. The first module determines for each individual periods during which the individual is obliged to commit to a certain activity, e.g., working at a predetermined location. These periods are called “blocked periods”. A set of blocked periods will then be supplemented by a set of “open periods”. A Hågerstrand prism is established for each open period: since the mode of travel is determined for each area if it can be seen during the open period, and if so, how much time can be devoted to this area before returning to the following mandatory activity. This procedure is repeated for all areas to identify for each area to the arrival time as soon as possible so that the start time is as late as possible.

#### 4.3.5. Activity-Based Spatial Accessibility Measures

Ben-Akiva and Bowman (1998) and Dong et al. (2006) study the properties and performance of what they call an activity-based accessibility measure that, they suggest, improves upon traditional measures of accessibility by calculating accessibility as a function of all activities perused throughout the day, including issues such as trip chaining and scheduling. In the Portland model system, the choice for activity pattern is done at the highest level. It conditions subsequent choices such as time-of-day, mode, destination, etc. It is therefore possible to define the activity-based accessibility measure as a utility-based accessibility measure using the expected maximum utility from the random utility model known as logsum terms.

### 4.4. Data Requirements: Activity Oriented Travel Surveys

The descriptive power of a model can never exceed that of the data from which it is estimated (Stopher and Greaves, 2007). Tour/Activity-based demand modeling paradigm introduces new data requirements that should be fulfilled by activity oriented travel surveys. The data requirements for activity-based models are in general more demanding than for conventional travel demand models. This is rather obvious since an activity-based model should be able to predict the travel behavior in more detail. On one hand, information should be provided about activity, i.e. the purpose of being at some place at a certain time. Trip-based survey diary, being the most popular design for household travel surveys, should be replaced by activity-based diary. In an activity-based diary, instead of asking first about what trips are made, and then inquiring about trip purposes, the diary starts by asking what were activities in which he/she participated, and questions about how he/she travelled come after. Thus, unlike trip-based diary, where the focus is on trips that the respondent has made, in activity-based diary the attention is paid to

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the actual activities the traveler has participated in. A variant of the activity-based diary is known as time-use diary, which is different in that travel is itself treated as an activity, rather than a means to reach an activity.

On the other hand, data are needed to be much more comprehensive and precise in both spatial and temporal contexts. The comprehensiveness requirement is due to the higher sensitivity of activity models to missing trips and missing activity locations. The precision requirement is due to an increasing desire to move as far as possible below current traffic analysis zone levels. These requirements are due to the disaggregate nature of the activity-based paradigm, but also due to the increasing involvement of private sector in the provision of transportation infrastructure and services where the importance of accurate forecasts is much greater than what is customary in government investments (Stopher and Greaves, 2007).

Behavioral data about activities are needed using full activity daily diaries, where, for instance, the respondent is asked to report the kind of activity according to a predefined scheme, day, start and end time, location of the activity, transportation mode, travel time, accompanying persons and if the activity was planned or not. Conventional socio-economic data should also be collected. Complementary data about the location of the facilities where activities can be carried out, the institutional context (e.g., opening hours) and the transportation system (travel costs and congested travel time matrices) are needed too.

Doherty (2003) discusses that while activity-based diaries have several practical advantages, the implications for analysts is the more challenging task of trying to understand and model a more complex set of observed activities and travel patterns. Doherty stated that data collection for travel demand models has largely focused on outcomes but design of surveys capable of eliciting behavioral processes has largely not been attempted. Bowman and Bradley (2008) identify the passage of time and the human purposeful planning as the two phenomena, which affect a person's activities and travel during a typical day, but they also reminisce that most data that so far are available for developing activity-based models describe observations but provide little or no information about how planning and the passage of time contributed to cause those observations. Doherty (2003) emphasizes on the importance of methods that allow observing interactively how decisions are made and the dynamics behind them, not just results of decisions in the form of static observed activity-travel patterns. This is in response to an emerging area in travel demand modeling which involves process models rather than outcome models. He identifies three mechanisms underlying the activity scheduling process including: preplanning, impulsive and dynamic scheduling,

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and adaptive rescheduling, and proposes appropriate methodologies to gather information regarding each of these mechanisms (see, § 4.6.2.2 for more discussion).

Stopher and Greaves (2007) explore new surveying methods as replacements for diaries and give a great emphasis to GPS surveys. They suggest that wearable GPS devices make it possible to get very precise information on time, speed and position of travelers. Further, once information is collected on the workplace addressees, school addresses, and frequently visited shops, it is possible to derive the purpose of the majority of trips from a detailed GIS of land use. Other important element being the mode of travel can also be identified very accurately using speed and route information. The devices provide very precise geography of the beginning and ending points of travel, and provide detailed data on the route used (data that have hitherto not been feasible to collect). GPS devices also can be used in combination with other positioning methods such as mobile phones to fill any data loss caused by signal degradation in city tunnels, buildings, etc.

#### 4.5. Approaches towards Activity-Based Modeling

Activity-based models do not constitute a well-defined family of models. Some models are fairly close to conventional models in so far that they apply the same kind of probabilistic discrete choice framework based on random utility maximization as in conventional models. Others focus more explicitly on the scheduling process. They usually make a distinction between fixed and flexible activities. The open periods between fixed activities can be filled up with different flexible activities. These activity choices can be modeled by discrete choice models or by decision tables representing decision rules. Yet, another approach is developed where the idea is to predict how observed activity patterns change in response to a specific policy. Different authors present slightly different ways of categorizing different approaches (Feil et al., 2009; McNally and Rindt, 2007; Algers et al., 2005):

- Econometric or random utility maximization based applications;
  - Computational process or rule-based models;
  - Microsimulation-based applications;
  - Mathematical programming approaches;
  - Survey-response approach.
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However, there is a consensus that the most active and forgoing approaches are the econometric models and computation process models. In this review, we will discuss these two categories.

#### 4.5.1. Random Utility-Based Applications

In this category of models, the travels' mobility behavior is represented by a series of discrete choice models. In a random utility based model system, the information exchange among different choice levels is done using logsums. For example, measures of accessibility to activities influence the activity scheduling through involvement of lower level logsum terms in activity pattern utility functions.

The Portland model concept, being practically the first in this category, is adopted as the basis for many applied models especially in the US. Figure 1.6 shows the activity schedule model system, implemented in the Portland model system. It contains five major parts, with Activity Pattern model at highest level, which handles activity choices for an individual throughout a day.

In Activity Pattern model, trip frequency for different trip purposes is modeled as a choice of a combination of activities. The Activity Pattern model contains 114 alternatives, differing with respect to involved activities and the order in which the activities are performed. The choice set is described as follows: First, there are the six "primary activities": Subsistence (work or school) on tour or at home, Maintenance (shopping, personal business, etc.) on tour or at home, and Discretionary (social, recreation, entertainment, etc.) on tour or at home. If the primary activity is on tour, the Activity Pattern model also determines the trip chain type for that tour.

There are eight possible types for Subsistence tours and four possible types for Maintenance/Discretionary tours. The number and sequence of the stops on the tour define the trip chain type. The alternatives that apply to all trip purposes are: simple tour, intermediate activities on the way from home to the primary activity, intermediate activities on the way from the primary activity to home, and intermediate activities in both directions. For work/school tours, four additional types are defined as above with the addition of a work-based sub-tour.

Simultaneously with primary activity and primary tour type, the Activity Pattern model predicts the number and purposes of "secondary tours", among six alternatives including: no secondary tours, one secondary tour for work or maintenance, several secondary tours for work or maintenance, one secondary tour for discretionary purposes, several secondary tours for discretionary

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purposes, several secondary tours with at least one for work or maintenance and at least one for discretionary purposes.

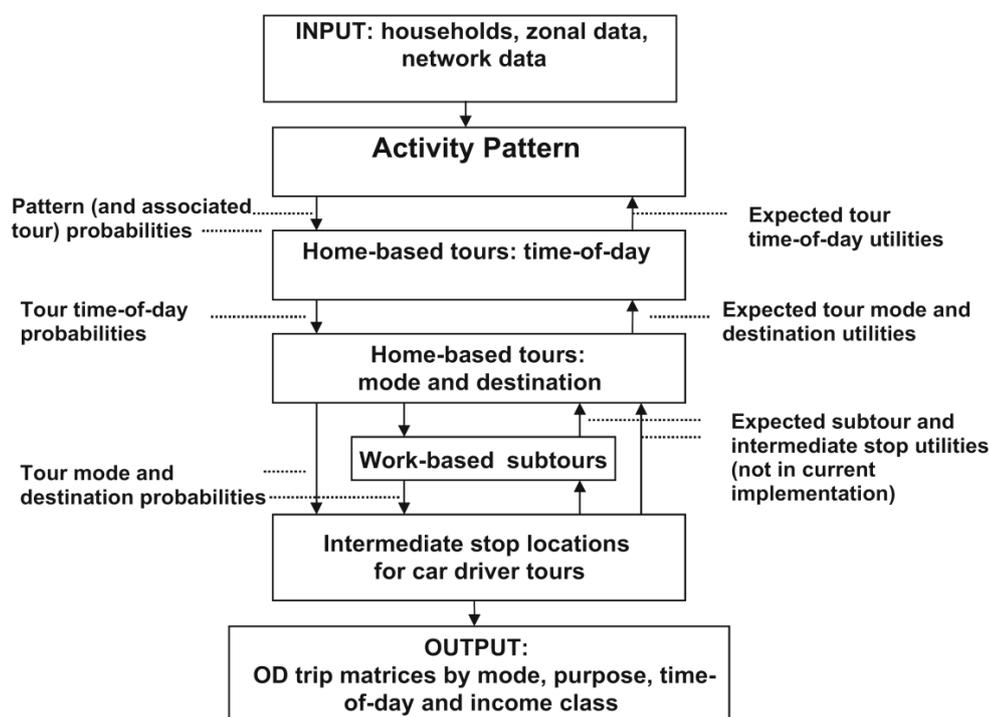


Figure 1.6. The Portland activity schedule model system (Bowman et al., 1998).

### 4.5.2. Rule-Based Applications

In this category of models, choices that are made at various stages in the scheduling process are governed by decision rules. A decision rule is represented in the form of a decision table, which consists of a list of condition variables and a list of action variables. Condition variables are related to characteristics of individuals, households, activities, physical environment, transport system, institutional context, and other schedule information. Action variables represent available alternatives for each choice situation. For each combination of condition variables, the decision table determines what action is taken.

The Albatross model system (Arentze and Timmermans, 2000) is of this category of models. Table 1.2 presents a “decision table” in Albatross model system for a case with two condition variables including: travel distance, and parking facilities at destination, and three mode choice action variables including: bike, car, or public choice. In Albatross, these decision rules are derived in a formalized way from empirical data. The applied algorithm requires a sample of person-days including observations on the condition

states with respect to a number of predefined condition variables, and the chosen actions.

**Table 1.2. Example of a decision table in Albatross (Arentze and Timmermans, 2000).**

yDshop	-	-	-	-	-	0	1	-	-	0	0	1
yLeis	-	-	-	-	-	-	-	-	-	0	1	-
Tmax1	0	0	0	0	0	0	0	1	2-3	2-3	2-3	2-3
Tmax2	0	0	0	0	1-2	3	3	-	-	-	-	-
Tmax3	0	0	1-2	3	-	-	-	-	0	1-3	1-3	1-3
Tmax4	0	1-3	-	-	-	-	-	-	-	-	-	-
< 10 am	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.32	0.25	0.16	0.08	0.05
10-12 am	0.00	0.00	0.00	0.00	0.41	0.47	0.23	0.37	0.29	0.15	0.42	0.13
12-2 pm	0.00	0.00	0.90	0.40	0.35	0.13	0.23	0.21	0.00	0.34	0.14	0.42
2-4 pm	0.00	0.81	0.11	0.48	0.24	0.22	0.50	0.05	0.21	0.27	0.33	0.30
4-6 pm	0.50	0.12	0.00	0.04	0.00	0.18	0.05	0.05	0.14	0.08	0.03	0.05
> 6 pm	0.50	0.08	0.00	0.08	0.00	0.00	0.00	0.00	0.11	0.00	0.00	0.06
N	30	26	19	25	37	60	22	19	28	74	36	64
yDshop	There is a daily shopping activity in the schedule (0 = no, 1 = yes)											
yLeis	There is a out-of-home leisure activity in the schedule (0 = no, 1 = yes)											
Tmax1-4	Available time in the widest open time slot within episode 1-4 of the day (0 = insufficient, 1 = sufficient and 2 = more than sufficient)											

In a sense, decision tables allow for a very flexible representation of behavior, since the action probabilities can take on just any values. On the other hand, it is not possible to let the action probabilities depend smoothly on continuous condition variables, such as travel distance, as is the case in random utility-based discrete choice models. This means that one will get sudden shifts among actions when states of condition variables change. To avoid this weakness of the rule-based approach, developers have recently proposed a more flexible form of decision tables, dubbed “parametric action decision trees”, where instead of using a continuous variable such as travel distance as a condition variable, it is incorporated in an action assignment rule. In the original probabilistic formulation of a decision table as described above, choice probabilities in a column are assigned to different actions, according to their relative observed frequencies in the data. Instead, in “parametric action decision trees”, these choice probabilities are set according to a parametric choice model estimated on the data using continuous variables as explanatory variables. Then, condition variables included in a decision table, which is part of a “parametric action decision tree”, serve the role of segmenting choice situations to determine which parametric choice model should be used.

In Albatross, the scheduling process is explicitly modeled as a heuristic search process represented in the form of decision rules. These rules have been derived as decision tables from activity diary data. The developers consider this as a deliberate attempt to represent non-optimizing, bounded-rational behavior of decision-makers. It is put forward as an alternative to the

commonly used logit model: even if it may be true that people are not capable of making perfect rational decisions, it is not at all clear in which way they are irrational.

One of the strong sides of Albatross is its strict handling of the many constraints that a household has to obey when forming an activity pattern. This means that Albatross should be particularly useful when one is interested in policies that involve changes in institutional and other constraints. Since the sequencing and duration of activities are modeled, policies which influence the order in which activities are performed and their duration are also natural candidates to be analyzed by Albatross.

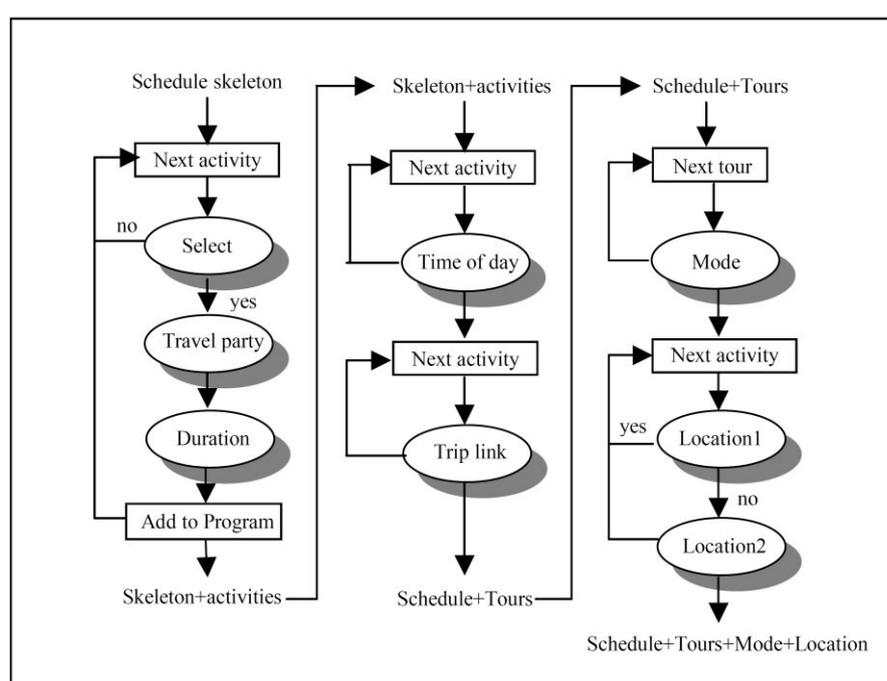


Figure 1.7. The sequential decision process of Albatross model system.

## 4.6. Activity-Travel Scheduling

### 4.6.1. Approaches to Activity-Travel Scheduling

During a day, an individual can make several chains of trips, called activity-travel tours, which create his daily activity-travel pattern. Two categories of activity-travel behavior models are briefly discussed here.

#### 4.6.1.1. Pattern Based Approach

The pattern-based approach for activity and travel scheduling involves modeling the choice of individuals from amongst a range of options at various

steps, to build up the pattern of travel for each individual during each day. For each household member a daily activity pattern is a listing of the sequence of activities undertaken by the household member as a series of tours made out from the home (and from the workplace as appropriate). Each household member is assigned an activity pattern by selecting from the probabilities of a pattern choice random utility model. The random utility function incorporates age and gender of household member, household income, work and school status, expenditure level and transport accessibilities at travel endpoints and so on as explanatory variables, and is estimated based on observations (Miller et al., 2004). This approach is especially useful when survey data show that an overwhelming number of daily activity programs follow only a few dominant patterns, so that a discrete choice model can easily be estimated to assign to each individual one of these activity patterns.

#### *4.6.1.2. Activity Scheduling Approach*

In this approach, the activity pattern for each individual is constructed from scratch, rather than selected from a set of representative patterns. In this approach, we are interested in interactively observing how decisions are made and their dynamics, not just the results of these decisions in the form of static observed activity-travel patterns (Doherty, 2003). Each person is considered to have a series of projects such as work, school, shopping, etc., which collectively define the universal set of possible daily activities in which this person might engage. The household containing the person will also have a set of household-level projects, such as child-care, home maintenance, etc. Each project has an agenda of specific activity episodes, which are candidates to be actually scheduled and executed within a person's daily activity/travel pattern. Activity episodes are generated randomly for each project of each person based on episode frequencies derived from survey data. Attributes of each episode include type, start time, duration and location. Work and school episode locations are assumed to be known a priori in most cases. For other episodes, locations are determined using a destination choice model.

#### **4.6.2. Activity Scheduling Decisions Process**

Doherty (2003) discusses the process of activity scheduling as being based on an "agenda" of household activities, which are derived from needs, desires, and goals of individuals and households and embody practical and physical constraints. To realize the household activity agenda activity-travel decisions should be made in order to provide a detailed program of individual's travel-activity participation. These decisions are categorized as: preplanned, impulsive and adaptive, which reflect the dynamics of the activity scheduling

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process at various levels regarding to the way they are thought and made, and result in individual (possibly household) activity-travel patterns, and affect an interactive ongoing process of habit formation and learning. Habits are considered as sets of activity-travel decision routines, which are executed with very little thought, which are formed through increased fixity of activity attributes over time, and are viewed as skeletal activities on person's schedule. Learning on the other hand is defined as the process of discovering new activity attribute information. In general, decisions made for mandatory purposes – which can be viewed virtually as everyday purposes – are more hysteretic than choices for less constrained purposes. For a work-trip, destination is predetermined and does not require a choice model. However, one can speculate that even the mode choice is predetermined because this is a very repetitive decision and commuters do not go through an everyday decisions making process for determining his travel mode to work. On the other hand, for non-mandatory travels, or in general travels that are less repetitive, the choice for mode and destination is more likely to be really made at instance. A model capable of taking into account habit formation can distinguish between the hysteretic behavioral and the instantaneous behavioral parts of a decision.

The activity scheduling decisions process seeks for the activity attributes and situational factors that serve as potential explanatory variables in the process, including:

- Activity attributes (e.g., frequency, duration, spatial or temporal fixity),
- Travel characteristics (e.g., travel time, travel distance, modes),
- Personal and household characteristics (e.g., age, gender, lifestyle, family life cycle),
- Structural characteristics (e.g., land uses and transport network, opening hours),
- Situational characteristics (e.g., time since last activity, time to next planed occurrence, available time window, congestion).

Episodes from the various agendas are scheduled into each person's plan for the day to maintain feasibility (for example, episodes cannot overlap, and travel between two locations should be feasible in the time available) and priority (which is determined by a fixed ordering which schedules high priority projects first). Associated with each activity episode are travel episodes representing trips from one episode location to another. Attributes of each travel episodes include start time, travel time, and travel endpoints. Each

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travel episode has also a mode of travel. Mode choice occurs as an integral part of the scheduling process, since the feasibility of a given schedule alternative depends on travel times, which in turn depend on the mode chosen to execute each trip. On the other hand, the utility of a given mode depends upon the activity episodes it serves. As in the pattern-based approach, the concept of the tour or trip-chain plays a key role in the combined mode choice/episode scheduling process. Travel modes are determined for home-based and work-based tours, given constraints on feasible modes for each trip on a tour and given auto availability for the given tour. That is if, for example, two drivers exist in a household with only one car, and if home-based tours for these two drivers overlap, then only one of the two will be able to choose the drive option and a household vehicle allocation model is used to determine which household member gets to use the car (Miller et al., 2004).

#### *4.6.2.1. Investigation of activity attributes*

Doherty (2003) emphasizes the importance of defining separate activities of the same basic type when their attributes are significantly different. For example, work and telecommute activities which are of the same basic type are distinguishable only regarding to their different attributes (in-home vs. out-of-home, start and times, weekly frequency, etc.). The types of attributes that should be taken into account include: frequency, duration, temporal flexibility, spatial flexibility, interpersonal dependency, interactivity dependency, travel modes, perceived travel times, costs and expenditures, etc.

It is important to draw a clear distinction between the fuzzy attributes of activities on the agenda that indicate their relative degree of fixity, flexibility, or constraint and their final observed static choice on a person's executed schedule. Embedding these attributes and constraints within the agenda is perhaps a more natural way to capture their effects, as opposed to "hardwiring" them into an eventual model. For instance, a household constraint that parent is at home at a certain hour to care for their children would be represented as a preplanned skeletal activity with highly fixed time and location, as opposed to the inclusion of a variable reflecting the presence of children. For forecasting purposes, this is particularly valuable, as policy changes are often materialized in the form of modifications to the constraints imposed upon activities. In other words, because econometric discrete choice models behave smoothly and are not capable of handling sharp and sudden shifts, any attribute that needs to be handled sharply, whether as a constraint or a decision with low flexibility, is better handled at the activity agenda level rather than during the activity scheduling decisions process.

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#### 4.6.2.2. Dynamics of the activity scheduling process

Doherty (2003) investigates different mechanisms involved in activity scheduling behavior. As Figure 1.8 illustrates the household activity agenda is fed into a dynamic and continuous series of shorter-term preplanning, impulsive and adaptive decision-making leading up to the real execution of activities.

Preplanning decision process regard a set of routine, regular activities that form a type of skeleton around which other scheduling decisions are made. Doherty (2003) reports that although the number of preplanned activities differs substantially between individuals, but averages about 40% of activities (60% of the time). Traditionally activity types such as work and school are considered as mandatory and thus constitute the primary pegs in a skeleton schedule. However, such an assumption should be revised considering a range of other activity types, which share the same characteristics of the mandatory activities such as children drop off or pick up at school (also see, Bowman and Bradley, 2008).

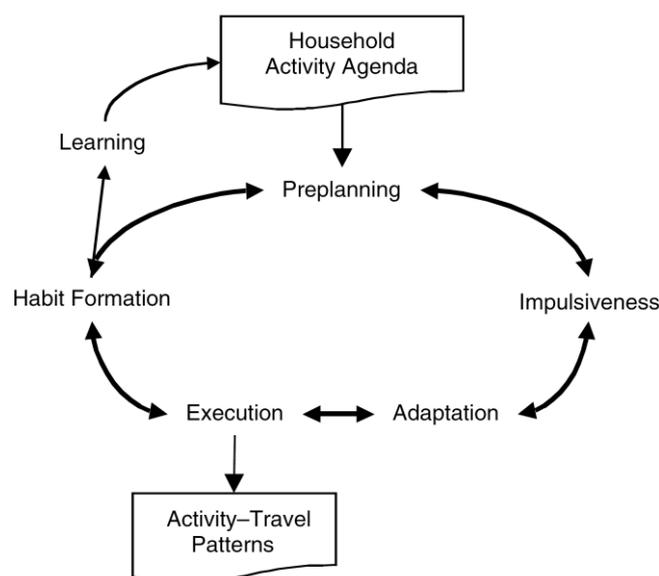


Figure 1.8. Schema of the main aspects of the activity scheduling process (Doherty, 2003).

A large portion of activities is planned impulsively or close to execution with continuous modification during execution. For example, a worker driving to his workplace on a preplanned trip, may encounter an unexpected congestion which results in an impulsive increase to the travel time, and associate delay in work start. The same worker driving home on a preplanned evening trip may receive a call from home to shop for a few grocery items on his way. This is where a real understanding of individual activity scheduling behavior is

required because merely based on observations it is impossible to identify the underlying impulsive nature of these type of activities.

Finally the habit formation stage comes which receives feedbacks from the activity execution and readjusts assumptions based on which the activity preplanning is performed. For example, the commuter whose impulsive increase in travel time becomes recurrent for a week, may finally decide to involve the new travel time in his activity preplanning stage and consider the delay caused by the congestion as a routine effect and no longer as an impulsive one (for further discussion on data and travel survey implications of this methodology, see Doherty, 2003).

### 4.6.3. In-Home/Out-of-Home Activity Purposes

With the emergence of new life styles, in-home activities can become of economic importance. This may have an impact on the travel behavior on as for instance telecommuting will save some home-work trips during the peak-hours. Therefore modeling in-home activities becomes a useful feature. As is the current state of practice, few models consider in-home activities. One example is the Portland model, where in-home activities are distinguished among three work/school, maintenance and discretionary purposes, but this distinction is only made for the “primary” activity of the day, and is only predicted in cases when the person has no out-of-home activities. None of the other models that this review has learned of distinguishes between types of in-home activities. Some of the models predict which people work primarily at home, providing some substitution between in-home and out-of-home work. However, they do not handle the phenomenon of part-time telecommuting, which is the focus of some demand management policies. In conclusion, there is some interest in predicting work-at-home as a separate activity type if the survey data supports it.

### 4.6.4. Microsimulation: Disaggregate Choice Modeling

When ordering the models in an activity-based system from “top” to “bottom”, it is not always clear which decisions should be modeled conditional on which other decision. In general, more broad and long run decisions, such as primary destination or day time period, are made at upper levels, and models for predicting detailed and short run decisions, such as mode or, somehow, time-of-day, are placed at lower levels. A conceptual order however can be established for different levels of individual decision-making and general functioning of an activity-based model:

- Population synthesis,

- Longer term decisions: auto ownership (in some cases) and work and school locations,
- Person-household-day level: choices that span the entire day for one or more persons in the household,
- Tour-level: the main destination, travel mode, begin and end times, and number of stops for each tour,
- Trip-level: intermediate stop location, and the mode and departure time of each trip.

More broad and less constrained in time-space decisions are made at an upper level. These decisions generally concern long-run choices of individual or household. As the decision-making level descends, decisions become more detailed and more precise in time and space.

#### *4.6.4.1. Stop purpose and frequency model*

It is not clear whether activities are planned and combined into trip chains when a person is planning their day, in which case the mode, timing, and location of the tours may depend on which stops they contain, or conversely, people make tours and then decide during the tour how often and where to make stops depending on their mode and location. Both of these describe real behaviors and deciding which description is more accurate depends on the particular person and the types of activities they are carrying out. The Portland and San Francisco model systems follow a day pattern approach in which the presence (and in case of Portland, basic purpose) of intermediate stops are predicted at the person-day level. In contrast, the Columbus, New York and Atlanta models predict only the number and purpose of tours at the person-day level, and then the presence, number and purpose of intermediate stops on any particular tour are predicted at the tour level once the tour destination, time of day and main mode are known. In the Sacramento models, another approach is used. Some information about stop making is predicted at the person-day level, predicting whether any intermediate stops are made for each activity purpose during the day (seven yes/no variables). These are predicted jointly with the choice of whether or not to make any tours for each of the activity purposes (seven more yes/no variables), thus capturing some substitution effects between the number of tours and the number of trips per tour. Then, when each tour is simulated, the exact number and purpose of stops on each tour are predicted conditional on the mode and destination of that tour and conditional on what types of stops still need to be simulated to fulfill the person-day level prediction. There is no proven behavioral reason for this structure, but it balances the model

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sensitivities between the two types of behavior that we described before. A similar approach is being used for Denver and PSRC.

#### 4.6.4.2. *Simultaneous mode and destination choice model*

It has become a state of practice to make mode choice decisions conditional upon the destination choice decisions, sometimes using a sequential nested structure where the mode choice logsum is used in the destination choice model. Starting from work and school purposes, the activity destination choice becomes increasingly arbitrary: the work and school locations are usually fixed a priori over a long term so that the destination choice is practically excluded from the choice sequence. On the other hand, for shopping or activities, there may sometimes be no sensible difference among shopping centers and the choice may more likely depend on accessibility measures, which in turn depend mostly upon mode choice decisions. Simultaneous estimation of mode and destination choice allows the modeler to test different nesting hypothesis. Such an approach is used in the Portland model, but not been used since by any of the implemented model systems.

#### 4.6.4.3. *Tour time-of-day choice model*

It is not yet obvious whether activity and departure times should be predicted before mode and destination choice, between them, or after both however there is some empirical evidence that shifts in time-of-day occur at two levels: the choice among broad periods of the day (e.g. morning or evening) is made fairly independently of accessibility, while smaller shifts of up to an hour or two are more sensitive to travel times and costs – the peak spreading effect. So in models that use broad network time periods, the tendency has been to model the choice. In some models, time-of-day choice is done between the destination and mode choice decisions, which allows the use of destination-specific mode choice logsums in the time of day model, but requires that the destination choice model assume a specific time of day for the impedance variables. The Sacramento model system places the time-of-day choice level below destination and mode. For DRCOG, the data support modeling tour time-of-day above mode choice for work and school tours, but below mode choice for other tour purposes.

Some model systems include a model called “lowest” model which, in lieu of predicting the overall tour time-of-day, predicts the departure time separately at the trip level to the more details periods, conditional on the mode, origin and destination of each trip. This may relieve the difficulty with the placement of the model tour time-of-day choice model.

#### 4.6.4.4. *Time periods and time constrained scheduling*

Most four-step models use two time periods – peak and off-peak – and use independent on time-of-day parameters. Activity-based models, on the other hand, use usually at least four time periods – morning peak, midday, evening peak, and off-peak. The more recent models, beginning with Columbus, use more precise time windows in order to schedule each tour and trip consistently during the day. This involves keeping track updating the available time at the end of each activity by blocking out the time spent for the activity and its associated travel. The Sacramento model is going even further by moving to half-hour periods to provide even more detail. Increasing the precision beyond half an hour, however, does not appear necessarily efficient. The main constraint on how small the time periods can be is the adequacy of the self-reported times in the diary survey data. There is evidence that people round clock times to 10, 15 or 30 minute intervals. Other issue regards the level-of-service data, which influence the travel times. The use of no more than four or five time periods for traffic assignment has not been satisfactory, increasing the pressure to use more time periods for traffic assignment, and to move to dynamic traffic assignment. Denver model system is implementing eight time periods for traffic assignment, and SFCTA and PSRC have implemented an assignment procedure that takes the equilibrated results of two three-hour peak period assignments and generates differentiated level-of-service skims for each half hour within the peak.

#### 4.6.5. Intra-Household Interactions

None of the current models explicitly treats linkages across household members explicitly. Instead, a wide range of person type and household composition variables are used to model the interactions among household members implicitly. However, the effort has been begun to use explicit linkages between the predicted activities and travel of different members of the same household. For instance, the Columbus model system includes a sequential model of these linkages, simulating children first, and then adults conditional on what the children do. The Atlanta model system includes a similar model that is estimated simultaneously across all household members, avoiding the need to assume the order in which they are simulated and thus the direction of causality. The Columbus and Atlanta model systems include models of household joint activity generation and participation. The application of the Columbus model has shown that predicating joint travel can have significant implications for mode choice. However, it is not yet known to what extent the additional accuracy of explicitly modeling joint

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activity interactions will merit the additional complexity, and as a result, for example, the Denver system will not include such models.

Capturing intra-household effects becomes more complex when activity patterns are concerned as compared to tours. In the Columbus system, three separate ways have been considered for capturing intra-household effects. One way is to condition activity patterns of one household member on activity of other household members. A second way is to generate home based tours made by more than one household member at the household level rather than at the individual level. A third way is to generate maintenance activities at the household level and then allocate them to individuals. The Columbus and Atlanta model systems assume that activities for certain purposes are conducted on behalf of the household, and include explicit models of the generation of these activities at the household level and then allocation to particular individuals. In the Atlanta case, this model was estimated jointly with the household joint travel generation model. Compared to explicitly linking people who make joint tours together, predicting which people within a household perform allocated activities seems to be less important to the model results – we are not changing anything fundamental about the tours by indicating just which person makes them. Therefore, the fourth key linkage appears less crucial than the joint travel models. In addition, it is difficult to determine reliably, from existing surveys, which activities are most likely to be allocated. For example, grocery shopping is mainly an allocated activity, while shopping for a good book to read is an individual activity, but both are usually coded the same. Therefore, without better survey data designed to distinguish activities by whether they achieve household or personal objectives, the quality of models that attempt to allocate household activities is questionable.

However, most of the models include a separate “escort” purpose, so that the most important special characteristics can be captured – particularly the fact that the mode is nearly always auto or walk. Children’s school locations can easily be included as special alternatives in the parent’s escort tour destination choice sets, so that at least the location is accurate, even if the exact trip timing and car occupancy are not matched.

#### 4.6.6. Land Use and Accessibility Measures

The issue of how to include accessibility and land use effects in the upper level models is extremely important, because it determines the accuracy with which the models represent sensitivity of activity, tour and trip generation and patterns to transport level of service and the distribution of activity

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attractions. Calculation of full logsums across all possible nests of lower level alternatives is infeasible with so many levels of choices. The earliest Portland models came closest to including “proper” individual-specific logsums, but the structure of the model was relatively simple, and the effect on model run-time was severe. Initially, the San Francisco model included mode-specific measures with set boundaries, such as the number of jobs accessible within 30 minutes by public transport; however, the rather arbitrary cutoff boundaries in such measures can cause unexpected sensitivities. It has recently been enhanced to use logsum-based accessibility measures. The New York and Columbus model systems use mode-specific travel time decay functions that approximate the logsum from a simple destination choice model. Such measures perform better, but still have the problem that they are mode-specific, and that auto and public transport accessibility tend to be correlated, so it is difficult to estimate model parameters for both of them. A method that solves this problem and is more consistent with discrete choice theory is to approximate joint mode/destination choice logsums, as implemented in Sacramento models. However, the mode choice logsums tend to vary widely across the population, so it is best to calculate different accessibility measures for different population segments. The Sacramento models use aggregate accessibility logsums for each combination of seven travel purposes, four car availability segments, and three walk-to-public transport access segments, as these tend to be the most important segmentation variables in the mode choice models. Both DRCOG and PSRC are using aggregate accessibility logsums similar to those used by SACOG.

#### 4.6.7. Spatial and Temporal Representation

The issue of aggregation bias has led the state of best practice aggregate four-step models to introduce significant socio-economic segmentation on variables such as income, auto ownership, household size and transit access. While adding additional socio-economic explanatory variables in an aggregate setting is extremely cumbersome, adding them in a microsimulation setting is straightforward as any number of socio-economic characteristics is trivially associated with each individual in the synthetic population. In the Atlanta model, land use is being treated at the 200 m<sup>2</sup> grid cell level. The level of geographical detail is important for modeling short trips as well as for modeling public transport access and egress. The degree of detail has been depending on zone sizes, but in principal can be extended to the level of GIS system resolution.

The level of temporal detail is quite important for a number of applications. The Portland model applied a five-period breakdown of the day. Still many

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important temporal substitutions will take place within a single period using this broad period breakdown. In the Columbus model, a greater temporal detail is allowed, and a day is broken down into one hour time periods. Generation and scheduling of tours are made in a consistent way, by first generating and scheduling work and school tours and then using the rest of the daytime to generate remaining non-mandatory tours.

#### 4.7. Summary on the Tour/Activity-Based Paradigm

Although the random utility-based approach and rule-based approach constitute the two major approaches towards activity-based modeling, they are not the only ones. In general, these two approaches provide more generalized and behaviorally better underpinned modeling framework compared to others. The approaches have become more similar over time in what is being modeled (behavioral mechanisms) and how it is being implemented (micro-simulation), even if there are considerable differences in how the models function. Albatross and the Portland model systems represent valuable improvements already in themselves and particularly with respect to their potential or already existing descendants.

The rule-based approach provides the possibility to define literally any decision rule and can consider any combination of conditions. However, the major obstacle would be how to estimate decision tables and parametric choice models in a coherent body and consistent way. The random-utility approach, on the other hand, implies a useful possibility to calculate consistent accessibility measures, which would provide a natural link to modeling interactions between the transport system and urban structure.

Although both approaches allow for time interdependencies, none of them is dynamic in the sense that they allow for behavioral changes caused by changes in travel conditions during the day relative to expected conditions. Algers et al. (2005) suggest that the random utility-based discrete choice framework seems to provide a smooth way of gradually introducing more realistic – and therefore more complex – behavioral features in transport decision support tools. In comparison, few Albatross-like models are currently available. The strong sides of Albatross, such as its ability to handle constraints and to model the sequence and duration of activities, are being subject to research in the random utility-base context. Yet, it is not clear which direction of research offers the best prospect for meeting future demands on transport planning tools.

Vovsha et al. (2005), Bradley and Bowman (2006) and Bowman (2009) present a historical review of activity-based models and the current state of

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the art developed in the US. Drawing on these papers, the applied modeling state of the art of the random utility-based family of activity-based models is summarized briefly in this section. Figure 1.9 shows a timeline of the development, calibration and use of applied activity-based models in the United States. The first tries for the development of applied activity based models have been started literally since 2000 with models for San Francisco County, New York and Oregon and early applications come in 2001 with the model of San Francisco County. Some of these models have trip-based predecessors (e.g., MTC for San Francisco Bay or PSRC for Seattle) and the others are developed from scratch.

These model systems are very similar in their overall structure with a hierarchy of levels, where lower level choice predictions are conditioned by those at higher levels, and higher-level choices are influenced by accessibility measures that capture the effect of choice opportunities occurring at lower levels. We also mention Dutch national model system (Gunn, 1994, de Jong et al., 2006), Stockholm model system (Algers et al., 1995), and two of the Parisian model systems, IMPACT4 (Garcia-Castello, 2010) and ANTONIN-2 (Debrincat, 2000), as examples of European tour based models. The two latter models will be reviewed briefly in the next chapter.

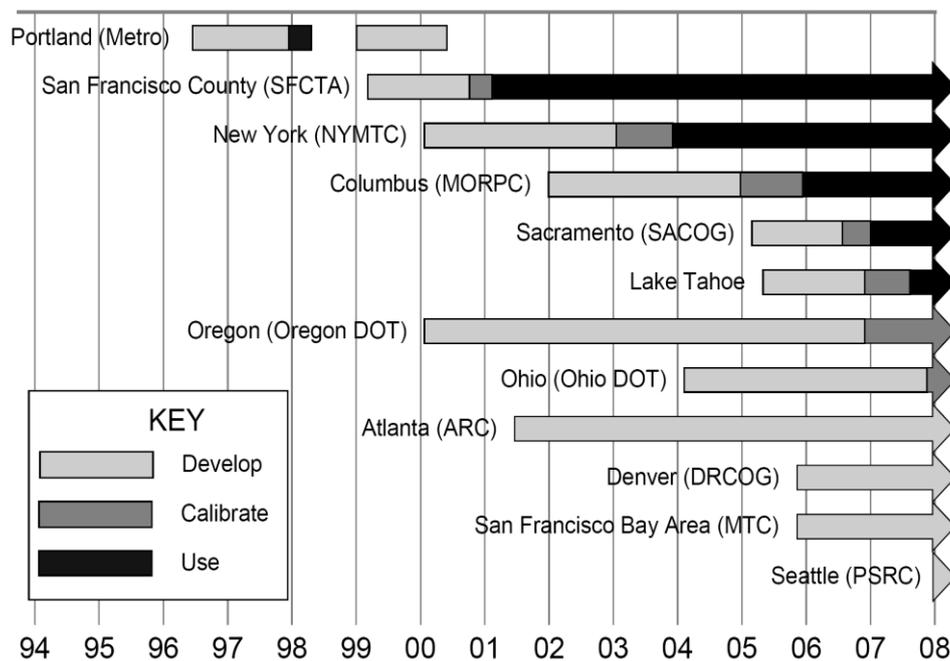


Figure 1.9. Timeline of activity-based models in the United States (Bowman, 2009).

## 5. Land-Use/Transport Interaction Modeling Paradigm

Land-use/Transport Interaction (LUTI) models are based on the idea that travel is derived from the need of households and businesses to interact with their environment. Figure 1.10 illustrates the interacting land-use versus transport aspects that a LUTI model deals with. Clearly, the spatial configuration of an urban system (also known as land-use pattern) influences the travel-related decisions that individuals make. Land-use aspects are on the long-run side where transport decisions are relatively short-term. For example, in an urban system where jobs are mostly concentrated at the central business district, the travel patterns will be different from the case where jobs are further shifted to suburbs. In the former case, commuters have to use centric itineraries in order to reach their daily activities, and spend considerable time in congestion. They also may prefer to rely on public transportation simply because it is less congested than roads. In the latter case, commuters will most likely depend on their personal vehicles to assure the accessibility to their job in suburban regions.

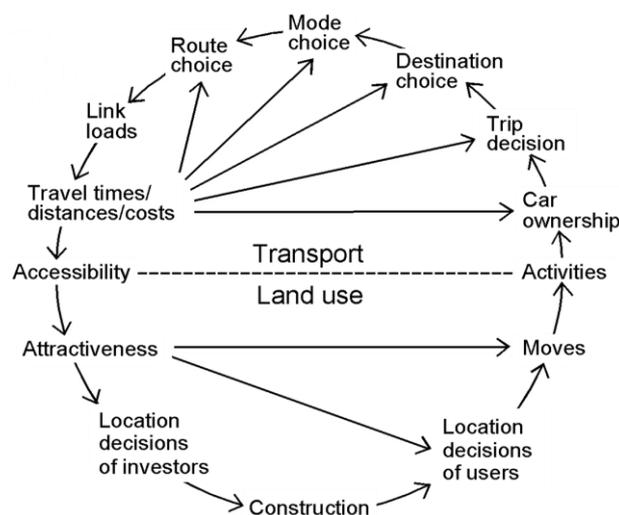


Figure 1.10. The land-use transport feedback cycle (Lautso et al., 2004).

### 5.1. Urban Economy Sectors

One can consider the whole system of urban economy as a combination of four economic sectors: mobility, labor market, housing market and land development. As Miller et al. (2004) state, market interactions play a central role in determining the evolution of urban areas because economic interactions of consumption and production across the full gamut of economic sectors provide a primary driving force for city formation and evolution. LUTI models

are complex systems that, in theory, try to contain all four parts of an urban activity system and their interactions in one single body.

### 5.1.1. Labor Market

Labor market is where employers (who need service) and workers (who offer service) interact. The interaction between mobility and labor market has two facets. On one hand, labor market, and more generally labor economics determines employment opportunities, wages and incomes and therefore influence socio-economic attributes of individuals and households, and consequently their mobility decisions. On the other hand, transportation system assures the flow of labor services from workers' residential locations to places of employment, which is the motivation behind commute trips.

Employment choices are decided at long-term. They depend upon internal dynamics the labor market whereas choices related to commute trips are taken on daily basis and are regarded as short-run decisions. Inside the labor market, unemployed individuals are competing for possessing business positions that are created by the employers. They offer competence and make a trade-off between accepting a modest salary, and spending more time searching for another job. Employed individuals also may compete for a promotion or changing to a higher professional status. On the other side, however, there is no competition for a dismissal.

The creation or loss of business opportunities may be sometimes considered as the result of urban scale policies but it is most of the time influenced by the national or even international economic situations. Therefore, to our knowledge, no model has so far tried to account for long-term employment decisions (internal interactions of the labor market) in an explicit manner. Instead, employment status is used as an important parameter in forming socio-professional demand categories, which will then define demand segments.

In general, it is adequate just to consider one single socio-professional category for unemployed persons. However, in order to explicitly model internal interaction of the labor market, one needs to re-categorize unemployed individuals based on their skills and competences (i.e. education level, previous job category, etc.) according to different business sectors (such as agriculture, high-tech, etc.). This because the evolution of business opportunities inside the labor market is heterogeneous so that one sector may be in rise while another is in loss.

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### 5.1.2. Housing Market

Any household needs a house. As there exist only a relatively limited number dwelling opportunities, a competition is formed among households in order to acquire “better” places, which will eventually determine house prices in a free market context. Factors contributing in the value of a house are of two categories. First, are general factors such as size, age, proximity to shopping center, etc. Second are individual factors that differ among households. For example, young households with minor children will favor places near schools.

The decision of where to dwell is one of the basic choices that a household should make in the long-run, which will directly affect transportation system. Classic housing demand models of the 1960s suppose that housing demand stems from labor demand. The number of residents per zone is spatially distributed according to a gravity model:

$$R_{ij} = u \frac{w_j \exp -\beta C_{ij}}{\sum_k w_k \exp -\beta C_{ik}} E_i$$

where  $R_{ij}$  represents the number of individuals working in zone  $i$  and residing in zone  $j$ ,  $u$  is a population to employment ratio,  $w_j$  is a residential attractor weight for zone  $j$ , and  $C_{ij}$  is the transportation costs from zone  $i$  to zone  $j$ . In this aggregate modeling approach, the number of dwelling units in each zone is determined by two competitions among zones: a competition in order to acquire more residential population, based on their relative attractiveness, and a competition to acquire more workforces based on the number of jobs they provide and transportation costs with other zones. These factors however are not economic as, for instance, no account is taken of house prices or household incomes. These classic entropic models were developed in the 1970s to include the household income. Techniques such as population stratification were also used to increase model explanatory power.

Considering the lack of micro-economic foundation of gravity models, next generation of models adopted a general spatial equilibrium framework. The next generation of urban system models was developed in the 1990s. TRANUS, which is one of the first and most famous spatial economics models, is based on the same seminal belief of the classic approach that housing demand is mainly derived from labor demand. Jobs located at zone  $i$  generate a demand for working households, who are stratified by income. Households in each income class choose their residential location according to the following Multinomial Logit formulation:

$$P_{ij} = \frac{w_j^\alpha \exp -\beta \bar{U}_{ij}}{\sum_k w_k^\alpha \exp -\beta \bar{U}_{ik}} \quad ; \quad \bar{U}_{ij} = \frac{U_{ij}}{\theta} \quad ; \quad U_{ij} = \lambda p_j + h_j + t_{ij}$$

where  $P_{ij}$  is the probability of dwelling at zone  $j$  and  $\bar{U}_{ij}$  is a scaled residential disutility based on average housing price  $p_j$ , shadow price  $h_j$ , and commuting cost  $t_{ij}$  between zone  $i$  and zone  $j$ . Household income constraint is partially taken into account through the parameter  $\lambda$  which depicts household's sensitivity to housing prices: rationally lower income households are more sensitive to housing prices and higher income households are less sensitive. This approach makes intensive use of the random utility maximization theory and its Multinomial Logit model.

General spatial equilibrium models are more successful in providing better econometric basis for housing demand modeling; however, they are criticized for their lack of a dynamic framework to take into account various temporalities of urban processes (Coulombel, 2010).

### 5.1.3. Land Development

Land development includes the ensemble of activities which aim for the growth over time of the built environment within which household and business activities locate. Two approaches are explored in the literature for modeling the land development: the grid-based approach and the building-based approach.

In the grid-based approach, the entire urban land is covered with a grid and the built environment is described in terms of the amount and the type of floorspace located in each grid cell. The primary task of the land development module is then to adjust the quantity and type of this floorspace over time in response to changes in price. For each grid cell, the model should decide whether to redevelop, to which category of space, and to what extent. These decisions can be made using simple discrete choice models.

In the building based approach, individual buildings are generated by the land development model, where each building is characterized by its type, floorspace, location, etc. In this approach, decision is made in two stages. First, a macro level model predicts region-wide building starts as a function of socio-economic variables and exogenous cost shifters. Then, a micro model predicts the spatial distribution of the new starts as the outcome of a spatial choice process of real estate developers.

The land development model is behavioral and represents the decisions of landowners regarding how to improve their properties. Landowners (developers) make their decisions based on current prices and vacancy rates.

## 5.2. Land use and Transport Interaction Models

Figure 1.11 presents a conceptual representation of a typical operational LUTI model. As the figure shows, the LUTI models in general consist of a travel demand or transportation component and a land-use component with a few links in between which will allow capturing the land use-transportation interactions. The most common link concerns location accessibilities: accessibility measures output by the land use component are fed into the travel demand component, and a feedback system is built-in to update the accessibilities in response to the output from the travel demand component.

The earliest land-use transport interaction models were static, driven by gravity or input-output formulations. Consequently, these models were not capable of responding to policy changes. Operational static LUTI models are typically or entropy-based and linked directly to a four-step demand models, or estimate equilibrium patterns of land-use according to the accessibilities output by a transport model, usually through iteration with the travel demand model. They cannot realistically capture urban spatial processes and their effects on the transport system. At the very core of the static approach, land-use and transport systems are regarded as being exogenous to each other. Nevertheless, some static models continue to be used to present day, either as a means of adding a land-use dimension to existing transport models, without undertaking the extra work needed to build a dynamic model, or because the static model represents an equilibrium state which is of interest by itself.

The development of improved modeling methodologies such as random utility maximization and non-linear optimization, together with significant computational advances, made it possible to model the land-use/transport interactions in a dynamic fashion. Sivakumar (2007) classifies LUTI systems into two broad categories based on the analysis unit and the operational theory, being General Spatial Equilibrium Models, such as MEPLAN (Hunt and Simmonds, 1993), and Agent-Based Microsimulation Models, such as DELTA (Simmonds, 1999), ILUTE (Miller et al., 2004) and UrbanSim (Waddell, 2002, 2003).

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- Aggregate representations of households and firms, and lack of representation of individuals as decision-making units separable from their household;
  - Lack of endogenous demographic and auto-ownership processes;
  - Lack of intricate linkages between land use and travel demand components;
  - Reliance on four-step travel demand components.

However, they also point out that these models are based on strong microeconomic formulations and have capabilities of multimodal transportation network analysis.

The new generation of LUTI models, address these shortcomings in parallel with the development of the activity-based approach to travel demand analysis. These efforts focus especially on replacing four-step travel demand components with activity-based models, and relieving aggregation biases using disaggregate modeling frameworks. Examples on newly developed models include ILUTE in Canada (Salvini and Miller, 2003), ILUMASS in Germany (Moeckel et al., 2003), RAMBLAS in Netherlands (Veldhuisen et al., 2000). Some of existing models such as UrbanSim and MUSSA (Martínez, 1996) are also continuing to evolve towards new approaches. The new generation of models conserves the strengths of currently operational models – especially their strong microeconomic formulations of land use and housing-floor space market and coherent frameworks for dealing with land use-transport interactions – and builds on experiences learnt during their development.

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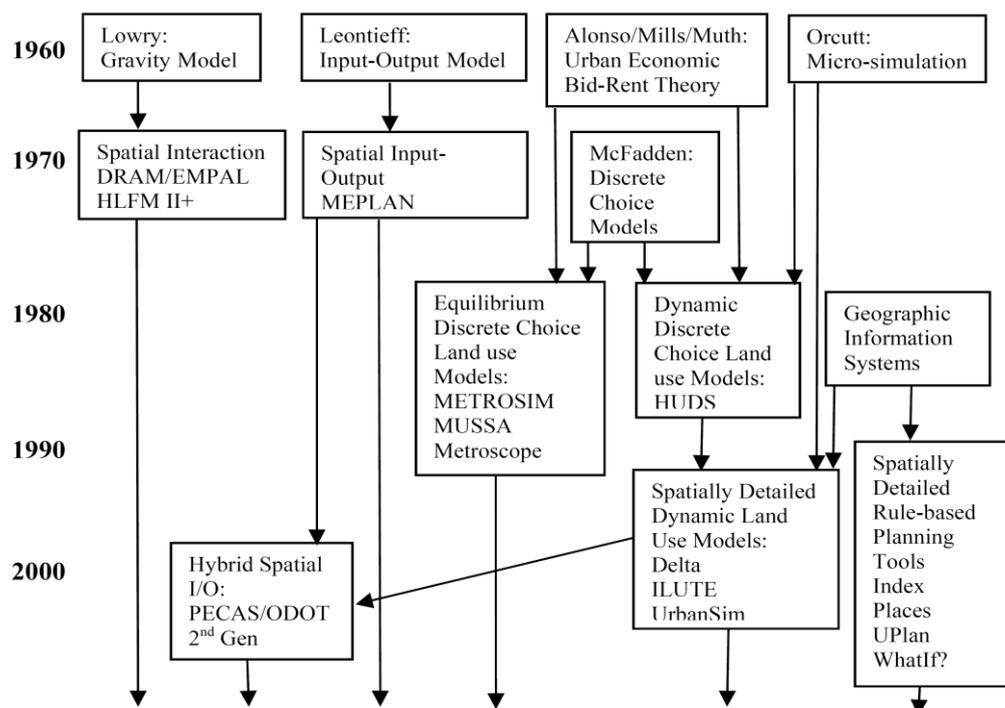


Figure 1.12. Evolution of land use-transportation modeling frameworks (Waddell, 2005).

### 5.3. Spatial Modeling Methodologies

Methodologies used for modeling the traffic flows in space have been evolved from basic macroeconomic frameworks to disaggregate microeconomic and behavioral decision-making theories. Methods based on Gravity Formulation or Entropy Maximization, in which the flow between two access and egress points is inversely related to their spatial distance, are probably the first to be used in applications. However, these models are aggregate and suffer from a fundamental lack of behavioral decision-making processes. The need for a model capable of describing individual choices of location give rise to the second paradigm known as Constrained Optimization. In this method, the utility of the individual decision-maker (person, household, firm, etc.) is constructed as a demand and supply function, wherein resources are consumed and utility is gained to varying degrees depending on the choice of alternatives. An optimization problem is formulated where the individual maximizes its utility subject to several resources constraints. However, this method is limited to pure mathematical assumptions and no econometric basis is provided.

Currently developing models use one of two major methodologies, one based on the random utility maximization and the other based on computational process. The random utility maximization paradigm brings the problem of

understanding individual choice behavior down to individual decision-maker level and at the same time acknowledges the discrete nature of these choices. Advances in the random utility maximization framework during last decades have made it possible to develop flexible and behaviorally realistic models for various individual decision-making steps.

Computational process models offer sets of rules in the form of condition-action pairs that specify how a task is solved. The modeling approach focuses on the process of decision-making and captures heuristics and short-cuts that are involved, as opposed to assuming overriding paradigms such as the random utility maximization. Hence, the modeling approach offers more flexibility than econometric models in representing the complexity of travel decision making. A major drawback of this approach is their lack of a statistical error theory, which makes it more difficult to generalize their outcomes and to apply them to policy evaluations. These models generally have very challenging data requirements for model estimation, application, and validation.

### 5.3.1. Spatial Representation

In an urban microsimulation system, many different spatial elements should be modeled at different spatial scales. From buildings as fundamental containers of activities to parcels and traffic zones should be considered together as spatial units in a land use-transport system. Buildings are located upon land, which can be divided into parcels, zones or grid cells. That is, a hierarchy of spatial elements exists, consisting of “occupancy units” (floorspace, dwelling units), which are contained within physical structures (buildings). An urban microsimulation system should be able to represent space clearly at all three levels of this hierarchy, which are occupancy, built structure and land. Miller et al. (2004) propose two different approaches to representing spatial elements in a microsimulation-based context: grid-based system and building based system.

#### 5.3.1.1. *Grid-based system*

This approach consists of covering the land with a fine grid system to represent space, and for each cell, the type of floorspace (single family housing, apartment, etc.), and the density of development are inquired. So spatial elements such as buildings or firms are not explicit entities of the modeling system and are implicitly modeled. This approach is computational efficient due to its uniformity of treatment that requires very little overhead

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in handling and storing the information. Besides, the representation can be very close to continuous that allows appropriate aggregate behavior to emerge.

#### 5.3.1.2. *Building based system*

This approach is a much more direct one. Buildings are inquired by their type (high-rise structure, bungalow, etc.) and usage (condominium, office building, mixed use, etc.). Each residential building contains one or more dwelling units while each commercial building contains a certain amount of floorspace, subdivided among one or more occupants. Dwelling units have tenure (own or rent) and size (floorspace). One advantage of this design is that it is relatively indifferent to the level of spatial aggregation.

### 5.3.2. Temporal Representation

In an urban microsimulation context, it is assumed that the urban state is path dependent, i.e. it does depend on the sequence of events taken place in between past and future states. In other words, the system is never in equilibrium but rather in a continuous dynamic disequilibrium, which evolves over time. So the only way that a future system state can be predicted is by explicitly “stepping the system through time”. Two classic approaches exist for handling time in microsimulation: discrete event approach – in which, like an analog computer simulator, a queue of timed events is maintained and the simulation clock advances to the time of the next event in the queue, and discrete time approach – in which the simulation clock advances by a fixed increment. In practice, the discrete event approach is not well suited to conventional urban sizes and modeling time spans. Because, for example, regularly-occurring decisions would need to be entered as “events” and this may finally define as many events as if it was a discrete time approach. Also, it may become difficult to keep the temporal coherence among different modeling modules because different decision models do not use the same time aggregation intervals (e.g. residential location decisions may be evaluated monthly whereas firm location decisions could be evaluated annually), and when no event can take place at a non-preregistered time, the effects of the events with finer time resolution on decisions with larger time resolution are difficult to be taken into account. More discussion on the subject is provided in Miller et al. (2004).

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## 5.4. New Generation Microsimulation Models

Miller (2003) defines the term “Microsimulation” as a method or approach for exercising a disaggregate model over time possessing one or both of the following characteristics:

- The system is dynamic whose behavior must be explicitly modeled over time;
- The system’s behavior is complex due to many possible sources, including: Complex decision rules for the individual actors within the system; Many different types of actors interacting in complex ways; System processes that are path dependent; A generally open system on which exogenous forces operate over time, thereby affecting the internal behavior of the system; Significant probabilistic elements (uncertainties) that exist in the system, with respect to random variations in exogenous inputs to the system or the stochastic nature of endogenous processes at work within the system.

New generation models are considered to be able to evaluate the impact of a wide range of different policies on the transportation system and the full impact of transportation policies on the entire urban system. Thus, theoretically the full range of short- and long-term interactions should be taken into account, including (Miller et al., 2004):

- evolution of the built environment;
- evolution of population demographics over time, in response to endogenous population changes as well as migration into and out of the region;
- simulation of the location choices of households and firms within the built environment;
- simulation of the internal economy of the urban area within an explicit spatial framework (i.e. all of the economic processes which generate person travel and goods movement within the urban area);
- simulation of the activity/travel patterns of the resident population and the internal flow of goods and services, by mode, route, and time of day;
- simulation of the performance of the road and transit systems (travel times and costs, congestion levels, etc.);

One may even include the estimation of atmospheric emissions generated by the transportation system and production points in this framework. The need

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for taking into account these complexities together with computational advances during last decade have promoted the implementation of the agent-based miscorrelation approach, where every individual (person, household, firm, etc.) is considered as an agent for which behavioral models and interaction law with other agents are explicitly described. The agent-based microsimulation is based inherently on tracing the path of evolution of a system so that path dependent nature of urban systems is well represented using this approach, something that is missing in the conventional static equilibrium models. However, integrated fully microsimulation land use-transport models are still rare. A notable exception is RAMBLAS (Veldhuisen et al., 2000), which is explicitly agent-based in both design and implementation. Urbansim is also currently evolving to include a microsimulation based activity/travel demand component, although it is not truly agent-based (Sivakumar, 2007).

## 5.5. Summary on the Land Use–Transport Interaction Paradigm

The task of modeling an entire system of complex interactions starting from micro level of individual actors and ending up with regional or even national organizations and administrations effective at urban level is huge. While modeling of daily activity patterns and estimating individual travels and decisions regarding the choice of departure time, travel mode, destination, etc. are not completely mastered, undertaking the task of incorporation many other factors, external constraints and policies, temporal evolutions, etc. is daunting. In long-term decisions, which in travel demand modeling context can often be satisfactorily taken into account using appropriate explanatory variables, need to be understood in more depth and represented explicitly. Modeling interactions between land use and transportation system often involves simultaneously simulating evolutions and interactions of multiple economic contexts such as individual utility maximization and housing market. LUTI models often have long history of development behind them as the number of aspects and the complex interrelationships were and still are to be understood. Therefore there is no surprise that four-step transportation cores are still in use in LUTI model systems, and equilibrium based models such as MEPLAN (versus dynamic microsimulation models such as ILUTE) still constitute main tools of urban and regional policy analysis. For example, MEPLAN, being one of the earliest LUTI model systems, is currently adopted by the Sacramento Area Council of Governments for policy analysis purposes.

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## 6. Conclusion

We have studied four main paradigms for transportation demand modeling. We started by conventional aggregate trip-based models and continued towards newer modeling approaches. We tried to point out main concepts and at the same time provide some applied examples to illustrate how those concepts are being applied in practice. Here we once more stress the two main purposes of this literature review which were to study: the quality of representation of the individual travel decision-making process (behavioral aspect), and the quality of simulation of the physical decision-making context both in terms of representativeness of transportation networks and local accessibilities (physical aspect). We also briefly compare between the state of the practice and the state of the art, and discuss on the possible reasons that has led to the wide gap between art and practice of transportation modeling.

### 6.1. Behavioral Modeling Aspect

Trip-based travel demand models implicitly assume that the choices relating to each origin-destination trip are made independently of the choices for other trips within the same and other journeys. This approximation is made to simplify the analysis, and is reasonable when most of the journeys consist of round trips (e.g., Home-Work-Home).

Tour-based travel demand models (also known as trip-chaining models), on the other hand, assume that choices concerning the entire journey influence each other. For example, the choice on an intermediate destination during the journey is made with regard to the preceding and the following destinations.

Activity-based travel demand models predict travel demand as the outcome of the need to participate in different activities in different places and at different times. They therefore take into account the relationships among different journeys made by the same person during a day and, in the most general case, between journeys made by the various members of the same households.

Land use-transport interaction modeling is where individual travel behavior modeling in combination with other contexts of urban economy culminates to a comprehensive modeling framework, which promises to provide a whole view of ongoing evolution of the entire urban system at different levels.

As McNally and Rindt (2007) point out, construction of models strictly based on the concept of utility maximization, undermines substantial evidence relative to alternate decision strategies involving household dynamics, information levels, choice complexity, discontinuous specifications, and habit

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formation. Travel is essentially a physical mechanism to access an activity site for participating in some activity. When trip-based models are satisfied with models that generate trips, activity-based approaches focus on what generated the activity that begot the trip.

## 6.2. Physical Modeling Aspect

Unlike travel demand models, which have been greatly improved during last four decades, travel supply modeling is less developed if not stagnated. Davidson et al. (2007) state that “conventional four-step models have been associated with extensive development of transport system by construction of new infrastructure facilities, so These models are less oriented to policy issues or demand management measures”.

It is useful to consider demand modeling and supply modeling separately, as it helps to understand the model system dynamism. The separate consideration of demand and supply modeling also allows identifying other more suitable alternative modeling approaches. Hunt (2006) investigates levels of disaggregation in demand and supply modeling and gives a cross-classification of models based on these two aspects. On the demand side, he introduces the spectrum of behavioral units ranging from entire aggregate population to observed agent (Figure 1.13). On the supply side, he introduces the spectrum of degrees of aggregate constraint ranging from aggregate system optimal to agent processes. On this scale, direct demand models are placed on the upper-left corner of the diagram whereas activity-based models find themselves somewhere close to the lower-center. He finds that much of the practical work in transportation system modeling tends to sit very broadly along a diagonal that runs from the combination of aggregate and equilibrium to that of disaggregate and process simulation. Hunt (2006) also mentions that the focus often seems to be the complexity of the representation of the behavior of individual agents or groups of individuals. However, dynamic assignment models have been under development but there are probably only a few examples where they are used in combination with state-of-the-art demand modeling paradigms such as activity-based approach. It is therefore plausible to state that despite all of the credible critiques of demand modeling side of the conventional aggregate paradigm, supply modeling is not yet outperformed by new generation models.

Davidson et al. (2007) concludes in the same way that so far no attempts have been made to extend the theory of the network equilibrium to the activity-based models. They relate this to the major theoretical problems, which are due to analytical complexity of the modeling chain.

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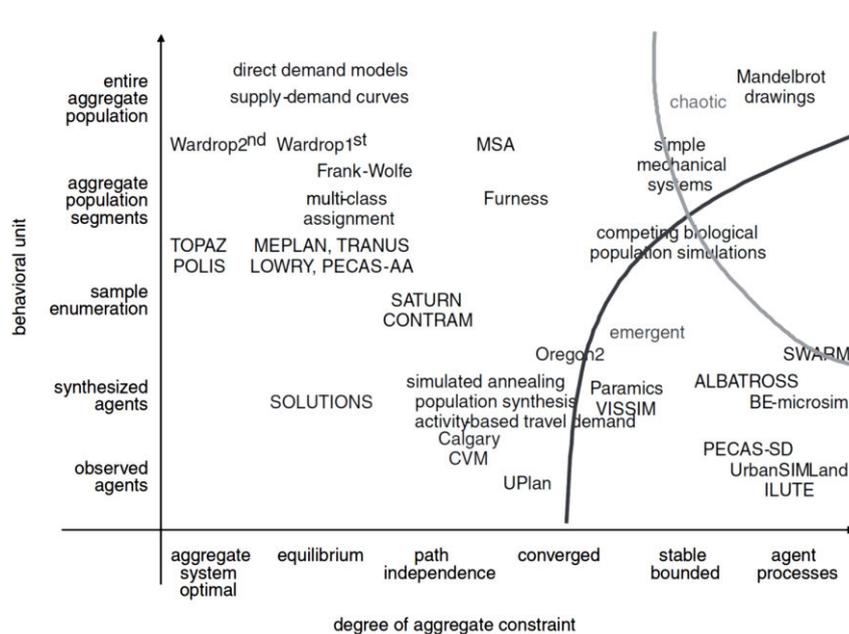


Figure 1.13. Level of aggregation and degree of aggregate constraint in models (Hunt, 2006).

Davidson et al. (2007) present a number of modeling principles, which they call of “best-practice”, recognized because of our improved understanding of how people make travel decisions. They include in their list suggestions with regard to the representation of the individual’s decision-making behavior in the model:

- To model travel decisions in a disaggregate fashion,
- To maintain intra-household linkages in all travel decisions,
- To explicitly consider relevant individual and household characteristics,
- To include short-term and long-term travel choices and household changes;

but moreover they point out the necessity to equip models with better spatial representations which in turn leads to a more realistic simulation of physical situations in which the individual traveler makes travel decisions, and suggest:

- To predict realistic highway and transit level of service, travel time and costs,
- To adequately define feasible choices for each travel decision,
- To use adequate accessibility measures to inform travel-related decisions.

The two last items of this list pinpoint the main purpose of this dissertation which aims to ameliorate mode choice modeling by introducing disaggregate spatial representations.

### 6.3. Art versus Practice of Modeling

Stopher and Greaves (2007) recall Lee (1973) who wrote of the demise of large aggregate four-step models of travel demand, however those models have shown themselves to be particularly resistant to the morbidity that was suggested for them. Almost 30 years after their requiem was suggested, they remain as mainstay of most metropolitan modeling efforts throughout most of the world. While new models and paradigms have been proposed and tried, the aggregate models have retained much of their place in the planning process.

The state of practice in travel demand modeling has been evolving relatively slowly, and much slower than the state of the art of modeling. The methods for trip generation (cross classification and regression) and trip distribution (singly- or doubly-constrained gravity models) have changed little, if at all, over past years, and the same aggregate modeling framework with the same four-step structure still maintains an important part in travel demand forecasting.

Davidson et al. (2007) and Walker (2005) address the broad gap between practice and the current state of the art in the field of travel demand forecasting. They point out that there are several resisting forces on the Metropolitan Planning Organizations' side, as their policy making needs does not necessarily require very accurate modeling tools. One other reason could be that these organizations have not yet experienced clear gains of using activity-based models because the number of actual demonstrable applications is quite a few (Walker, 2005). Even when they are interested in more advanced models, they do not always possess adequate funding or technology (including resources required for conducting compatible surveys). Only a handful of agencies in major cities find it useful and can afford to develop new generation models and replace their traditional four-step models.

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# Chapter 2: Transportation Demand Modeling: A State of the French Practice

## 1. Introduction

As an element of method, French local authorities, along with other European metropolitan areas, have developed and adopted modeling tools for planning and policy making purposes. Transportation modeling provides local authorities by the engineering tool required in the decision-making and planning process. It enables them to base their decisions on economical evaluation and quantitative comparison among alternatives. This allows acquiring “solid” control over the whole transportation planning process by defining more measurable objectives and eventually making defensible decisions. Transportation modeling practice by French local authorities has been boosted as a response to the need to provide rigorous quantitative evaluations of the level of accomplishment of the current PDUs and to sketch out the objectives for the next ones. In this chapter, we present a review of French transportation demand modeling efforts. We will distinguish between Ile-de-France and other French metropolitan areas, owing to the significant weight of Ile-de-France both in social and economic terms.

It is important to mention at this point that applied transportation models evolve and improve constantly. On the other hand, models are oftentimes poorly, if at all, documented and most of the time information on different aspects of these models is difficult to acquire. In this review we use the most up-to-date references that were available to us. However we do recognize the possibility that some of the details in the reviewed models may have been changed at the time these lines are being red.

### 1.1. What is an Urban Mobility Plan?

Urban transportation planning for French metropolitans is based on the Urban Mobility Plan (PDU). It is a planning and programming document, which defines the objectives and the actions to be undertaken in order to organize the mobility in a sustainable manner. Measures that are to be undertaken should help to organize individual and freight transportation as well as the traffic and parking. It also includes spatial planning issues (STIF, 2009, Mestayer et al., 2010).

Elaboration of an urban mobility plan is mandatory for the urban transportation perimeters of urban areas of more than 100,000 residents according to the French 1996 law on Air Quality and the Rational Use of Energy “loi sur l’air et l’utilisation rationnelle de l’énergie 1996” (LAURE). The LAURE can be considered as the French equivalent of the 1990 Clean Air Act in the United States.

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## 2. Demand Modeling in Ile-de-France

Ile-de-France covers an area of over 12000 square-kilometers and with more than 11 million inhabitants (over 18% of the French population), it is the most densely populated French metropolitan area. It provides about 5.3 million employments and represents 29% of the French GDP. Its inhabitants make in average 3.4 trips per person per day – less than the provincial average of 3.9 – but spend about 82 min in transportation – more than the provincial average of 64 min (Caenen et al., 2010).

The first urban mobility plan of Ile-de-France (PDUIF) was worked out in 2000, which recommended, for the first time at the regional level, a break from the car-only alternative. The process of revising the PDUIF 2000 is started since December 2007.

A number of transportation demand models are being used in Ile-de-France by different actors. Some of these models are used by planning organizations (such as STIF and DRIEA), and serve to test and evaluate transportation policies in the region. Others are operated by transportation operatives (such as RATP and SNCF) and serve to improve their service and to provide concrete basis for dialoging with planners. In the following, we will provide a short review of these models. Our purpose is not to describe these models exhaustively, but to give a synthetic account of their general function and structure.

### 2.1. ANTONIN-2

ANTONIN<sup>1</sup> is the transportation model of the Ile-de-France Public Transport Executive, STIF, for demand forecast and policy evaluation. Its first version was developed in the 90s and was estimated using the 1991 Paris Household Travel Survey. The new version of the model, ANTONIN-2, is updated using the 2001 Paris Household Travel Survey and is operational since 2006 (Debrincat et al., 2006).

The model is structured in the following five successive steps: tour generation, mode-destination choice, time of the day process, pivot point process and traffic assignment. The tour generation step estimates the number of tours per tour-purpose per day that a traveler makes, based on his/her personal attributes. Then each generated tour will go through the mode-destination choice step and by aggregating the corresponding results, the model estimates the amount of traffic per transportation mode. These traffic flows are then

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<sup>1</sup> Analysis of Transport Organization and New Infrastructure

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proportioned and assigned to different periods of day using simple coefficients to match the pattern observed in the survey. Consequent results are then fed to the pivot point process, which recalibrates aggregated traffic flows so that they correspond to the amounts observed in the survey. The final traffic flows are then assigned to highway and transit networks (Debrincat, 2000, Debrincat et al., 2006).

### 2.1.1. Data

#### 2.1.1.1. *Zoning system*

In the first version of the model, the Greater Paris Region was divided into 984 zones with 300 zones for Paris only. In ANTONIN-2 the number of zones is increased to around 1400 zones. For each zone data on the population (including the total number, and breakdowns by gender, age class, income class, and ownership status), number of employments, commercial surfaces, number of school places, and average parking price, are provided.

#### 2.1.1.2. *Transportation networks*

The highway network contains some 30000 links, and detailed information on each link such as type, length, free flow speed, etc. Public transport networks are described for the morning peak and off peak hours. Rail, metro and bus services in Paris and inner suburbs are fully described and kept up-to-date. The description of bus services in the outer suburbs is considerably improved in the second version of the model but is not exhaustive. However, for the study of a precise sector, in practice, the entire bus network of the sector will be coded. The description of the fare system considers only full price tickets and monthly passes.

### 2.1.2. Transportation Demand Representation

ANTONIN-2 is a tour-based disaggregate model. Successive trips of the traveler from the moment he/she leaves home until his/her return constitute a tour which can be characterized by an anchor purpose (i.e., home) and a main purpose (e.g., work). As we have previously discussed, the choice of transportation mode is highly correlated between different trips in a tour. Therefore, in this model the mode is associated to the whole tour and not only to a single trip. ANTONIN-2 uses a simplified tour representation: it only remembers anchor and main purposes and ignores other activities. The main purpose among activities of the tour is determined according to a hierarchical order. The model identifies ten tour purposes including eight home-based and

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two non-home-based tour purposes. The eight home-based tour purposes, in decreasing order of priority, are:

- Home-Work (high income),
- Home-Work (low income),
- Home-Business,
- Home-School (children below 18 years),
- Home-Education (students above 18 years),
- Home-Regular shopping,
- Home-Other shopping,
- Home-Social activities,

and the two non-home-based tour purposes, in decreasing order of priority, are:

- Work-Business,
- Work/Education-Others.

The first step in the modeling process is the tour generation (tour frequency). For every disaggregate traveler, the tour generation model estimates the total number of tours that he/she will make per tour-purpose per day. It is implemented in four sequential sub-models (Figure 2.1).

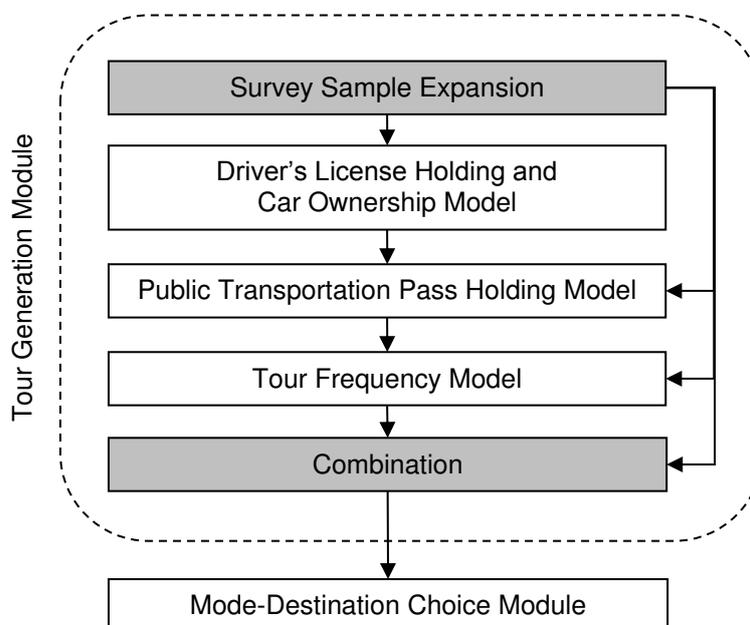


Figure 2.1. Anatomy of the tour generation module in ANTONIN-2 (Debrincat et al., 2006).

It is worth mentioning that these steps are ordered so that the more long-run a decision is, the earlier it is modeled. In this case, the car and driver's license ownership model is placed on top of the public transportation pass ownership model.

In the first version of the model, the public transportation pass ownership step did not exist. In addition, the driver's license ownership status was decided before the car ownership status and in a separate step.

#### *2.1.2.1. Survey sample expansion*

ANTONIN-2 synthetically expands the sample population of each zone so that it matches with the real population. In order to preserve the heterogeneity the demand, is segmented into reference household groups. The number of household groups was 35 in the first version of the model and has been increased to 86 in the second version. Groups are defined based on the age class of the household's reference person, household size, number of workers, and income level of the household. Each household group is weighted so that a number of objective values are matched. Some of the objective values include: the total number of persons and households, total number of men and women of different age classes, total number of worker men and women, total number of households with 1, 2, and 3 or more persons.

#### *2.1.2.2. Driver's license holding and Car ownership*

This is a logit model applied to each household to determine whether:

- only the reference person has a driver's license,
- only the spouse has a driver's license,
- both have a driver's license,
- non has a driver's license,
- other adults in the household have a driver's license.

The first version of the model also included a cohort model to take into account the change of the total number of driver's license. The cohort model is eliminated and the total number of driver's license is supposed to remain unchanged since the survey reference year. Some of the explanatory variables included in this model are: education level, gender, household size, geographic sector, number of workers in the household, income level, etc.

Once the number of licenses is determined, the car ownership model determines the number of cars in the household. If there is no driver's license in the household, it is assumed that there is no car as well. If there is only one

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driver's license, the model decides between none or one car. If there are two or more licenses, it is assumed that there is at least one car. Some of the variables included in this model are: driver's license holder's attributes, number of workers in the household, income level, parking cost, and geographic sector, etc.

#### *2.1.2.3. Public transportation pass holding model*

This model is applied to the individual, and determines if the traveler holds: no pass, a normal pass, or a student pass. Some of the explanatory variables in this model include: category of profession, driver's license and car ownership, age, gender, geographic sector, etc.

#### *2.1.2.4. Tour frequency model*

The tour frequency model is implemented in two steps. First, a logit model decides if the individual will travel at all or not. If it is decided that the traveler will make at list one tour, then a second stop or repeat model determines whether the traveler will make a second tour for the same tour purpose, and it continues until the outcome is "stop".

By applying the results from the tour frequency model to the synthetic expanded population, the model determines the number of tours, per tour-purpose, per traveler, and in each zone of origin.

### 2.1.3. Mode and Destination Choice Model

For each generated tour, the mode-destination choice model will determine the mode and the destination (the latter only in the case of non-mandatory tour purposes). The model's mode choice set includes 13 mode alternatives including three private and 10 public transportation composite modes:

- Auto driver,
  - Auto passenger,
  - Slow modes,
  - Train with walk access,
  - Train with drive access,
  - Metro with walk access,
  - Metro with drive access,
  - Bus with walk access,
-

- Train/Metro with walk access,
- Train/Metro with drive access,
- Train/Bus with walk or auto access,
- Metro/Bus with walk or auto access,
- Train/Metro/Bus with walk or auto access.

The relatively detailed set of public transportation composite modes<sup>1</sup> is to reflect the sophisticated public transportation system in Ile-de-France.

For each tour purpose, different discrete choice specifications are tested and preferred based on their econometric performance. Tested model specifications include four Nested Logit structures specified based on:

- whether the mode choice is on top of the destination choice or vice versa;
- whether the mode alternatives are grouped under four subsequent nests including: auto (driver and passenger), slow, transit with train (six alternatives), and transit without train (four transit alternatives), or are all at the same level (Significance, 2007).

For the destination choice level (where it applies), all nearly 1400 zones are considered and no sub-sampling is carried out.

## 2.2. IMPACT4

IMPACT is the transportation demand model of the Autonomous Operator of Parisian Transports, RATP, for testing and evaluating transportation policies. It also provides the RATP with concrete analysis to support its dialogue with other authorities and actors in the Parisian region. It is currently available in its fourth version IMPACT4 released in 2009. The new version is updated based on the 2001 Paris Household Travel Survey (Garcia-Castello, 2010a).

IMPACT4 is the only operational Parisian model capable of taking into account effects the search for a parking place or the limited capacity of public transportation.

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<sup>1</sup> We call them “composite modes” as they actually are combinations of several simple travel modes including access, transit, and egress sections.

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### 2.2.1. Data

#### 2.2.1.1. Zoning system

IMPACT4 uses a zoning system of 639 zones. These zones are characterized mainly by employment data.

### 2.2.2. Transportation Demand Representation

IMPACT4 is a tour-based disaggregate model and associates the transportation mode to the tour instead of a single trip-leg. However, IMPACT4 also uses a simplified tour representation:

For simple tours of Home-X-Home shape, it only models one leg. For more complex tours of Home-X-Y-Home shape, it only considers Home-X and Y-Home legs with an even probability of occurrence for each, and ignores the X-Y leg. Simple tours are supposed to be executed by the same mode for both legs (Garcia-Castello, 2006).

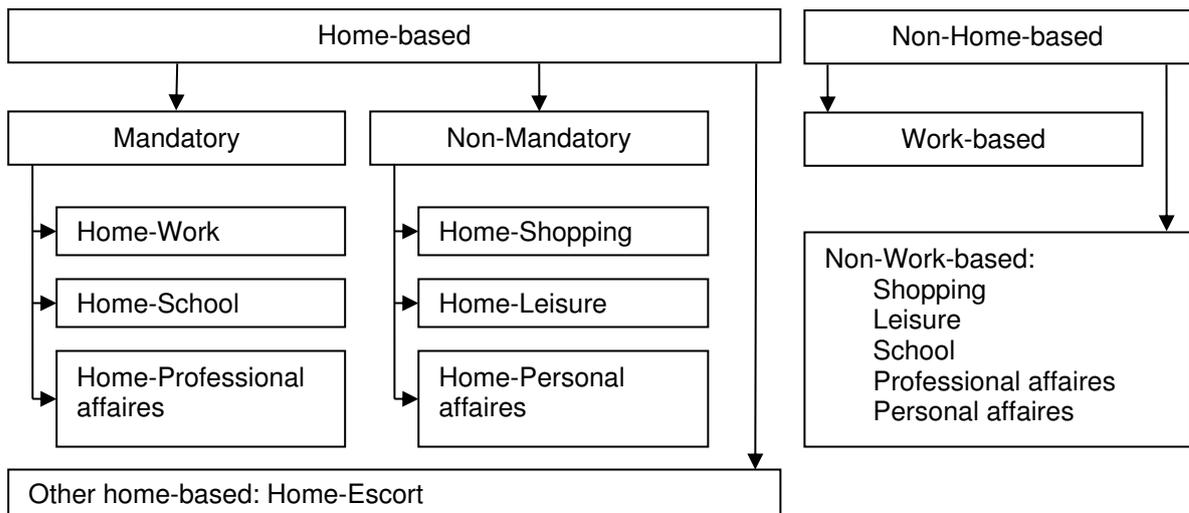


Figure 2.2 Tour purposes in IMPACT4 model (Garcia-Castello, 2010a).

Tour purposes are divided into two main categories: home-based versus non-home-based. Home-based purposes are further divided into three sub-categories: mandatory home-based, non-mandatory home-based, and other home-based. The mandatory tour purposes are work, school, or professional affaires whereas the non-mandatory tour purposes are shopping, leisure or personal affaires.

The non-home-based purposes are also divided into two main categories including purposes based on work or professional affaires, and purposes based

on other purposes. These categories include a limited but highly heterogeneous part of the total transportation demand and require special simplified treatment.

### 2.2.3. Mode and Destination Choice Model

The transportation mode choice includes six different mode alternatives: walk, auto driver, auto passenger, surface public transportation, rail public transportation and mixed public transportation. The choice structure however is different based on the tour purpose.

For mandatory home-based purposes, it is supposed that the destination is fixed and is not subject to a short-term choice. The six modes are structured in a Nested Logit architecture where the three public modes belong to a separate nest.

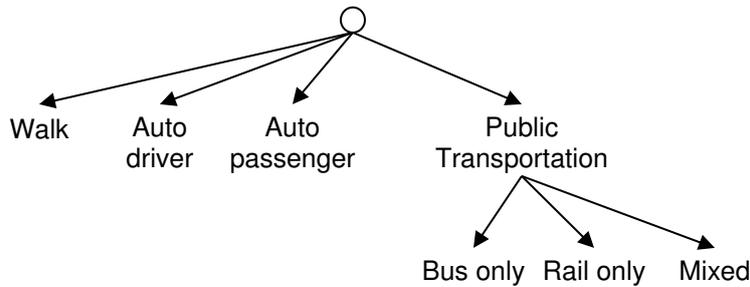


Figure 2.3 Mode choice structure for mandatory tour purposes (Garcia-Castello, 2010a).

For non-mandatory home-based purposes, the choice of destination is jointed with the choice of mode. The joint choice structure is a Nested Logit where the six mode alternatives are placed on the upper level and each on top of a nest of 15 randomly chosen candidate destination zones.

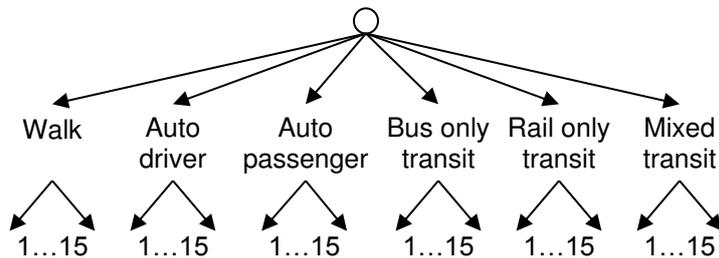


Figure 2.4. Mode-destination choice for non-mandatory purposes (Garcia-Castello, 2010a).

The other-home-based category is mainly concerned with escort trips. These trips are divided into two groups based on whether they are followed by a return to home or not. The amount of traffic due this tour purpose is

considered a linear combination of the traffic flow of auto modes. This is mainly because escort trips are captive to the auto mode because of their very nature (escorting children, or people with limited abilities).

The non-home-based category of trip purposes regroups highly heterogeneous trips. They are regrouped in two categories, one for those based on work or professional affairs and one for others. Likewise, escort trip purpose, traffic flows due to non-home-based trip purposes are considered linear combinations of walk, auto, and transit flows.

#### 2.2.4. Transportation Supply Representation

IMPACT4 is endowed with a relatively rich representation of the transportation supply and the demand-supply equilibrium. It implements four different demand-supply equilibrium modules:

The first module called HCONG (Highway CONGestion) uses a network of 67 links representing the major highway infrastructure of Ile-de-France, with a zoning system of 23 zones. Auto mode traffic demand is put in equilibrium with the capacity of the network and travel times are modified taking into account the effect of the congestion.

The second module called BSPD (Bus SPeed) evaluates congestion effects of the travel time of Buses. It uses the same network as the HCONG module but also takes into account the existence of a dedicated Bus lane and the density of stops along the line.

The third module called PTOC (Public Transport Over-Crowding) reevaluates traveler's perception of the utility of public modes to incorporate over-crowding effects. It distinguishes between surface modes (Bus) and rail modes (Metro and Train) and is capable of simulating two phenomena: if the capacity of the vehicle is reached and travelers can no longer find a free seat, the generalized cost of the travel is increases due to the discomfort. On the other hand, if the vehicle is too crowded, the traveler may prefer to wait for the next shuttle and the perceived travel cost increases.

The fourth and last equilibrium module is called PARK. It allocates parking places at trip destinations and simulates the parking search time and cost. It is capable of considering different parking types (free/paid, surface/underground, public/private). It also takes into account whether the traveler is well acquainted with the destination zone (e.g. in a work trip). This module uses a specific zoning system of 40 zones.

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## 2.3. MODUS

MODUS is an aggregate trip-based four-step model. It the transportation model of the State Department for Regional and Interregional Infrastructure Planning of Ile-de-France, DRIEA. The MODUS version 2.1 is operation since 2008 and is based on the 2001 Paris Household Travel Survey (DREIF, 2008).

The model follows the classic four-step structure. Trip generation, distribution and mode choice steps are applied straightforwardly. The model produces its results for two time periods corresponding to the morning and evening peak hours: the former is from 7 to 9 and the latter is from 17 to 19.

The traffic assignment to the transit network is based on all-or-nothing. For the highway network, however, it is possible to take into account congestion effects. The model can feedback updated level-of-service characteristics to the trip distribution and mode choice steps.

### 2.3.1. Data

#### 2.3.1.1. Zoning system

In MODUS 2.1 two different zoning systems are used for the highway and the public transportation networks. The zoning system for the highway network includes 1277 zones to which 28 zones are added to represent external traffic flow. The public transportation zoning system is divided into 1192 zones.

### 2.3.2. Transportation Demand Representation

The model considers eight trip purposes including:

- Home – Work,
- Work – Home,
- Home – Shopping or Personal affairs,
- Shopping or Personal affairs – Home,
- Work-based and Non-Home-based,
- Non-Work-based and Non-Home-based,
- Home – Leisure,
- Leisure – Home.

It also distinguishes between car owners who can choose between auto mode and public transportation, and those who are captive to the public transportation.

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The trip generation step the number of daily trip emissions and attractions per zone are calculated for the eight motifs. They are estimated by linear combination of land-use data for each zone. Some of the variables include: total population, number of employments, number of workers, number of students, etc.

Once emissions and attractions are evaluated for the eight trip purposes, they are disaggregated for the two individual categories so that the proportions between the two categories match those observed in the survey.

The trip distribution step is based on a doubly-constrained gravity model. It is a single-parameter exponential. Between each pair of zones, the logsum of the three utility functions – corresponding to the auto, transit and walk modes – represents the impedance.

### 2.3.3. Mode Choice Model

The model considers three transportation mode alternatives including: auto, public transportation, and walk. Multinomial Logit models are estimated and used to evaluate the probability of use of each mode. For car owners the all the three modes are taken into account. For non-owners public transportation and walk modes are only alternatives.

## 2.4. GLOBAL

This is an aggregate trip-based four-step demand model developed and maintained by the Autonomous Operator of Parisian Transports, RATP, for forecasting travel demand. The model is being constantly updated since 1970s (RATP, 2004). It serves for evaluating the overall travel demand, volume and structure, design and dimensioning of networks, and evaluating socio-economic and financial viability of projects. The eighth version of the model is operational since 2010. Like other Parisian models, it is based on the 2001 Paris Household Travel Survey (RATP, 2010).

### 2.4.1. Data

#### 2.4.1.1. Zoning system

The zoning system of the model covers the area of the Greater Paris Region by about 2300 zones.

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#### 2.4.1.2. *Transportation networks*

The model highway network includes about 27000 links provided the free flow and congested travel times. The transit network covers about 1600 services covering Train, Metro, Tramway, and Parisian and Suburban bus.

#### 2.4.2. Transportation Demand Representation

Demand modeling in GLOBAL is minimalistic. It is an aggregate model with a classic trip generation. The trip distribution step is based on a constrained gravity model. The model concentrates mainly of the work trips during the morning peak-hour. The transportation demand at morning peak-hour is segmented into four classes of trips, regrouped based on “distance criteria and mode choice behavior” (RATP, 2010). Then linear combinations are used to project the peak-hour work traffic to the total peak-hour traffic and total daily traffic (Garcia-Castello, 2010).

#### 2.4.3. Mode Choice Model

The mode choice set includes four transportation modes including: Auto, Transit with walk access, Transit with auto access, and Walk. Walk utility function is only a function of direct intrazonal distance. Auto utility function includes the total travel time, as well as explanatory variables for parking generalized cost (monetary cost and search time), kilometeric cost of use of automobile. For the transit mode, explanatory variables include access time, wait time, in-vehicle time, number of transfers, transfer time and transfer penalty, and transit fares.

### 3. Demand Modeling in French Metropolitan Areas

In response to the requirements of urban mobility plans, many French metropolitan areas have already undertaken the development of transportation demand models. These models cover a wide spectrum in terms of their level of sophistication and representativeness. Some of them are disaggregate tour-based models, whereas others remain aggregate trip-based forecast tools. In the following, we briefly review two typical models.

#### 3.1. Grenoble Area

The development of a multimodal transportation model for the region of Grenoble was decided in 2001 to replace an older descriptive tool used since 1997. The older model was bimodal with auto and public transportation being

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the only alternatives. It also was limited to the area of the city of Grenoble. The new model extends the modeling area to the entire region of Grenoble and adds new capabilities by expanding the mode choice set to include non-motorized modes. It is estimated mainly based on data from the 2001-2002 household travel survey. The development of the new model was finished in 2005 and it is operational since.

The multimodal demand model of the region of Grenoble is a disaggregate tour-based four-step model implemented on the VISEM/DAVISUM platform. The model covers two periods of day corresponding to the morning and evening peak hours. The morning peak-hour is from 7 to 8 for the auto mode and from 7 to 9 for public transportations. The evening peak hour is from 17 to 18 for the auto mode and from 16 to 19 for public transportations. The model first predicts daily traffics and then transposes to peak-hour traffics using linear combinations (CETE de Lyon, 2008a).

### 3.1.1. Data

#### 3.1.1.1. Zoning system

The model uses a zoning system with 1744 zones, including a few zones to represent external traffic.

### 3.1.2. Transportation Demand Representation

The demand is segmented into 12 categories including:

- Workers owning a car,
  - Other workers,
  - Part-time workers owning a car,
  - Other part-time workers,
  - Nonworkers owning a car,
  - Other nonworkers,
  - Pensioners owning a car,
  - Other pensioners,
  - Students (university),
  - Students (secondary),
  - Students (primary),
  - Workers working outside the model perimeter.
-

In this segmentation, all travelers aged over 18 whose household owns at least a car are considered car owner. In addition, the last category includes travelers who make only a part of their travel inside the area of the model. For this group, work trips are eliminated if the workplace is outside the model area; their other trips are taken into account for modeling.

The model recognizes 9 different activity purposes including:

- Home,
- Work,
- Education (university),
- Education (secondary),
- Education (primary),
- Shopping or Affairs,
- Leisure (sport, restaurant, walking),
- Visit,
- Escort.

#### *3.1.2.1. Trip generation model*

The tour generation model proceeds in two steps: Firstly, it reconstitutes observed travel tours according to the reference household travel survey. Tours are simplified to include maximum three trips. Secondly, it identifies traveler groups with similar daily “time schedule” so that the people who are in the same group attend to similar activities at similar periods of the day. For example, according to the survey, most workers tend to go shopping in the evening whereas pensioners do the same activity mostly in the morning, and counting workers and pensioners together leans to a biased estimation. Consequently, 6 categories are considered: Workers, Part-time workers, Non-workers, Pensioners, College students, and School students. Finally, for modeling non-work travels of workers whose workplace is outside the model area, it is decided to use the same tour patterns that are observed for non-work travels of inside workers.

For each zone, the probability of generation of a given tour pattern is determined by its proportion in the reconstructed database. This probability multiplied by the total zone population gives the emission flow per purpose and demand segment.

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### 3.1.2.2. Trip distribution step

The distribution step is based on a gravity model. The probability of choosing a particular destination zone is a function of both its attractiveness among other zones and its impedance from the zone of origin. The attractiveness of a zone is determined by a linear combination of variables such as the zone population, number of residents of the zone, number of employments, total number of school and university seats, total shopping surface, and number of visitors of parks, museums, hospitals, etc. For each demand segment, the probability of choosing zone  $j$  from zone  $i$  for purpose  $a$  is given by:

$$P_{aij} = \frac{A_{aj} \exp -\alpha \cdot w_{aij}}{\sum_k A_{ak} \exp -\alpha \cdot w_{aik}}$$

where  $A_{aj}$  is the attractiveness of zone  $j$  for the purpose  $a$ , and  $w_{aij}$  is the impedance between the two zones. Impedances are interzonal travel times from the charged highway network. These times are readapted based on the stated travel times from in the survey so that they are more realistic.

### 3.1.3. Mode Choice Model

The model considers a total number of five available modes. In the case of multimodal trips, the mode with the highest weight is considered for the entire trip. The five modes in increasing order of weight are: walk, bike, auto driver, auto passenger, and public transportations. For non-owners auto driver mode is eliminated from the choice set. The model specification is a Multinomial Logit and utility functions are composed of travel time, distance, service frequency, and number of transfers, as main explanatory variables.

## 3.2. Area of Pays de Montbéliard

The multimodal model of Pays de Montbéliard is a four-step tour-based model developed under DaVISUM<sup>®</sup> platform. It models the traffic and transit trips during the evening peak period (5 to 6 p.m.). The estimation of traffic flows in the model is first done on a daily basis and the transposed to the evening peak hour using the ratio between the park-hour and observed daily traffics.

The model is based on the 2004 Belfort-Montbéliard Household Travel Survey. Other data sources are also employed including a cordon survey, an origin-destination survey and several traffic counts (CETE de Lyon, 2008b).

### 3.2.1. Data

#### 3.2.1.1. *Zoning system*

The model covers a main area corresponding to the 29 municipalities of the Pays de Montbéliard agglomeration, and an external area corresponding to the surrounding metropolitan area. The zoning system includes 96 zones for the main area and 34 zones for the external area. In addition, four injectors have been considered between the external perimeter and the outside.

#### 3.2.1.2. *Transportation networks*

The standard traffic and transit networks are used. The precision of the traffic network is limited to the inter-neighborhood level and does not cover terminal travel sections.

### 3.2.2. Transportation Demand Representation

The internal demand generation and forecast is based on a four-step model. For the external demand, a growth-curve model is used. The objective is to forecast the traffic and transit demand in 2015 and 2025.

Based on a mobility analysis, the most determinant individual characteristics are: socio-professional category, possession of a driver's license, gender, age, income, and motorization rate of the household. Further observations show that actives are highly mobile, mainly by the auto mode and for the work purpose; students are mainly constrained to the transit mode. High degree of correlation has been observed between the household motorization rate and the income, and between the socio-professional category and the age. Finally, seven segments have been constructed only based the socio-professional category and the motorization rate: Motorized Workers, Non-motorized Workers, Motorized Nonworkers, Non-motorized Nonworkers, University Students, Students of secondary school, and Students of primary school.

Based on the survey data, a total number of 12 activity purposes have been identified: Home, Work, Shopping (proximity), Shopping (supermarket), Health care, Education (primary), Education (secondary), Education (university), Leisure, Escort, Affaires, and Other.

#### 3.2.2.1. *Trip generation model*

The model first reconstructs travel tours as observed in the reference household travel survey and determines the proportion of each tour pattern in each demand segment. Given the zone population, it is possible to calculate

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the total number of tours per tour patterns per zone for each demand segment. All closed home-to-home tours composed of maximum 6 trips are considered. They represent 91% of all of the observed trips inside the model area.

### 3.2.2.2. Trip distribution model

The distribution step is based on a doubly-constrained gravity model. The probability of choosing a particular destination zone is a function of both its attractiveness among other zones and its impedance from the zone of origin. For each demand segment, the number of trips from zone  $i$  to zone  $j$  for purpose  $a$  is given by:

$$F_{aij} = E_i A_{aj} \exp -\alpha \cdot w_{aij}$$

where  $E_i$  is the emission from zone  $i$ ,  $A_{aj}$  is the attractiveness of zone  $j$  for the purpose  $a$ , and  $w_{aij}$  is the impedance between the two zones. Impedances are interzonal travel times from the charged highway network. These times are readapted based on the stated travel times from in the survey so that they are more realistic.

### 3.2.3. Mode choice model

The mode choice stage uses a Multinomial Logit model with four modal alternatives: auto driver, auto passenger, urban public transportation, and walk. Variables comprised in modal utility functions include interzonal travel time, sum of all access/egress times, monetary cost of travel, and the logarithm of the interzonal distance.

## 4. Synthesis of French Models

Table 2.1 shows a synthetic review of several applied transportation demand modeling examples in France. It is noticeable that these models are of different levels of sophistication and demand representativeness to respond to different needs. In Ile-de-France modeling examples vary from totally aggregate trip-based models, such as GLOBAL which serve as short-term demand forecast tools, to relatively advanced tour-based models, such as ANTONIN which address complex structure of the Parisian transit networks much more thoroughly.



Table 2.1. A recapitulative synthesis of applied transportation demand modeling examples in France.

Model		Year	Survey Date	Tour-based	Zoning System	Time Periods	Mode Choice Set	Activity Purposes
Parisian Models	ANTONIN (STIF)	2006	2001-2002	Yes	1400	AM peak/ PM peak/ Off peak/	13 Modes including 10 Transit alternatives	8 Home-based: Work (high income)/ Work (low income)/ Business/ School (children below 18 years)/ Education (students above 18 years)/ Regular shopping/ Other shopping/ Social activities/ + 2 Work-based: Business/ Others/
	IMPACT4 (RATP)	2009	2001-2002	Yes	639	AM peak/ PM peak/	Auto driver/ Auto passenger/ Bus only/ Rail only/ Mixed transit/ Walk/	7 Home-based: Work/ School/ Professional affaires/ Shopping/ Leisure/ Personal affaires/ Escort/ + 2 Non-Home-based: Work-based/ Non-Work-based/
	MODUS (DRIEA)	2008	2001-2002	No	1277 + 28 External (Highway)/ 1192 (Transit)/	AM peak/ PM peak/	Auto/ Transit/ Slow/	6 Home-based: Work/ Shopping or Personal affaires/ Leisure/ + 3 Returns + 2 Non-Home-based: Work-based/ Non-Work-based/
	GLOBAL (RATP)	2010	2001-2002	No	2300	AM peak/	Auto/ Transit + walk access/ Transit + auto access/ Walk/	

<b>Other French areas</b>	Grenoble	2004	2001-2002	Yes	1700	AM peak/ PM peak/ Whole Day/	Auto driver/ Auto passenger/ Transit (bus, tramway, metro, coach, train)/ Bike/ Walk/	Home/ Work/ Education (university)/ Education (secondary)/ Education (primary)/ Shopping or Affairs/ Leisure/ Visit/ Escort
	Pays de Montbéliard	2007	2004-2005	Yes	130 + 4 External	PM peak	Auto/ Transit/	Home/ Work/ Shopping (proximity)/ Shopping (supermarket)/ Health care/ Education (primary)/ Education (secondary)/ Education (university)/ Leisure/ Escort/ Affaires/ Other
	Toulouse <sup>†</sup>	2005	2003	Yes	1000 to 1200	AM peak/ PM peak/ Whole Day/	Auto driver/ Auto passenger/ Transit (urban, coach, train)/ Park-and- ride/ Bike/ Motorbike/ Walk/ Urban freight/	Different tour-patterns according to the Reference Household Travel Survey.
	Toulon <sup>†</sup>	2005	1997-1998	No	46 + 3 External (Demand)/ 192 (Assignment)/	PM peak/ Off peak/	Auto/ Transit (bus, tramway, train)/ Walk/	
	Saint- Etienne <sup>†</sup>	2003	2000	No	302 + 21 External	AM peak/ PM peak/ Off peak/	Auto/ Transit (bus, tramway, train)/ Walk/	Work/ School/ Educations/ Shopping/ Leisure/ Other Home-based/ Other Non- Home-based
	Greater Clermont <sup>‡</sup>	2006	2003	No	30 + 6 External (Demand)/ 100 + 20 External (Assignment)/	PM peak/ Whole Day/	Auto/ Transit (urban, train, coach)/	Work or Professional affaires/ Education (primary and secondary)/ Education (university)/ Shopping/ Other Home-based/ Other Non-Home-based

<sup>†</sup> CERTU (2005)

<sup>‡</sup> CERTU (2008c)

# Chapter 3: Characterization of Daily Mobility in Ile-de- France

## 1. Introduction

Daily mobility of residents exhibit regularities in their mobility behavior. From the point of view of transportation mode choice, such regularities provide the key to identifying demand segments and to understanding mobility patterns. This chapter provides a mobility analysis of the Greater Paris area and investigates such regularities. We will particularly show that primary indicators such as the number of activity tours per person and per day are remarkably stable with respect to the gender, age class, socio-professional category and residential sector. It will be shown that constrained (i.e. mandatory) purposes dominate the mobility practice in terms of the daily number of tours as well as the travel time and distance.

To simulate travel behavior in an urban area realistically, it is necessary to model situations and mobility behaviors, in conjunction with the localization of activities and the local availability of transportation services. There are two main types of models, namely trip-based and tour-based, where the former, oldest, is in particular based on the “invariants” of mobility. We study these invariants according to four individual characteristics: gender, age class, socio-professional category and residential sector. We show that the number of tours per person and per day is very stable.

Following on from previous works based on the 1991-1992 survey (see, Leurent and Polacchini, 1995a, Leurent and Samadzad, 2010), our aim is to provide an accurate and quantitative description of the daily mobility of Parisian residents, with a focus on two priorities. The first priority is to find “mobility invariants” – mobility values that remain the same within the population, regardless of age and gender, socio-professional status and place of residence. To this end, we look at the average number of activities per day and per person, together with the number of trips within a tour.

The second priority is to establish a hierarchy of presences and movements, i.e. of time spent and distances travelled, and relate it to the purpose of the activity and the mode of transport. We link an activity tour and all the trips that it generates with a primary purpose and a primary mode, to bring out the dominant purposes and fundamental modes governing mobility as a whole, more clearly than if we looked at individual trips without considering their status as part of a tour.

Our investigation is entirely based on the 2001 Paris Household Travel Survey (DREIF, 2004, 2005). It is therefore synchronic, but above all geographical. We proceed by looking at places of residence, traveled distances and socio-economic, attributes and by considering the activities and mobility patterns of

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individuals. We analyze daily mobility from two linked perspectives. Firstly, in terms of the individual who invests time in the activities and in the associated transportation with regard to traveled distance and time, and secondly in terms of a tour, a mobility unit constituted around a primary activity and effected with a primary mode of transportation. That is why our approach stands midway between classic uses of household travel surveys and disaggregated mobility models based on activity and trip tours. This modeling process has become standard international practice since the 1980s: in France, it has two primary exemplars, both of them in Paris – in order of age, IMPACT4 of the RATP, and ANTONIN-2 of the STIF.

### 1.1. Survey Data Source

In Ile-de-France, inhabitant mobility is measured by the Paris Household Travel Surveys, conducted with resident households at intervals of 7 to 10 years: the last survey covered the period 2001-2002 and the most recent was launched at the end of 2009. This survey is carried out with a sample of households: each household is described in terms of the number of individuals living together, income and vehicle ownership; each individual is described in terms of demographic category and socio-professional occupation, with the number of trips he or she made the day before the survey; each of these trips is described in terms of activities at departure and arrival, times and places, duration and means of transport; finally, each mean of transport used in the course of the trip is described in terms of modes, times and starting and ending points.

The wealth of collected information makes the Paris Household Travel Survey an irreplaceable resource: the survey sample is used as a basis for simple or sophisticated statistical analyses, and even for models to simulate travelers' responses to different scenarios of transportation offering. Each survey has been used extensively by its commissioning bodies, starting with the DRIEA-IF. DREIF (1995) and DREIF (2004) describe average daily mobility per inhabitant; the time spent in transit and the distances covered; the endpoints and times of travel; the use of transport modes, and even the organization of individual trips into activity tours. Certain specific subjects have been explored in depth. For example, Leurent and Polacchini (1995b) study mobility for accompaniment and group travel, or certain specific patterns such as shopping, or the spatial structure of trips, or mobility in a particular part of the city, or the use of a given mode of transport are addressed in the brief analysis report collection of the 2001-2002 Paris Household Travel Survey (DREIF, 2005).

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From these studies, the professional community has identified certain key facts about individual mobility: a daily average of around 3.5 trips and approximately 84 minutes spent travelling. The fact that these two indicators have remained stable over the last 20 years and through three successive surveys, have made them central factors – alongside regional demographic growth – in discussions, projects and policies regarding the development of transportation networks.

## 1.2. General Outline

We describe the daily mobility of the residents of the Paris region in 2001-2002, focusing on the activities for which journeys are made, the organization of activities and trips in the form of tours, and the way presences and movements are structured in space and time and according to the means of transport employed. We show that the number of tours per day and per person and the number of trips per tour are indicators that remain stable across the population, in the sense that they vary little by gender and age, socio-professional category or geographical area of residence. Creating a hierarchy of activities and trips based on the primary activity purposes for travelling and the primary mode of the tour reveals the influence of constrained activities on the daily life of the inhabitants and on the area, whether those activities relate to work or education. Lastly, a novel indicator of “presential moment” is provided to measure spatial interaction between activities and residences.

## 2. Population, Activities and Mobility

### 2.1. Population Composition

In 2001, the population of the Paris region stood at 11.6 million, 11 million of them aged six or above (Debrincat et al., 2006). Within this population, women slightly outnumbered men (52% compared with 48%), and in terms of age group the majority were of working age, between 25 and 54 (49%). The two decades under the age of 24 were slightly less represented (27%), as were the two highest age groups (24%).

Looking at the average mobility rate by gender and age category, i.e. the number of trips per day and per person – where the regional average amounts to 3.45 trips per individual and per day – women are slightly more mobile than men: the difference is +10% in the 25-34 age group, where women are most likely to combine work and family obligations, but falls to +4% between the ages of 35 and 54. Then the order is reversed, with older men being more

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mobile than their female counterparts are. Between the two extreme category averages, the difference is 60% of the overall average.

## 2.2. Socio-Professional Categories

We identified nine socio-professional categories. The largest category is Students, in school and higher education (23.7%), followed by six categories of average size (each 11 to 15%) – Managers and Professionals, Intermediate Professions, Employees, Pensioners and Nonworkers, then two smaller classes for Unskilled Workers (6.9%) and the Self-Employed, Tradesmen and Business Owners (2.1%) and finally a very small category, Farmers (0.16%).

The most mobile categories are Farmers (with 3.87 trips per person per day), Tradesmen, the Self-Employed and Business Owners (3.82), Managers and Professionals (3.70), and the Intermediate Professions (3.81), followed by Employees (3.60), Unskilled Workers (3.63) and Nonworkers (3.68). Finally, Students (3.20) and above all Pensioners (2.93) are less mobile than average. Between the two extreme category averages, the difference is still 60% of the overall average.

The difference between men and women subsists for Pensioners, for “Nonworkers” (as it happens, female so-called “Nonworkers” are particularly mobile) and for Managers and Professionals.

## 2.3. Activities and Mobility

The “number of trips per day” indicator reflects the total number of activities, including outside activities but also a home-based activity: this is because a trip to home probably corresponds to an activity that has to be carried out there.

In principle, within such a large metropolitan population, the average mobility rate is an aggregate that covers a wide variety of individual situations. This is evidenced by the distribution of individuals based on the number of trips they made in a day: 2 for 40% of the individuals, 4 for 25%, 3 or 5 or 6 for around 8% each, or 0 for 5%, significantly below the 1991 Paris Household Travel Survey. We can thus identify patterns of low mobility (fewer than three trips per day), of medium mobility (three or four) and of high mobility (five and above).

A breakdown by purpose of trip shows that the more trips there are, the more likely they are to be linked, since there are fewer returns to the Home. The proportion of necessary purposes – Work and Education – is fairly stable between 2 and 4 trips per day and then falls, whereas Accompaniment and

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Personal Business increase. Overall, purposes overlap within a daily activity schedule: an increase in trips is associated with the accomplishment of less constrained or more chosen activities, as well as with Professional purposes.

## 2.4. Breakdown by Residential Sector

By residential sector, or urban morphology as defined by the IAU-IdF macro zoning system, we observe a high degree of stability in the average mobility rate: Inner Paris, the new towns and the outskirts are higher, and the peripheral cities are lower; but the gap between the two extremes is only 15% of the overall average. The time spent travelling is even more concentrated, between 84 and 88 minutes per day and per person, with a relative difference of only 5%. However, the distances travelled vary from single to quadruple, as distances from the center increase and urban density decreases.

**Table 3.1. Mobility breakdown by residential sector.**

<b>Residential sector</b>	<b>Mobility Rate</b>	<b>Travel Time (min)</b>	<b>Travel Distance (km)</b>	<b>In-Activity Time (min)</b>
Paris	3.61	85.1	11.5	393
Inner suburbs	3.40	86.3	13.7	384
Outer suburbs	3.39	85.5	17.3	380
Conurbation outskirts	3.58	84.5	21.5	393
New towns	3.53	84.1	22.2	412
Well-served towns	3.45	86.8	27.8	380
Secluded towns	3.32	87.7	33.2	376
Rural communities	3.11	86.7	41.0	383
<b>Combined</b>	3.45	85.6	18.0	387

## 2.5. Provisional Synthesis

We observed significant differences in average daily mobility between genders, age categories and socio-professional categories. On the other hand, the average rate is much more regular when we look at residential sector, as is the time spent travelling each day: in a sufficiently large sector, the population is sufficiently varied and its distribution probably sufficiently regular in structure from one sector to another, for average regional values to emerge. These average values therefore have primarily an aggregated form of spatial

stability – they do not constitute a model for a particular demographic or socio-economic category.

### 3. Activities Explain Tour Formation

We aim to characterize activities and mobility by means of less variable indicators than the daily number of trips, by looking at activity and trip tours. Such a tour is defined from a starting or anchor point, which may be the Home or the Workplace, by a primary activity carried out in another place that constitutes the connection point, possibly with other activities inserted between the anchor point and the connection point.

The dominant purpose of a tour is the nature of the activity at the connection point, distinguished in the case of multiple activities by the highest position in a hierarchy of purposes. We sort purposes based on the intensity of the external constraints on the individual. Excluding the Home, which is a singular constraint, the hierarchy of constraints is, in descending order: Work and Education; Professional Business; Personal Business (including health) and Accompaniment; Shopping; Visits; Leisure.

Table 3.3 shows the trip-based and tour-based weight of different travel purposes in the daily activity program of travelers. By comparing results from the two approaches, we notice a significant change in the share of each activity purpose in structuring travel demand. Work purpose clearly is the dominant activity purpose according to both approaches. In addition, it is easy to witness a dramatic change in the share of Education and Professional business. This shows that Professional business is most of the time chained with Work as there are actually very few tours that give the highest priority to the Professional business. On the other hand, Education is much more present in a tour-based analysis showing that other activity purposes of lower priority are chained with Education which is of highest priority after Work.

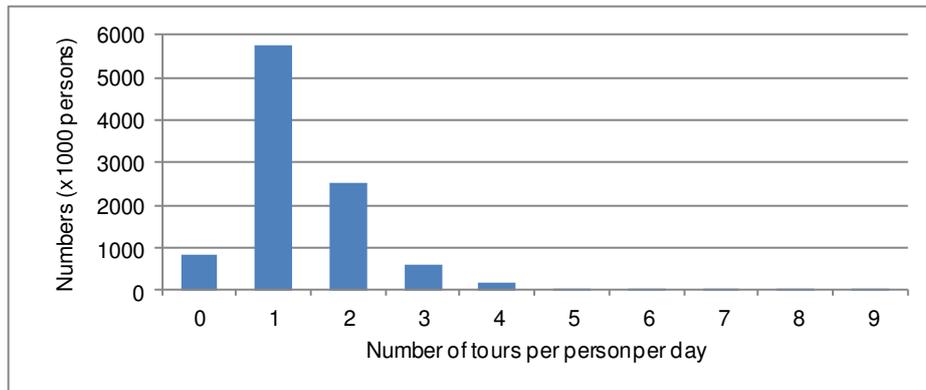
This is a clear demonstration of how dramatic can be the change of perspective between tour-based and trip-based approaches to mobility analysis.

**Table 3.2. Purposes and modalities of activity tours.**

Purpose	Trip Percentage	Tour Percentage	In-Activity Time (min)	Travel Time (min)	Travel Distance (Km)
Work	24.5%	29.3%	471	79.7	20.7
Professional business	12.8%	2.7%	301	98.7	24.8
Shopping	5.3%	14.7%	65	34.2	5.3
Personal business	16.6%	16.2%	91	47.5	8.1
Education	7.8%	18.2%	359	46.0	6.4
Accompaniment	15.7%	5.7%	38	31.2	6.1
Visits	6.4%	4.3%	191	54.8	13.1
Leisure, Outings	11.1%	8.1%	106	46.2	5.8

### 3.1. Daily Tour Numbers and Purposes

In any given day, an individual performs far fewer tours than trips: daily schedules of four tours or more are very rare, which shows that for highly mobile individuals, multiple trips are combined into tours, in time-efficient combinations (Figure 3.1a). The hierarchy of purposes remains fairly stable from one to three tours per day; above this, Accompaniment and Personal Business become highly dominant purposes (Figure 3.1b).



**Figure 3.1a. Breakdown of daily number of tours per individual.**

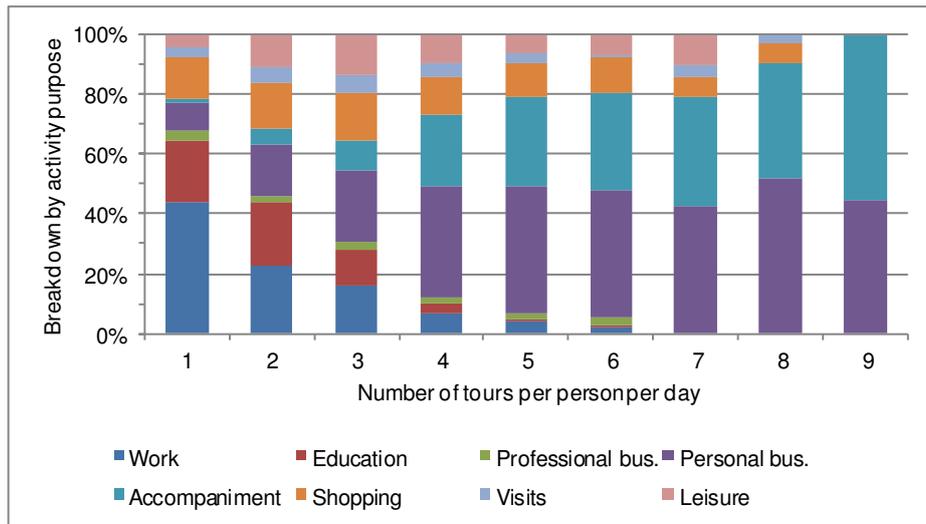


Figure 3.1b. Purposes of main activities, based on the daily number of tours.

### 3.2. Breakdown by Demographic Group

If we look at gender, women make 1.39 tours per day, in average, slightly more than men with 1.34 tours per day, mainly due to Shopping and Accompaniment of children. As purposes, Education, Visits and Leisure are similar. Men carry out more Work and Professional Business activities, which is more than balanced out by women with Personal Business, Shopping and Accompaniment.

In terms of age category, the daily number of tours per person is also regular, with an average of close to 1.4, falling in the two higher age categories to 1.2. The relative difference remains around 20% between the extremes. In terms of purposes, Education and Work dominate for the age categories in question. Professional Business affects people of working age, but generates few tours. Activities for Shopping and Personal Business are more frequent in the higher age groups. Leisure is primarily significant for children and older people, whereas Accompaniment applies mainly to parents of dependent children.

Broken down by socio-professional category and residential sector, in keeping with the general distribution, the daily number of tours per person is much more stable than the average number of trips. Apart from Farmers, who represent a very small percentage of the sample, the extreme variations go from Pensioners to Nonworkers, with a relative difference of 20%, a third of the difference in trip numbers. In addition, the Intermediate Professions, Employees, Unskilled Workers and Student categories are very close to the overall average, whilst Tradesmen etc., and Managers and Professionals are slightly below. By residential sector, dense urban areas have the same average,

less dense areas a slightly higher average, whereas rural communities have a lower average.

### 3.3. Anatomy of Tours

The number of trips within a tour is also fairly regular across socio-professional categories and residential sectors. By socio-professional category, the averages go from 2.26 to 2.72, a relative difference of 20%. By sector, the averages are once again very close, with a slightly greater incidence of linkage in conurbation centers.

### 3.4. Hierarchy of Travel Purposes

By linking trips to tours, i.e. by linking secondary activity purposes to the primary activity purposes, it is possible to extrapolate to describe the circumstances of traveler mobility across the region. Seventy percent of the distances covered are accounted for by constrained purposes such as Work, Education and Professional Business, a further 17% for Shopping, Personal Business and Accompaniment, whereas “optional” purposes – Visits, Leisure, etc. – only account for 10%. In terms of trip time, the three blocks respectively represent 64%, 26% and 10%. In numbers of tours, they respectively correspond to 50%, 37% and 13%

These proportions are heavily weighted in favor of constrained activities. As regards the number of people travelling, some commentators had inferred a relative decline, which we have disproved (Table 3.3).

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**Table 3.3. Impact of purposes for travel by different criteria.**

Purpose at destination	Based on “Trip”			Based on “Tour”		
	Number	Distance	Time	Number	Distance	Time
Home	40.2%	40.0%	39.7%			
Work	14.8%	24.4%	19.4%	29.3%	54.4%	44.3%
Professional Business	3.2%	7.7%	6.0%	2.7%	5.5%	4.5%
Shopping	9.0%	5.2%	4.9%	14.7%	6.4%	8.6%
Personal Business	9.9%	7.6%	7.7%	16.2%	10.8%	13.1%
Education	7.9%	3.7%	5.4%	18.2%	9.8%	14.6%
Accompaniment	4.9%	2.0%	2.2%	5.7%	2.8%	3.0%
Visits	3.7%	5.2%	4.8%	4.3%	4.5%	3.9%
Leisure, Outings	6.4%	4.3%	9.8%	8.1%	3.9%	6.5%

### 3.5. Synthesis: Detection of Invariants

A travel tour by starting from an anchorage place (mostly the home) chains one or more activities in destination places. The daily activity schedule of an individual may contain zero, one or more tours. The average number of trips per person and per day varies sensibly among individuals (standard deviation of 2.20 for an average of 3.45). The average number of tours per person and per day is much more stable (standard deviation of 0.85 for an average of 1.37), with a regularity in the number of activities per tour (standard deviation of 1.01 for an average of 2.46).

The most mobile age class from 25 to 55 years old coincides with the professional activity. By socio-professional category Intermediate and higher professions make more trips but almost the same number of tours, due to increased chaining (Table 3.4a). By residential sector, according to the IAU-IdF macro zoning system (especially the distance from the center), a higher urbanization degree is associated with a slightly higher number of tours (Table 3.4b).

Above all, the organization of the tours reveals the subordination of the activities to the most constraint purposes: Work and Education, which determine the tours in which “secondary” activities are inserted “on the way”.

Per person, the number of daily tours, at almost 1.4, is an indicator of regular activity and mobility, and is much more stable than the daily number of trips. This regularity persists across gender, age group, socio-professional categories

and residential sectors. Likewise, the average number of linked trips within a tour is very regular at around 2.4.

The product of the indicators – the average number of tours per individual and the average number of trips per tour – at approximately  $1.3 \times 2.4 = 3.36$ , is slightly below the average number of trips per individual, due to a structural effect.

**Table 3.4a. Influence of socio-professional category on the rate of mobility.**

<b>Socio-professional Categories</b>	<b>Number of Trips per Day</b>	<b>Number of Tours per Day</b>
Farmers	3.87	1.59
Tradesmen, the self-employed and business owners	3.82	1.33
Managers and professionals	3.70	1.28
Intermediate professions	3.81	1.37
Employees	3.60	1.37
Unskilled workers	3.63	1.38
Students	3.20	1.39
Pensioners	2.93	1.25
Nonworkers	3.68	1.55
<b>Total</b>	3.45	1.37

**Table 3.4b. Influence of residential sector on the rate of mobility.**

<b>Residential Sector</b>	<b>Number of Trips per Day</b>	<b>Number of Tours per Day</b>
Paris	3.61	1.36
Inner suburbs	3.40	1.36
Outer suburbs	3.39	1.36
Conurbation outskirts	3.58	1.42
New towns	3.53	1.41
Well-served towns	3.45	1.38
Secluded towns	3.32	1.36
Rural communities	3.11	1.24
<b>Total</b>	3.45	1.37

## 4. Spatial and Temporal Impact

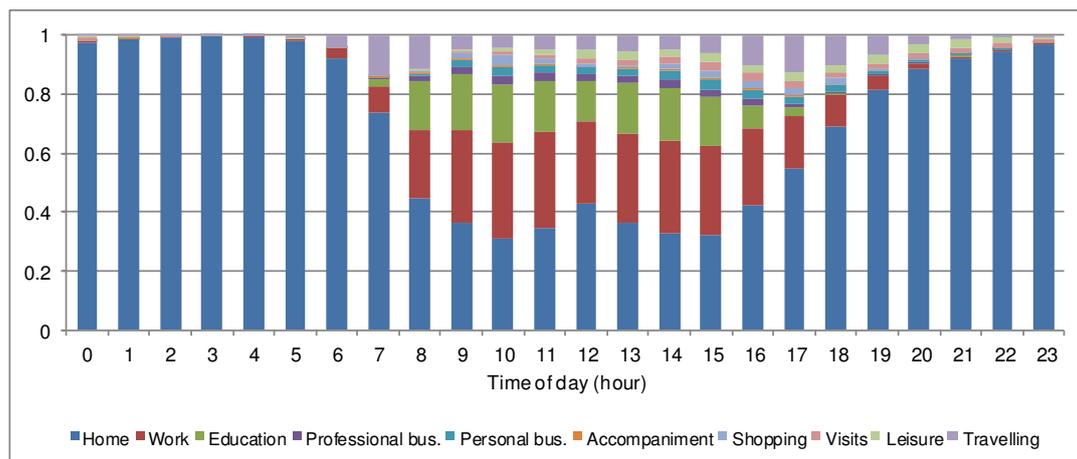
Through their presence and the nature of the activity undertaken, each person exercises a pressure on the place they are in and at the time when they are in it. We are going to characterize the impact of activities on the Paris region (based on the 2001-2002 survey), by successively describing: involvement in activities; presence in space; passing through as an activity; and the “presential moment” which measures the gap between current location and home across the pool of individuals. It should be recalled that the analysis does not take account of the presence of visitors in the region for work or personal purposes, nor of the absence of Paris residents from the region.

### 4.1. Involvement in Activities

Let us retrace the activities conducted by the individuals in the course of the day, separating the individuals at each moment based on the purpose of the activity. Home, Work and Education play a significant role during the day, whereas Home is almost entirely dominant at night. Time spent travelling accounts for a significant proportion.

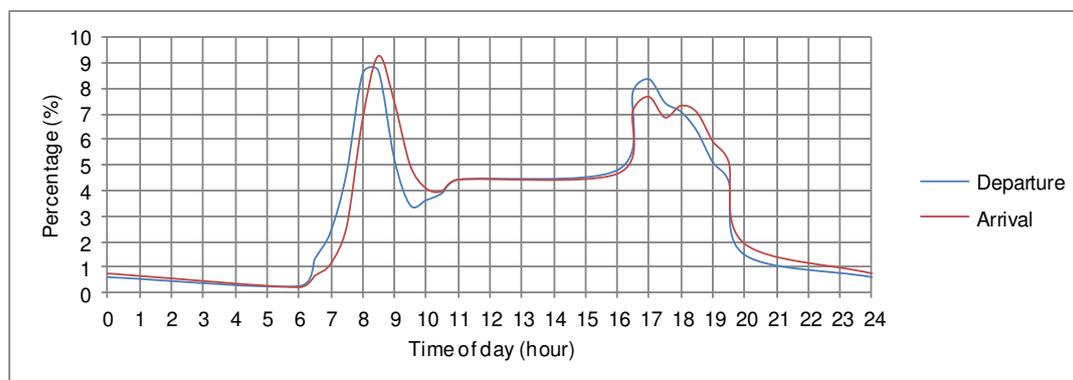
In a day, the time spent outside the home is an average of 7.5 hours, of which 86 minutes is spent travelling and 6 hours (359 minutes) in a fixed activity outside the home. The variations between socio-professional categories are very large, depending on the person’s “activity status”: from 2 hours for a Pensioner and 2.5 hours for a Nonworker up to 8 hours 20 minutes for a Manager or Professional, around 7 hours for a Student or Shopworker or Tradesman or Unskilled Worker, 7 hours 45 minutes for an Intermediate Profession. These variations between socio-professional categories are much greater than those between residential sectors (see, § 2.3).

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**Figure 3.2. Involvement of individuals in activities.**

In the course of the day, trips by residents peak in two periods, one in the morning (7 a.m. to 9 a.m.) and one in the evening (4:30 p.m. to 7:30 p.m.), plus a relative quiet period in late morning and a not insignificant level of night-time trips. Between 11 a.m. and 4 p.m., the level is remarkably slack. There is a difference of around half an hour between morning departure and arrival times and more variations in evening arrival times (Figure 3.3).



**Figure 3.3. Breakdown of departure and arrival timeframes for daily trips.**

## 4.2. Presence in Space

Figure 3.4a and Figure 3.4b show the distribution of individuals by sector of presence and by nature of activity. We have distinguished a daytime period between 8 a.m. and 8 p.m. and an additional night-time period. The conurbation center, the primary location for employment, services, shops and leisure attracts more “activity clients” than it exports. The daytime distribution of activities reflects each sector’s socio-economic function:

residential specialization in the remote outskirts, productive specialization in the center and the new towns.

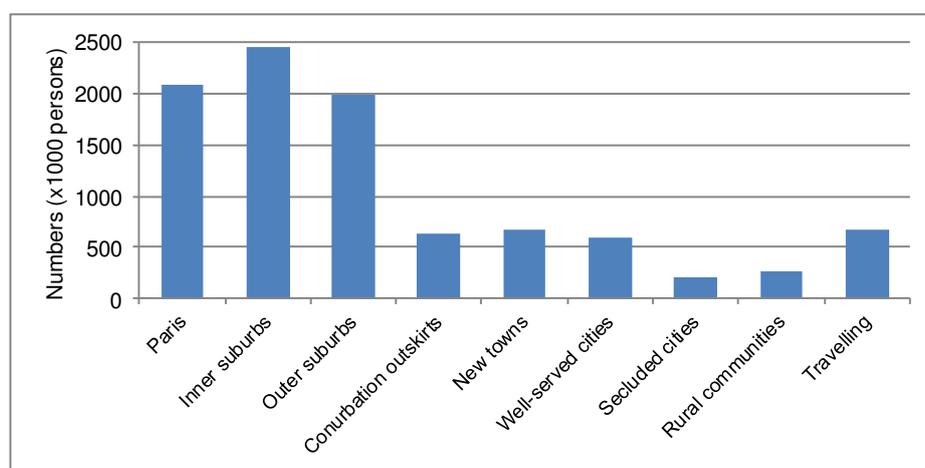


Figure 3.4a. Breakdown of presence by residential sector, daytime 8 a.m. to 8 p.m.

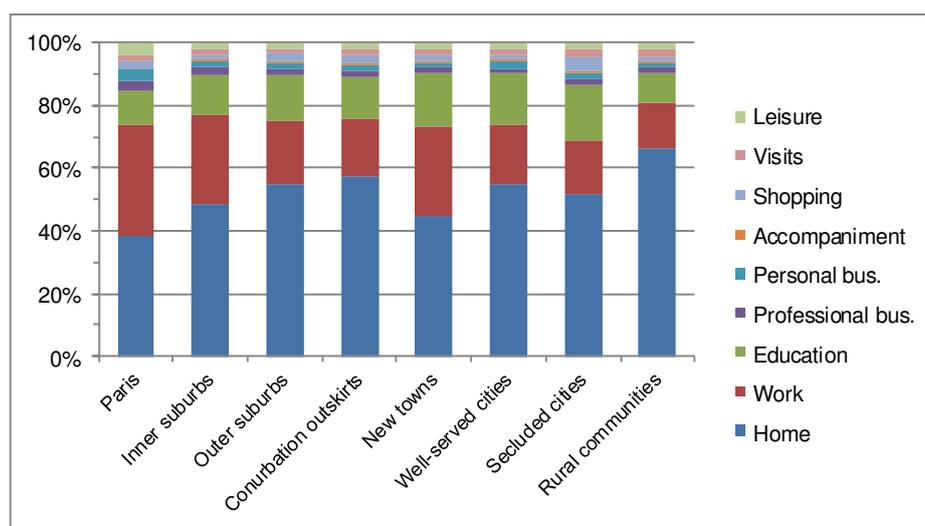


Figure 3.4b. Breakdown of activity purposes by residential sector, daytime 8 a.m. to 8 p.m.

### 4.3. Travel as an Activity

We have already looked at the time spent travelling every day and the distance travelled per person and by residential sector (see, § 2.3). The increase in distances travelled for individuals living further from the center, without change in travel times, reveals increased use of faster forms of mechanized transport. Per resident individual, the budget for the distance travelled on a daily basis doubles between the center and outskirts of the conurbation, and doubles again for rural communities.

The distance travelled, i.e. the spatial range of the trip, largely depends on the purpose of the trip. Home as a activity purpose for travel retains the same importance whatever the distance, but the proportion of Work, Professional Business and Visits as purposes for travel significantly increases with distance (twice the average above 7 km for Work trips), by contrast with the other purposes (Shopping, Leisure, Accompaniment, Personal Business).

#### 4.4. Presential Moment

At every moment, the presence of individuals each in their place of activity constitutes a potential demand for travel to return home, the individual's anchor point. The distance between the current activity and home is like a "lever arm", the individual representing the "unitary mass" to be moved. Added together, these distances constitute a stock of space to be travelled. The total is approximate, since the individual performs a sequence of linked activities and may make detours before returning home. Nonetheless, the dimension of the stock is a measure of the spatial interaction between activities and residences.

The center of the metropolitan area is the busiest in the morning and especially in the afternoon, due to the professional activities and services that it contains. During the day, a "debt of distance" between the present place and the home increases in the morning until late afternoon, then decreases regularly during the evening peak. It is a "presential moment" locally exerted.

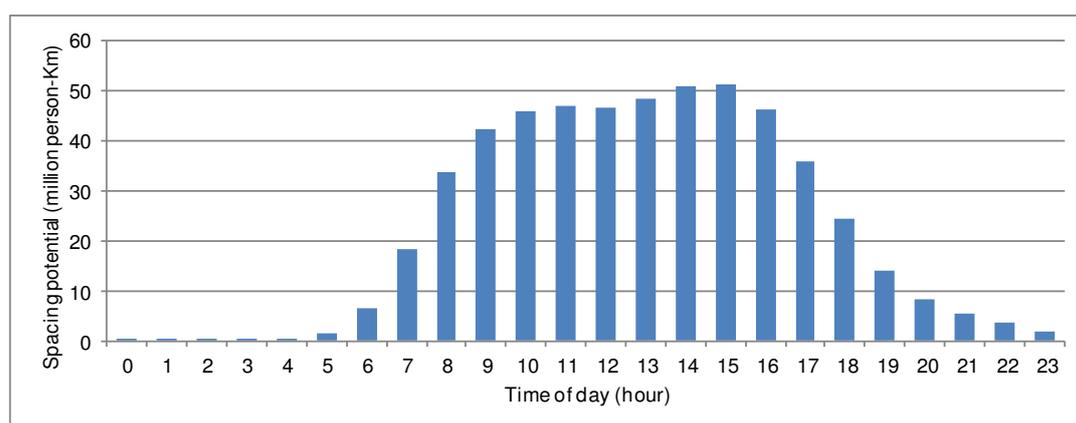


Figure 3.5a. Evolution of the presential moment in the course of the day.

The time distribution of our indicator for the Paris region is unimodal: the nighttime value is virtually zero; the level rises rapidly during the morning peak period and continues to rise more slowly in late morning. It reaches its maximum in early afternoon and then declines steadily until midnight.

The distribution by purpose of trip is instructive: at night, travel as an activity is the main reason for absence from home; then Work occupies a major role during the day, between 7 a.m. and 6 p.m., Visits and Leisure activities are perceptible during the day, but significant in the evening.

In terms of morphological sector, as defined by the IAU-IdF, Paris plays an important role from the morning onwards, a role that further increases in the evening. Its share of the moment is markedly greater than that in the residential population. The Inner suburbs are important during the day but less so in the evening and the New towns show a similar pattern. The outer suburbs have a stable role, which increases in the evening, without matching its proportion of the population.

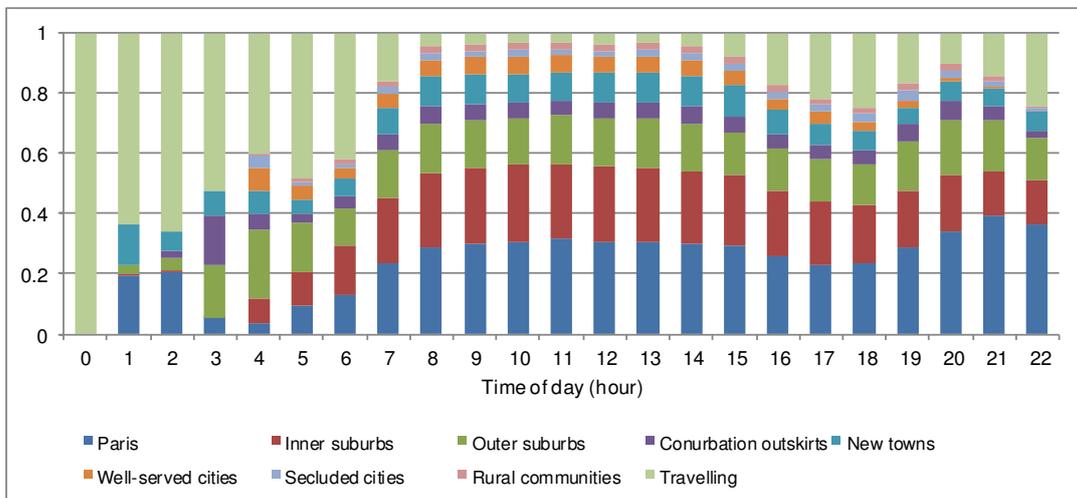


Figure 3.5b. Distribution of the presential moment among residential sectors.

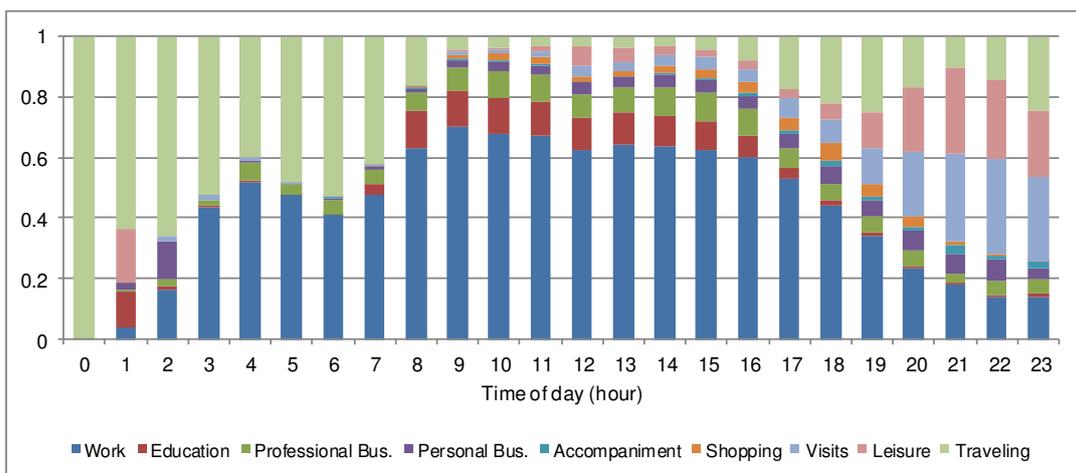


Figure 3.5c. Distribution of the presential moment among activity purposes.

The time spent in out-of-home activities and travels is significant: from 6 to 7 hours on average, from the Pensioners to the higher professions. The residential sector influences the time budgets weakly but the traveled distances strongly, thanks to the use of motorized transportation modes, including automobiles.

## 5. Means of Transportation

Means of transport refers not only to real-time physical resources such as vehicles and infrastructures, but also to individual ownerships and holdings: season tickets for public transport services, vehicles (in particular cars) and even driver's license. Individuals thus put together their own mobility packages. We will now look at certain aspects of transport usage, before focusing on facilities and their impact on practices.

### 5.1. Modes of Transportation

We divided the modes of transport into Walk, Auto (Driver or Passenger), Bicycle, Motorbike, Taxi, and three forms of mass transit service: Bus, Metro, and Regional Train.

Now we look at the modal distribution of the main forms of transport in Paris, based on length: a trip with a range of less than 1 Km is defined as "short"; a trip of between 1 Km and 5 Km as "medium"; and a trip of more than 5 Km as "long". The three categories respectively account for 38, 34 and 28% of trips. For short trips, walking is by far the dominant mode of travel. Motorized travel then takes over, with the car predominating for medium distances. The role of public transport is significant, accounting for a quarter of medium length trips and almost 40% of long trips. Two-wheeled vehicles, with or without engines, and taxis, play a minor role. It should be recalled that an individual might use several means of transportation successively within a single trip. In this case, the trip is allocated to the highest position in a hierarchy based on vehicle size.

The modal distribution based on place of destination for long-range trips shows the impact of the radial layout of the public transport network, which is more useful in the center than in the outskirts, where the car plays an essential role.

Probably because of distance, the purpose of travel largely governs the choice of transportation mean. Walking is therefore very common for local trips (daily Shopping, School) but much less for work trips, where motor vehicles are often preferred.

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## 5.2. Car/Parking Ownership

Ninety per cent of men over 25 hold a driver's license, 75% of women between 25 and 64, and a smaller proportion of older women in consequence of the generation effect. By contrast, public transport season tickets are more widespread amongst women than men; the age effect is the same for both sexes, falling from 45-60% for the 15-24 age group to 18% for the "65 and over" age group.

For car ownership, we refer the reader to the in-depth study by Bertrand [6]. Car ownership in terms of the number of cars per household was 1.0 in 2001, but varied widely from 0.54 in Paris to 0.96 in the Inner Ring and 1.32 in the Outer Ring. The average individual rate is 42%: this varies from 29% in Paris, to 39% in the Inner Ring and 42% in the Outer Ring. For individuals holding a driver's license, the average rate rises to 71%, with a distribution of 47%, 71% and 83% corresponding to distance from the center of Paris. The socio-professional categories with the most diversified professional activities have the highest level of ownership (1.54 cars per Tradesman household as compared with 1.284 Managers and Professionals, 1.21 for Intermediate Professionals, 1.14 for Unskilled Workers, and 0.85 for Employees).

Finally, 89% of individuals have a parking space at home: in 73% of cases a private space (39% owned, 21% rented and 12% free of charge) as compared with 24% on the public street, of which 21% are free of charge. 33% of individuals have a second parking space, of which 70% are private and 26% free on the public street.

## 5.3. Interaction between Ownership and Usage

There was a positive correlation between the possession of a driver's license and the number of daily tours: the individual acquires a skill in order to use it. The impact of season-ticket holding is more complex: non season-ticket holders travel more than season-ticket holders (apart from Pensioners), in other words, the use of an individual mean of transport tends to generate more tours than the use of public transport. Amongst people of working age with jobs and holding a season-ticket, the daily number of tours is steady at around 1.20: these individuals are less mobile than the average.

As regards the influence of car ownership, Bertrand (2005) shows that not just car ownership, but car use is lower in central areas: in Paris, one vehicle in two remained unused on the survey day, compared with 31% in the Inner Ring and 23% in the Outer Ring. He also indicates that an individual who uses his car on a given day makes on average one more trip than a non-user.

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The zone of residence also influences car use: 24% of people living in Paris, 40% in the Inner Ring and 59% in the Outer Ring make at least one car trip per day. The level is highest for people of working age in jobs, standing at some 60% for Managers, Intermediate Professions and Unskilled Workers, but only 49% for Employees. Finally, the level of use increases with the number of vehicles per household: 8% for households without cars, 46% with one car, 71% with two cars or more, making a combined of 46%.

## 6. Conclusion

We have provided a general outline of the activities and trips carried out by inhabitants of the Paris region, for an “average” working day in 2001-2002. Regular features emerge from it: the number of daily tours per individual, and the number of trips within a tour, are stable by gender, age group, socio-professional category and area of residence. The daily number of trips per person and the time spent in travelling are only stable in relation to residential sector, because of an aggregation effect across the different population categories. The stability over time (or slow evolution) of these latter indicators reveals inertia in practices and demographic structure rather than regularity in individual behavior patterns.

The analysis of the tours reveals the dominance of constrained purposes for travel, which account for 70% of the distances travelled and 63% of the time in transit. Activities outside the home are very largely conducted during daytime hours from 7 a.m. to 9 p.m. We have defined and applied a new indicator – the “presential moment” – to describe the stock of potential traffic distributed across an area at a given moment.

The ultimate purpose of our study of transportation means is to characterize the range of mobility types and track its impact on global choices. Future stages of the analysis will look at modal distribution based on activity tours and the range of transportation means to which the individual has access.

The observed regularities suggest a tour-based approach to the modeling of individual mobility situations and behaviors, rather than a trip-based approach. The hierarchy of travel purposes according to their constraint level requires that trip chains are formed based on the most constraining purposes. Subsequently, the subsidiary travel purposes should be grafted on the main tours or executed on autonomous tours. Finally, it is required that the choice of travel mode and activity destination should be modeled jointly.

Based on observations of this study, we will focus in the rest of this dissertation on commutes as our analysis demand segment and we narrow it

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down by two more constraints: We consider only commuters who come from, households with only one worker, and which own at least one vehicle.

- Firstly, with 29% of all tours, work is the most practiced activity in the region. it is also the most constrained travel purpose in both spatial and temporal terms, and dominates the daily activity program of the commuter. It also significantly influences the daily activity program of the other household members;
  - Secondly, commute tours are simple and in more than 87% of the commute tours the home-to-work leg of the tour is composed of only one single trip, i.e., no other activity is chained to the “go” leg (IAU-IdF, 2010). This allows us to effectively simplify the structure of commute tours and concentrate on our main purpose, which is the disaggregation problem.
  - Thirdly, by considering households with only one worker we aim to minimize the effects of intra-household interactions, and by limiting the analysis to those among them that own at least a vehicle, we make sure that the auto mode is available in the mode choice set of our commuters.
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## PART II

# Disaggregation of Trip-Ends in a Traffic Assignment Model

# Chapter 4: A Statistical Perspective to Modeling a Population in a Space

## 1. Introduction

This chapter studies aggregate and disaggregate representation concepts from a mathematical point of view. We first recall some basic statistics. Then we discuss, from a purely statistical point of view, the disaggregation of a population into segments as a requirement for preserving the maximum of the dataset information content and avoiding the loss of information due to employing aggregate approaches. Next, we will consider the representation of space in a transportation model and discuss disaggregate versus aggregate representations. This provides a framework for disaggregate representation of trip-ends in an origin-destination relation and lays out the basis for a stochastic disaggregate traffic assignment model, which is the subject of the next chapter.

In the first section of this chapter, Wonnacott and Wonnacott (1969), Chung (1979), and Ben-Akiva and Lerman (1985) are used, where necessary, as principal references for vocabulary and definitions of statistical concepts.

## 2. Statistical Analysis Perspective: True vs. Perceived

Statistics is the science of deduction through observation. In a statistical analysis, the basic assumption is that one can describe an observable “population”, infer its characteristics and understand its underlying patterns and behaviors by applying statistical methods to an adequately large number of observations, which construct a representative “sample”. For example, in the study of travelers’ mode choice behavior, individuals residing within the borders of an urban area during a particular time period constitute the population, from which censuses and surveys draw random samples.

Statistical analysis does not provide access to the underlying governing dynamics of the system, whether because it does not exist at the first place (e.g., the case of a human decider whose decision process cannot be “truly” replaced by any mechanistic model), or because interior components of the system, despite being adequately identifiable, are beyond the capacity or interest of the study context. From the point of view of the statistician, the population is a black box of which analyst can only make approximate inferences, which should account for randomness. In other words, analyst’s understanding of the system is limited to an approximation of the “true” system characteristics. Therefore, one should distinguish between what a characteristic truly values and what the analyst can “perceive” about it by employing a statistical approach. Statistical models should account for the uncertainty in the perception of the true state of the observed system.

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## 2.1. From Statistical Population to Random Variables

### 2.1.1. Statistical Population

Population is defined as the set of individuals, items, or data. In typical transportation contexts, the population is very large, making a complete enumeration of all individuals, impractical or even impossible. Therefore, samples of manageable sizes are collected and statistics are calculated from the samples so that one can make inferences from the sample to the population. As a trade-off, using random samples introduces uncertainty in the estimation of the statistical inferences about the entire population.

### 2.1.2. Individual Attributes

Each individual in the population is characterized by one or several quantitative (e.g., age, income, household size ...), or qualitative (e.g., gender, level-of-comfort ...) attributes. A quantitative variable, real or cardinal, indicates a computable mathematical value. Qualitative variables, on the other hand, can be ordinal (e.g., level-of-comfort on a scale of one to five) which are comparable but non-computable, or nominal (e.g., residence postal code) which are neither comparable nor computable, or state flags (e.g., car ownership status) which are simple Boolean attributes.

### 2.1.3. Random Variables

A statistical population contains individuals, who hold attributes. At the level of a single individual, each attribute describes a particular characteristic of an individual such as age, gender, socio-professional category... and can be surveyed “deterministically”. At the level of the entire population, on the other hand, these attributes are regarded as “random” variables, which describe the population as a whole “probabilistically”, and individual values of attributes are considered as particular instances, which occur within the population with a certain frequency. A random variable can be thought of as the numerical result of operating a non-deterministic mechanism or performing a non-deterministic experiment. Probability density functions of random variables are determined by combining instant values and their frequencies.

### 2.1.4. Analyst’s Position towards the Population

The statistical approach is based on deriving inferences from a limited number of samples, containing a limited number of attributes, gathered at particular

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periods of time, in particular areas of space. The statistician reduces an entire population with its many agents into a simplified probabilistic representation. In fact, the statistician is not interested in each individual agent, but in the outcome of their collective effort. In other terms, the analyst replaces a deterministic attribute at disaggregate individual level by a random variable at aggregate population level.

The posture of the statistician is that he/she pretends to have a perfect knowledge of the population system under study and assumes that the statistical inferences are “true” so that a statistical model can be parameterized using such statistical estimations to correctly represent the population system. In fact, a perfect control over parameters only can be achieved in numerical simulations carried out in laboratory situations. In reality, the analyst deliberately omits the omnipresent uncertainty of estimators caused by the incompleteness of the sample.

## 2.2. Statistics Estimators

An estimator is a mathematical operator defined as a function of observations. It operates over the sample to produce an estimation of the true value of an unknown parameter. Small sample estimators operate over samples with limited number of observations while asymptotic estimators operate over very large number of observations. An estimator defined as a function of random variables, is itself a random variable with an expected value and a variance. The quality of estimation of an estimator is determined based on several criteria, of which four are primary: unbiasedness, efficiency, consistency and robustness. Unbiasedness is the quality that the expected value of the estimator in the sample equals the expected value of the estimated random variable in the population. Efficiency is the quality of an unbiased estimator that among all possible unbiased estimators produces the most certain estimation; i.e. the expected value of its variance is minimal. Consistency is the quality of being convergent as the size of the sample grows. Robustness is the quality of being resistant to outlier observations; this will be discussed in more depth later in this chapter.

In a random sample of size  $N$ , observations can be considered as “random” variables  $\tilde{X}_1 \dots \tilde{X}_N$ , with sample observations  $x_1 \dots x_N$  being realizations of them. The sample sum is defined by:

$$\tilde{S} = \sum_{n=1}^N \tilde{X}_n \quad (4.1)$$

The sample mean is the value around which the observations can be considered as being “evenly” distributed. A mean estimator is given by:

$$\tilde{\mu} = \frac{1}{N} \sum_{n=1}^N \tilde{X}_n \quad (4.2)$$

which is an asymptotic unbiased estimator of the true population mean,  $\mu$ , and is asymptotically Normal according to the central limit theorem. The expected value and the variance of this sample mean estimator are given by:

$$\mathbb{E}[\tilde{\mu}] = \mu \quad ; \quad \text{var}[\tilde{\mu}] = \frac{\sigma^2}{N} \quad (4.3)$$

with  $\sigma^2$  being the true population variance.

### 2.2.1. Sample Proportions

For the probabilistic methods can be applicable to the study of population via sample datasets, the sample should be drawn in a “random” way, i.e., it should not be “biased” for favoring any particular observation. In a “random” sample every individual has an equal chance to be drawn for the sample. Different sampling methods are described in the literature (See for example, Ben-Akiva and Lerman, 1985).

The sample proportion is defined as the fraction of successes out of a Bernoulli sampling trial (with 0 or 1 outcomes). Let there be  $x$  successful success out of  $N$  Bernoulli trials. Then a sample proportion estimator is given by:

$$\tilde{\pi} = \frac{x}{N} \quad (4.4)$$

which is an unbiased estimator of the true success proportion in the population, denoted by  $\pi$ , and is asymptotically Normal according to the central limit theorem. The expected value and the variance of this sample proportion estimator are given by:

$$\mathbb{E}[\tilde{\pi}] = \pi \quad ; \quad \text{var}[\tilde{\pi}] = \frac{\pi(1-\pi)}{N} \quad (4.5)$$

This is used for the normal approximation of the binomial confidence interval. The other way around, given the confidence level and the amount of admissible relative error, this estimator can be used to estimate the minimum number of required trials.

### 2.2.2. Data Sample Moments

Statistical measures are used in order to describe random variables based on a population of experimental or surveyed data. Each random variable is supposed to be perfectly described by its probability density function, which gives the probability that the random variable assume a value within a particular interval. Analogous to the case of algebraic functions, which can be approximated by a series expansion, a probability density function can be described by its moments. We define the sample central moment of order  $r$ ,  $m_r$ , and the sample raw moment of order  $r$ ,  $m'_r$ , as the following:

$$m_r = \frac{1}{N} \sum_{n=1}^N x_n - \mu^r \quad (4.6)$$

$$m'_r = \frac{1}{N} \sum_{n=1}^N x_n^r \quad (4.7)$$

In general, sample central moments are considered as measures of central tendency whereas sample raw moments are measures of statistical dispersion. The first order raw moment of a random variable is called the expected value. It determines the central value around which the population is “expected” to be distributed “evenly”. The second order central moment of a random variable is called the variance. It measures the level of dispersion of values about the mean. Variance can also be considered as a measure of the “information content” of the population for a greater variance indicates a more dispersed population. The mean and variance estimators for discrete population are given by:

$$\mu = \mathbf{E}[X] = \sum \omega_i x_i \quad (4.8)$$

$$\sigma^2 = \text{var}[X] = \sum \omega_i x_i^2 - \mu^2 \quad (4.9)$$

where  $\omega_i$  represents the normalized weight of the individual  $i$ . The mean and variance estimators for continuous population are given by:

$$\mu = \mathbf{E}[X] = \int x \omega(x) dx \quad (4.10)$$

$$\sigma^2 = \text{var}[X] = \int x^2 \omega(x) dx - \mu^2 \quad (4.11)$$

where  $\omega(x)$  is a probability density function. Another important moment is the standardized moment, which is defined as the normalization of the  $n$ th central moment with respect to the standard deviation. The third-order standardized moment is called skewness, which describes the lopsidedness of the distribution. The fourth order standardized moment is called the kurtosis which is a measure of whether the distribution is tall and skinny or short and squat.

Other measures of central tendency can also be defined. Some of the most notable such estimators are median (value separating the higher half of a population from the lower half), mode (the value that occurs most frequently) or geometric mean ( $n$ th root of the product of data where  $n$  is the count of data in the dataset, each one providing more convenience in specific cases). Other measures of statistical dispersion such as average absolute deviation, median absolute deviation, and interquartile range, can also be used in specific applications to provide more statistical robustness or coherence (e.g., in association with  $L_1$  norm statistics). For instance, the average absolute deviation is defined as (for a discrete data sample):

$$\text{AD}[X] = \text{E}\left[|X - m(X)|\right] = \sum \omega_i |x_i - \mu| \quad (4.12)$$

where  $\omega_i$  represents the normalized weight of the individual  $i$ .

### 2.2.3. Robust Statistics

Statistics of a population are estimated using “estimators”. Robustness of an estimator is defined as its quality of being resistant to small departures from model assumptions, i.e., to outlier data not obeying the assumed noise model, which can cause a non-robust conventional estimator to produce arbitrarily bad results. In order to quantify the robustness of a method, it is necessary to define some measures of robustness. The two most common measures of robustness are the breakdown point and the influence function, described below.

The breakdown point of an estimator determines the proportion of incorrect extreme observations (i.e. arbitrarily large or small observations) an estimator can handle before giving an arbitrarily deviated result. For example the maximum likelihood estimator of the mean of independent and identically distributed Normal random variables is given by the Equation 4.2. This estimator may produce severely deviated results if only one of the  $N$  realizations is outlier. Therefore, such an estimator is not robust to outlier data. In other words, the mean estimator has a small sample breakdown point

of  $\beta = 1/N$  and an asymptotic breakdown point of zero. On the other hand, the median, as another measure of central tendency, is indeed much more robust than the mean because even a severe change in the value of a data situated at either extreme of the series of random variables does not affect the order of positioning of the rest of the numbers, and in consequence the median remains unchanged. In fact, the median can resist to as many outlier realizations as the half of the total number of variables. Therefore, the median estimator has a breakdown point of 50%. In the same way, trimmed estimators can provide some level of robustness: the breakdown points for 5%-trimmed and 10%-trimmed mean estimators are 5% and 10% respectively. As for the measures of statistical dispersion, the standard deviation and the range are non-robust estimators, whereas the median absolute deviation (although being inefficient) and the interquartile or interdecile ranges are considered as robust measures of scale.

The search for appropriate unbiased and efficient robust estimators to replace classic measures can significantly improve the quality of data analysis. If, for example, an underlying normal distribution is established for a particular random variable, which exhibits identical mean and median, using the median as the measure of location instead of the mean, can lead to a more robust evaluation of model parameters using a smaller number of observations, thus achieving a higher quality of analysis at lower cost. For further discussion of this subject, see Rousseeuw and Leroy (1987).

### 3. Population Segmentation

Consider breaking a population  $P$  into several mutually exclusive collectively exhaustive subpopulations,  $P_j$ , with  $p_j$  being the proportion of individuals in the subpopulation  $P_j$ . Each subpopulation represents a statistical class. The total variance over the population is given by:

$$\sigma^2 = \sum_j p_j \left[ \sum_{i \in P_j} \omega_i x_i - \mu \right]^2, \quad \mu = \sum_j p_j \mu_j \quad (4.13)$$

where,  $\mu_j$  is the average values in the class  $P_j$ , and  $\mu$  is the average value in the entire population  $P$ . By expanding the above equation, we obtain the law of total variance:

$$\sigma^2 = \sum_j p_j \sigma_j^2 + \sum_j p_j \mu_j - \mu^2, \quad \mu = \sum_j p_j \mu_j \quad (4.14)$$

Now we consider the case of a random variable  $\tilde{X}$  segmented over two mutually exclusive collectively exhaustive classes with  $p_1$  and  $p_2 = 1 - p_1$  portions of the entire population. The expected value of  $\tilde{X}$  in the population can be written in terms of its expected values in two subpopulations:

$$\mu = E X = p_1\mu_1 + p_2\mu_2 \quad (4.15)$$

where  $\mu_1$  and  $\mu_2$  represent the expected values of  $\tilde{X}$  over each one the two the classes. According to the law of total variance, we have:

$$\sigma^2 = \text{var } X = p_1\sigma_1^2 + p_1p_2 (\mu_1 - \mu_2)^2 + p_2\sigma_2^2 \quad (4.16)$$

The formula illustrates the fact that the total variance in the main population is captured in terms of the two intra-class variances and the difference between class means, i.e., two intra-class portions and one inter-class portion.

Breaking a population into two or several subpopulations is called “segmentation”. The context is analogous to the centroid-based centripetal representation of space associated with a zoning system in transportation models. We are interested in the spatial information that is lost because of lumping the intrazonal space on the centroid point. Trip-ends are scattered over the urban area. Models represent the space as a system of adjacent zones. Let us consider a zoning system of  $\bar{z}$  zones, thus  $\bar{z} - 1$  origin-destination zone pairs. Each origin-destination zone pair can be viewed as a statistical class. We can arrange trips into classes, which correspond, to a pair of origin-destination zones. More precisely all trips that start from some place inside zone  $o$  and end in zone  $d$  are members of the class  $od$  and there are a total number of  $\bar{z} - 1$  of this origin-destination classes. Due to aggregation, model ignores the scatteredness of trip-ends in the space. Instead, all trips of the class  $od$  are supposed to start from the centroid of the zone  $o$  and end at the centroid of the zone  $d$ . In other words, varying travel characteristics of trips of the class  $od$  are all replaced by the centroid-to-centroid level-of-service characteristics. Ignoring the scatteredness of trip-ends in space is analogous to ignoring all intrazonal variance terms,  $p_j\sigma_j^2$ , in the Equation 4.14 and preserving only the part due to differences between mean values, i.e., centroid-to-centroid level-of-service characteristics. Therefore, due to the application of aggregate representations, a part of the total variance will be lost. This provides a criterion for designing optimal zoning systems. Based on such a criterion, the number and the geometry of zones are determined so that the portion of the total variance captured in terms of differences between mean values reaches some objective value. We illustrate by two examples.

### 3.1. Optimal Segmentation

#### 3.1.1. Double-hump Normally Distributed Population

Let  $\tilde{X}$  be a random variable defined over the population  $P$  with a double hump probability density distribution,  $\omega(x)$ , defined based on the general form of the Normal distribution family as follows:

$$\omega(x) = \frac{1}{2}\phi_1(x) + \frac{1}{2}\phi_2(x) \quad (4.17)$$

where  $\phi_i(x; \mu_i, \sigma_i^2)$  represents the normal probability density function with mean  $\mu_i$  and variance  $\sigma_i^2$ :

$$\phi_i(x; \mu_i, \sigma_i^2) = \frac{1}{\sqrt{2\pi\sigma_i^2}} \exp\left[-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right] \quad (4.18)$$

We propose to break the population  $P$  into two classes,  $P_1 = (-\infty, a]$  and  $P_2 = (a, +\infty)$ , separated by a boundary  $\Gamma(x) = a$ . We denote by  $p_i$  the proportion of population in class  $P_i$  as follows (for the sake of readability we henceforth denote  $f(a)$  by  $f^a$ ):

$$p_1 = \frac{1}{2}\Phi_1^a + \frac{1}{2}\Phi_2^a \quad ; \quad p_2 = \frac{1}{2}(1 - \Phi_1^a) + \frac{1}{2}(1 - \Phi_2^a) \quad (4.19)$$

where  $\Phi_i(x)$  is the cumulative distribution function of the Normal distribution given by:

$$\Phi_i(x; \mu_i, \sigma_i^2) = \int_{-\infty}^x \phi_i(u; \mu_i, \sigma_i^2) du \quad (4.20)$$

Also  $m_i$  represents the mean of the random variable  $\tilde{X}$  in the class  $P_i$ . The expression for the mean is given by (see, Appendix A):

$$m_1 = \frac{[\mu_1\Phi_1^a - \sigma_1^2\phi_1^a] + [\mu_2\Phi_2^a - \sigma_2^2\phi_2^a]}{\Phi_1^a + \Phi_2^a} \quad (4.21)$$

$$m_2 = \frac{[\mu_1(1 - \Phi_1^a) + \sigma_1^2\phi_1^a] + [\mu_2(1 - \Phi_2^a) + \sigma_2^2\phi_2^a]}{1 - \Phi_1^a + 1 - \Phi_2^a} \quad (4.22)$$

According to the Equation 4.16, in order to minimize the loss of information due to aggregation, the inter-class portion,  $p_1 p_2 (m_1 - m_2)^2$ , should be maximized as a function of boundary  $\Gamma a$ .

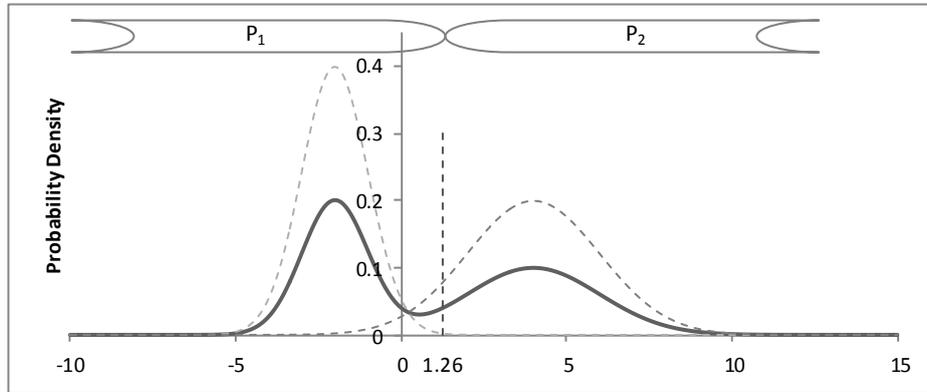


Figure 4.1. A double-hump Normal distribution.

We assume two Normal distributions  $N(-2, 1^2)$  and  $N(4, 2^2)$  for  $\phi_1$  and  $\phi_2$ . Figure 4.1 illustrates the resulting double-hump distribution. The boundary  $\Gamma a$  breaks the population into two classes. Figure 4.2 shows the total variance decomposition in terms of the intra-class variance of  $P_2$  (left), inter-class portion due to difference of mean values (center), and intra-class variance of  $P_1$  (right).

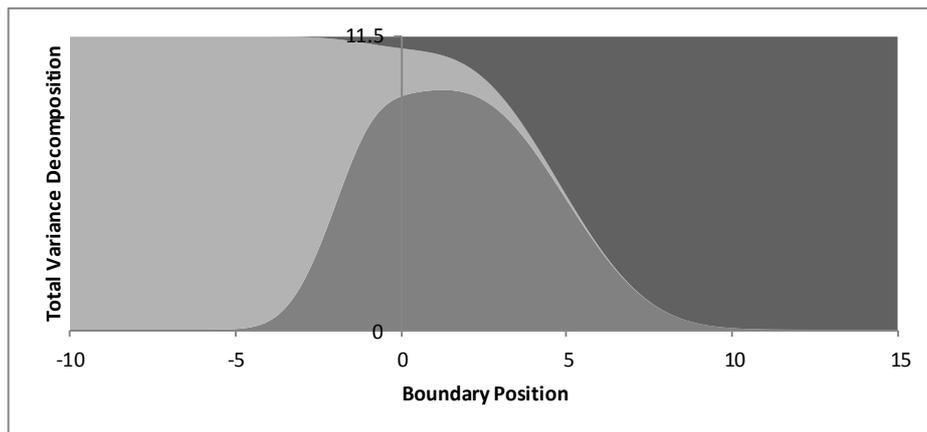


Figure 4.2. Total variance decomposition depending on boundary position.

According to Figure 4.2, with  $\Gamma$  at extreme left, the total variance is entirely captured by the intra-class variance of  $P_2$ , and vice-versa. Actually somewhere in the middle, the majority of the total variance is captured by the

inter-class portion. The abscissa of the maximization point determines the optimal position for the segmenting boundary  $\Gamma$ . In this case, the optimal position is at  $a \simeq 1.26$  where 81.1% of the total variance is captured by the inter-class portion, and therefore preserved from loss due to aggregation.

In transportation modeling practice, the analyst often has some *a priori* indications on variables that may have structural effects on behavior. Equally, variables presenting large variances are usually more informative therefore more preferable for segmentation.

### 3.1.2. Double Uniformly Distributed Population

Let  $\tilde{X}$  be a random variable defined over the population  $P$  with a double uniform probability density distribution,  $\omega x$ , defined based on the general form of the Uniform distribution family as follows:

$$\omega x = \frac{1}{2}u_1 x + \frac{1}{2}u_2 x \quad (4.23)$$

where  $u_i x; a_i, b_i$  represents a Uniform probability density function over the interval  $[a_i, b_i]$ . Figure 4.3 shows  $\omega x$  for  $u_1 = U[-4, 0]$  and  $u_2 = U[0, 8]$ .

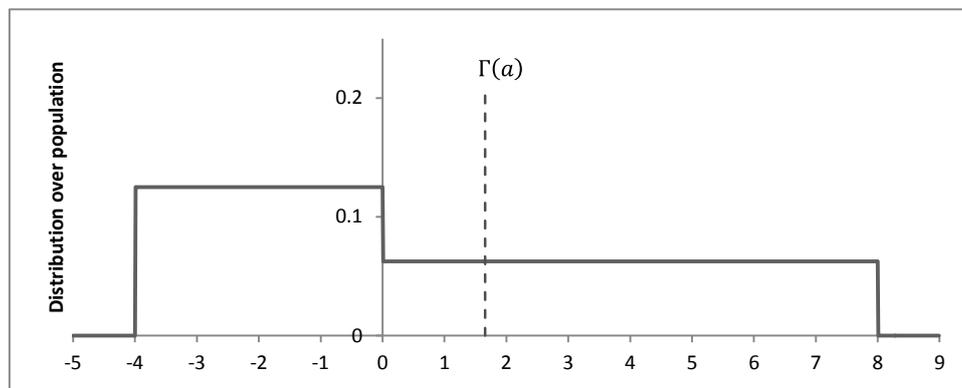


Figure 4.3. Double uniform distribution.

Figure 4.4 shows the total variance decomposition as a function of  $\Gamma$  in terms of intra-class and inter-class portions. This time the optimal position for the boundary  $\Gamma$  is at  $a \simeq 1.66$  where 78.1% of the total variance is captured by the inter-class portion, and therefore preserved from loss due to aggregation.

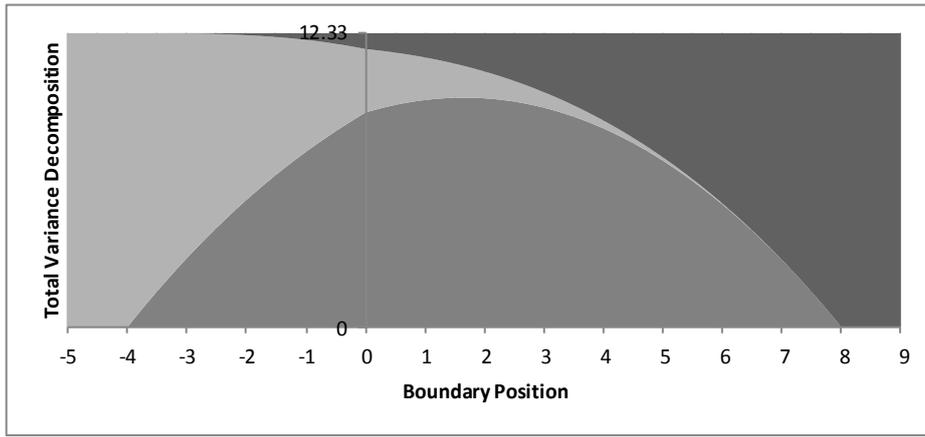
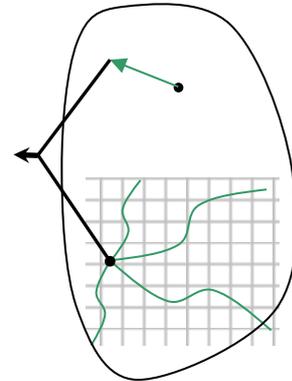


Figure 4.4. Total variance decomposition depending on boundary position.

## 4. Spatial Framework

### 4.1. Measuring Distance in Flat Space

At the interzonal scale, highways networks provide relatively complete representation of urban axes; therefore, interzonal travel characteristics can be satisfactorily simulated. At the intrazonal scale, on the contrary, the urban network representation is often sparse. In the case where a detailed representation of local streets is available, intrazonal travel characteristics can be evaluated using the local network. In the absence of such detailed information, the urban space as a bi-dimensional flat continuum should not necessarily be associated with a Euclidian distance measure because travelers do not travel as the crow flies neither by walking nor by taking motorized modes. The figure on the right illustrates the difference: on the upper half of the zone, a dummy link connects the centroid to the network whereas on the lower half, a detailed street-level representation of local network provides intrazonal accessibility allowing for spatial dispersion.



The generalized distance measure for two generalized coordinates  $P p_1 \dots p_n$  and  $Q q_1 \dots q_n$  in an n-dimensional flat space, also known as Minkowski distance, is given by:

$$\delta_m P, Q = \left( \sum_{i=1}^n |p_i - q_i|^m \right)^{1/m} \tag{4.24}$$

where  $\delta_m P, Q$  is called the  $m$ -norm or  $L_m$  metric between points  $P$  and  $Q$ . The parameter  $m$  is a positive integer however cases other than  $m = 1$ ,  $m = 2$  and  $m \rightarrow \infty$  are rarely used. For the special case  $m = 1$  the generalized Minkowski distance measure is reduced to rectilinear or  $L_1$  distance. It is also known as the Manhattan distance, which is the shortest distance a traveler could take in a city laid out in square blocks. The latter name alludes to the grid layout of most streets on the island of Manhattan.

$$\delta_1 P, Q = \sum_{i=1}^n |p_i - q_i| \tag{4.25}$$

For the special case  $m = 2$  the Minkowski distance measure is reduced to the Euclidian or  $L_2$  distance which corresponds to traveling in bee-line.

$$\delta_2 P, Q = \sqrt{\sum_{i=1}^n |p_i - q_i|^2} \tag{4.26}$$

In general, the Manhattan metric seems to offer a more realistic measure of “accessibility” for measuring intrazonal “travel” time and distance. On the other hand, the Euclidian metric is a more consistent measure of “proximity” for spatial analyses.

### 4.2. Defining a Population in a Space

In this section, we study a geographic space with two dimensions of localization. It is assumed that a perfect pixel-by-pixel knowledge of space is available. Space contains individuals with specific spatial localization and individual attributes.

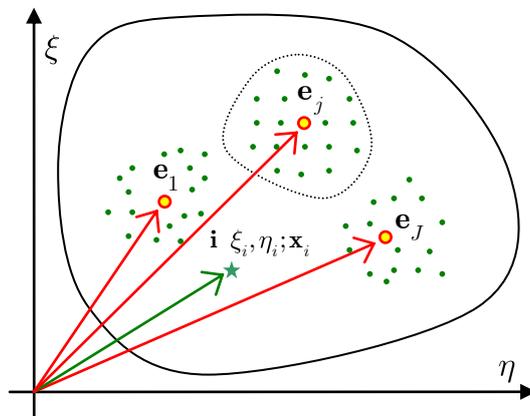


Figure 4.5. Intrazonal localization of population at intrazonal level.

We denote by  $\mathbf{i} \xi_i, \eta_i; \mathbf{x}_i$  an individual located at Cartesian coordinates  $\xi_i, \eta_i$  by a location vector  $\vec{i} \xi_i, \eta_i$  and holding the individual attributes vector  $\mathbf{x}_i$ . In the following, the Euclidian metric is used as proximity measure in the study of statistical properties of spatial locations. As it has been discussed before, where in the population a particular attribute assumes distinctive values (e.g., double hump Normal distribution), it is statistically more efficient if the population is divided to a number of sub-populations in order to preserve more information content after aggregation. The same statistical basis is applicable to the spatial context. We now consider an area  $\mathbf{Z}$  with a scattered population distribution, in which  $J$  distinct population concentrations can be identified. We define  $J$  mutually exclusive collectively exhaustive population concentrations  $Z_j$ , containing each  $p_j$  portion of the entire population.

Each population concentration can be spatially associated with a representative point. We call such a point an “elementary place”. We denote by  $\mathbf{e}_j$  the geometric center of the  $j$ th population concentration, and  $\vec{e}_j$  is its location vector:

$$\vec{e}_j \xi_j, \eta_j = \sum_{i \in Z_j} \omega_i \vec{i} \xi_i, \eta_i \quad (4.27)$$

where  $\omega_i$  is the normalized weight of the individual  $\mathbf{i}$ . Thus, the coordinates of an anchor point  $\mathbf{e}_j$  are given by:

$$\mathbf{e}_j \xi_j, \eta_j : \xi_j = \sum_{i \in Z_j} \omega_i \xi_i \quad ; \quad \eta_j = \sum_{i \in Z_j} \omega_i \eta_i \quad (4.28)$$

The spatial dispersion of the individual localization around the anchor  $\mathbf{e}_j$  is measured by the bidimensional variance of the relative individual localizations around the anchor:

$$\sigma_j^2 = \sum_{i \in Z_j} \omega_i \left[ \vec{i} - \vec{e}_j \cdot \vec{i} - \vec{e}_j \right] \quad (4.29)$$

The vector version of the Equation 4.14 is given by the following equation as a generalization to the unidimensional case:

$$\sigma^2 = \sum_{j=1}^J p_j \sigma_j^2 + \sum_{j=1}^J p_j \vec{e}_j - \vec{e}_\mu \cdot \vec{e}_j - \vec{e}_\mu \quad , \quad \vec{e}_\mu = \sum_{j=1}^J p_j \vec{e}_j \quad (4.30)$$

where  $\sigma^2$  represents the total variance of individual locations with respect to the geometric center  $\mathbf{e}_\mu$ , located by the location vector  $\vec{e}_\mu$ .

### 4.3. Centroids as Elementary Places

In aggregate demand analysis, elementary places are defined in order to, geographically as well as statistically, represent, the center of a concentration of individuals who attend to access to transportation services. An “elementary place” represents a zone – or subzone – towards the transportation supply. It designates the actual geographic coordinate form where aggregated travelers depart and to which aggregated travelers arrive. It also holds the average characteristics of different demand segments, which are lumped on one single point and are generalized to all individuals.

In the simplest case, the entire geographical zone is assigned to one center point, which is conventionally its geometric center or “centroid”. The zone center is connected to the assignment network via one or several dummy links called “connectors” which provide the connectivity between the demand and the supply. In the case of regular zones, with simple geometry and uniformly distributed demand, the assumption of one elementary place, being its geometric center, is usually adequate. However, in the general case as the zone geometry gets more complicated or the localization of demand and supply becomes more segregated, it is possible to have multiple elementary places situated at population concentrations where purposes take form and activities take place.

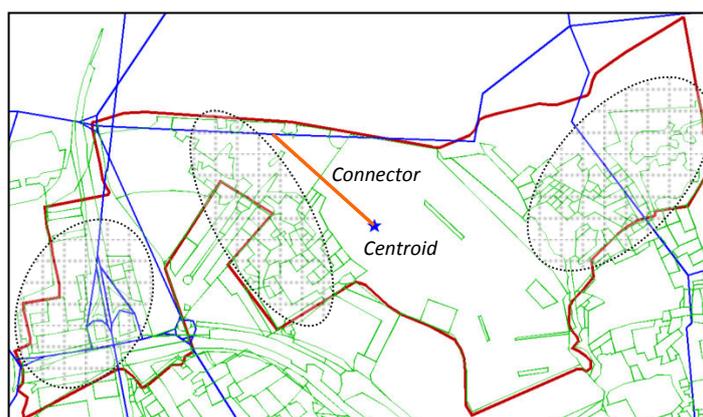


Figure 4.6. Sparse built area within a geographical zone.

Figure 4.6 shows an example where the geometric center of zone is located in some unused lands. Red line shows the boundary of the zone. The three dotted ellipses show population concentrations. Blue lines represent highway network and pink line is the connector. It is a clear example of a case where

more than one elementary place can be employed to represent the zone. In general, using long connectors to relate elementary places to the network can entail unrealistic terminal travel times and should be avoided.

## 5. Zoning System

The discrete zoning system is an imperfect representation of the spatial framework of the transportation model. It is a simplification of the geographical context that reflects the unavailability or unaffordability of a pixel-by-pixel knowledge. Because of geographical discretization in aggregate demand analysis, attributes, land-use and especially traffic flow data are averaged over traffic analysis zones (TAZ). Averaging operator, when applied to disaggregate data, preserves central values and ignores intrazonal variations. As a result, a potentially important portion of the information content is lost.

In this context, the most important dilemma to which the analyst is faced is how to preserve the maximum amount of the “useful” spatial heterogeneity information in the discrete urban zoning system. The more the individual and land-use attributes are variable within a zone, the more would be the information loss caused by spatial aggregation. Therefore, try should be made to regroup those spatial units, which already demonstrate less variation in their key parameters and to separate spatial units, which exhibit fundamentally different characteristics. In statistical terms, to each zoning system can be attributed a variance threshold, defining the maximum level of admissible variation of different characteristics within each zone in the entire zoning system. Coarser zoning systems will be attributed to bigger admissible variances and vice versa.

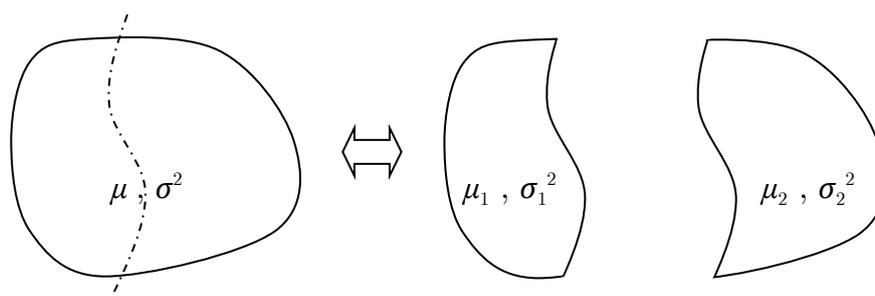
The literature on the zoning problem has mostly focused on giving descriptive and qualitative guidelines, which are sometimes divergent, i.e. satisfying some would violate others. Less attention has been paid to the quantitative assessment of the effects of the zoning system and in most studies, the zoning system has been considered as being given a priori. Decisions regarding the zoning system are not trivial indeed. Martínez et al. (2007, 2009), in their study of the Lisbon Metropolitan Area, and Lesage and Fischer (2010) point out that even a regular grid can sometimes – according to their criteria – outperform a standard official zoning system. However, the problem with a regular grid is that it does not conform to external constraints such as topographic or statutory limits. Martin (2000) divides the zoning system design into three steps. In the first step, basic boundaries are sketched from scratch following real-world topographic features and conforming to higher-

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level statutory boundaries. In the second step, “hard” zoning constraints are applied so that all output areas comprise contiguous building blocks, and contain a minimum amount of population. In the final step, “soft” zoning constraints are applied to ensure, for example, the internal social homogeneity of output areas.

Systematic search for an optimal zoning system or automated zone design (AZD) has been formulated into single- or multi-objective constrained optimization problems. The AZD can be viewed in two ways: On one hand, it can be regarded as a top-down process in which the urban area is first sketched into a few large subareas merely based on external criteria (e.g., topographic or statutory limits); then is cut into smaller zones to minimize some information loss. On the other hand, it can be considered as a bottom-up process in which “basic spatial units”<sup>1</sup> are agglomerated into bigger spatial units called zones. In practice it is a combination of both which applies. Computational aspects of the AZD are discussed by Openshaw and Rao (1995) who propose the use of soft computing approaches (e.g., tabu search and simulated annealing) for solving the highly nonlinear AZD optimization problem.

The total variance decomposition rule provides a robust theoretical basis for spatial aggregation. In the design of zoning systems, either by cutting coarser areas to obtain finer ones or by reattaching fine spatial units to obtain traffic analysis zones (see, Figure 4.7), one should try to minimize the amount of information that will be lost due to aggregation, by maximizing the inter-class portion of the total variance (see, Eq. 4.30).



**Figure 4.7. Decomposition of total variance in terms of decomposed intrazonal statistics.**

The AZD objectives can be put in different categories based on whether the zoning process aims to optimize the representation of the spatial interaction information (e.g., traffic flows), accessibility measures (e.g., modal network

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<sup>1</sup> Terminology adopted after Openshaw (1977) signifying the smallest spatial unit for which data are available.

access/egress time), land-use attributes (e.g., population, land occupation), or mobility parameters (e.g., trip generation rate). Openshaw (1977) supposes that a good zoning system is the one, which minimizes the amount of intrazonal trips. Alvanides et al. (2000) also concentrate on traffic flows as the main criterion for designing a zoning system. Martínez et al. (2009) present a detailed list of different objectives and constraints from the literature. They use a direct optimization algorithm to minimize a combined objective function of trip density deviation between basic spatial units and percentage of intrazonal trips. In general, land-use-based zoning systems will favor the agglomeration of areas with similar population densities, for instance, within a zone. On the other hand, accessibility-based zoning system will agglomerate locations around public transportation stations or highway axes. In this respect, accessibility-based optimization objectives may lead to different zoning systems for different modes of transport.

If spatial localization data are available with an adequate level of precision (i.e. at building or postcode level), given a set of boundaries,  $\vec{e}_\mu$  and  $\vec{e}_j$  can be estimated using the discrete sample formulation. Where this is not the case, one can make the hypothesis of uniform distribution of spatial localizations over intrazonal parcels and land lots. Then it is possible to use a continuous sample formulation for estimating intra-class and inter-class statistics (See, Appendix B).

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# Chapter 5: Stochastic Model of Traffic Assignment with Trip-end Disaggregation: Theoretical Framework

## 1. Introduction

The model representation of the urban space is based on a zoning system where the continuum space is discretized into several traffic analysis zones. At the intrazonal level, the representation of the transportation supply is incomplete and sparse whereas at the interzonal level the representation of the transportation network is more realistic. The sparse intrazonal network representation leads to devising approximate methods for estimating intrazonal trip characteristics. For instance, Venigalla et al. (1999) point out that because of the lack of a network representation at intrazonal level, trip characteristics cannot be evaluated directly. To acquire intrazonal trip characteristics they first determine the nearest zone centroid for each zone centroid. Intrazonal trip time/distance is chosen as the half of the travel time/distance from the current zone centroid to the nearest neighbor centroid.

The model representation of the transportation supply is a mathematical idealization of the reality. In the urban highway network the representation of intersections, interchanges, weaving sections... can be simplified and minor passages, alleys and streets can be completely ignored or regrouped and represented by one single link. The geometric and level-of-service characteristics of links approximate the reality. The underlying traffic flow model is a simplified representation of vehicles and interactions, which make the traffic flow. Congestion and queuing effects are modeled using representative link-performance functions.

The travel demand is usually given in the form of a lumped origin-destination flow matrix, which reflects the traffic flow over a discrete urban space. Static Traffic Assignment is the process of loading the traffic flow matrix to the highway network to simulate the behavior of drivers in choosing their route from the origin to the destination. It is founded on the concept of equilibrium put forth by Wardrop (1952), henceforth called the Wardrop equilibrium. Wardrop distinguishes between two different states of equilibrium, namely the user equilibrium, resulted from the “selfish” behavior of trip making agents, and the social equilibrium, promoted by some level of social cooperation. The Wardrop user equilibrium principle postulates: “the journey times in all routes actually used are equal and less than those which would be experienced by a single vehicle on any unused route.” It is a rather intuitive but non-rigorous statement; however its application to real network assignment problems has proven not to be as much intuitive.

Different static traffic assignment methods have been proposed based on different hypothesis. The simplest of all is the all-or-nothing assignment method, which per each origin-destination pair assigns all the traffic demand

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to the shortest route. In other words, the all-or-nothing assignment method establishes the Wardrop user equilibrium state in a network where link travel costs are constant and does not depend on the link traffic volume. At its core, it consists of a graph shortest path algorithm such as that of Dijkstra (1959) (for reviews on shortest path algorithms, see, Pollack and Wiebenson, 1960; van Vliet, 1978). The all-or-nothing method has two principal shortcomings. Firstly, it does not take into account the link capacity constraint: driving on a congested link is costlier (i.e. in terms of travel time) than a free link so where several alternative routes are available, the one offering the shortest travel time is the first to be chosen, but once it is congested other alternatives become competitive. Secondly, it supposes that travelers are absolutely strict in their route choice behavior.

Research in the first direction has led to the development of methods which take into account the congestion effect in the formulation of link cost functions. Then the search for an equilibrium state is formulated as an optimization program. Beckmann et al. (1956) are the first to formulate an equilibrium state. The hypothesis underlying their work is that the travel cost function is separable (i.e. it depends only on the traffic flow over the link) and non-decreasingly monotonic. They prove that under such conditions an equilibrium state exists and is unique. Their simplified version of the problem remains the most practiced approach for traffic assignment to an urban network.

Research in the second direction has led to another general family of models in which link characteristics are represented as random variables so that multiple routes have each a certain probability of being chosen. This family of models is further divided into two subgroups, namely those based on the discrete choice theory and those based on the stochastic simulation (Ortúzar and Willumsen, 2001).

## 2. Demand–Network Connectivity

Assignment networks, used in traffic assignment applications, are simplifications of the real urban highway and public transportation networks. Although try is made in order to include all major streets and public transportation lines, regarding to the span of the assignment model network, finer details at neighborhood-level are generally ignored. One can split traveler's itinerary into two parts: First, a main section, consisting of major links, most of them explicitly represented in the assignment model. Second, two end-sections at origin and destination, which take the traveler from the

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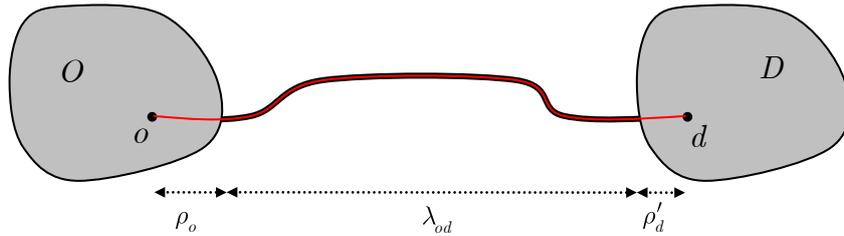
“actual” departure point to one end of the main section, and from the other end of the main section to the “actual” arrival point.

The “true” origin-destination travel distance and travel time of the individual  $i$  are denoted  $l_{od}$  and  $t_{od}$ , where  $o \in Z_o$  denotes a “precise” departure position in the origin zone  $Z_o$ , and  $d \in Z_d$  denotes a “precise” arrival position in the destination zone  $Z_d$ . The travel itinerary of the individual can be divided into three sections: the intrazonal terminal section at origin, the interzonal main section, and the intrazonal terminal section at destination. The total travel time is considered as the sum of the one main travel time and the two terminal travel times:

$$l_{od} = \rho_o + \lambda_{od} + \rho'_d \quad (5.1)$$

$$t_{od} = \tau_o + \theta_{od} + \tau'_d \quad (5.2)$$

The distinction between intrazonal terminal sections and the interzonal main section is based on the assumption of aggregate spatial representation due to spatial discretization. Accordingly, the precision of the spatial representation of the model, including the transportation network and the land-use, is limited to the aggregate discrete zone level and further intrazonal details are ignored. As a result, the transportation network is represented quite differently at intrazonal and interzonal levels. Interzonal links, including the main urban roads or transit services, are represented with relative fidelity whereas the intrazonal level is considered beyond the precision of the model.



**Figure 5.1. Schematic decomposition of itinerary into terminal and main sections**

In practice, terminal sections are usually represented by dummy links called connectors, generated to connect elementary places, mainly zone centroids, to main itinerary sections. All travelers represented by a particular elementary place are supposed to begin/end their travel there, regardless of their actual departure/arrival point. Characteristics of connectors (i.e. free velocity, capacity ...) should be assigned so that the average straight-line travel time is a “correct” estimation of the mean terminal travel time.

As discussed before, the analyst has no knowledge of the “true” trip characteristics in the model environment. The model can only estimate trip characteristics by making consistent hypothesis and applying statistical methods. However, the model estimations can be obtained with different levels of precision or “certainty” depending on the abundance and exhaustiveness of demand data and the precision of supply data. The more aggregate is the representation of the travel demand and transportation supply within the model, the more uncertain would be the model’s estimation of trip characteristics.

Let us define  $\tilde{l}_{od}$  as an estimator of total travel distance, and  $\tilde{t}_{od}$  as an estimator of total travel time. The difference between the “true” value of a travel characteristic, for instance the total travel time, and its estimated value can be interpreted as a measure of model’s representativeness. We define an estimator – for instance – of the total travel time unbiased, if its OD expected value, i.e. the expected value over the population of trips having the same origin-destination pair, equals the “true” value of the total travel time, for all origin and destination zones in the zoning system  $\mathbf{Z}$ :

$$\forall Z_o \in \mathbf{Z}; \forall Z_d \in \mathbf{Z} : \mathbf{E}[t_{od} - \tilde{t}_{od}] = 0 \quad (5.3)$$

Then the variance of the difference between the true total travel time and its estimated value,  $\text{var}[t_{od} - \tilde{t}_{od}]$ , measures the efficiency of the estimator.

We now consider different levels of aggregation and define estimators of total travel distance,  $\tilde{l}_{od}$ , and total travel time,  $\tilde{t}_{od}$ , with different degrees of precision.

## 2.1. Aggregate Trip Characteristic Estimation

### 2.1.1. First Aggregate Trip Estimator

At the most aggregate level there is the zoning system without a network. Itinerary consists of only a main section and the two terminal sections are missing. The model therefore estimates the true travel distance and time with the direct centroid-to- centroid values.

$$\tilde{l}_{od}^1 = \overline{\mathbf{ee}'} \quad (5.4)$$

$$\tilde{t}_{od}^1 = \overline{\mathbf{ee}'} / v_{od} \quad (5.5)$$


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where  $\mathbf{e}$  is the centroid of the origin zone,  $\mathbf{e}'$  is the centroid of the destination zone and  $v_{od}$  is the travel velocity. However because the estimation of the travel time depends also on the estimation of mean interzonal travel velocity, it would be statistically more tractable if the analysis is based on the estimator of the travel distance as the estimation of the mean travel velocity involves uncertainty being itself a random variable.

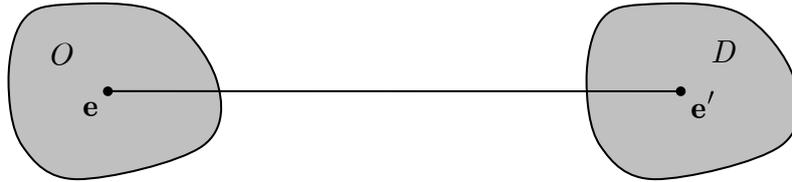


Figure 5.2. First aggregate idealization of the interzonal route.

First aggregate trip estimators are potentially very biased estimators of travel characteristics and therefore very inefficient ones. Although it is possible to adjust the average interzonal velocity in order to make it unbiased, the total travel distance estimator depends only on the geographical coordinates and is completely biased as no travel is made following the direct line. The variance of the travel distance and travel time among all  $OD$  trips is zero as all trips with the same origin-destination are attributed the same travel distance and time. This implies that the first aggregate estimators do not contribute at all in capturing the variance or uncertainty in trip characteristics. In total, at this level of aggregation the estimators are inefficient and unable to capture intrazonal uncertainties in the estimation of travel characteristics.

### 2.1.2. Second Aggregate Trip Estimator

The most trivial improvement to the preceding aggregate spatial representation is to allow the zoning system to connect to the transportation network via connectors. In this case, the precise departure and arrival points are ignored and all trips are considered to depart from the origin zone center and to arrive at the destination zone center. As intrazonal transportation networks are not explicitly modeled, the two terminal sections are represented using connector links that connect zone centers to the assignment network.



Figure 5.3. Second aggregate idealization of the interzonal route.

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The total travel distance and total travel time estimator are defined as a combination of two intrazonal terminal sections and an interzonal main section:

$$\tilde{l}_{od}^2 = \rho_o + \lambda_{od} + \rho'_d \quad (5.6)$$

$$\tilde{t}_{od}^2 = \tau_o + \theta_{od} + \tau'_d \quad (5.7)$$

Where  $\rho_o$  and  $\rho'_d$  represent connector travel distances at origin and destination,  $\lambda_{od}$  represents the main section travel distance,  $\tau_o$  and  $\tau'_d$  represent connector travel times at origin and destination, and  $\theta_{od}$  represents the main section travel time. The evaluation of the main section travel time is based on the characteristics that are provided in the assignment network, such as free flow velocity, road capacity and congestion model. Terminal travel times on the other hand are calculated by dividing the terminal travel distances by the average intrazonal terminal travel velocities, being itself a random variable.

$$\tilde{t}_{od}^2 = \frac{\rho_o}{\bar{v}_o} + \theta_{od} + \frac{\rho'_d}{\bar{v}_d} \quad (5.8)$$

## 2.2. Disaggregate Trip Characteristic Estimator

At a disaggregate level, each traveler is treated as being travelling between “true” departure and arrival points. Each individual trip uses a particular set of access/egress nodes in order to enter and exit the transportation network and the choice of the access/egress nodes depends only on the geographical position of the individual and the representation of the transportation network at the proximity. In the case that the intrazonal transportation network representation is detailed enough to allow a micro-level simulation, the trip departure/arrival points can be addressed directly. Otherwise, the connection between the departure/arrival points and the access/egress nodes is made using connector links that are established per individual trip. Disaggregate trip estimators are defined as follows:

$$\tilde{l}_{od}^3 = \tilde{\rho}_o + \lambda_{od} + \tilde{\rho}'_d \quad (5.9)$$

$$\tilde{t}_{od}^3 = \tilde{\tau}_o + \theta_{od} + \tilde{\tau}'_d \quad (5.10)$$

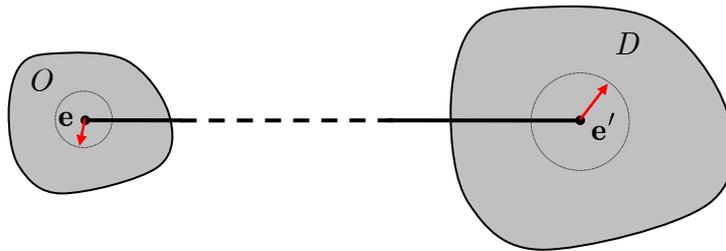
Where  $\tilde{\rho}_o$  and  $\tilde{\rho}'_d$  represent connector travel distances at origin and destination,  $\lambda_{od}$  represents the main section travel distance,  $\tilde{\tau}_o$  and  $\tilde{\tau}'_d$

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represent connector travel times at origin and destination, and  $\theta_{od}$  represents the main section travel time. The estimation of the main section travel time is based on the characteristics that are provided by the assignment network.

### 3. Capturing Uncertainty via Re-Aggregation

Aggregate travel modeling practice uses a lumped representation of zonal travel demand at zone centers. Such an approach ignores terminal travel distances and times. The aim of this section is to study the information loss due to aggregation. In aggregate modeling, elementary places instead of the actual departure/arrival coordinates define the extremities of travel, and each elementary place is connected to the network via one or a few connectors. First, we consider the simplest, yet the most common, case of having only one network node available per each zone at its center point, connected to the network via one single connector. In this case, given an origin-destination pair, all individuals are supposed to depart from the same origin point (i.e. origin centroid), and arrive at the same destination point (i.e. destination centroid). So, all individuals traveling during a particular period of time are assigned to an identical itinerary. As a result, the variance of the estimated travel time between the given origin-destination pair is equal to zero. For the sake of simplicity, we use a Euclidian intrazonal distance measure so that all distances are measured in a bee-line; consequently at this stage we do not account for the intrazonal road network which introduces curve-lined distances.



**Figure 5.4. Single-anchor representation at origin and destination.**

For individuals whose departure and arrival points are respectively situated at radiuses  $r_i$  and  $r'_j$  from the origin and destination zone centers, the main section travel time and distance are identical. Where an exhaustive enumeration of  $N$  individuals traveling between origin zone  $O$  and destination zone  $D$  and their exact departure/arrival points is available, the  $OD$  expected values and variances of the estimators of terminal travel distance are given by:

$$\mu_\rho = \bar{\rho}_o = \sum_{i=1}^N \omega_i r_i \quad ; \quad \sigma_\rho^2 = \sum_{i=1}^N \omega_i (r_i - \bar{\rho}_o)^2 \quad (5.11)$$

$$\mu_{\rho'} = \bar{\rho}'_d = \sum_{j=1}^N \omega'_j r'_j \quad ; \quad \sigma_{\rho'}^2 = \sum_{j=1}^N \omega'_j (r'_j - \bar{\rho}'_d)^2 \quad (5.12)$$

where  $\omega_i$  is the normalized weight of the individual  $i$ . Therefore the disaggregate trip estimators can be re-aggregated to the interzonal level, incorporating two random variables representing the terminal travel sections:

$$\tilde{l}_{od}^3 = \tilde{\rho}_o + \lambda_{od} + \tilde{\rho}'_d \quad (5.13)$$

where,

$$\mathbb{E}[\tilde{\rho}_{od}] = \bar{\rho}_{od} \quad , \quad \text{var}[\tilde{\rho}_{od}] = \sigma_\rho^2 \quad (5.14)$$

$$\mathbb{E}[\tilde{\rho}'_{od}] = \bar{\rho}'_{od} \quad , \quad \text{var}[\tilde{\rho}'_{od}] = \sigma_{\rho'}^2 \quad (5.15)$$

Thus, the  $OD$  expected values and variances of the estimators of total travel distance are given by:

$$\mathbb{E}[\tilde{l}_{od}^3] = \mathbb{E}[\tilde{\rho}_o] + \mathbb{E}[\lambda_{od}] + \mathbb{E}[\tilde{\rho}'_d] = \bar{\rho}_o + \lambda_{od} + \bar{\rho}'_d \quad (5.16)$$

$$\text{var}[\tilde{l}_{od}^3] = \text{var}[\tilde{\rho}_o] + \text{var}[\lambda_{od}] + \text{var}[\tilde{\rho}'_d] = \sigma_\rho^2 + 0 + \sigma_{\rho'}^2 \quad (5.17)$$

The variances of terminal section travel distance random variables measure the amount of uncertainty that a “typical” individual encounters in his/her travel distance, and consequently travel time. This allows incorporating measures of uncertainty in an aggregate model where the aggregation operator ignores variations and maintains averages.

If such disaggregate data about travelers are not available, one can still assume that the departure point density of travelers at origin (e.g. residents) and the arrival point density of travelers at destination (e.g. businesses) are distributed as functions of position vector  $\vec{r}$  according to normalized density functions  $\omega(\vec{r})$  and  $\omega'(\vec{r})$ .

The  $OD$  expected values and variances of the estimators of terminal travel distance can be evaluated by:

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$$\mu_\rho = \int_O r \omega \vec{r} \, dA \quad ; \quad \sigma_\rho^2 = \int_O r - \mu_\rho \omega \vec{r} \, dA \quad (5.18)$$

$$\mu_{\rho'} = \int_D r \omega' \vec{r} \, dA \quad ; \quad \sigma_{\rho'}^2 = \int_D r - \mu_{\rho'} \omega' \vec{r} \, dA \quad (5.19)$$

The basic assumption of one network node per zone situated at located at the zone center as the only elementary place, and the distribution of residences (departure points) at origin and businesses (arrival points) at destination can be replaced with more sophisticated and realistic ones. However, the idea of preserving variations in the model by incorporating variance estimators in the assignment procedure or the composition of utility functions is the one, which allows an aggregate level model to overcome, to some extent, its fundamental shortcoming, which is the loss of information due to applying aggregate methods.

In the preceding case, only one elementary place is accessible therefore “all” of travelers are restrained to choose the same elementary place. Multiple elementary places bring up complexity at two levels: firstly the choice of proper elementary places, and secondly the network connectivity issues. In the case of multiple elementary places, individuals are considered to be choosing among available alternatives. In addition, the choice of a departure elementary place is nevertheless conditional upon the itinerary and the arrival elementary place at destination to which it leads.

The next level of sophistication involves discrete zonal representations using multiple elementary places. Again, it is possible to take into account the spatial dispersion of individuals and to calculate the mean terminal travel time/distance as well as the uncertainty in the evaluation of the terminal travel time/distance. However, the problem is how to find the demand share for each origin elementary place. We consider two elementary places at origin connected to one single elementary place at destination (Figure 5.5).

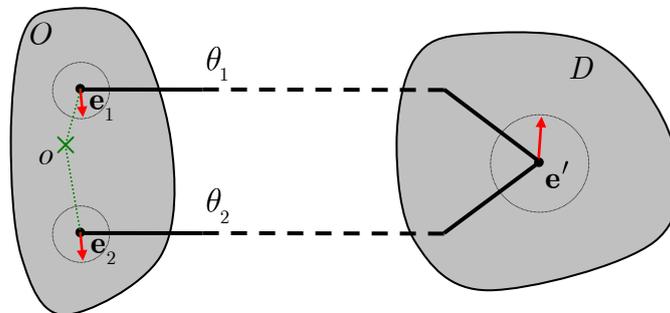


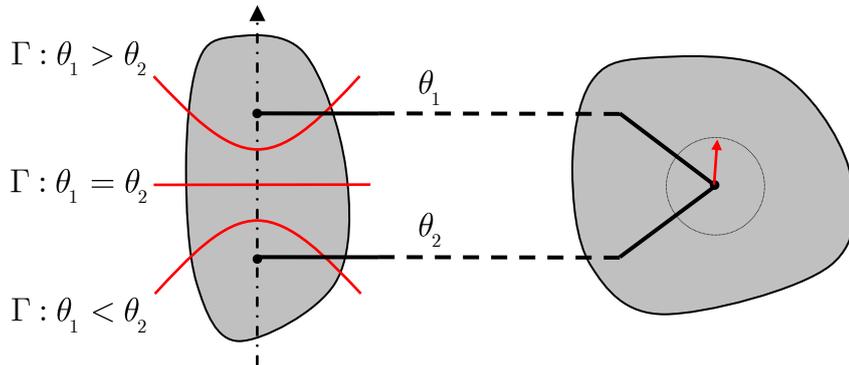
Figure 5.5. Double elementary-place representation at origin.

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We assume that between two available access elementary places, the traveler will choose the one, which leads to the minimum total travel time. According to the illustration, the choice of the access elementary place does not influence traveler's terminal itinerary at destination. Therefore, the choice of the access elementary place depends merely on the terminal travel time at origin plus the main section travel time: the traveler departing from  $o$  chooses the elementary place  $\mathbf{e}_1$  if the condition  $\tau_1 + \theta_1 < \tau_2 + \theta_2$  holds, and vice versa. Thus, the condition  $\tau_1 + \theta_1 = \tau_2 + \theta_2$  defines the spatial boundary  $\Gamma$ , which separates between catchment areas of the two elementary places. Based on the assumption of measuring the travel distance in a beeline, we have:

$$\Gamma : \frac{\rho_1}{v_o} + \theta_1 = \frac{\rho_2}{v_o} + \theta_2 \quad \Rightarrow \quad \rho_1 - \rho_2 = v_o \theta_2 - \theta_1 \quad (5.20)$$

This describes a hyperbolic locus of which  $\mathbf{e}_1$  and  $\mathbf{e}_2$  are focal points. Once the intrazonal catchment areas of the two elementary places are identified, one can estimate the mean and the variance of the terminal travel time at origin and destination zones corresponding to each main travel section on the network. The case for more than two elementary places at origin or destination is analogous: the intrazonal catchment areas determining the demand share of elementary places are geographically identifiable. However, the problem gets more complicated when both origin and destination zones are discretely represented by more than one elementary place. Here, the choice of elementary place at origin becomes conditional on the choice of elementary place at destination.



**Figure 5.6.** Anchor catchment area as a function of anchor-to-anchor travel time.

In the lack of further detail, following the travel-time-minimization line of reasoning, one can suggest to explicitly include all departure/arrival coordinates as dummy nodes (the same has been done for zone centroids) and to connect them to a number of nearby network nodes so that the assignment

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model will decide among all possible alternative routes the one offering the least total travel time. Thus, the problem of access/egress elementary place will be treated as a part of the route choice problem. This can mitigate, or even resolve, the problem of access/egress node choice by increasing the number of connectors in order to make sure that the path offering the least total travel time is included in the disaggregate individual's path choice set. This however adds a very large number of dummy nodes and connectors to the initial road or transit network, and requires cumbersome calculations.

Inside a particular zone, the choice of elementary places is not done independently. One hand, being geographically closer to one elementary place implies being relatively further away from the others introducing a negative correlation. On the other hand, the intrazonal road network providing the liaison between traveler's departure point and elementary places includes many shared links, which introduce covariance through traveler's intrazonal route choice behavior. Therefore, the elementary place choice model should be capable of dealing with a heteroscedastic structure.

## 4. Route Choice with Stochastic Representation of Trip-ends

In this section, we introduce the probabilistic representation of the intrazonal travel time. We propose that the intrazonal travel time depends on the intrazonal spatial localizations but due to the lack of precision on the intrazonal transportation network and spatial localization data, the estimation of intrazonal travel characteristics is subject to uncertainty. On the other hand, we suppose that the interzonal network is represented accurately enough so that the travel characteristics over the network links can be estimated with certainty.

The aim is to develop a stochastic assignment model with trip end disaggregation. It is disaggregate as it eliminates the centroid-connector representation and directly addresses intrazonal trip-end locations. It is stochastic as it accounts for the uncertainty due to the probabilistic representation of intrazonal locations.

### 4.1. A Brief Review of Stochastic Modeling

In stochastic traffic assignment the route choice model is based on probabilistic representation of travel characteristics to account for these different sources of variability, which can be put in two general categories (Leurent, 2006): On the supply-side, traffic-carrying characteristics of

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roadways are subject to variability caused by fluctuations due to whether, unpredictable traffic conditions, or simply measurement errors (physical variability). This is a physical variability as if all travelers were identical human beings, the travel cost offered by each route section would not be measurable deterministically. On the demand-side, travelers' perception of travel characteristics is variable according to their attitudes and personal attributes (perceptual variability). This is a perceptual variability as if all costs on all routes were determined, different travelers would still behave differently due to secondary personal factors (Leurent, 1998a).

This suggests that the model must allow and account for variability in the characteristics of the network elements and the attributes of the traveler. The important point is that in stochastic modeling, for whatever variability source, travel cost is no longer a deterministic constant. Instead, it is a random variable with a certain distribution, which accounts for different variability sources. Stochastic assignment methods have been implemented in various ways but mainly in two different directions namely known as simulation-based methods and proportion-based methods (Ortúzar and Willumsen, 2001):

In the simulation-based approach (Burrell, 1968), travel cost characteristics of network links (in particular free flow travel time) are associated with distributions allowing for variability. Briefly speaking, it is a Monte-Carlo method in which, first, random number generators are used to sample instances from these distributions, and then a static assignment model is solved supposing sampled cost values, in a repetitive sequence, and at the end, link traffic flows are aggregated to produce final results. The use of a simulation-based approach is somehow forced, as the choice of probability density distributions is somewhat arbitrary: for instance, Burrell (1968) uses uniform distribution. Daganzo and Sheffi (1977) also proposed a simulation-based method based on the Multinomial Probit model. Because of the very nature of simulation-based methods, results may be "noisy" but the quality of results improves with the number of random generations involved. Advanced Monte-Carlo methods can be used to improve the performance even more.

In the proportion-based approach (Dial, 1971), unlike the simulation-based approach, the reasoning is in terms of origin-destination routes instead of individual network links: here, travel costs of origin-destination routes are considered random variables. Other important difference is that the choice of distribution is not arbitrary so that the model can be solved analytically. In Dial (1971), the traffic is assigned to different origin-destination routes using a Multinomial Logit model (Ben-Akiva and Lerman, 1985). The Multinomial Logit model is characterized by its fundamental property that travel cost variables are independently and identically distributed (*i.i.d.*) type I extreme

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value (Gumbel) variables. The choice of Gumbel distribution is probably done to take advantage of the simplicity of the Multinomial Logit model (not necessarily owing to its objective appeal), however this is certainly one of the cases where the independence assumption is very difficult to defend as it turns out to be significantly restrictive in route choice problems (see, Maher, 1992).

Route alternatives within a traffic network often share several common links and therefore are highly inter-correlated. In Ile-de-France, it is particularly true for long-range origin-destination relations, which share common sections of the Parisian Boulevard Périphérique. It is hence unrealistic to assume that these routes are irrelevant alternatives. This suggests that the simplest discrete choice model is not nearly adequate to address the full extents of the traveler's choice behavior and more elaborated models must be employed to deal with complex covariance structures. Whilst trying to maintain the analytical simplicity of the Multinomial Logit model, many authors have tried to improve it in order to deal with correlated origin-destination routes. Of these models, we shall simply give an impressionistic inventory.

The first category of models to mention includes those, which are based on the Multinomial Logit with minor modifications. The C-Logit by Cascetta et al. (1996) and the Path-Size Logit by Ben-Akiva and Bierlaire (1999) are the two best-known examples. In this category the systematic part of the route alternative utility (negative generalized cost) in a Multinomial Logit model is modified by including an additional attribute which for each route alternative is calculated as a function of its overlap with other routes in the choice set and supposedly measures the correlation with other route alternatives. The idea being the same, the two formulations are different and based on different theoretical grounds.

Although both C-Logit and Path Size Logit liberate to some extent the independence assumption of the Multinomial logit model but they are still restricted owing to the fact that the Multinomial Logit model is incompetent to account explicitly for a complex covariance structure. Therefore, within the analytically appealing GEV-family, more elaborate models have been developed capable of dealing with more complex covariance structures. The Paired Combinatorial Logit by Chu (1989), and Koppelman and Wen (2000) allows for an independent similarity relationship for each pair of alternatives. Demonstrative applications of this model to the route choice problem can be found in Gliebe et al. (1999). The Link Nested Logit by Vovsha and Bekhor (1998) is an adaptation of the Cross Nested Logit (Vovsha, 1997) to the route choice problem, where each link of the network corresponds to a nest and each route to an alternative. The estimation of this model for large networks however has been proved difficult (Ramming, 2001). The Multinomial Probit

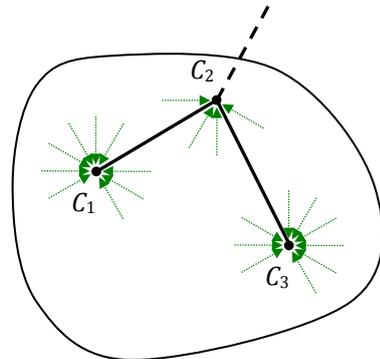
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with Logit kernel by Ben-Akiva and Bolduc (1996) combines the logit and probit models by adding normal error components to a core Multinomial Logit model in order to account for correlation between alternatives. Application of this model to the route choice problem is demonstrated in Bekhor et al. (2002). Lately Frejinger and Bierlaire (2007) used the Multinomial Probit with logit kernel by introducing the notion of subnetwork component. A subnetwork component is defined as a behaviorally meaningful part of the network, which induces a perceptual correlation among routes that are not necessarily physically overlapping. In Ile-de-France, for instance, two paths, which use the Parisian ring road, may share unobserved attributes even if they do not share any common links.

It should be remembered that all abovementioned efforts for developing enhanced GEV-based models aimed to address the unavoidable need to account for the highly heteroscedastic nature of network route choice problems whilst the Multinomial Probit model (Daganzo, 1979) offered heteroscedasticity from the beginning. The reason that the Multinomial Probit model was neglected for so long has attributed to its computational cumbersomeness. Daganzo (1980a, 1980b) is the first to have studied the stochastic disaggregate representation of trip-ends for traffic assignment to a monomodal network and Sheffi and Trexler (1980) have checked the accuracy of his algorithm. Maher (1992) proposed a proportion-based method using the MNP model and proposed using Clark's analytical approximation to overcome computational cumbersomeness. See Patriksson (1994), and Bell and Iida (1997) for further exploration of stochastic network assignment methods.

## 4.2. Notion of Anchor Point

In reality, the search for an appropriate access from the inside of the neighborhood to the main transportation network is not an arbitrary one. The geographical form of neighborhoods can be looked upon as a drainage system, which at origin collects the traffic on a number of “anchor points” from where the traffic enters the main network; and at destination redistribute the traffic inside the zone. In the case of transit networks, the identification of such collectors is rather straightforward: train or subway stations are evident collectors, which provide access to the transit network. In the case of road networks, however, the task of identifying such collectors is more delicate, and requires detailed information at micro-zone level. We consider that networks nodes that are located



inside a zone can potentially represent anchor points. Once the intrazonal traffic reaches anchor points, the anchor-to-anchor travel times per origin-destination pair are known deterministically.

### 4.3. Route Choice in an Idealized Network

We investigate the route choice problem in an urban context by studying an idealized urban road network. We elucidate the correspondence between disaggregate and aggregate representations of intrazonal routes. We develop the concept of probabilistic representation of intrazonal travel and apply it to the aggregate route choice problem in order to verify the pertinence of this approach for the evaluation of travel characteristics at intrazonal level.

#### 4.3.1. Idealized Urban Network

We consider an idealized urban network composed of two rectilinear meshes representing a primary road grid superposed on a secondary one (Figure 5.7). The primary grid is coarser and is characterized by regular horizontal span,  $S$ , and vertical span  $D$ ; it represents major urban axes and highways providing constant travel velocity of  $V$ . The secondary grid is finer and is characterized by regular horizontal span  $s$ , and vertical span  $d$ ; it represents local streets and provides a constant travel of  $v$ . The ratio between the major grid velocity  $V$  and the minor grid velocity  $v$  is denoted by  $\kappa \geq 1$ . Numbers of intrazonal blocks in each direction are denoted by  $N = S/s$  and  $M = D/d$ .

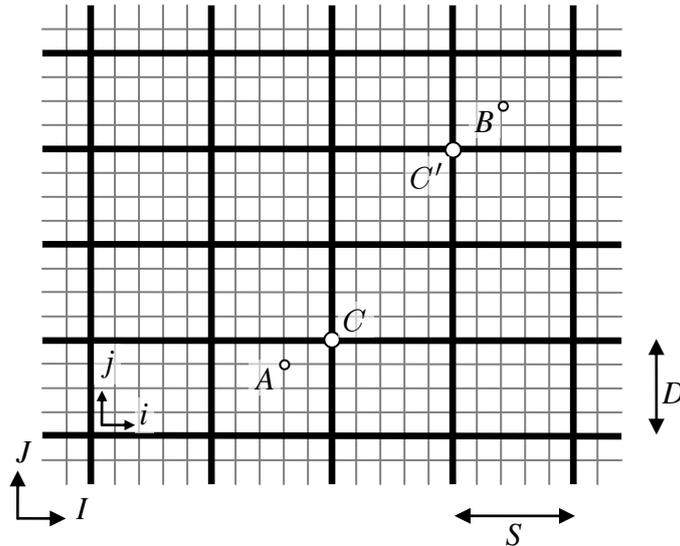


Figure 5.7. The idealized representation of the urban transportation network.

#### 4.3.1.1. Intrazonal Coordinate System

The coordination system for a point  $A$  is based on two pairs of coordinates,  $A I, J i, j$ , where major coordinates  $I, J$  locate the primary crossroad situated at the southwest of the zone in which the point  $A$  is situated, and minor coordinates  $i, j$  locate the position of the point  $A$  inside the zone. We represent by  $\bar{i} = N - i$  and  $\bar{j} = M - j$ , two intrazonal complementary coordinates. It is supposed that the departure and arrival points are distributed uniformly over minor grid crossings.

#### 4.3.1.2. Measuring Distance

The metric of the idealized city form resulted from the superposition of two rectilinear taxicab geometric spaces is defined based on the Manhattan distance is also a  $L_1$  metric. Given a departure point  $A I, J i, j$  and an arrival point  $B I', J' i', j'$  the distance  $\Delta A, B$  between two points  $A$  and  $B$  is defined as follows:

$$\Delta A, B = \left| I' - I S + i' - i s \right| + \left| J' - J D + j' - j d \right| \quad (5.21)$$

Accordingly, the travel time over a minor itinerary is given by:

$$t_m = \frac{\Delta A, B}{v} \quad (5.22)$$

The travel time over a major itinerary is given by:

$$t_M = \frac{\Delta A, C}{v} + \frac{\Delta C, C'}{V} + \frac{\Delta C', B}{v} \quad (5.23)$$

The individual will tend to choose between two available alternatives, one depending entirely on local networks and the other taking advantage of the interzonal network, the itinerary which offers the least travel time.

#### 4.3.1.3. Interzonal Routes: Minor versus Major

There are two alternative routes for traveling from  $A$  to  $B$ . The first involves only the minor grid by traveling only on intrazonal streets and through contiguous zones; such an itinerary is called a minor itinerary. The minor itinerary that provides the shortest minor travel time between  $A$  and  $B$  is denoted by  $r A, B = A, B$ .

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The other alternative tries to take advantage of the higher velocity of the major grid by traveling the two intrazonal distances at origin and destination in order to access to/egress from the major interzonal network and to travel the interzonal distance on the major grid; such an itinerary is called a major itinerary. The major itinerary that provides the shortest major travel time between  $A$  and  $B$  is denoted by,  $R_{A,B} = A, C, C', B$ , where  $C$  and  $C'$  represent the access crossroad situated on the major mesh approached from the departure point  $A$ , and the egress crossroad from which the traveler approaches the arrival point  $B$ , respectively, and  $C, C'$  represents the part traveled on the major grid.

It is the important property of taxicab geometry that there is more than one shortest path between two given points (In fact there are exactly  $\binom{m+n}{n}$  different routes between two points situated  $n$  rows and  $m$  columns apart from each other). Consequently, although the notation  $A, B$  does not uniquely identify a particular itinerary on the minor grid, it is adequate for our purpose in that it uniquely designates the shortest travel time on all shortest paths. In the same way, the notation  $A, C, C', B$  adequately identifies the shortest major travel time regardless of precise route. Technically it is more correct to say “one” shortest minor or major itinerary instead of “the” shortest minor or major itinerary.

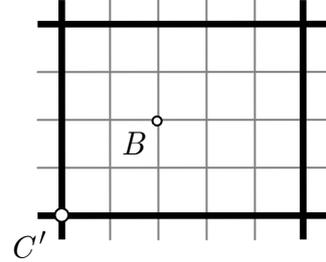
### 4.3.2. Optimal Intrazonal Approach Scheme

For each zone, four crossroads situated are available at four corners. Although only one minor travel time  $t_m$  can be attributed to a given disaggregate trip  $A \rightarrow B$ , one can calculate  $4 \times 4 = 16$  different major travel times depending on which combination  $C, C'$  – with  $C$  representing the chosen exit crossroad at origin zone and  $C'$  representing the chosen entry crossroad at destination zone – is chosen; among the 16 alternative major travel times  $t_M$  represents the least one. We aim to study algorithmically the choice of optimal  $C, C'$  combination in order to uniquely identify the optimal major itinerary  $R_{A,B}$ . Without loss of generality, we consider the case where the destination zone is located northeast of the origin zone as illustrated in the Figure 5.7 (the southeast, southwest and northeast cases are obtained by rotating clockwise the northeast case  $90^\circ$ ,  $180^\circ$  and  $270^\circ$ ).

Let us consider a traveler situated at destination crossroad  $C' (I', J' = 0, 0)$  willing to arrive at the final arrival point  $B (I', J' = i', j')$  inside the destination zone. There are four different approaching possibilities corresponding to the

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four corner crossroads. The traveler can approach directly from the crossroad  $C'$  or move over adjacent major axes and approach from one of the three other crossroads. In fact, although approaching directly from  $C'$  requires the least travel distance, if the major grid speed,  $V$ , is high enough and the arrival point  $B$  is closer to another corner, it is probable that traveling the one or both sides of the zone on the major grid and approaching from a farther corner crossroad results in a shorter total travel time. Four different travel times are calculated corresponding to four crossroads. For instance, approaching directly from the coordinates



$I', J'$  is preferred to approaching from the coordinates  $I' + 1, J'$  if,

$$\begin{aligned} \frac{i's}{v} + \frac{j'd}{v} < \left( \frac{S}{\kappa v} + \frac{S - i's}{v} \right) + \frac{j'd}{v} &\Rightarrow \frac{i's}{v} < \frac{S - i's}{v} + \frac{S}{\kappa v} \\ &\Rightarrow i' < \frac{1}{2} \left( 1 + \frac{1}{\kappa} \right) \frac{S}{s} \end{aligned} \tag{5.24}$$

$$\begin{aligned} \frac{i's}{v} + \frac{j'd}{v} < \frac{i's}{v} + \left( \frac{D}{\kappa v} + \frac{D - j'd}{v} \right) &\Rightarrow \frac{j'd}{v} < \frac{D - j'd}{v} + \frac{D}{\kappa v} \\ &\Rightarrow j' < \frac{1}{2} \left( 1 + \frac{1}{\kappa} \right) \frac{D}{d} \end{aligned} \tag{5.25}$$

Solving for all combinations, a set of conditions are obtained which determine the optimal approaching coordinates depending on the intrazonal position of the final arrival point (Table 5.1). The optimal intrazonal approach scheme, which divides the zone into four tributary areas, is obtained by satisfying all conditions as follows:

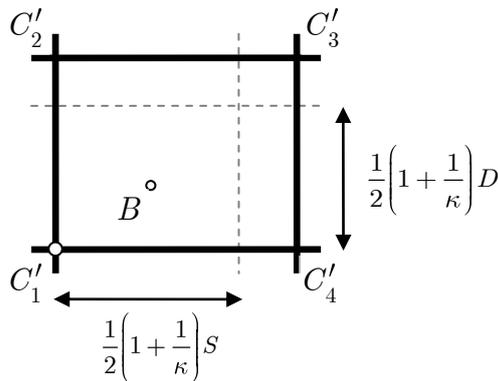


Figure 5.8. Partitioning according to the Optimal Intrazonal Approach Scheme.

The main partition, directly approachable from  $C'$ , is called a “first type” partition. The two partitions approachable from crossroads one side apart

from  $C'$  are called “second type” partitions, and finally the fourth and smallest partition approachable from the crossroad opposite to  $C'$  is called a “third type” partition.

Table 5.1. Approach times for a traveler situated at the base corner.

Anchor number	Anchor coordinates		Anchor approach time	Anchor tributary area
$C'_1$	$I'$	$J'$	$\frac{i's}{v} + \frac{j'd}{v}$	$\frac{1}{4} \left( 1 + \frac{1}{\kappa} \right)^2$
$C'_2$	$I'$	$J' + 1$	$\frac{D}{\alpha v} + \left( \frac{i's}{v} + \frac{\bar{j}'d}{v} \right)$	$\frac{1}{4} \left( 1 + \frac{1}{\kappa} \right) \left( 1 - \frac{1}{\kappa} \right)$
$C'_3$	$I' + 1$	$J' + 1$	$\left( \frac{S}{\alpha v} + \frac{D}{\alpha v} \right) + \left( \frac{\bar{i}'s}{v} + \frac{\bar{j}'d}{v} \right)$	$\frac{1}{4} \left( 1 - \frac{1}{\kappa} \right)^2$
$C'_4$	$I' + 1$	$J'$	$\frac{S}{\alpha v} + \left( \frac{\bar{i}'s}{v} + \frac{j'd}{v} \right)$	$\frac{1}{4} \left( 1 - \frac{1}{\kappa} \right) \left( 1 + \frac{1}{\kappa} \right)$

Assuming that the travel demand is uniformly distributed over the intrazonal space, anchor tributary area portions in the Table 5.1 give also “exact” disaggregate anchor choice probabilities. Figure 5.9 illustrates choice probabilities as functions of speed ratio,  $\kappa$ .

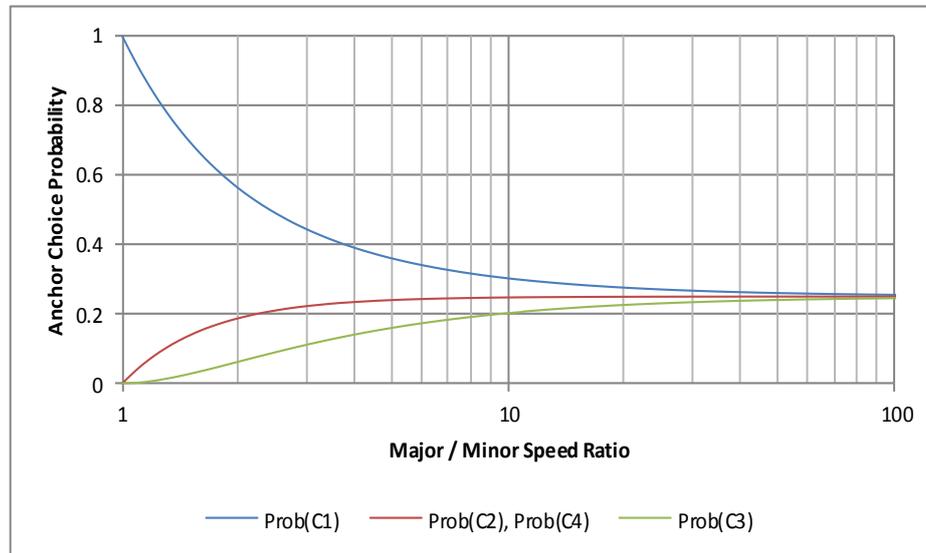


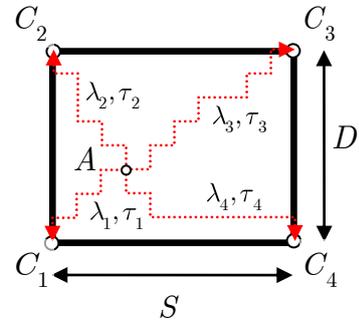
Figure 5.9. Exact anchor-choice probabilities.

### 4.3.3. Probabilistic Modeling of the Terminal Travel Distance

In the previous section the idealistic zone has been studied from a disaggregate point of view with an explicit representation of the intrazonal space. In this section, the aim is to replace the explicit disaggregate representation of intrazonal space with a stochastic representation by regarding the terminal travel distance as a random variable.

#### 4.3.3.1. Terminal Travel Distance as a Random Variable

The aggregation operator filters variability and preserves the mean and in doing so, it causes a huge loss of information. The mean terminal travel time does not provide any information on the intrazonal spatial structure of the travel demand. On the contrary, using disaggregate data, the spatial distribution of the intrazonal travel demand is used to measure the variability of the travel time and the uncertainty of individuals in their choice of itinerary. However, it is possible to preserve some measures of variability in aggregate spatial representations by means of higher order statistical inferences. We maintain the hypotheses of Manhattan distance and uniform distribution of travel demand over the zone. Therefore:



$$\tilde{\lambda}_1 = \tilde{X} + \tilde{Y} \quad ; \quad \tilde{X} \sim U(0, S) \quad , \quad \tilde{Y} \sim U(0, D) \quad (5.26)$$

As a result the probability density function of the terminal travel distance in a rectangular space of dimensions  $S$  and  $D$  is given by (the detail procedure for obtaining is omitted for the sake of readability):

$$f(\lambda) = \frac{1}{2SD} \left( |\lambda| - |\lambda - D| - |\lambda - S| + |\lambda - S - D| \right) \quad (5.27)$$

It has a trapezoidal form which for the particular case of a square zone becomes triangular (without any loss of generality we assume  $S > D$ ).

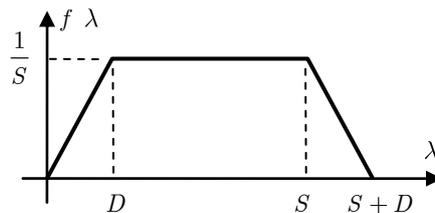


Figure 5.10. Distribution of intrazonal travel distance on idealized network.

The mean and the variance of the terminal travel distance according to the above probability density function are given by:

$$E[\lambda_1] = \int_0^{S+D} \lambda f \lambda \, d\lambda = \frac{S+D}{2} \quad (5.28)$$

$$\text{var}[\lambda_1] = \int_0^{S+D} \left[ \lambda - \frac{1}{2} (S+D) \right]^2 f \lambda \, d\lambda = \frac{S^2 + D^2}{12} \quad (5.29)$$

Similarly, the covariance structure of the intrazonal travel distance can be obtained (See, Appendix C):

$$\begin{aligned} \text{cov}[\lambda_1, \lambda_2] &= \int_0^S \int_0^D \left( X + Y - \frac{S+D}{2} \right) \left( X + D - Y - \frac{S+D}{2} \right) \frac{dY}{D} \frac{dX}{S} \\ &= \frac{S^2 - D^2}{12} \end{aligned} \quad (5.30)$$

$$\begin{aligned} \text{cov}[\lambda_1, \lambda_3] &= \int_0^S \int_0^D \left( X + Y - \frac{S+D}{2} \right) \left( S - X + D - Y - \frac{S+D}{2} \right) \frac{dY}{D} \frac{dX}{S} \\ &= -\frac{S^2 + D^2}{12} \end{aligned} \quad (5.31)$$

In the general case, a convenient discrete choice model should be specified. The arbitrarily heteroscedastic covariance structure of choice options implies that any Generalized Extreme Value (GEV)-based model specification would be inappropriate. The classic Multinomial Logit (McFadden, 1973) is founded on the very assumption that unobserved costs (here, the intrazonal travel time) of choice alternatives are independent and identically distributed (*i.i.d.*), to which it owes its closed analytical form and estimation simplicity. Although more advanced GEV-based model specifications (e.g., Nested Logit, Cross Nested Logit, and Paired Combinatorial Logit) try to circumvent the intrinsic *i.i.d.* property of the Multinomial Logit, their extent of covariance liberation remains limited as they are still subject to prefixed covariance structures and do not achieve full heteroscedasticity.

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Here the intrazonal travel time random variables are all dependent and differently distributed (*d.d.d.*) per origin-destination zone pair. The alternative model specification, which allows for an arbitrary covariance structure is the Multinomial Probit (Daganzo, 1979) where random intrazonal travel times follow the Multivariate Normal Distribution.

$$\begin{bmatrix} \tilde{\lambda}_1 \\ \tilde{\lambda}_2 \\ \tilde{\lambda}_3 \\ \tilde{\lambda}_4 \end{bmatrix} \sim \text{MVN} \left( \begin{bmatrix} \frac{S+D}{2} \\ \frac{S+D}{2} \\ \frac{S+D}{2} \\ \frac{S+D}{2} \end{bmatrix}, \begin{bmatrix} \frac{S^2+D^2}{12} & \frac{S^2-D^2}{12} & -\frac{S^2+D^2}{12} & \frac{S^2-D^2}{12} \\ & \frac{S^2+D^2}{12} & \frac{S^2-D^2}{12} & -\frac{S^2+D^2}{12} \\ & & \frac{S^2+D^2}{12} & \frac{S^2-D^2}{12} \\ \text{Sym.} & & & \frac{S^2+D^2}{12} \end{bmatrix} \right) \quad (5.32)$$

The exact evaluation of the MNP model involves the numerical evaluation of multidimensional improper integrals, which is not computationally convenient. Given the practical issues and for the sake of computational simplicity we suggest using an approximate approach to evaluate the extreme value distribution of a set of random variables. We suggest using Clark's algorithm (Clark, 1961, Nadarajah and Kotz, 2008) to solve the model and evaluate choice probabilities in a Multinomial Probit model.

#### 4.3.3.2. Clark's algorithm for Multinomial Probit model

Let us consider  $N$  Normal random variables  $X_1, \dots, X_n, \dots, X_N$  representing disutilities of  $N$  choice alternatives. Without any loss of generality, we consider the probability of choice of the  $N$ th alternative. It can be stated as follows:

$$p_N = \Pr X_N < \min[X_1, X_2, \dots, X_{N-1}] \quad (5.33)$$

Clark's approximation method starts by reformulating the problem as follows:

$$p_N = \Pr X_N < \min[\min X_1, X_2, \dots, X_{N-1}] \quad (5.34)$$

By substituting  $X_m = \min X_1, X_2$ , we have:

$$p_N = \Pr X_N < \min X_m, X_3, \dots, X_{N-1} \quad (5.35)$$

In general,  $X_m$  itself is not a Normal variable, but Clark suggests that it can be approximated as a Normal random variable. Therefore, the same procedure can be progressively applied and repeated all over again, until the problem is reduced to a binary probit model.

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The problem of imposing bounds on the moments of the extrema of two Normal variables has been studied by many authors for different cases including independent and identically distributed, dependent and identically distributed, or dependent and differently distributed variables (for a review see, Ross, 2003). Let us consider  $X_1$  and  $X_2$  two dependent and differently distributed Normal random variables with:

$$\begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \sim \text{MVN} \left( \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}, \begin{bmatrix} \sigma_1^2 & \nu_{12} \\ \nu_{12} & \sigma_2^2 \end{bmatrix} \right) \quad (5.36)$$

We define  $X_m$  the minimum of the two *d.d.d.* Normal variables  $X_1$  and  $X_2$ :

$$X_m = \min X_1, X_2 \quad (5.37)$$

Clark (1961) gives exact formulas for the first four moments of the extremum (maximum or minimum) of the two *d.d.d.* Normal random variables (Nadarajah and Kotz, 2008). We summarize here the formulas for the expected value and the variance-covariance of the minimum of two *d.d.d.* Normal variables:

$$\mu_m = E \left[ \min X_1, X_2 \right] = \mu_1 \Phi -\alpha + \mu_2 \Phi \alpha - \sigma \phi \alpha \quad (5.38)$$

$$\begin{aligned} \sigma_m^2 &= \text{var} \left[ \min X_1, X_2 \right] \\ &= \mu_1^2 + \sigma_1^2 \Phi -\alpha + \mu_2^2 + \sigma_2^2 \Phi \alpha - \mu_1 + \mu_2 \sigma \phi \alpha - \mu_m^2 \end{aligned} \quad (5.39)$$

where,

$$\sigma = \sqrt{\sigma_1^2 + \sigma_2^2 - 2\nu_{12}} \quad , \quad \alpha = \mu_1 - \mu_2 / \sigma \quad (5.40)$$

and  $\phi$  is the standard Normal density function and  $\Phi$  is the corresponding cumulative distribution function,

$$\phi x = \frac{1}{\sqrt{2\pi}} \exp -x^2/2 \quad , \quad \Phi x = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} \exp -u^2/2 du \quad (5.41)$$

The covariance between the minimum variable  $X_m$  and any other Normal variable  $X_n$  is given by :

$$\text{cov} \left[ X_m, X_n \right] = \Phi -\alpha \text{cov} X_1, X_n + \Phi \alpha \text{cov} X_2, X_n \quad (5.42)$$


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Once the problem for two random variables is solved, it is possible to provide a recursive approximation of the moments of the minimum of more than two variables. An implementation of the Gaussian approximation method is provided in Table 5.2. We suppose  $N$  Normal random variables  $X_1 \dots X_N$ , where  $[\mu_i]_N$  is the mean vector, and  $[\nu_{ij}]_{N \times N}$  is the covariance matrix.

**Table 5.2. Evaluating Multinomial Probit choice probability by Gaussian approximation.**

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1. exclude the disutility variable of the chosen alternative as  $X_N$ ;
  2. sort the rest of random variables in ascending order of mean and permute mean vector and covariance matrix accordingly;
  3. initialize  $\mu_m = \mu_1$  and  $s_{1\dots N}^m = \nu_{1,1\dots N}$ ;
  4. for  $1 < i < N$ :
    - a. assign  $\sigma = \sqrt{s_1^m + \nu_{ii} - 2s_i^m}$  and  $\alpha = \mu_m - \mu_i / \sigma$ ;
    - b. assign  $\mu_* = \mu_m \Phi(-\alpha) + \mu_i \Phi(\alpha) - \sigma \phi(\alpha)$ ;
    - c. assign  $s_* = \mu_m^2 + s_1^m \Phi(-\alpha) + \mu_i^2 + \nu_{ii}^2 \Phi(\alpha) - \mu_m + \mu_i \sigma \phi(\alpha) - \mu_*^2$ ;
    - d. assign  $\mu_m = \mu_*$  and  $s_1^m = s_*$ ;
    - e. for  $i < j \leq N$ :
      - i.  $s_j^m = s_j^m \times \Phi(-\alpha) + \nu_{ij} \times \Phi(\alpha)$ ;
    - f. iterate over Step 4.e.
  5. iterate over Step 4.
  6. assign  $\sigma = \sqrt{s_1^m + \nu_{NN} - 2s_N^m}$ ;
  7. return  $p_N = \Phi[\mu_m - \mu_N] / \sigma$ .
- 

Once choice probabilities for all alternatives are estimated, it is often the case that they do not sum up to 1. This is due to the approximate nature of the algorithm. Therefore, choice probabilities have to be normalized by  $1/\sum_i p_i$  at the end.

The performance of the Clark-approximated probit solution can be assessed in comparison with the exact disaggregate solution of the anchor choice model for the idealized network. Figure 5.11 compares the exact choice probability of a first-type anchor point, with probability evaluated by a probit model solved

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according to Clark's method, and a solution by Monte-Carlo simulation. Figure 5.12 compares probit results with the exact probabilities for all of the four anchor points. It is clear that Clark's method performs very satisfactorily and except for speed ratios close to 1, approximate and exact results match almost perfectly.

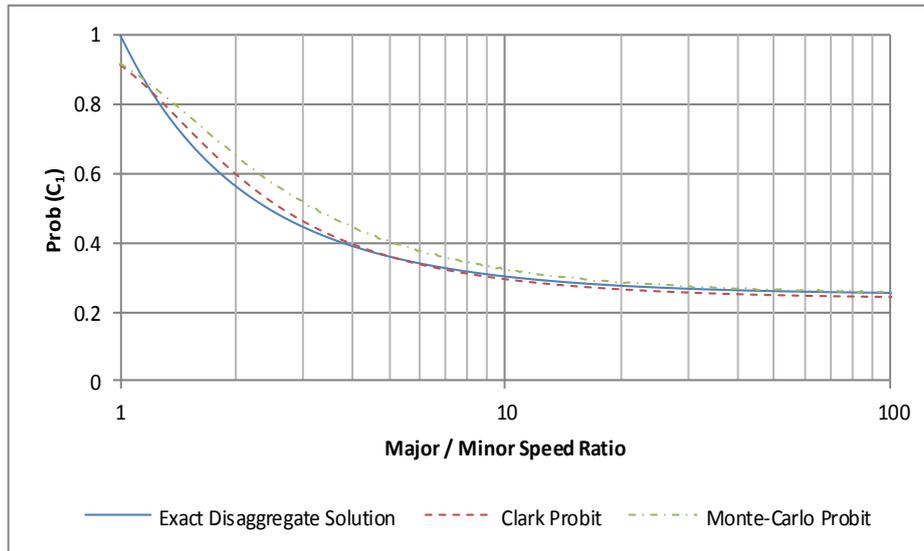


Figure 5.11. Performance assessment of the Clark-approximated probit anchor choice model.

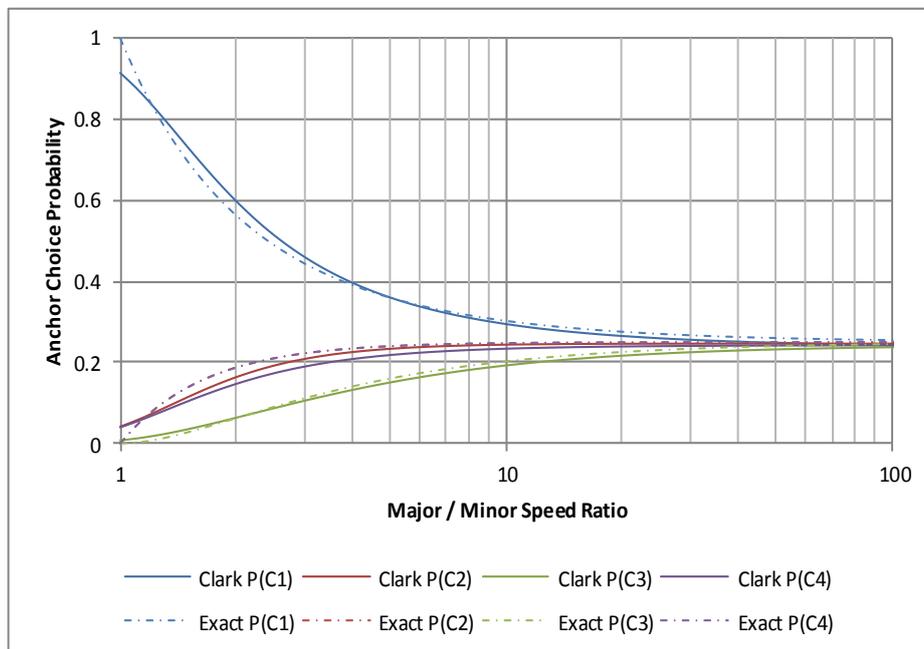


Figure 5.12. Clark's probit anchor choice model solution for the idealized network.

Specifying terminal travel time variables as Normal random variables is indeed an approximation. Normal distribution allows negative or infinitely large travel times, which are not physically admissible. It also does not take into account the zone shape and the intrazonal distribution residential or business localizations. Nevertheless, such specification is justifiable for three reasons. First, the contribution of the Normal distribution tails can be effectively controlled by an appropriate estimation of travel time mean and variance. Second, as random variables are combined in linear combinations the resultant distribution gets closer to Normal (according to the weak central limit theorem). Finally, the assumption of multivariate Normal distribution is analytically more convenient than dealing with arbitrary distributions, which can be done only by simulation-based methods.

The use of Clark's algorithm to the Multinomial Probit model has been found very successful by a number of authors (Daganzo et al., 1977, Albright et al., 1977, Sheffi and Trexler, 1980, Maher and Hughes, 1997). Others on the other hand have found that the algorithm can be inaccurate in some situations. Horowitz et al. (1982) studied of a wide range of numerical experiments and concluded that the Clark-approximated MNP in comparison with an "exact" MNP estimation method performs quite satisfactorily in many cases but in others, the error is relatively considerable. Despite this observation, they conclude that in contexts where choice options are not intrinsically independent and identically distributed – which is exactly the case here – the error resulting from a Clark-approximated MNP would be less than the error caused by the use of a MNL model specification. According to Ortúzar and Willumsen (2001), "the approximation is not satisfactory when the variables have similar means and very different variances". Patriksson (1994) also points out that the performance of Clark's approximation declines when the number of alternatives is large. Nadarajah and Kotz (2008) illustrate the exact distribution and the Gaussian approximation of the maximum of two Normal random variables. They demonstrate that the performance of the Gaussian approximation gets poorer as the difference between two variances gets larger.

Fortunately, our application is within limits of admissibility of the Gaussian approximation as it deals almost always with variances that are not very different and does not involve very large choice sets. Other point is that in the traffic assignment context, uncertainties due to different sources are likely to be dissipated due to the equilibrium and the application of many constraints. For instance, Zhao and Kockelman (2002) in their study of uncertainty propagation through the classic four-step model structure have shown that the error propagation actually decreases in the assignment step. This undoubtedly

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endorses the attractiveness of probit-based methods for route choice modeling (see, Rosa, 2003; Sheffi, 1985).

See Connors et al. (2011) for a review of alternative analytic approximation approaches, and Genz and Bretz (2009) for numerical implementations.

## 5. Stochastic Traffic Assignment Model

### 5.1. Route Choice with Stochastic Terminal Time

Let us  $Z_o \in \mathbf{Z}$  represent an origin zone and  $Z_d \in \mathbf{Z}$  represent a destination zone from the zoning system  $\mathbf{Z}$ , with  $C_o$  the set of anchor points at origin, and  $C'_d$  the set of anchor points at destination. Then  $c_i \in C_o$  represents an anchor point at origin, and  $c'_j \in C'_d$  represents an anchor point at destination. Also  $\mathbf{R}_{od}$  is the set of anchor-to-anchor routes between  $Z_o$  and  $Z_d$ , and  $R_{ij} \in \mathbf{R}_{od}$  represents the shortest anchor-to-anchor route corresponding to the anchor pair  $c_i, c'_j \in C_o \times C'_d$ .

The total travel time for the traveler who takes the interzonal route  $R_{ij} = \rho_i, r_{ij}, \rho'_j$  is composed of three route sections:  $\rho_i$  is the route from the precise intrazonal departure location to the anchor point  $c_i \in C_o$ ;  $r_{ij}$  is the interzonal route between the pair of origin-destination anchor points  $c_i, c'_j \in C_o \times C'_d$ ; and  $\rho'_j$  is the route from the anchor point  $c'_j \in C'_d$  to the precise intrazonal arrival location. Given the stochastic representation of intrazonal locations, characteristics of the two intrazonal sections are random variables whilst those of the interzonal section can be known deterministically. Accordingly,  $[\tilde{\tau}_i]$  is the vector of random intrazonal travel times at origin, where  $\tilde{\tau}_i$  is the least travel time from the intrazonal space to  $c_i \in C_o$  anchor point;  $[\theta_{ij}]_{od}$  is the matrix of deterministic interzonal anchor-to-anchor least travel time, where  $\theta_{ij}$  is the shortest travel time between an anchor pair  $c_i, c'_j \in C_o \times C'_d$  estimated by applying the shortest path algorithm over the highway network; and  $[\tilde{\tau}'_j]$  is the vector of random intrazonal travel times at destination, where  $\tilde{\tau}'_j$  is the least travel time from the intrazonal space to  $c'_j \in C'_d$  anchor point. The total travel time over the route  $R_{ij} \in \mathbf{R}_{od}$  is thus a random variable given by:

$$\tilde{t}_{ij} = \tilde{\tau}_i + \theta_{ij} + \tilde{\tau}'_j \quad (5.43)$$

where  $\tilde{t}_{ij}$  is the total travel time, corresponding to the shortest path from the intrazonal departure point at origin to the intrazonal arrival point at destination passing by  $c_i, c'_j$  pair of anchor points.

At the interior of a zone, depending on the respective location of anchor points, distances from different anchor points may be positively or negatively correlated, i.e. being further from one anchor point implies being closer to other anchor points on the same side and further from other anchor points on the opposite side. Thus, intrazonal travel characteristics have heteroscedastic covariance structures. The two random intrazonal travel time vectors are Normal random variables and are specified as follows:

$$\forall c_i \in C_o : [\tilde{\tau}_i] \sim \text{MVN} \left[ \bar{\tau}_i, [\nu_{ik}] \right] \quad (5.44)$$

$$\forall c'_j \in C'_d : [\tilde{\tau}'_j] \sim \text{MVN} \left[ \bar{\tau}'_j, [\nu'_{jl}] \right] \quad (5.45)$$

where  $[\bar{\tau}_i]$  and  $[\bar{\tau}'_j]$  represent intrazonal mean travel time vectors, and also  $[\nu_{ik}]$  and  $[\nu'_{jl}]$  are intrazonal covariance matrices. Being the sum of two Gaussian random variables,  $\tilde{t}_{ij}$  is itself a Gaussian random variable:

$$\forall c_i, c'_j \in C_o \times C'_d : [\tilde{t}_{ij}] \sim \text{MVN} \left[ \bar{t}_{ij}, [\Sigma_{ij,kl}] \right] \quad (5.46)$$

According to Equation 5.43 the mean total travel time  $\bar{t}_{ij}$  is given as:

$$\bar{t}_{ij} = \text{E}[\tilde{t}_{ij}] = \text{E}[\tilde{\tau}_i] + \text{E}[\theta_{ij}] + \text{E}[\tilde{\tau}'_j] = \bar{\tau}_i + \theta_{ij} + \bar{\tau}'_j \quad (5.47)$$

Also entries of the covariance matrix  $[\Sigma_{ij,kl}]$  are given as:

$$\Sigma_{ij,kl} = \text{cov}[\tilde{t}_{ij}, \tilde{t}_{kl}] = \text{cov} \left[ \tilde{\tau}_i + \theta_{ij} + \tilde{\tau}'_j, \tilde{\tau}_k + \theta_{kl} + \tilde{\tau}'_l \right] \quad (5.48)$$

Since  $\theta_{ij}$  and  $\theta_{kl}$  are deterministic, Equation 5.48 is expanded to:

$$\Sigma_{ij,kl} = \text{cov}[\tilde{\tau}_i, \tilde{\tau}_k] + \text{cov}[\tilde{\tau}_i, \tilde{\tau}'_l] + \text{cov}[\tilde{\tau}'_j, \tilde{\tau}_k] + \text{cov}[\tilde{\tau}'_j, \tilde{\tau}'_l] \quad (5.49)$$

We make the hypothesis that the departure localization at origin and the arrival localization at destination are irrelevant, i.e. trips may depart from any location at origin towards any location at destination with equal odds:

$$\forall c_i, c'_j \in C_o \times C'_d : \text{cov } \tilde{\tau}_i, \tilde{\tau}'_j = 0 \quad (5.50)$$

Therefore:

$$\Sigma_{ij,kl} = \text{cov}[\tilde{\tau}_i, \tilde{\tau}_k] + \cancel{\text{cov}[\tilde{\tau}_i, \tilde{\tau}'_l]} + \cancel{\text{cov}[\tilde{\tau}'_j, \tilde{\tau}_k]} + \text{cov}[\tilde{\tau}'_j, \tilde{\tau}'_l] = \nu_{ik} + \nu'_{jl} \quad (5.51)$$

The uncorrelatedness condition of Equation 5.50 between origin and destination intrazonal travel times is not obvious. For instance, existence of a high capacity highway can induce an absorbing effect on the traffic and introduce correlation between origin and destination intrazonal travel times.

Now that the travel time vector  $[\tilde{t}_{ij}]$  is known, the probability of choosing the route  $R_{ij}$  in  $\mathbf{R}_{od}$  is given by:

$$\begin{aligned} p_{ij}^{od} &= \Pr \left( \tilde{t}_{ij} < \tilde{t}_{kl} \mid \forall c_k \in C_o, \forall c'_l \in C'_d, k \neq i \vee j \neq l \right) \\ &= \Pr \left( \tilde{t}_{ij} < \min_{k \neq i \vee j \neq l} \tilde{t}_{kl} \right) \end{aligned} \quad (5.52)$$

This corresponds to the choice probability of a pair of anchor points  $c_i, c'_j$  which uniquely identify the route  $R_{ij}$ . Equation 5.52 describes a Multinomial Probit discrete choice model. We use Clark's method for solving the model and evaluating choice probabilities. Let us define  $\tilde{t}_m$  as follows:

$$\tilde{t}_m = \min_{k \neq i \vee j \neq l} \tilde{t}_{kl} \quad (5.53)$$

According to Clark's Gaussian approximation,  $\tilde{t}_m$  is an approximately Normal variable:

$$\tilde{t}_m \approx N \left( \bar{t}_m, \sigma_m^2 \right) \quad (5.54)$$

By centralizing the probability density function, we have:

$$\tilde{t}_m = \bar{t}_m + \hat{t}_m \quad ; \quad \hat{t}_m \approx N \left( 0, \sigma_m^2 \right) \quad (5.55)$$

By substituting in Equation 5.52 we obtain:

$$p_{ij}^{od} = \Pr \left( \tilde{t}_{ij} < \tilde{t}_m \right) = \Pr \left( \hat{t}_{ij} - \hat{t}_m < \bar{t}_m - \bar{t}_{ij} \right) \quad (5.56)$$

thus the Multinomial Probit is reduced to a Binary Probit model which can be easily solved.

$$p_{ij}^{od} = \int_{-\infty}^{\frac{\bar{t}_m - \bar{t}_{ij}}{\sigma}} \phi(u) du = \Phi\left(\frac{\bar{t}_m - \bar{t}_{ij}}{\sigma}\right) \quad ; \quad \sigma = \sqrt{\sigma_{ij}^2 + \sigma_m^2 - 2\nu_{ij,m}} \quad (5.57)$$

where  $\phi$  . and  $\Phi$  . represent standard Normal probability density function and its cumulative distribution function (see, Equation 5.41), and  $\nu_{ij,m}$  is the covariance of  $\tilde{t}_{ij}$  and  $\tilde{t}_m$ , estimated by Clark's algorithm.

## 5.2. Traffic Assignment Procedure

Let us  $[q_{od}]$  represent the origin-destination matrix of centroid-to-centroid traffic flows, and  $q_{od}$  the traffic flow from origin zone  $Z_o$  to destination zone  $Z_d$ . Since all traffic is assigned to the network through anchor points, it is relevant to define  $[x_{ij}]$  as the matrix of anchor-to-anchor traffic flows, and  $x_{ij}$  as traffic flow between an anchor pair  $c_i, c'_j \in C \times C$ . The procedure to assemble the anchor-to-anchor flow matrix  $[x_{ij}]$ , from the centroid-to-centroid flow matrix  $[q_{od}]$  follows:

**Table 5.3. Procedure for the assembly of the anchor-to-anchor traffic flow matrix.**

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1. initialize  $[x_{ij}]$  to zero;
  2. per origin-destination pair  $Z_o, Z_d \in \mathbf{Z} \times \mathbf{Z}$ ;
    - a. evaluate  $\bar{t}_{ij}^{od}$  and  $\Sigma_{ij,kl}^{od}$  where  $\alpha$  and  $\beta$  count  $i, j$  anchor pairs;
    - b. evaluate  $p_{ij}^{od}$  using Clark's algorithm (cf. Table 5.2);
    - c.  $x_{ij} = x_{ij} + p_{ij}^{od} q_{od}$ ;
  3. iterate over Step 2.
- 

In Table 5.3,  $p_{ij}^{od}$  represents the choice probability of the  $c_i, c'_j \in C_o \times C'_d$  anchor pair in  $C_o \times C'_d$  and is estimated by Clark's algorithm.

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### 5.3. Resultant Interzonal Impedence

The minimum interzonal travel time the traffic flow from origin zone  $Z_o$  to destination zone  $Z_d$  is a random variable given by:

$$\forall c_i, c'_j \in C_o \times C'_d : \tilde{t}_m^{od} = \min \tilde{t}_{ij}^{od} \quad (5.58)$$

It represents perceived travel time between the two zones with disaggregate intrazonal representation. Given the specification of the Equation 5.46, its mean and variance can be evaluated using Clark's method. Its mean can be considered as a measure of the average interzonal travel time and in this respect it is the disaggregate equivalent of the centroid-to-centroid interzonal travel time. Its variance is a measure of the variability of interzonal travel time due to the scatteredness of trip-ends over intrazonal space at origin and destination.

# Chapter 6: Stochastic Model of Traffic Assignment with Trip-end Disaggregation: Implementation with Application to Ile-de-France

## 1. Introduction

The theoretical framework for the stochastic trip-end disaggregation traffic assignment model (or simply the disaggregate assignment model) has been provided in the previous chapter.

In this chapter, the aim is to implement the stochastic assignment model and to study its performance in comparison with a classical assignment. Our study context is the Greater Paris Region. We use the standard zoning system of Ile-de-France and assign the peak-hour origin-destination matrix to the highway network.

We will analyze results from the two assignment models statistically. Three categories of indicators will be defined and presented based on the Ile-de-France macro zoning system,

## 2. Model Implementation

The stochastic traffic assignment model with trip-end disaggregation consists of two conceptual assignment stages (Leurent et al., 2011). At the first stage anchor-to-anchor shortest paths are identified on the traffic network providing deterministic anchor-to-anchor travel costs (or times). At the second stage, per origin-destination zone pair, the choice probability of each origin-destination anchor pair is evaluated and the interzonal traffic flow is distributed among anchor-to-anchor shortest paths.

The first stage requires the implementation of a network shortest path search algorithm similar to the one proposed by Dijkstra (1959), which are widely available in any typical GIS package; here we use Caliper's TransCAD 5.0 and its GISDK scripting language. The second stage requires has been implemented properly in Fortran 90/95. The technique is to transform the matrix of centroid-to-centroid traffic flows into a matrix of anchor-to-anchor traffic flows through the application of the stochastic trip-end disaggregation model. The anchor-to-anchor matrix will be assigned to the network using the all-or-nothing assignment algorithm.

### 2.1. Demand and Supply Representation

Both demand and supply representations are provided by DRIEA-IF:

On the supply side, we use the traffic network of the Greater Paris Region including about 15000 nodes, 40000 unidirectional links and 1277 zones.

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On the demand side, we use the all motif combined origin-destination matrix of traffic flows at the evening peak-hour.

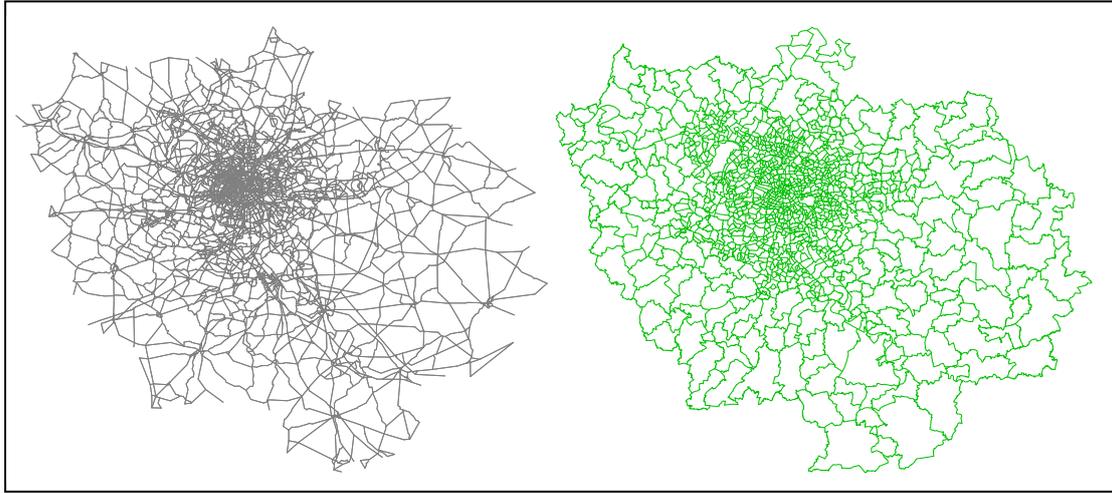


Figure 6.1. Ile-de-France traffic network and zoning system (DRIEA-IF).

## 2.2. Characterization of Terminal Travel Conditions

We derive the terminal travel conditions by combining three detailed databases as follows: (1) the “*BD TOPO*” acquired from IGN, which provides a comprehensive description of roads with metric accuracy; (2) the “*MOS*” acquired from IAU-IdF, which provides the type and the intensity of land use; and (3) the General Population Census by INSEE which provides the number of people and jobs at the urban block level.

Using TransCAD GIS, four anchor nodes are selected for each zone. The choice of anchor nodes at this level is done using an automated procedure that does not account for all relevant criteria for identifying a node as an anchor. For example, it guaranties that the anchor nodes are segregated over the zone but it does not necessarily check for an important traffic flow through the highway to which an anchor node gives access.

As for the aggregate assignment model, dummy connector links are generated from zone centroids to anchor points and their travel time is set equal to the corresponding mean intrazonal travel time.

## 3. Statistical Analysis of Results (Post-processing)

The disaggregate assignment model is used for trip assignment in Ile-de-France. An aggregate trip assignment is also performed as reference. We

define macro-level statistical indicators in order to compare between the two assignments. For comparability, both assignments are in all-or-nothing.

### 3.1. Statistical Analysis Framework

In the assignment stage, origin-destination traffic flows are aggregated at zone level. Origin-destination zone pairs can be viewed as aggregation classes that exhibit intra-class and interclass variability. Because of the fact that in aggregate assignment model, spatial dispersion of trip ends is ignored below the zone level, this method is unable to capture intra-class variability of travel characteristics. The disaggregate assignment model, on the other hand, is capable of measuring both interclass and intra-class variability and by doing so allows evaluating the portion of the variability which is lost due to the application of aggregate assignment models.

For aggregate assignment, we represent by  $t_{cc}^{od}$  the centroid-to-centroid total interzonal travel time. For disaggregate assignment, we represent by  $\tilde{t}_m^{od}$  the random variable of the minimum interzonal travel time over all anchor-to-anchor route alternatives:

$$\tilde{t}_m^{od} = \min_{i,j} \tilde{t}_{ij}^{od} \quad (6.1)$$

Accordingly,  $\bar{t}_m^{od}$  and  $\chi_m^{od}$  represent mean and variance of the minimum interzonal travel time:

$$\bar{t}_m^{od} = \mathbb{E}[\tilde{t}_m^{od}] \quad ; \quad \chi_m^{od} = \text{var}[\tilde{t}_m^{od}] \quad (6.2)$$

Macro-level indicators are defined in three categories:

Mean zone-to-zone travel time, which indicates the mean of origin-destination total travel time, calculated over all non-identical origin-destination zone pairs. For disaggregate assignment it is the average of the expected minimum interzonal travel time,  $\bar{t}_m^{od}$ ; For aggregate assignment it is the average of the centroid-to-centroid travel time,  $t_{cc}^{od}$ . Averages are weighted by origin-destination traffic flows,  $q_{od}$ .

Interclass variance of zone-to-zone travel time, which indicates the variability of origin-destination total travel time from one OD zone pair to another. For disaggregate assignment it is the variance of the expected minimum interzonal travel time,  $\bar{t}_m^{od}$ ; For aggregate assignment it is the variance of the centroid-to-centroid travel time,  $t_{cc}^{od}$ . Variances are weighted by origin-destination traffic flows,  $q_{od}$ .

Mean intra-class variance of zone-to-zone travel time, which indicates the mean variability of origin-destination total travel time for a typical origin-destination pair. For disaggregate assignment, it is the average of the variance of minimum interzonal travel time random variable,  $\chi_m^{od}$ . For aggregate assignment, it is equal to zero, by definition. Averages are weighted by origin-destination traffic flows,  $q_{od}$ .

It is assumed that origin-destination classes are independent, i.e. there is no correlation among travel statistics of different classes. Table 6.1 summarizes the definitions for the three categories of indicators.

**Table 6.1. Definition of the statistical indicators.**

Statistical indicator	Disaggregate assignment model	Aggregate assignment model
Mean of zone-to-zone travel time	$\bar{t}_m = E_{o,d}[\bar{t}_m^{od}] = \frac{\sum_o \sum_{d \neq o} q_{od} \bar{t}_m^{od}}{\sum_o \sum_{d \neq o} q_{od}}$	$\bar{t}_{cc} = E_{o,d}[t_{cc}^{od}] = \frac{\sum_o \sum_{d \neq o} q_{od} t_{cc}^{od}}{\sum_o \sum_{d \neq o} q_{od}}$
Interclass variance of zone-to-zone travel time	$X_m = \text{var}_{o,d}[\bar{t}_m^{od}] = \frac{\sum_o \sum_{d \neq o} q_{od} \bar{t}_m^{od} - \bar{t}_m^2}{\sum_o \sum_{d \neq o} q_{od}}$	$X_{cc} = \text{var}_{o,d}[t_{cc}^{od}] = \frac{\sum_o \sum_{d \neq o} q_{od} t_{cc}^{od} - \bar{t}_{cc}^2}{\sum_o \sum_{d \neq o} q_{od}}$
Mean intra-class variance of zone-to-zone travel time	$\bar{\chi}_m = E_{o,d}[\chi_m^{od}] = \frac{\sum_o \sum_{d \neq o} q_{od} \chi_m^{od}}{\sum_o \sum_{d \neq o} q_{od}}$	$\bar{\chi}_{cc} = E_{o,d}[\chi_{cc}^{od}] = 0$

### 3.2. Analysis of Results: Departmental Macro-zoning

Results from both the aggregate and the stochastic disaggregate assignment model are calculated for all  $1276 \times 1277$  non-identical origin-destination pairs. For presentation, these results are aggregated according to two macro-zoning systems: The macro zoning according to the administrative departments and the IAU-IdF macro zoning system that is based on the level of urban development. As for indicators, only “Mean of zone-to-zone travel time”, and “Mean intra-class variance of zone-to-zone travel time” are reported here.

The Greater Paris Region is divided into eight administrative departments shown in the Figure 6.2. The evening peak hour traffic origin-destination matrix contains a total hourly flow of about 1,138,000 p.c.u. and Table 6.2

shows the traffic flow exchange among the eight administrative departments in percentage.

According to Table 6.2, trips are predominantly made within departments, and the amount of exchange between departments is minimal. The total departmental traffic emissions as well as the total traffic attractions are relatively equal.

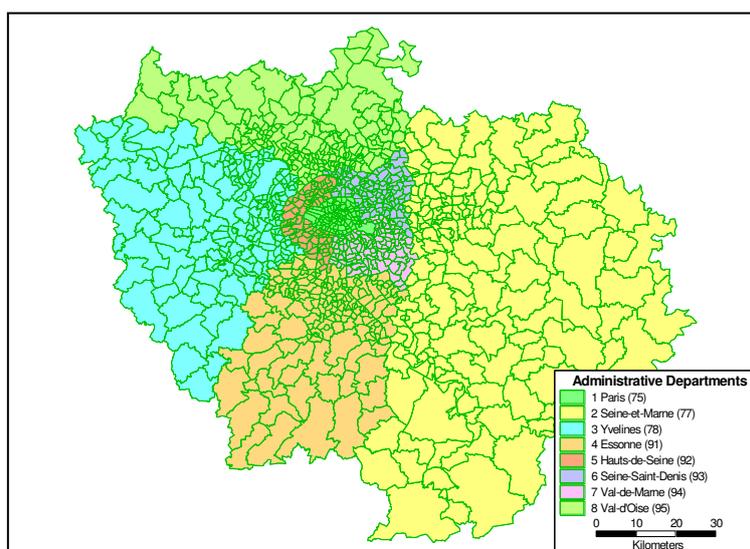


Figure 6.2. Île-de-France administrative departments.

Table 6.2. Distribution of peak-hour inter-departmental traffic flows (percent).

Origin	Destination								Combined
	Paris	Seine-et-Marne	Yvelines	Essonne	Hauts-de-Seine	Seine-Saint-Denis	Val-de-Marne	Val-d'Oise	
Paris	6.35	0.16	0.37	0.31	2.42	1.76	1.79	0.31	13.46
Seine-et-Marne	0.04	9.12	0.00	0.64	0.02	0.93	0.42	0.09	11.26
Yvelines	0.16	0.00	11.64	0.48	1.27	0.04	0.07	1.13	14.80
Essonne	0.09	0.71	0.50	9.28	0.38	0.02	0.37	0.00	11.37
Hauts-de-Seine	1.24	0.04	1.61	0.63	7.66	0.53	0.74	0.77	13.21
Seine-Saint-Denis	0.82	1.15	0.07	0.06	0.51	7.23	1.03	1.10	11.97
Val-de-Marne	0.74	0.73	0.09	0.97	0.70	0.98	6.94	0.05	11.19
Val-d'Oise	0.08	0.11	1.22	0.00	0.27	0.76	0.03	10.25	12.74
<b>Combined</b>	9.51	12.04	15.51	12.36	13.23	12.25	11.39	13.7	100

### 3.2.1. Mean Zone-to-Zone Travel Time

Mean zone-to-zone travel time indicates the mean of origin-destination total travel time, calculated over all non-identical origin-destination zone pairs. For disaggregate assignment it is the average of the expected minimum interzonal travel time,  $\bar{t}_m^{od}$ , and Table 6.3 shows departmental values for the results from the disaggregate assignment.

**Table 6.3. Mean interzonal travel time, disaggregate assignment (min).**

Origin	Destination								Combined
	Paris	Seine-et-Marne	Yvelines	Essonne	Hauts-de-Seine	Seine-Saint-Denis	Val-de-Marne	Val-d'Oise	
Paris	6.01	23.14	19.94	20.11	9.59	10.36	10.6	19.29	9.05
Seine-et-Marne	22.29	12.68	35.36	16.97	26.09	10.63	12.89	21.03	12.89
Yvelines	20.28	36.77	9.41	16.88	13.01	24.52	21.77	13.57	10.51
Essonne	19.48	17.71	17.29	8.63	11.21	24.39	12.13	31.75	9.91
Hauts-de-Seine	9.25	27.50	12.97	13.02	5.61	11.29	10.24	11.99	8.12
Seine-Saint-Denis	9.76	12.60	22.79	25.37	11.11	5.96	10.14	11.17	8.12
Val-de-Marne	9.36	15.54	22.45	13.11	9.95	9.99	5.94	24.42	8.23
Val-d'Oise	19.66	21.47	13.32	34.07	12.22	10.39	23.86	7.93	8.94
<b>Combined</b>	7.58	13.43	10.74	10.33	7.81	7.87	7.94	9.29	9.46

As expected, intra-departmental travel times are significantly smaller compared to inter-departmental travel times. Intra-Paris trips take in average 6.01 min. This is significantly shorter than the average time of travel from Paris to inner departments: Hauts-de-Seine, Seine-Saint-Denis, and Val-de-Marne, which takes about 10 min. This in turn is also significantly less than the time of travel from Paris to outer departments: Seine-et-Marne, Yvelines, Essonne, and Val-d'Oise that takes around 20 min in average.

For aggregate assignment it is the average of the centroid-to-centroid travel time,  $t_{cc}^{od}$ , and Table 6.4 shows departmental values for the results from the aggregate assignment. As theoretically expected, disaggregate mean values are slightly smaller than aggregate mean values  $\bar{t}_m^{od} < t_{cc}^{od}$ .

**Table 6.4. Mean interzonal travel time, aggregate assignment (min).**

Origin	Destination								Combined
	Paris	Seine-et-Marne	Yvelines	Essonne	Hauts-de-Seine	Seine-Saint-Denis	Val-de-Marne	Val-d'Oise	
Paris	6.10	24.88	20.16	20.37	9.72	10.49	10.72	19.50	9.19
Seine-et-Marne	24.18	13.88	37.95	17.69	28.22	11.62	14.16	22.06	14.05
Yvelines	20.48	38.50	9.71	17.40	13.21	24.76	21.95	13.97	10.81
Essonne	19.73	18.35	17.89	9.10	11.47	24.66	12.48	32.05	10.39
Hauts-de-Seine	9.37	29.20	13.20	13.31	5.75	11.43	10.41	12.19	8.29
Seine-Saint-Denis	9.90	13.65	23.05	25.65	11.25	6.12	10.27	11.38	8.36
Val-de-Marne	9.47	16.64	22.67	13.41	10.12	10.13	6.08	24.63	8.45
Val-d'Oise	19.86	22.60	13.74	34.37	12.41	10.61	24.06	8.33	9.32
<b>Combined</b>	7.69	14.58	11.05	10.79	7.97	8.09	8.13	9.66	9.83

By comparing results from Table 6.3 and Table 6.4 we observe that the outer the department is situated, the more deviated are the results of the two indicators. For example, the deviation between  $\bar{t}_m^{od}$  and  $t_{cc}^{od}$  is about 1.5% over intra-Paris trips; it is about 2.5% over intra-departmental trips of the inner departments: Hauts-de-Seine, Seine-Saint-Denis, and Val-de-Marne, but amounts to 3% to 5% in outer departments: Yvelines, Essonne, and Val-d'Oise, and even reaches 9.5% for Seine-et-Marne. The same trend can be observed over exchange trips. This is in accordance with theory: outer departments are generally less populated, and the population is more scattered in space. Therefore, disaggregation effects become more apparent.

### 3.2.2. Interclass and Intra-class Variances of Zone-to-Zone Time

Interclass variance of zone-to-zone travel time for the disaggregate assignment model,  $X_m$ , is reported in Table 6.5. Mean intra-class variance of interzonal travel time indicator for the disaggregate assignment model,  $\bar{X}_m$ , is reported in Table 6.7.

We expect the two indicators to behave differently. The interclass indicator is expected to depend on the size of the department and the number of zones. Greater number of zones and bigger geometrical area imply that intra-

departmental travel times can be more variable; therefore, the variance will be greater. In Table 6.5, we observe that the three inner departments: Hauts-de-Seine, Seine-Saint-Denis, and Val-de-Marne, exhibit the smallest interclass variances ranging from 36 to 63  $\text{min}^2$ . Paris is next with about 68  $\text{min}^2$ . The outer departments: Yvelines, Essonne, and Val-d'Oise, systematically show greater interclass variances ranging from 82 to 100  $\text{min}^2$ , with Seine-et-Marne showing the greatest value of 196  $\text{min}^2$ .

On the other hand, the mean intra-class variance reflects the amount of variation due to trip-end disaggregation. Therefore, this indicator depends mainly on the average size of zones. Bigger zones imply greater variability thus greater intra-class variance. Paris is at the center where the average zone size is the smallest and this corresponds to the least mean intra-class variance of 0.2  $\text{min}^2$ . The three inner departments: Hauts-de-Seine, Seine-Saint-Denis, and Val-de-Marne, with values ranging from 0.27 to 0.42  $\text{min}^2$ . The three outer departments: Yvelines, Essonne, and Val-d'Oise, exhibit values from 1.24 to 1.60  $\text{min}^2$ , and Seine-et-Marne has the greatest mean intra-class variance of 4.15  $\text{min}^2$ .

**Table 6.5. Interclass variance of interzonal time, disaggregate assignment ( $\text{min}^2$ ).**

Origin	Destination								Combined
	Paris	Seine-et-Marne	Yvelines	Essonne	Hauts-de-Seine	Seine-Saint-Denis	Val-de-Marne	Val-d'Oise	
Paris	67.76	8.44	7.10	5.33	38.10	27.52	26.44	5.09	37.05
Seine-et-Marne	2.33	196.5	0.10	15.21	0.77	19.36	9.73	1.99	34.75
Yvelines	3.38	0.16	96.68	10.60	25.18	0.67	1.35	17.18	26.73
Essonne	1.60	18.13	11.01	99.78	8.04	0.25	5.70	0.03	25.16
Hauts-de-Seine	19.64	1.84	29.57	15.79	63.23	11.26	14.03	15.78	30.68
Seine-Saint-Denis	12.43	32.49	1.10	0.63	10.22	40.87	14.34	17.61	22.64
Val-de-Marne	10.02	21.39	1.80	14.21	12.26	12.69	36.49	0.51	21.04
Val-d'Oise	1.65	2.94	19.39	0.03	7.75	12.75	0.47	81.65	21.69
<b>Combined</b>	18.45	40.04	29.02	28.14	25.98	18.96	17.01	24.07	28.49

By comparing the mean intra-class variance and the interclass variance, we observe that, for example, for trips with one end at Seine-et-Marne, the ratio between the mean intra-class variance and the sum interclass and mean intra-

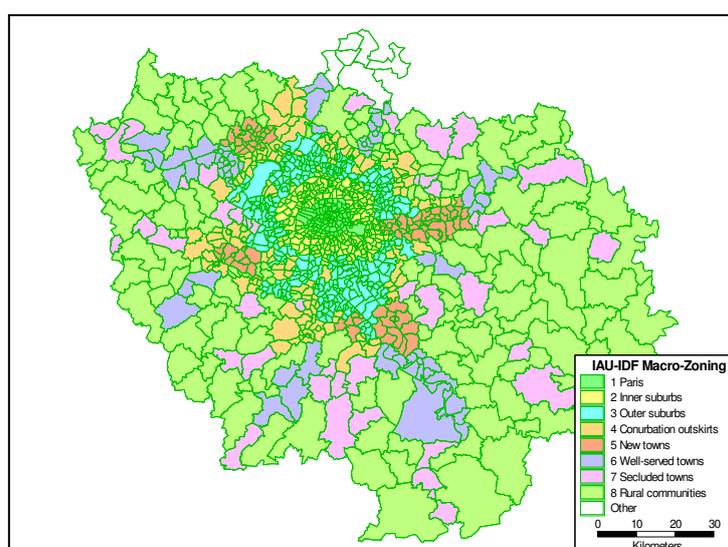
class variances reaches 8% to 9%. This is a measure of the typical amount of information loss due to aggregate centroid-based assignment.

**Table 6.6.** Mean intra-class variance of interzonal time, disaggregate assignment ( $\text{min}^2$ ).

Origin	Destination								Combined
	Paris	Seine-et-Marne	Yvelines	Essonne	Hauts-de-Seine	Seine-Saint-Denis	Val-de-Marne	Val-d'Oise	
Paris	0.20	0.92	0.59	0.53	0.24	0.26	0.29	0.41	0.26
Seine-et-Marne	0.86	4.15	1.40	2.37	0.88	0.78	1.07	1.97	3.62
Yvelines	0.60	1.55	1.28	1.75	0.56	0.57	0.64	1.22	1.22
Essonne	0.52	2.34	2.01	1.60	0.61	0.56	0.76	0.64	1.59
Hauts-de-Seine	0.24	1.05	0.55	0.62	0.27	0.23	0.37	0.34	0.33
Seine-Saint-Denis	0.27	0.90	0.60	0.56	0.24	0.35	0.34	0.49	0.40
Val-de-Marne	0.30	1.15	0.67	0.72	0.38	0.33	0.42	0.53	0.48
Val-d'Oise	0.47	2.03	1.28	0.79	0.37	0.55	0.63	1.24	1.18
<b>Combined</b>	<b>0.23</b>	<b>3.48</b>	<b>1.21</b>	<b>1.49</b>	<b>0.31</b>	<b>0.37</b>	<b>0.43</b>	<b>1.11</b>	<b>1.10</b>

### 3.3. Numerical Analysis of Results: Sectorial Macro-zoning

Figure 6.3 shows the eight sectors of the IAU-IdF macro-zoning system of the Greater Paris Region.



**Figure 6.3.** Ile-de-France sectorial macro-zoning system (IAU-IdF).

Table 6.7 shows the distribution of peak-hour traffic flows among the eight sectors of the IAU-IdF macro-zoning system of Ile-de-France. According to Table 6.7, trips are predominantly made within sectors, and the amount of exchange between sectors is minimal. The amount of the total sectorial traffic emissions/attractions as well as the intra-sectorial traffics are significantly higher for Inner suburbs and Outer suburbs. Paris has the next place, followed by New towns. Conurbation outskirts, Well-served towns, Secluded towns, and Rural communities have the least traffic flow.

Contrary to the macro zoning by administrative department where emissions and attractions very evenly distributed among departments, here Paris, Inner suburbs and Outer suburbs together provide about two thirds of the total traffic emissions/attractions. This is because IAU-IdF macro zoning is based on the level of urbanization and Secluded towns or Rural communities generate and absorb much less traffic than Paris, or Inner and Outer suburbs.

**Table 6.7. Distribution of peak-hour origin-destination inter-sectorial traffic flows (percent).**

Origin	Destination								Combined
	Paris	Inner suburbs	Outer suburbs	Conurbation outskirts	New towns	Well-served towns	Secluded towns	Rural communities	
Paris	6.44	5.47	1.20	0.20	0.20	0.06	0.03	0.05	13.66
Inner suburbs	2.63	17.25	5.88	0.72	0.80	0.19	0.11	0.16	27.74
Outer suburbs	0.40	3.89	14.68	2.96	1.77	0.53	0.40	0.55	25.16
Conurbation outskirts	0.07	0.41	2.69	2.91	1.17	0.61	0.41	0.69	8.95
New towns	0.06	0.49	1.73	1.27	4.74	0.59	0.21	0.56	9.66
Well-served towns	0.02	0.14	0.38	0.54	0.46	2.68	0.52	1.28	6.01
Secluded towns	0.01	0.06	0.31	0.37	0.18	0.50	0.45	1.03	2.91
Rural communities	0.02	0.10	0.45	0.62	0.44	1.22	0.97	2.09	5.91
<b>Combined</b>	9.66	27.81	27.30	9.59	9.77	6.38	3.10	6.40	100

### 3.3.1. Mean zone-to-zone travel time

Mean zone-to-zone travel time indicates the mean of origin-destination total travel time, calculated over all non-identical origin-destination zone pairs. For disaggregate assignment it is the average of the expected minimum interzonal

travel time,  $\bar{t}_m^{od}$ , and Table 6.8 shows sectorial values for the results from the disaggregate assignment.

**Table 6.8. Mean interzonal travel time, disaggregate assignment model (min).**

Origin	Destination								Combined
	Paris	Inner suburbs	Outer suburbs	Conurbation outskirts	New towns	Well-served towns	Secluded towns	Rural communities	
Paris	6.01	9.53	16.85	21.78	19.70	28.00	26.90	29.64	9.03
Inner suburbs	9.00	6.06	10.22	16.67	14.04	23.49	22.65	24.7	8.02
Outer suburbs	16.46	9.37	6.25	9.60	11.27	18.04	15.02	18.00	8.28
Conurbation outskirts	21.52	16.12	9.19	7.47	10.48	13.98	13.17	14.68	10.13
New towns	19.07	12.53	10.62	10.33	6.24	14.93	17.25	16.91	9.37
Well-served towns	28.29	22.72	17.40	13.5	14.37	9.29	15.54	14.76	12.65
Secluded towns	26.17	20.99	14.15	12.52	16.22	15.24	12.44	14.96	14.48
Rural communities	27.95	21.51	15.73	13.59	15.7	14.51	14.89	16.02	15.34
<b>Combined</b>	7.56	7.64	8.53	10.42	9.57	13.05	14.99	16.01	9.44

As expected, intra-sectorial travel times are significantly smaller than inter-sectorial travel times. Intra-Paris trips take in average 6.01 min. This is significantly shorter than the average time of travel from Paris to the other sectors ranging from 9.5 for Inner suburbs, up to 29.6 min for Rural communities.

For aggregate assignment it is the average of the centroid-to-centroid travel time,  $t_{cc}^{od}$ , and Table 6.9 shows sectorial values for the results from the aggregate assignment. As theoretically expected, disaggregate mean values are slightly smaller than aggregate mean values  $\bar{t}_m^{od} < t_{cc}^{od}$ .

By comparing results from Table 6.8 and Table 6.9 we observe that the outer the department is situated, the more deviated are the results of the two indicators. For example, the deviation between  $\bar{t}_m^{od}$  and  $t_{cc}^{od}$  is about 1.5% over intra-Paris trips; it constantly increases reaching 9.9% in Rural communities. The same trend can be observed over exchange trips. This is in accordance with theory: less urbanized sectors are generally less populated, and the population is more scattered in space. Therefore, disaggregation effects become more apparent.

**Table 6.9. Mean interzonal travel time, aggregate assignment model (min).**

Origin	Destination								Combined
	Paris	Inner suburbs	Outer suburbs	Conurbation outskirts	New towns	Well-served towns	Secluded towns	Rural communities	
Paris	6.10	9.65	17.13	22.06	20.39	28.25	27.43	30.33	9.17
Inner suburbs	9.12	6.20	10.46	16.97	14.55	23.74	23.15	25.38	8.19
Outer suburbs	16.72	9.59	6.53	9.96	11.88	18.52	15.72	18.98	8.61
Conurbation outskirts	21.79	16.42	9.54	7.81	10.91	14.44	13.79	15.40	10.54
New towns	19.69	12.99	11.25	10.79	6.69	15.39	17.93	17.92	9.89
Well-served towns	28.50	22.94	17.83	13.94	14.82	9.70	16.19	15.76	13.20
Secluded towns	26.62	21.38	14.71	13.06	16.74	15.89	13.56	16.14	15.35
Rural communities	28.57	22.05	16.50	14.26	16.58	15.50	16.10	17.78	16.57
<b>Combined</b>	7.68	7.80	8.85	10.82	10.08	13.59	15.88	17.25	9.81

### 3.3.2. Interclass and Intra-class Variances of Zone-to-Zone Time

Interclass variance of zone-to-zone travel time for the disaggregate assignment model,  $X_m$ , is reported in Table 6.10. Mean intra-class variance of interzonal travel time indicator for the disaggregate assignment model,  $\bar{\chi}_m$ , is reported in Table 6.11.

We expect the two indicators to behave differently. The interclass indicator is expected to depend on the size of the sector and the number of zones. Greater number of zones and bigger geometrical area imply that intra-sectorial travel times can be more variable; therefore, the variance will be greater. In Table 6.10, we observe that Inner suburbs, Outer suburbs, Conurbation outskirts, New towns and Rural communities exhibit the smallest interclass variances ranging from 22 to 60 min<sup>2</sup>. Paris is next with about 68 min<sup>2</sup>. Secluded towns and Well-served towns show the maximum interclass variance with 125 min<sup>2</sup> and 143 min<sup>2</sup> respectively.

On the other hand, the mean intra-class variance reflects the amount of variation due to trip-end disaggregation. Therefore, this indicator depends mainly on the average size of zones. Bigger zones imply greater variability thus greater intra-class variance. Paris is at the center where the average zone size is the smallest and this corresponds to the least mean intra-class variance

of 0.2 min<sup>2</sup> over intra-sectorial trips. This increases constantly towards less urbanized areas, reaching 7.75 min<sup>2</sup> in Rural communities.

**Table 6.10. Inter-class variance of interzonal time, disaggregate assignment (min<sup>2</sup>).**

Origin	Destination								Combined
	Paris	Inner suburbs	Outer suburbs	Conurbation outskirts	New towns	Well-served towns	Secluded towns	Rural communities	
Paris	67.76	34.62	7.06	3.25	7.91	4.36	4.83	2.06	36.87
Inner suburbs	16.63	35.27	18.10	6.54	14.84	5.69	5.51	3.41	26.54
Outer suburbs	2.40	11.53	22.64	17.12	16.89	14.17	17.45	9.60	20.97
Conurbation outskirts	1.12	3.88	14.76	29.09	16.59	33.57	30.58	18.50	19.43
New towns	2.45	8.61	14.91	16.66	48.78	38.04	28.96	23.27	28.20
Well-served towns	1.72	3.28	9.53	28.74	28.20	142.7	89.57	62.07	36.75
Secluded towns	2.01	3.22	11.90	25.92	20.98	85.27	125.0	88.32	30.75
Rural communities	0.83	2.27	6.66	14.80	16.06	57.20	81.91	60.26	19.59
<b>Combined</b>	18.28	21.13	21.81	21.11	29.25	42.27	35.37	23.39	28.04

**Table 6.11. Mean intra-class variance of interzonal time, disaggregate assignment (min<sup>2</sup>).**

Origin	Destination								Combined
	Paris	Inner suburbs	Outer suburbs	Conurbation outskirts	New towns	Well-served towns	Secluded towns	Rural communities	
Paris	0.20	0.25	0.40	0.65	0.39	1.07	1.40	1.73	0.26
Inner suburbs	0.26	0.28	0.42	0.69	0.41	1.07	1.38	1.71	0.34
Outer suburbs	0.39	0.42	0.53	0.86	0.73	1.39	1.59	1.95	0.63
Conurbation outskirts	0.66	0.72	0.85	1.28	1.17	2.18	2.28	2.65	1.32
New towns	0.39	0.37	0.74	1.17	0.67	1.43	2.34	2.34	0.91
Well-served towns	1.02	0.94	1.31	2.04	1.41	2.13	3.28	4.05	2.49
Secluded towns	1.25	1.05	1.43	2.06	2.18	3.20	4.53	6.59	4.16
Rural communities	1.52	1.32	1.62	2.42	2.16	3.96	6.50	7.75	5.19
<b>Combined</b>	0.23	0.31	0.58	1.22	0.84	2.40	3.97	5.11	1.07

By comparing the mean intra-class variance and the interclass variance, we observe that, for example, for trips with one end at Rural communities, the ratio between the mean intra-class variance and the sum of interclass and mean intra-class variances reaches almost 20%. The same ratio is about 11% for trips with one end in Secluded towns, and is around 6% for trips with one end in Conurbation outskirts and Well-served towns. As for the other sectors, the ratio is about 3% at Outer suburbs and New towns, 1.2% for Inner suburbs and 0.7% for Paris. This is a measure of the typical amount of information loss due to aggregate centroid-based assignment.

## 4. Conclusion

The mean intra-class portion of the total variance over the entire metropolitan area is about 4%. In Paris where zones are small, this ratio is negligible but for origin-destination relations with one end in rural communities the ratio can reach up to some 10% to 20% (depending on the macro zoning). This shows that the aggregation effect may not be so significant in dense areas where the zoning system is itself relatively fine but its effect cannot be ignored over suburban areas. This application also shows how the total variance law can provide an effective measure of the goodness of a zoning system.

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## PART III

# Towards a Disaggregate Treatment of Trip-Ends in Mode Choice

# Chapter 7: Mode Choice in a Multimodal Network: Theoretical Framework

## 1. Introduction

So far, we studied the correspondence between intrazonal and interzonal scales of spatial representation in a probabilistic framework for the traffic assignment to a monomodal network. We developed a stochastic traffic assignment algorithm which preserves spatial information on disaggregate localization of trip-ends. This was accomplished by identifying pairs of origin-destination zones as statistical classes and preserving the intra-class portion of the total variance that was typically lost in aggregate assignments. In this chapter, we extend the stochastic traffic assignment framework of the previous chapter to the general context of a multimodal traffic-transit assignment framework including auto and transit modes. The aim is to provide a methodology which can serve to ameliorate our understanding of travelers' mode choice behavior in an urban area by incorporating a disaggregate representation of the local space at both ends of the trip.

Private modes such as auto or motorbike are generally considered as being immediately accessible modes of transportation. This is not quite true: at origin, the vehicle may be parked at the residential parking place, on the street or in a nearby parking lot. At destination, the vehicle may be leaved at a dedicated parking place (provided by the employer, for example), on the street or in a nearby parking lot as well. Therefore an auto driver has to access to his personal vehicle at the origin by walk before being able to use it, and has to egress from it again by walk once he arrives at his destination. Analogously, in public transportations the traveler has to access to a transit platform in order to board a public transportation vehicle and egress from one once he alighted. In other words, the main transportation mode is nearly always preceded and succeeded by access/egress feeder modes. A trip is therefore a succession of access, main and egress modes; it is multimodal. The notion of multimodality applies commonly to both private and public transportation modes. In a multimodal framework, we try to account for different trip stages explicitly.

By simplifying a multimodal itinerary to a monomodal one, where the main travel mode is considered as the only travel mode, conventional models overlook "behavioral" factors that influence traveler's perception of the utility of different modal alternatives. Consequently, the model is unable to explain the propensity of an auto driver for taking any pair of anchor points other than the one offering the apparent shortest path. Such a propensity may be for example due to the availability of better parking opportunities nearby other anchor points. Capturing such behaviors requires a proper modeling of, in this case, traveler's choice of parking place. This in turn introduces

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additional terms into the composition of the perceived utility of the auto mode: search time or monetary cost for a parking place, for instance. The same is true for the transit modes. A transit traveler may choose not to take a shorter station-to-station transit itinerary because it involves longer access or egress walking distances at origin or destination.

In order to be able to address such issues in a comprehensive way, it is necessary to elaborate an appropriate system of representation. In the case of the auto mode, the multimodal representation requires modeling (explicitly or implicitly) the choice of a parking place. Such a model introduces additional parameters involved in finding a parking place, and allows accounting for tradeoffs between a paid but closer and a free but further parking place. In the case of public modes, the multimodal representation should explicitly account for the terminal sections of the trip as well as the chain of different public modes between the access and egress transit platforms. In the following of this chapter, we will focus on transit modes, as the subject of parking modeling requires a separate treatment, which we should not venture to address in an unsatisfactory manner.

The purpose of this chapter is to develop a consistent modeling framework in which the stochastic spatially disaggregate representation of the local space, on one hand, and the behavioral aspects underlying the formation of multimodal itineraries, on the other hand, are combined. Our ultimate aim is to acquire a deeper insight into the mode choice behavior of travelers by looking to the ways in which the local space conditions traveler's perception of mode alternatives. From the mode choice modeling point of view, the choice of the main transportation mode should be understood within the whole sequence of legs that constitute together a multimodal itinerary. In other words, we recognize that the travel mode choice is not decided at only one instant, but that the choice of the main mode is conditional upon a number of mode choice decisions, which occur "physically" at transfer points between legs. This enables us to account explicitly for factors that influence the mode choice behavior of the individual, but were left out of the scope of classic models. We suggest that this approach leads to a more conceptually consistent and econometrically explanatory model.

The chapter is organized in three main parts: Firstly, we undertake the question of how the multimodal transit itineraries are represented in models. Secondly, we study the mode choice behavior of a single traveler in a multimodal framework. Finally, we combine the mode choice model with a stochastic disaggregate representation of the local space at trip ends.

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## 2. Multimodal Transit Itinerary Representation

In the preceding chapter, we represented a monomodal itinerary as a composition of three legs: the access leg from the departure coordinates to an anchor point at the origin, the main leg from the origin anchor point to an anchor point at the destination, and the egress leg from the destination anchor point to the arrival coordinates. We have proposed a deterministic representation for the main leg and a stochastic representation for the two end legs. Then we proceeded to elaborate the appropriate modeling framework required to address the shortest path problem within a stochastic representation of disaggregate local space.

We extend the concept of leg by attributing a transportation mode to it, hence a modal leg. The concept of modal leg is quite essential for representing multimodal itineraries. Because in a multimodal network several legs may have the same physical coordinates yet differ due to their corresponding transportation modes. This is contrary to the case of a mono-modal network where a leg can be uniquely identified by its spatial coordinates. In theory, a multimodal itinerary is considered as a succession of an arbitrary number of modal legs, conforming to the modeling requirements.

A transit route is abstracted as a chain of modal legs. In general multimodal routes can be identified based on a number of different aspects such as access/egress modes, boarding/alighting train stations, train service types, transfer stations, etc. (Bovy and Hoogendoorn-Lanser, 2005). Some of these aspects such as access/egress modes or train service types are related to the way different modes of transportation are chained together between departure and arrival points. Others such as boarding/alighting stations or transfer stations are related to the way the transit system interacts with the urban space.

Models capture these aspects to different extents. Simpler models (including most of the applied models) define transit routes as a mere succession of modal legs and omit spatial coordinates of stations situated at leg ends. More advanced models take into account transit stations and the connectivity and topology of the network. In the first category of models, the representation of the space is implicit within characteristics (e.g. leg distances) and the physical description of transit routes is qualitative. In the second category of models, the representation of the spatial configuration of the transit network is explicit and physical characteristics of transit legs can be measured.

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## 2.1. Multimodal Route Representation: Implicit Approach

Let us consider a traveler who walks from home to a nearby metro station and gets on board, then transfers to another Metro service, then transfers to train at an intermediate station, then retransfers to a bus service until the egress stop, and walks to his workplace. Here, a detailed description of that itinerary can be given as “Walk-Metro-Metro-Train-Bus-Walk”. However, model’s account of the traveler’s transportation mode should be simplified. It can be identified as a Walk access mode, a “Metro-Train-Bus” transit chain, and a Walk egress mode. It can be as well identified as a Walk access mode, a “Metro-Train” transit chain, and a Bus egress mode. Even, the modeler may decide to simplify the whole transit section as one Transit mode and consider it as a “Walk-Transit-Walk” composite mode.

This approach is qualified as being qualitative for a number of reasons:

Firstly, the multimodal chain is treated in an abstracted way, i.e. having chosen a composite mode alternative such as “Metro-Train-Bus” does not imply that exactly one Metro, one Train and one Bus services are used. Instead, “Metro”, for instance, refers to all metro legs including all transfers.

Secondly, the definition of the composite modes is not given in a physical (i.e. objective) way. Instead, it is a choice of the analyst (i.e. subjective) to decide how to combine basic modes into composite modes in order to obtain the most explanatory model. Ideally, different composite mode alternatives can be obtained by enumerating all viable successive combinations of available basic modes. The list can then be truncated for those combinations that do not correspond to any significant number of observations. However, none of these composite modes can be physically identified because their very definition depends on conventions that the modeler makes for enumerating the basic simple modes. The analyst may decide to distinguish between, for instance, Metro and Train modes (as is in ANTONIN model) or to consider them together as one single Transit mode (as is in NYMTC model). In this respect, it seems that the conformity between observations and the model not only determines the specification of the mode choice model, but also the very definition of the composite mode alternatives.

Thirdly and probably the most importantly, the spatial dimension is implicit. The qualitative multimodal representation ignores the spatial configuration of access, transfer and egress stations as well as the topological configuration of the transit network. The important question now is the following: how a composite mode that is identified independently from the model representation of the space, can acquire a spatial interpretation?

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Le Nechet (2010) in his analysis of spatial interactions between employment and residential areas in Ile-de-France suggests the following: Bus is used only over short-range local distances, Metro on midrange intermediate distances and Train over long-range regional distances. He then suggests an escalatory order in which a higher mode may be fed by a lower (Figure 7.1).

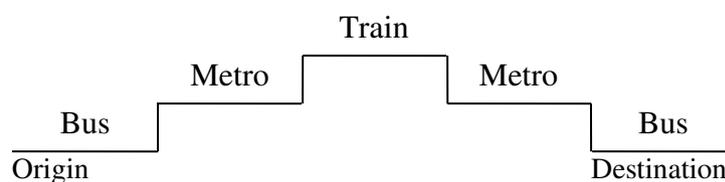


Figure 7.1. A qualitative hierarchy between different transit modes.

Thereby, the best interpretation of a “Metro-Train-Bus” composite mode is that: the traveler has chained Metro, as a midrange mode, and Train, as a regional mode, which in turn implies that the traveler is obliged to leave his local zone and go to work abroad. Such a rudimentary representation informs very little about the behavioral factors underlying mode choice and is more appropriate for observatory purposes.

van Nes (2002) proposes that a hierarchal order can be established between different basic public modes so that modes of a lower hierarchical level can serve as feeder for modes of a higher hierarchical level and thereby define multimodal chains. Combes and van Nes (2012) use this approach to study Ile-de-France transportation. In this approach, for instance, because Train moves fast but makes few stops compared to Metro, which is slower but serves more stations, over long distances Train prevails as an alternative of higher hierarchical level compared to Metro. This is a useful concept but there are subtleties in its application that should be taken into consideration.

As Seekings and Miller (1995) point out, the major problem with the qualitative representation of multimodal routes is the difficulty to characterize the attributes of composite modes within a mode choice model, properly. Multimodal transit routes can become highly heterogeneous combining several modal legs of different hierarchical levels and it is far from obvious how attributes of different modal legs can be measured, and how a generalized cost can be specified for a multimodal transit itinerary (which composing terms, what weighting structure, ...).

The implicit approach is widely used in applied multimodal transportation models (Debrincat, 2000, Vovsha and Chiao, 2008) as it is not excessively demanding in terms of data precision. For instance, ANTONIN-2, the tour-based model of Ile-de-France (cf. Chapter 2, § 2.1), identifies 13 mode

alternatives of which 10 are transit multimodal alternatives including bus, metro and regional train, which may be accessed by walk or auto if bus is not included in the mode chain and only by walk if bus is included in the mode chain. The model uses the Paris Household Survey as its empirical database and its identification of transit multimodal alternatives closely matches the way the survey trip modes have been preprocessed and regrouped into multimodal chains. As another example, NYMTC, the model of the New York metropolitan area, (Vovsha et Chiao, 2008), identifies 11 mode alternatives of which 4 are transit multimodal alternatives including transit (bus, subway, and ferry) with walk access, transit with drive access, commuter rail (with transit feeder lines) with walk access, commuter rail with drive access.

## 2.2. Multimodal Route Representation: Explicit Approach

In the spatially explicit approach, the representation of different aspects of multimodality especially the spatial dimension in the model is explicit. That is, the model takes into account effects of the spatial configuration of transit platforms and the topological structure of the network on the choice behavior of the traveler. Transit platforms are represented explicitly in the model space. In this way, feeder sections and main transit section are separated by actual transit stations, and correspond to precise physical coordinates. A composite mode is not a mere recounting of a chain of modal legs; instead, different sections of the itinerary correspond to specified coordinates in the space. Transit platforms are located in between modal legs.

The literature on explicit transit representation has paid particular attention to the feeder sections of the trip. The choice of feeder modes, alone, or as a joint choice along with the choice of access stations, is studied (Liou and Talvitie, 1974, Kumar and Gur, 1982, Kastrenakes, 1989, Mukundan et al., 1991, Talvitie, 1992, Tsamboulas et al., 1992, Fan et al., 1993, Khan et al., 2007, Debrezion et al., 2009). To serve our purpose, we review previous works mainly to elucidate aspects such as the way in which different models abstract multimodal itineraries, or identify alternative choice sets.

In an early work, Liou and Talvitie (1974) study the joint feeder mode and access station choice for work trips in Chicago. They use data from an origin-destination rail trip survey in Chicago. A sample of 150 work trips and two samples of 25 work trips have been randomly drawn from the surveys, respectively for the model estimation and test of the operational models. Data include access mode, access station, access distance, and indicate trip origins by a quarter square mile centroid precision. Three alternative feeder modes are walk, auto and bus. The auto mode is considered as always available. The

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walk mode is considered available if the walking time does not exceed 20 min. Bus is considered available if the traveler is within half a mile from a bus route. For the station choice set, alternatives stations are chosen usually near the stated chosen station. Explanatory variables include line-haul travel time, access time in auto, bus or walk, operation cost of an automobile during the access trip, out-of-pocket parking cost, for the auto mode, or bus fare, for the bus users, and finally a dummy variable for the availability of parking for the auto mode. The authors consider three different model specifications: simultaneous choice of mode and station, mode choice conditional upon station choice, and station choice conditional upon mode choice. In addition, they consider that the access trip can be completely separated from the rest of the journey (which is not obvious). They find that only the station-then-mode specification leads to an admissible model estimation. Their results imply that spending time inside an automobile is disliked by travelers compared to the bus feeder mode, and that as a result "... it should not be difficult to convince a traveler to choose access modes such as walking and even the bus ..." This result is contrary to the case where the entire trip is considered. They suggest that the two different behaviors may be justified considering that for an entire trip, where the origin-destination distance is large, flexibility, comfort or privacy of the automobile become more important. Instead, in an access trip, various inconveniences of using the automobile such as finding a parking place, leaving the automobile in a parking lot where it is no longer accessible for other household members, or having someone else drive the traveler to the station, become predominant disadvantages. They further suggest that car ownership and location decisions of households may have an important role in work trip decisions.

Talvitie (1992) has also developed a joint transit feeder mode and access station choice model for the Bay Area Rapid Transit (BART). Their model includes four access modes (walk, bus, auto, and kiss-and-ride) and up to three transit stations per origin zone and is based on the *i.i.a.* assumption. The research shows that the model does not significantly violate the underlying *i.i.a.* assumption and highlights that the proper representation of the local network has a critical effect on the quality of the model.

Fan et al. (1993) study feeder mode and access stations choice problem for work trips in the Greater Toronto Area. Transit service in the area is provided by two transit systems, namely the Government of Ontario (GO) Transit's commuter rail network and the Toronto Transit Commission's subway network. Two data sources are used: for the commuter rail network the data is provided by the 1987 on-board survey of the riders of commuter rail system, and for subway network data is provided by the 1986

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Transportation Tomorrow Survey. For the commuter rail network the walk, auto and transit feeder modes are modeled. For the subway system, only the auto feeder mode is modeled. This is partly because the combination of a surface transit (e.g., bus) as the feeder mode and the subway as the main mode has not revealed to be a sufficiently distinct alternative relative to taking the surface transit for the entire travel. In this respect, the model aims to study the distinction between the “transit all-way” and “transit part-way, auto part-way” modes within the work-trip mode choice model. It is observed that catchments areas for the auto feeder mode around commuter rail network stations overlap significantly, indicating that travelers do not necessarily choose the closest station for accessing the transit network (see also, Brons et al., 2009). A similar effect is detected for the transit feeder mode and this suggests that the choice of transit access station needs to be implemented by an explicit choice model as it is “likely to be best modeled probabilistically” (Fan et al., 1993). For the walk feeder mode, however, no station choice model is used because transit stations are sufficiently far apart so that at most one transit station will be within feasible walking distance of a worker’s home. Detailed analysis has been carried out in order to make up rules for access station choice set identification. As for the commuter rail access stations on the home-end it is concluded that by including the two closest stations on the two closest lines nearly 95% of the observations on a station-basis and 99% of the observation on a line-basis are accounted for. As for the subway access stations on the home-end it is concluded that by including the five closest stations nearly 98% of the cases are accounted for. The feeder mode and access station choice model for the rail transit mode is a Nested Logit with feeder mode choice at the upper level access station choice at the lower level (the inverse specification has been tested and strongly rejected). The authors did not find the access and line-haul travel times to have statistically different parameters so the sum of transit access and line-haul in-vehicle travel times is directly used in the model. Parameter estimates for “transit out-of-vehicle”, “auto access cost” and “rail line-haul fares” were found inconclusive. Final explanatory variables for the lower-level station choice model for the transit feeder mode alternative include: “transit access plus rail in-vehicle time”, “total number of a.m. peak-period trains stopping at the station” and “transit access fare”, and for the auto mode alternative include: “auto access plus rail in-vehicle time”, “total number of a.m. peak-period trains stopping at the station”, “logarithm of the number of parking spaces at the station”, “dummy variable enabled if station is closest of all to the home”. It is noted that the inclusion of a “closest station” dummy variable yielded a significantly improved model in terms of both goodness-of-fit and reasonableness of other parameter estimates. Final explanatory variables

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included in the upper-level feeder mode choice model, for the transit feeder mode alternative include: “logsum inclusive value form the lower-level station choice model”, “dummy variable enabled if transit feeder mode”, “dummy variable enabled if age is in 31-50 range”. Explanatory variables for the auto feeder mode alternative include: “logsum inclusive value form the lower-level station choice model”, “dummy variable enabled if age is in 31-50 range”, “dummy variable enabled if female”, “dummy variable enabled if annual income superior to \$50000”. Explanatory variables for the walk feeder mode include “walk distance from home to station”, “dummy variable enabled if walk feeder mode”. Except for age and gender dummy variables, all parameter estimates are statistically significant.

Fan et al. (1993) report an inclusive value parameter estimate of about 0.4 which is significantly different from either 0 or 1 indicating that the hierarchical “feeder mode then access station” specification is statistically significant and cannot be rejected. That is the choice of feeder mode and access station is neither a completely disjoint one where the two choices are made independently nor a joint one where the two choices are made always the same way (as assumed in Liou and Talvitie, 1974).

The access station choice model for the subway with auto feeder mode is a Multinomial Logit. Model explanatory variables include “auto driver in-vehicle home to station time”, “auto passenger in-vehicle home to station time”, “transit in-vehicle time”, “transit out-of-vehicle time”, and “dummy variable enabled if station is closest of all to the home”. From the estimation of the model, they conclude that parameter estimates differ significantly for the auto driver and auto passenger feeder modes. This suggests that these two modes should be modeled separately. Model estimation also has shown that the transit out-of-vehicle time is weighted over one order of magnitude more heavily than the transit in-vehicle time, and this is found to be consistent with the effect of subway-to-subway transfer times and egress walk times.

Bovy and Hoogendoorn-Lanser (2005) develop a joint feeder mode and access station choice model as a part of their study of the influences of multimodal trip attributes on the competitiveness of interurban multimodal train alternatives. They consider the interurban train as the main travel mode, and combine the feeder mode and access station choices into a single multimodal route choice problem.

The empirical database is from in-train and telephone surveys, observing multimodal trips in the western part of the Netherlands. As these surveys focus on train users only, observations may be biased due to the positive attitude of the users towards the transit mode. To avoid the bias, a subset of

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235 out of 1700 observations (individual respondents) is eventually used corresponding to a region where for most trips “sufficient” multimodal alternatives are available. Per individual, a number of trip alternatives have been considered, varying from 1 to 62 alternatives and summing up to a total number of 3435 alternatives for the 235 individuals. Possible overlaps between alternatives have been ignored. The route alternatives are generated by combining the train as the only main mode with different feeder mode alternatives at origin and destination. Private feeder mode alternatives include walk, bike, and auto (both driver and passenger). The availability of a private feeder mode is determined based on distance range, status of ownership, and trip end (home- versus activity-end). The access distance has been considered reasonable if it lies between 10th and 90th percentile values of mode-specific access distances for trips between 10 and 30 Km. Public feeder mode alternatives include bus, tram and metro. A transit-feeding trip itself usually has two legs distinguishing between the walk to/from the bus stop and the in-vehicle part between the bus stop and the train station. Limited number of transfers is allowed both in the main and terminal sections.

An interurban itinerary is abstracted into three sections including the access section from the origin to the boarding platform, the main interurban rail-haul section, and the egress section from the alighting platform to the destination. The two end travel sections are distinguished based on whether they are access or egress sections, or, home- or activity-end sections. The research tests several different model specifications based on the Nested Logit model and the multi nest generalized extreme value models. Nests are defined based on the feeder mode (i.e. private versus transit) and the station type (i.e. intercity versus non-intercity), on the home-end or the activity-end. Test models are specified as two- and three-level Nested Logit and three-level Multi-Nested Generalized Extreme Value (MN-GEV)<sup>1</sup>. The effectiveness of the model has been judged by comparing it to a conjugate Multinomial Logit model. The study takes into account only the alternative-specific characteristics as opposed to the socioeconomic attributes: variables considered in the composition of the utility functions include mode-specific access and egress travel times, transfer times, wait times, transfer frequency, parking costs and

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<sup>1</sup> The MN-GEV model is originally known as the Principles-of-Differentiation Generalized Extreme Value model (PD-GEV). The model is developed by Bresnahan et al. (1997) to study rents from innovation in the computer industry. In the Nested Logit model, the order of the nests matters. The PD-GEV model is able to use two dimensions of differentiation, without ordering them. With the exception of dealing with the problem of ordering the nests, this model retains all the advantages and disadvantages of the nested logit.

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a number of dummy variables concerning origin and destination feeder modes, train service, and train station type. They find that the best Nested Logit specification is the one where home-end station choice is on the middle level and the home-end feeder mode choice is on the lower level. The more flexible MN-GEV structure allows including both home-end and activity-end choice contexts by inserting the best found Nested Logit specification on one branch, and its correspondent on the activity-end side, on the other branch. This leads to a significantly better model. Having both trip ends included, the MN-GEV model clearly shows that the train users are predominantly concerned with their choice of feeder mode and access station at the origin. The estimation results are quite consistent between the Nested Logit and the MN-GEV models. Setting the train in-vehicle travel time (main section travel time) as reference, both models propose that the access time on the private access modes is perceived 1.6 times more onerous. This ratio is 0.8 for the access time on the transit feeder modes, 2.2 for wait times (including the first wait time and wait times at transfers), and nearly 2 for walk time at transfers. One interesting point is the distinction that the authors have considered between a transfer to a lower frequency service and a higher frequency one. They find that the former is perceived nearly twice as costly as the later.

Debrezion et al. (2009) develop a joint feeder mode and transit station choice model in the Netherlands based on data from Dutch Railway Company customer satisfaction survey. The database covers 365 stations aggregated over 1440 postcode areas. A Nested Logit specification is used implementing four feeder modes (walk, bike, public transportation and car) and three transit stations per postcode area. As for feeder mode identification, all of the four feeder modes are considered available all over the postcode area. As for transit station identification, in each postcode area the three most frequently accessed transit stations are considered for the model – which sum up to a total number of 346 stations. Individual is supposed to decide first the feeder mode (upper choice level) and then the transit station (lower choice level) (the reverse specification is tested and found inappropriate). The choice of a departure station is dependent on three factors: the accessibility of the station, the level of transportation service accessible from the station, and the availability of accessory facilities offered at the station.

The accessibility of the station is measured using the Euclidian distance between the centroid of the postcode area and the station. The level of transportation service accessible from the station among others depends on the frequency of train services and the level of network connectivity and coverage by different transit lines. This is done by defining a Rail Service Quality Index (RSQI) that combines three different measures of rail service

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quality into one single index. The first measure is the average wait time at the station, which in turn is determined by the frequency of transit services. The second measure is the level of connectivity of the station to the entire network. This is approximated by the number of stations, which can be directly accessed from the station in consideration. For stations that are not directly connected, the number of transfers is used as a connectivity indicator. The third measure is the relative distance (in time and in space) of the station in consideration with respect to the other stations. This is well approximated by the in-vehicle travel time, which depends on the speed at which trains operate. These three factors are combined into one RSQI for each origin station. In order to construct the RSQI, the authors use a doubly constrained spatial interaction model that is estimated based on number of travels per origin-destination station pair. The generalized journey time is not introduced directly but its effect is taken into account through two supplementary functions. The first one is defined as a stepwise discontinuous function of the generalized journey time where function parameter differs based on the time interval within which the generalized journey time occur. The second one is defined as an exponential function of the ratio of the generalized journey time to the Euclidian distance between origin-destination stations. Once the doubly constrained spatial interaction function is estimated, the RSQI for each origin station is defined by summing over all destination stations. Finally, factors such as availability of a dedicated parking place, a bike stand or storage facilities at the station are also expected to increase the use of the station.

Utility functions for feeder mode options include car ownership ratio in the postcode area as the only explanatory variable. Utility functional forms for transit station options are conditional on feeder mode. For all feeder modes the Euclidian distance between of the transit station and the centroid of the postcode area, and the RSQI are included as explanatory variable. For car and bike feeder modes respective dummy variables are included to capture the availability of a parking or a bike-stand at the transit station. For the public transportation feeder mode, the mean travel time and mean frequency are also included as explanatory variable.

Seekings and Miller (1995) discuss the implementation of feeder mode and access station choice for the demand model of the Greater Toronto Area using the Inro's EMME/2 platform. This appears to be one of the rare instances where the choice of transit access station is actually implemented in an applied modeling framework. This is a partially explicit implementation where transit access station choice is based on an explicit spatial representation, but composite modes are still used to capture multimodality. We study this modeling instance especially to address important aspects that it approaches

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based on practical evidence. Their model identifies 7 mode alternatives including auto-driver, auto-passenger, walk, and four transit modes, transit all-way, subway with auto access, commuter rail with transit or walk access, and commuter rail with auto access (Miller, 2001). At the very heart of their discussion is the question of how the transit modes should be represented in the model, with the differences between these modes being in terms of the main mode taken (commuter rail, subway, other), the feeder mode (walk/transit or auto), and in the case of the rail modes, the station chosen for access. They propose a Nested Logit structure where at the upper level the traveler first chooses among one of the seven mode alternatives including the three composite modes (the transit allway is not considered as a simple mode) and at the lower level the traveler chooses an access station. The access station choice is spatially disaggregate. Based on findings of Fan et al. (1993) on the Greater Toronto Area, for the subway with auto access composite mode, the five closest subway park and ride stations to the origin zone centroid are initially selected. For the two remaining composite modes, which involve the commuter rail, the two closest rail stations on the two closest lines to the origin zone centroid are initially selected. Additional feasibility constraints are also taken into account. However, their model of access station choice is based on the *i.i.a.* assumption, which is difficult to hold in this context. This is because being closer to one station does require being closer to all stations at the same side and further from all stations at the opposite side, and the covariance structure is heteroscedastic. Other shortcoming of their model is its centroid-based spatial representation. Authors emphasize also the effect of transit fare structure on traveler's perception of the different transit modes.

### 2.3. Implicit versus Explicit Approach: A Critical Reflection

We have reviewed the two approaches to the representation of transit itineraries for modeling purpose. Differences between the two approaches can be summarized in two fundamental points:

- How traveler identifies different transit modes. For example, whether Metro or Train are regarded as two different transit modes or are considered as both providing the same type of service?
- The decomposition of a multimodal chain into main and feeder legs is it consistent with an implicit representation of the multimodal chain? In other words, having chosen a composite mode such as "Metro-Train" is it plausible to consider that metro is used for access to the Train? Based on what criteria, the main mode and the modes that have served

as its feeder can be distinguished? Should the main mode be determined based on a distance criterion, i.e. the main mode is the one which has covered the longest distance? Or could it be simply based on the “naive” assumption that the main mode is the one which is perceived as mechanically “heavier”?

These points have to be clarified as to allow for a plausible association between the choice of a composite mode and the mode choice behavior of the traveler. Our first question regards the very definition of the main transit mode in an implicit representation, and the second question regards multimodality. In the aim of elucidating these two inquiries, we propose to study two examples in the Parisian context:

Firstly, let us consider a transit trip between two stations that have access to both the regional train (RER) and the metro system, namely the two Parisian transit stations “*Nation*” and “*Châtelet*”. Departing from “*Nation*” to the destination of “*Châtelet*”, two direct transit alternatives are available: RER A, and Metro 1. In this particular case, the two alternatives are quite competitive; metro prevails for closer stations and train prevails for farther stations. In this context, a Parisian model such as ANTONIN-2, which uses an implicit representation of transit multimodal routes, distinguishes between Metro and Train alternatives as two different modes. The question that comes to mind here is the following: Is there any fundamental distinction between RER A as a train alternative and Metro 1 as a metro alternative except that the train is less frequent but moves faster and the metro is more frequent but moves slower? In other words, besides level-of-service characteristics, can it be identified any inherent perceptual difference between the train and the metro alternatives per se due to the former’s “train-ness” or the latter’s “metro-ness”? Should these two modes be distinguished as being of two different hierarchical levels, as Combes and van Nes (2012) suggest? Such a coexistence of two such alternatives may prove rare but it certainly sheds light on some fundamental aspects. The decisive consequence of this dilemma for the modeling purpose is the following: Should train and metro alternatives be considered as two different mode alternatives to be distinguished in the mode choice stage? Or is it more plausible to assume that they both correspond to one single mode alternative, e.g. rail public transportation, and the two route alternatives should be dealt with in the assignment stage based on their level-of-service characteristics? More elaborately, is multimodality only arising from the way interconnected networks of different hierarchical levels interact to provide transit solutions to the traveler? Or is it a behavior that should be understood not at the level of interconnected networks but down at the level of individual trip?

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Secondly, let us consider two transit trips both departing from the Parisian Metro station “*Saint-Mandé*”, one to the destination of “*Gare de Lyon*”, and the other to “*La Défense*”. Among all possible alternative itineraries, we consider those that take Metro 1 up to the station Nation and then transfer to RER A for the rest of the trip. In the Parisian model ANTONIN-2, these trips will be described as being both taking “Metro+Train” itineraries; hence a “Metro+Train” composite mode. This raises the following question: Traveler’s choice for taking these two “apparently” similar itineraries does it arise from similar mode choice behaviors?

In this discussion, our purpose may be better understood by clarifying our meaning of “behavior”. By “behavior”, we mean “reproducibility” due to a recognizable “necessity”. That is, an observation, an act is recognized as a behavior if there can be recognized a “necessity” to motivate its reproduction. A “necessity” is recognized in two ways: firstly, if there can be identified an economic gain that promotes a choice; this we call a “utility”. Secondly if there can be identified a restraint which prevents a choice; this we call a “captivity”.

As for the first question, Seekings and Miller (1995) as an evidence from practice, report that attempts to deal with multimodality as an assignment-only problem has failed in the context of the Greater Toronto Area. In this particular region, public transportation is provided mainly via two interconnected commuter rail and subway networks with commuter rail being mostly used for long-range regional trips and subway being used for short-range trips in the center of the region. Authors report that several attempts to determine commuter rail trips through a conventional transit assignment algorithm has led to commuter rail trips being “very poorly” predicted. This, put into van Nes (2002)’s vocabulary implies that conventional transit assignment methods which distribute the modal travel demand among available transit routes based on their mechanistic characteristics perform well for networks composed of transit modes of the same “hierarchical” order. In other words for transit networks composed of hierarchically similar transit service route choice behavior is reasonably well explained by the difference of utility composed only of mechanistic characteristics. However, other behavioral aspects are at work when an individual decides between two routes of two different “hierarchical” orders that need to be addressed at a higher level. Thus, it can be concluded that wherever RER and Metro are acting as two modes of two different hierarchical levels – for example, for trips with one end outside the metro coverage zone – they need to be recognized as two different main modes. More precisely speaking, hierarchical levels cannot be

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attributed to different transit services in a unique way: one hierarchical order may hold for some trips, its opposite for the others.

As for the second question, in the first trip the station “*Gare de Lyon*” destination is also very well served by Metro 1 and the transfer to the regional train does not seem to be offering any particular advantage over the metro alternative. In the second trip, the station “*La Défense*” is served by Metro 1 but this time, contrary to the first case, transferring to the train service appears to be quite effective because of the significant gain of time that it provides over the metro alternative. It seems that for trips inside Paris, which are mostly of middle distance class, RER is more likely to be considered simply as a replacement to Metro. In the first trip, the traveler does not seem to feel any necessity to transfer to RER as he/she can find other equally efficient alternatives. On the contrary, in the second trip the traveler is quite motivated to make the transfer, i.e., by taking Metro he/she aims to access RER and does not afford to choose any other option. This is the reason why only in the second trip, one can recognize a feeder mode/main mode relationship. In fact, one can identify cases where RER and Metro are acting as two transit modes of two different hierarchical levels, but there other cases where such distinction is not clear. The regional train may be used over some short-range intra-Parisian itineraries due to better accessibility that it provides for some origins and destinations. It is only in long-range regional trips that RER can be recognized as an “inherently” more “necessary” mode.

Now, one may qualify our discussion as being biased by arguing that we had the undeniable advantage of having deliberately chosen our examples in favor of our purpose. The only conclusion that we hope to establish with regard to the implicit representation method is to stress its implicitness! The implicit representation, if carefully implemented, is indeed an effective modeling approach at least for two reasons: Firstly, it is less demanding in terms of empirical mobility data and spatial precision of the model. Secondly, it is technically simpler: modeling feeder mode and access station choice by explicit spatial representation requires more sophisticated assignment techniques. In the absence of an appropriate assignment tool, the modeler can still ameliorate the performance of his model by introducing composite mode alternatives in the mode choice stage using the implicit multimodal representation.

We conclude that the implicit representation of itineraries is a less systematic approach, i.e. the definition and composition of different composite modes as well as the distinction between different transit alternatives from the point of view of the mode choice behavior, cannot be set or understood independently of the context and the “subjectivity” of the modeler. For example, the fact that in the Parisian public transportation system some train services are

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comparably as effective as some metro lines over short- or midrange distances, or the way they are used by travelers to form multimodal itineraries, is the particularity of this territory and this situation may not appear in another context. Yet even in the Parisian context, two different models will not use the same set of composite modes due to different interpretations by different modelers. In summary, it is not always evident how a clear relation can be traced between an implicit representation and its behavioral implications as a composite mode. It depends largely on the geographical context, the quality of geographical transit supply, the density of the urban system ..., but especially on the practice of mobility.

From the mode choice modeling point of view, the contrast between the implicit and explicit approaches to the representation of multimodal trips, either in traffic or transit contexts, comes to the following inquiry: Is it a matter of mode choice or traffic/transit assignment? The implicit approach, as stated before, deals with the behavioral implications of multimodality in an indirect fashion via its implementation in the mode choice stage of the model; it is not a systematic approach and does not necessarily correspond to a concrete spatial representation. The explicit approach, on the other hand, explicitly recognizes the spatial dimension and proceeds systematically by representing the transportation network, the transit platforms or parking lots. It is disaggregate in the sense that traveler's residence and activity place are represented by their coordinates in their local spaces; and it is behavioral in the sense that the traveler at each instant of the trip is constantly presented by the set of alternative modal legs that are locally available. Elements such as feeder and main mode, access, transfer or egress points are all clearly identified. Contrary to the conventional mode choice modeling, where only the main travel mode is concerned, the explicit multimodal representation allows modeling the choice of the main mode within a comprehensive framework which views the entire chain of modal legs so that the choice of the main mode is conditioned by feeder modal legs and local spatial situations. Ultimately, it can be concluded that the implicit approach deals with multimodality at the higher mode choice stage whereas the explicit approach deals with multimodality as at a lower level as a combined mode choice and assignment problem based on the notion of modal legs.

Finally, it is worth reminding that our discussion applies only to the kind of feeder mode/main mode association that arises from multiple coexistent interconnected transit networks. This is not however the only kind of multimodality that a traveler may experience. Down at the transit assignment level, one question that remains unasked is with regard to the nature of multimodality. Is multimodality only arising from the way interconnected

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networks of different hierarchical levels interact to provide transit solutions to the traveler? Or can multimodality occur down within the same transit network with for instance, one metro service being systematically preferred to another metro service between two origin-destinations that they both serve? We shall not venture to complicate the landscape anymore as the implication of this particular multimodal behavior, whatever they are, certainly come second to the former case where transit modes of different hierarchical levels interact.

### 3. Mode Choice in a Multimodal Network

From a behavioral point of view, individual decides his mode of travel among a number of available modes organized in a particular structure. The two issues of availability and structure are addressed as *mode choice set identification* and *mode choice model specification*. The performance of a mode choice model in describing the individual behavior depends upon both its identification and specification qualities. In the former case, identifying an alternative that is not available in the real situation is both statistically and economically inconsistent. This is because, on one hand, the empirical observation database does not support that alternative and it does not suffice just to include “zero” observations as it results in a poorly estimated model; and on the other hand, there is an obvious behavioral distinction between “not choosing” and “not being able to choose”. In the latter case, specifying a choice structure unable to capture consistently the interdependencies among different available alternatives will result in a biased and behaviorally inappropriate model.

Sheffi and Daganzo (1980) study the equilibrium on a hypernetwork, where mode legs and route links can be represented together as hyperlinks. They consider a basic road network, connected to the origin and destination centroids by a number of access links. Links in the basic network are characterized by deterministic impedances. Impedance of an access link, on the other hand, is characterized as the sum of an average value and an unobserved additive disturbance, which varies from individual to individual according to a multivariate normal distribution. They work out the equilibrium state for such a hypernetwork. Their model takes into account only one level of randomness, which can be employed to account for either the variability due to stochastic spatial disaggregation, or the variability due to disturbance terms in the composition of modal utility functions. Our model however requires both.

According to our setting, disaggregate mode choice modeling in a multimodal context is subject to several levels of complexity:

First, in a multimodal network, there are different available modes and by each mode, there are a number of routes between the departure and arrival points.

Second, the abstraction of main transit section is an important modeling decision, which directly influences model performance. Some of the main decisions include:

- How to identify basic modes and decide, for instance: Whether Metro and Tramway are two different modes or can be regrouped as one single mode? Whether Bus functions as a feeder to heavier modes or should it be identified as a public mode fed by walk? ...
- How to represent a transit itinerary and identify legs. Whether a new leg corresponds to a change of service at a transit station (physical junction) or to a change of mode regardless of physical coordinates (modal junction)? ...
- How to account for order in the transit chain? For instance, is “Metro-Train” different from “Train-Metro”? ...

Eventually practical issues should also be taken into account. Limitations of GIS tools particularly may override many of the aforementioned modeling decisions.

Third, definition of anchor points is not straightforward. This is because the size of catchment area varies significantly among feeder modes. For example, auto feeder mode allows traveling relatively long distances to access far transit platforms whereas walk covers much shorter spans.

### 3.1. Joint Choice of Feeder mode and Access/Egress Stations

We simplify by assuming that given a mode, the traveler will always choose among all routes that are travelable by that mode, the route that offers the least generalized cost. Therefore, each mode is associated with the route that offers the least generalized cost. Therefore, the assignment of traffic to a multimodal network comes to the choice of the composite mode alternative, which offers the least generalized cost among all mode alternatives.

### 3.2. Mode Choice Set Identification

The identification problem has both temporal and spatial dimensions. The temporal choice set identification deals with the availability of travel modes

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during different periods (e.g., some bus services may not be functional during late hours). The spatial choice set identification, which is the subject of this chapter, deals with the availability of travel modes within different spatial unit (e.g., urban metro is not generally available at conurbation suburbs). From an econometric point of view, the spatial choice set identification aims to ameliorate the performance of the mode choice model by appropriating the mode choice set to the spatial context so that travelers are presented systematically with travel modes that, for instance, their residential zones provides.

Following the line of reasoning of the two preceding chapters, we distinguish between intrazonal and interzonal spatial scales. At intrazonal level, walk, bike, and auto are examples of feeder modes and intrazonal bus may be used as a feeder mode for transit network. At interzonal level, regional train and urban metro are examples of principal travel mode. For the public mode and the transit network, we identify major intrazonal transit platforms (e.g., train or metro stations) as anchor points. At the intrazonal level, available transit feeder modes are walk, bike, auto, and intrazonal bus. The walk and auto feeder modes (the later exclusively at the home end of the trip) are almost immediately accessible to the traveler. The bus feeder mode is a transit service, presenting the traveler with additional fares and wait time which itself should be accessed before being used as a feeder mode to heavier transit means (e.g., urban metro or regional train). We suppose that a bus stop can be accessed only by walk.

Between each pair of departure and arrival points, there exist a number of possible transit routes, which are identified as transit composite modes. Each route consists of two feeder sections at both ends of the trip and a main transit section in the middle. Transit composite mode alternatives are constructed by enumerating all plausible combinations of available access/main/egress modes. The main transit section contains a chain of transit means abstracted as a composite mode.

### 3.2.1. Main Transit Mode Abstraction

There are two levels of complexity. Firstly, the dense and highly interconnected structure of public transportation services in Ile-de-France allow for lots of different combinations between any pair of access and egress stations. For most of the cases, there are more than a few options available, which may include only one transit mean or a chain of a few means of different hierarchical levels. Secondly, and especially at close-to-center areas there are many transit stations which can provide access to transit services.

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Accounting for every single such combination is not plausible for the following reasons. Firstly, alternatives often become redundant. As a result, it might occur that even though the traveler has stated a particular path, the model is not able to provide a consistent econometrical explanation for preferring that particular path to other alternatives. For instance, a model that uses a fraction of the headway time as the traveler's wait time, will not be able to explain decisions that traveler has made using a precise timetable. This is related to our second reason: most applied assignment networks are not of such a precision to allow explaining stated route choice decisions. The third reason that we put forward is that many of the decisions may be made based on aspects that are absent from the model. For example, a particular route may be preferred over another because it is served by vehicles that are more comfortable, or because it involves less number of stairs at connections. Such details are usually not well represented in assignment models, and even most of the time, are totally left out of the scope of models.

On the contrary, changes between means of different hierarchical level reveal more significant behavioral aspects. That is, we no longer account for transfers between modes of the same hierarchical level (e.g., between two Metro services), instead we focus on transfers that occur between means of different hierarchical levels (e.g., from Metro to Train). In this way, we merge all Bus legs, all Metro legs and all Train legs together and measure total distances traveled on each level of transit means. The mean used over the longest portion of the trip, if it is of the highest hierarchical rank is considered as the main mean.

We adopt an identification of the main transit chain into 7 different composite mode alternatives including: Bus only, Metro only, Train only, Bus+Metro, Bus+Train, Metro+Train, and Bus+Metro+Train. We ignore the order in which transit modes are used. In order to decide which of the seven composite mode alternatives should be attributed to a given transit chain, we follow a distance based criterion. First, we calculate the total (i.e., cumulative) distance traveled on each mode:  $D_T$  for Train,  $D_M$  for Metro, and  $D_B$  for Bus. The flowchart of the Figure 7.2 describes the way main transit section is identified. A similar identification approach has been successfully implemented in the Parisian model, ANTONIN (cf. Chapter 2), and is preserved in its newer version ANTONIN-2.

The main transit section of the trip is contained by access and egress feeder sections. At the home-end, obvious feeder modes are walk, bike (private or public) and auto (driver or passenger). At the activity-end, the obvious feeder mode is walk; public bike and auto passenger modes may be observed but

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much rarer than walk<sup>1</sup>. We suppose that private bike and auto driver modes are not available at the activity-end of the trip.

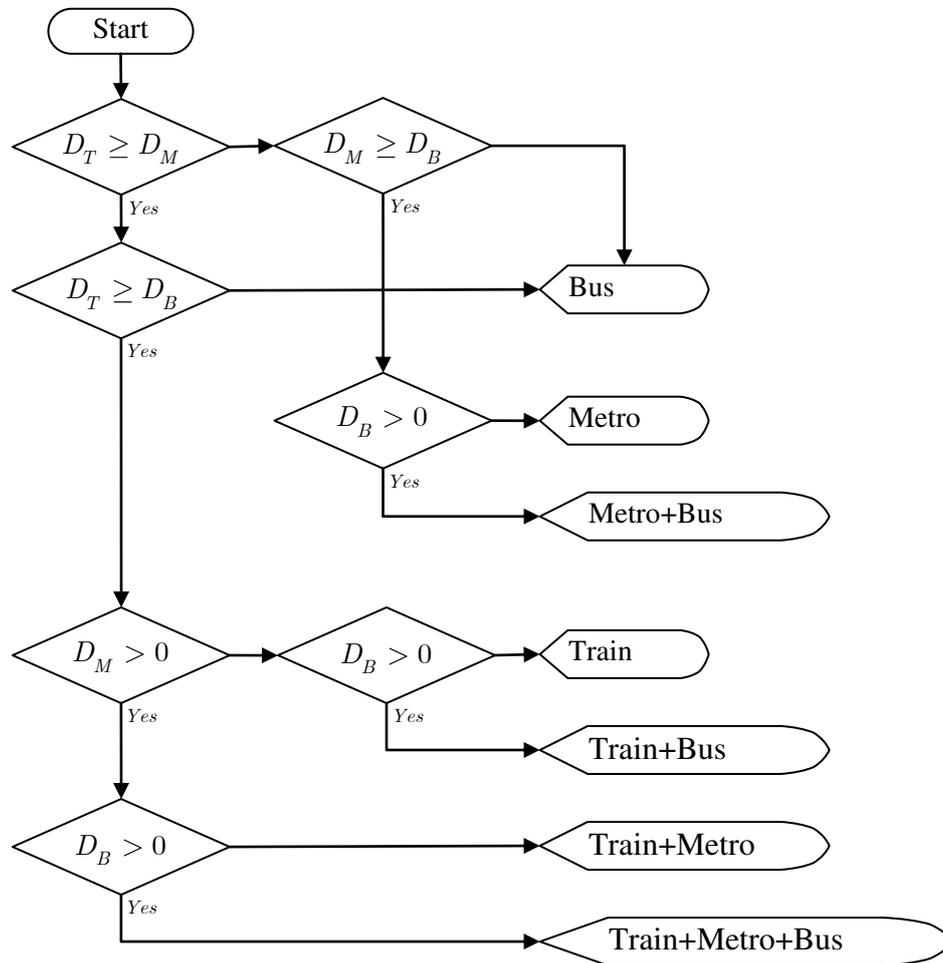


Figure 7.2. Identification of the main section transit alternatives.

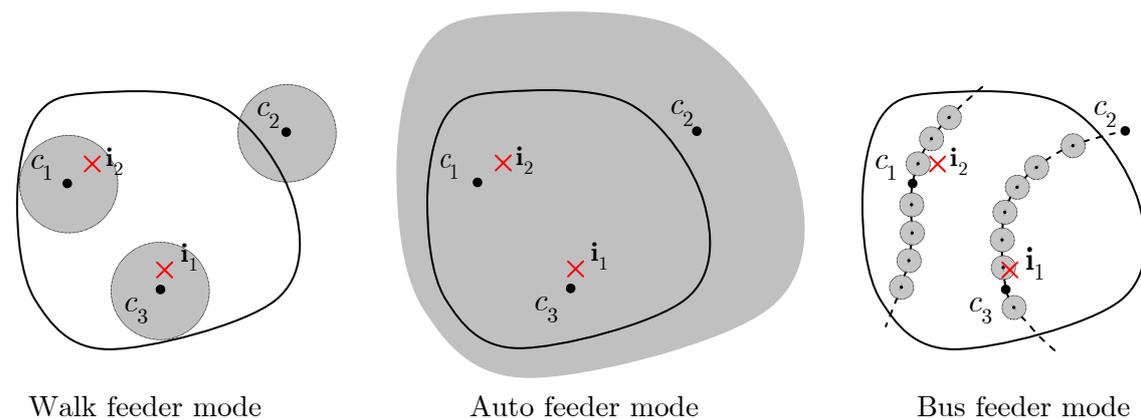
Bus is an intermediate transit mode: it can be used as a main transit mode over relatively short distances, and it can be used as a feeder for Metro/Train lines. In the latter case, it can compete with the auto as a fast feeder mode. Accordingly, we will design two transit trip simulators. In the first simulation design, we consider Bus only as a transit mode that can be chained to other transit modes in the main section of the route. If Bus is used as the first transit mean of the trip (or the last mean), the access mode of the whole trip is considered to be Walk (used to access the Bus stop). In the second simulation design, we recognize the bivalent role of Bus. If Bus is used as the first transit mode of the trip after an access Walk (or the last transit mean of the trip before an egress walk), it is considered as an access (or egress) feeder

<sup>1</sup> Paris area currently offers limited numbers of public automobiles, which also may be used for access or egress to/from the main transit section.

mode. If Bus is used within the main section, it is considered for identifying the appropriate main transit mode.

### 3.2.2. Local Feeder Mode Availability

Access and egress determine the availability of public transport (Krygsman et al., 2004, Murray, 2001, Ortúzar and Willumsen, 2001). For the walk feeder mode, we define a maximum access radius beyond which walk is considered as too costly to be used for access to a transit service. Although, the maximum access radius can be identified as a function of total travel characteristics (Krygsman et al., 2004); here we ignore such variability as the precision it provides is easily surpassed by the lack of precision in empirical database. The maximum access radius is bigger around major transit platforms and smaller around bus stops. The catchment area of the transit station is broader for bike feeder mode and it can grow even beyond zone boundaries for the auto feeder mode. This is illustrated in Figure 7.3, where  $c_i$  represents transit anchor points.



**Figure 7.3.** Catchment areas for different intrazonal transit feeder modes.

An individual  $i$ , depending on his/her intrazonal position and the anchor point that he/she intends to use for accessing the interzonal transit network, finds one or some of the feeder modes accessible. For instance,  $i_1$ 's feeder mode choice set is *bus, auto* for reaching  $c_2$ ; it is *walk, bus, auto* for reaching  $c_3$ . We call each one of these choice sets an *anchor-ward* choice set. It reflect the situation of an individual with respect to each one of the transit anchor points based on his/her disaggregate intrazonal position. An individual has as many anchor-ward choice sets as there are anchor points in the zone. The ensemble of an individual's anchor-ward choice sets is called a *zone-ward* choice set. For instance,  $i_1$ 's zone-ward choice set for reaching  $c_1, c_2, c_3$  is

*auto* , *bus,auto* , *walk,bus,auto* ; the same for the individual traveler  $i_2$  is *walk,auto* , *auto* , *auto* .

### 3.2.3. Enumeration of Transit Composite Modes

#### 3.2.3.1. Multimodal Path Enumeration Scheme I

In the Multimodal Path Enumeration Scheme I (MPES-I), access modes are Walk, Bike and Auto. The only egress mode is Walk. Bike and Auto feeder modes can only give access to Metro and Train stations whereas Walk can be used for all stations including Bus stops. The main section is associated with a main mode identified according to the flowchart of the Figure 7.2. The three access modes and one egress mode combined with the seven main transit alternative amount to a total number of 21 potentially identifiable transit composite mode alternatives (Figure 7.4).

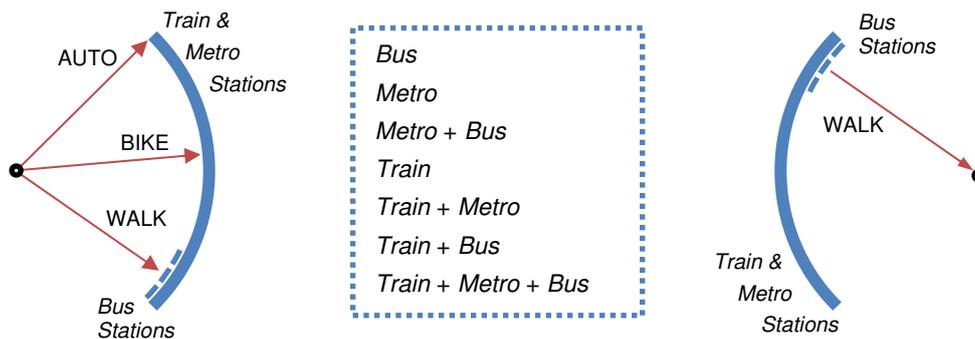


Figure 7.4. Multimodal Path Enumeration Scheme I (MPES-I).

#### 3.2.3.2. Multimodal Path Enumeration Scheme II

In the MPES-I, the Walk feeder mode can be used to access all stations including bus stops. At the regional scale however, most of the time, a Walk to Bus stop is followed by a short trip on board of Bus to a Train or Metro station. In other words, Bus is used to access Metro/Train stations: it is an access feeder mode. In a symmetrical way, Bus can also serve as an egress feeder mode. Identifying Bus as a distinct feeder mode has at least two advantages: Firstly, it helps to homogenize the hierarchical level of transit stations that are explicitly represented. Secondly, in Ile-de-France there are some ten times as many Bus stops as there are Metro/Train stations. Therefore, dealing with Bus stops within the Bus access leg, dramatically decreases the number of potential anchor points that should be identified per zone.

In the Multimodal Path Enumeration Scheme II (MPES-II), access modes are Walk, Bus, Bike and Auto. Egress modes are Walk and Bus. The main section is associated with a main mode identified according to the flowchart of the Figure 7.2. The four access modes and two egress modes combined with the seven main transit modes amount to a total number of 56 potentially identifiable transit composite mode alternatives. Contrary to the MPES-I, here Bus stops are distinguished from Metro and Train stations and main section can only start and end at Metro/Train stations. Walk, Bike, and Auto access modes as well as Walk egress mode only feed Metro/Train stations. For using the Bus feeder mode for access and egress, local Bus stops are accessed by a short walk (Figure 7.5).



Figure 7.5. Multimodal Path Enumeration Scheme II (MPES-II).

### 3.3. Reconstruction of Competing Mode Alternatives

Observed travel behavior reported in a travel survey usually involves a series of choices that the traveler makes with respect to different aspects of the travel such as destination, mode, route, and departure time. As for the choice of the mode of transportation, the survey reports the chosen mode, with some level of detail on the chain of means, and the mechanical characteristics of the trip. Traveler's choice reflects his/her perception of the utility of different available alternative options. For modeling purpose, the analyst has to reconstruct the different alternatives choice options that are identified in the choice set.

Each traveler states the “composite” mode he/she has taken for his/her travel (in fact, the traveler states his/her route from which the analyst deduces the composite mode). In order to be able to measure the competitiveness of the chosen mode compared to other modal alternatives, we need to investigate other alternative options.

In order to estimate a mode choice model based on data from a state's preferences survey, it is mandatory first to provide travel characteristics for all

competing modes that are included in traveler's choice set. Because usually surveys provide travel characteristics only for the used mode, characteristics of the competing alternatives should be simulated.

The simulator explores all possible transit routes and among all routes of the same composite mode, the one offering the least generalized cost is included in the modal choice set to compete with other modal alternatives. The investigation should be carried out in two steps: first, the transit shortest path should be found between a pair of access and egress stations. Then, the investigation should be carried out through different possible pairs of access and egress stations to identify the route that offers the absolute minimum generalized cost per composite mode.

We define  $\mathbf{H}$  as the set of all home places and  $\mathbf{W}$  as the set of all work places, where  $H_i \in \mathbf{H}$  and  $W_i \in \mathbf{W}$  respectively represent home and workplace for an individual  $i$ . We define  $\mathbf{C}$  as the set of all public transportation stations and  $\mathbf{C} = C_B \cup C_M \cup C_R$ , where  $C_B$  is the set of all bus stations,  $C_M$  is the set of all metro stations, and  $C_R$  is the set of all RER and train stations.  $C_o \subset \mathbf{C}$  is the set of all transit access stations at origin, and  $c_\alpha \in C_o$  is a transit station at origin.  $C'_d \subset \mathbf{C}$  is the set of all transit egress stations at destination, and  $c'_\beta \in C'_d$  is a transit station at destination. Then we define  $\mathbf{T} = [T_{\alpha\beta}]$  as the matrices of station-to-station detailed level-of-services.

### 3.3.1. Identification of Transit Stations: MPES-I

For each access mode, we define the set of available access stations for the individual  $i$  in the following way:

$$C_{io}^{walk} = c_\alpha \in \mathbf{C} \mid d(H_i, c_\alpha) < L^{walk} \quad (7.1)$$

$$C_{io}^{bike} = c_\alpha \in C_M \cup C_R \mid d(H_i, c_\alpha) < L^{bike} \quad (7.2)$$

$$C_{io}^{auto} = c_\alpha \in C_M \cup C_R \mid d(H_i, c_\alpha) < L^{auto} \quad (7.3)$$

For the walk egress mode, we define the set of available egress stations for the individual  $i$  in the following way:

$$C_{id}^{walk} = c'_\beta \in \mathbf{C} \mid d c'_\beta, W_i < L^{walk} \quad (7.4)$$

where  $d \cdot$  is the directional physical distance operator.

### 3.3.2. Identification of Transit Stations: MPES-II

For each access mode, we define the set of available access stations for the individual  $i$  in the following way:

$$C_{io}^{walk} = c_\alpha \in C_M \cup C_R \mid d H_i, c_\alpha < L^{walk} \quad (7.5)$$

$$C_{io}^{bus} = c_\alpha \in C_M \cup C_R \mid T c_\varphi, c_\alpha < T_L^{bus}; c_\varphi \in C_B, d H_i, c_\varphi < L^{bus} \quad (7.6)$$

$$C_{io}^{bike} = c_\alpha \in C_M \cup C_R \mid d H_i, c_\alpha < L^{bike} \quad (7.7)$$

$$C_{io}^{auto} = c_\alpha \in C_M \cup C_R \mid d H_i, c_\alpha < L^{auto} \quad (7.8)$$

For the walk egress mode, we define the set of available egress stations for the individual  $i$  in the following way:

$$C_{id}^{walk} = c'_\beta \in C_M \cup C_R \mid d c'_\beta, W_i < L^{walk} \quad (7.9)$$

$$C_{id}^{bus} = c'_\beta \in C_M \cup C_R \mid T c'_\beta, c'_\psi < T_L^{bus}; c'_\psi \in C_B, d c'_\psi, W_i < L^{bus} \quad (7.10)$$

where  $d \cdot$  is the directional physical distance operator.

### 3.3.3. Shortest Path Search Procedure

The procedure for exploring all modal shortest paths between a departure point  $H_i \in \mathbf{H}$  and an arrival point  $W_i \in \mathbf{W}$  is given in Table 7.1.

**Table 7.1. Procedure for modal shortest path search.**

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1. for access mode  $a \in M_o$  and egress mode  $e \in M'_d$ :
    - a. create  $C_{io}^a$  and  $C_{id}^e$  transit station sets,
  2. for  $c_\alpha \in C_{io}^a$  and  $c_\beta \in C_{id}^e$ :
    - a. read shortest path characteristics  $T_{\alpha\beta}^* = \left\{ T_{\alpha\beta}^{s*}, T_{\alpha\beta}^{c*} \right\}$
    - b. use  $T_{\alpha\beta}^{s*}$  to detect main mode (c.f. Figure 7.2) as  $p$
    - c. determine composite mode  $m = a, p, e$
    - d. use  $T_{\alpha\beta}^{c*}$  to calculate the temporary generalized cost  $GC^*$
    - e. if  $GC^* < GC_{min}^m$  then
      - i. assign  $GC_{min}^m = GC^*$
      - ii. assign  $T_{\alpha\beta_{min}}^c = T_{\alpha\beta}^{c*}$
    - f. save  $T_{\alpha\beta_{min}}^c$  for all  $m$
  3. iterate over Step 2.
  4. iterate over Step 1.
- 

In the procedure of the Table 7.1,  $M_o$  and  $M'_d$  represent access and egress feeder mode sets, respectively. For the Multimodal Path Enumeration Scheme I the two sets are,

$$M_o = \text{walk, bike, auto} \quad ; \quad M'_d = \text{walk}$$

whereas for the Multimodal Path Enumeration Scheme II the two sets are,

$$M_o = \text{walk, bus, bike, auto} \quad ; \quad M'_d = \text{walk, bus}$$

Also,  $a$ , counts access feeder modes,  $p$ , counts main transit modes,  $e$ , counts egress feeder modes, and  $m$ , counts composite modes.  $GC^*$  is the generalized cost of the current transit route.  $GC_{min}^m$  is the minimum generalized cost offered by a transit route of composite mode  $m$ , up to the current iteration.

$T_{od}^*$  is the vector of current transit route characteristics.  $T_{od}^{s*}$  is the vector of current route skim characteristics used to identify the main transit

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mode,  $p$ , according to the flowchart of the Figure 7.2.  $T_{od}^{c*}$  is the vector of current route level-of-service characteristics.  $T_{od_{min}}^{c_m}$  is the vector of level-of-service characteristics of the route offering the minimum generalized cost, up to the current iteration.

## 4. Mode Choice with Trip-end Disaggregation

### 4.1. Mode Choice model Specification

Let us consider a decomposition of a public transportation itinerary into three legs with  $\bar{a}$  access modes,  $\bar{p}$  main mean chains, and  $\bar{e}$  egress modes, amounting to a total number of  $\bar{m} = \bar{a} \times \bar{p} \times \bar{e}$  compost modes. The choice probability of mode  $m = 1 \cdots \bar{m}$  is given by:

$$\Pr m = \Pr \left[ \tilde{U}_m > \max_{n \neq m} \tilde{U}_n \right] \tag{7.11}$$

where  $U_m$  is the random utility of composite mode  $m$ , and  $m = a, p, e$  :

$$\tilde{U}_m = V_m + \tilde{\varepsilon}_m \quad ; \quad V_m = -GC_m \tag{7.12}$$

where  $V_m$  is the systematic part of the utility,  $GC_m$  is the generalized cost (i.e., disutility), and  $\tilde{\varepsilon}_m$  represents the random part of the utility. We consider the following composition for the systematic utility:

$$-V_m = \delta_m + \alpha \tau_a + \sum_{\iota} \gamma_{\iota} \theta_{p_{\iota}} + \beta \tau_e' \tag{7.13}$$

where  $\delta_m$  is the alternative specific constant,  $\alpha$  is the coefficient for the access time,  $\tau_a$ ,  $\gamma_{\iota}$  are coefficients for the main transit section level-of-service characteristics,  $\theta_{p_{\iota}}$ , and  $\beta$  is the coefficient for the egress time,  $\tau_e'$ . To these composite transit mode utilities, we add one final utility for the Auto mode,

$$-V_{auto} = \gamma_{auto} \theta_{auto} \tag{7.14}$$

where  $\gamma_{auto}$  is the coefficient for the total auto travel time  $\theta_{auto}$ .

Different discrete choice models can be specified, depending on the definition of random error terms,  $\tilde{\varepsilon}_m$ . For instance, where the random terms follow Multivariate Normal distribution,

$$\left[ \tilde{\varepsilon}_m \right] \sim \text{MVN } \mathbf{0}, \left[ \nu_{mm'} \right] \quad (7.15)$$

where  $\left[ \tilde{\varepsilon}_m \right]$  is the vector of  $\tilde{\varepsilon}_m$ , and  $\left[ \nu_{mm'} \right]$  is the associated covariance matrix, the resulting model will be Multinomial Probit. Accordingly, we have:

$$\left[ \tilde{U}_m \right] \sim \text{MVN } \left[ V_m \right], \left[ \nu_{mm'} \right] \quad (7.16)$$

In practice however, GEV-based family of models, such as Multinomial Logit and Nested Logit, offer more convenience in both estimation and evaluation stages, thanks to their closed form solutions.

## 4.2. Stochastic Representation of Disaggregate Trip-ends:

Let us consider  $\bar{i}$  anchor points at origin, and  $\bar{j}$  anchor points at destination amounting to a total number of  $\bar{g} = \bar{i} \times \bar{j}$  pairs of anchor points. Based on a stochastic representation of the intrazonal space, and similar to the treatment of terminal times in a monomodal network (cf. Chapter 5), the access terminal time by feeder mode  $a$ , to anchor point  $i$ , at the origin can be specified as:

$$\left[ \tilde{\tau}_{ai} \right] \sim \text{MVN } \left[ \bar{\tau}_{ai} \right], \left[ \sigma_{ii'}^{aa'} \right] \quad (7.17)$$

Similarly, on the destination side, the egress travel time by feeder mode  $e$ , to anchor point  $j$ , can be specified as::

$$\left[ \tilde{\tau}'_{ej} \right] \sim \text{MVN } \left[ \bar{\tau}'_{ej} \right], \left[ \sigma_{jj'}^{ee'} \right] \quad (7.18)$$

These are what we call zone-ward terminal time vectors, combining feeder modes and access stations in one stochastic structure. Assuming that feeder modes at both origin and destination are independent, the spatial dispersion remains as the only source of covariance. Therefore,  $\left[ \tilde{\tau}_{ai} \right]$  and  $\left[ \tilde{\tau}'_{ej} \right]$  can be uncoupled into so-called mode-wisely independent anchor-ward terminal time vectors. At the origin zone, we obtain:

$$\left[ \tilde{\tau}_i \right]_a \sim \text{MVN } \left[ \bar{\tau}_i \right]_a, \left[ \sigma_{ii'} \right]_a \quad (7.19)$$

Similarly, at the destination zone, we obtain:

$$\left[ \tilde{\tau}'_j \right]_e \sim \text{MVN } \left[ \bar{\tau}'_j \right]_e, \left[ \sigma'_{jj'} \right]_e \quad (7.20)$$

In this manner, terminal modal legs acquire explicit spatial dimension. This provides the required basis for addressing behavioral variability in mode choice, and physical variability due to disaggregate trip-ends, within one single framework. Based on the Equation 7.13, we define  $\tilde{V}_{mg}$ , as the systematic utility of choosing a composite mode  $m = a, p, e$ , over the route identified by a pair of anchor points  $g = i, j$  :

$$-\tilde{V}_{mg} = \delta_m + \alpha \tilde{\tau}_{ai} + \sum_t \gamma_t \theta_{pij,t} + \beta \tilde{\tau}'_{ej} \quad (7.21)$$

Using the uncoupled specification of terminal travel times, according to the Equations 7.19 and 7.20, spatially explicit systematic utility vector is itself Multivariate Normal, and uncoupled with respect to travel mode. Therefore, we have:

$$[\tilde{V}_g]_m \sim \text{MVN} [\bar{V}_g]_m, [\Sigma_{gg'}]_m \quad (7.22)$$

where  $[\bar{V}_g]_m$  is the vector of mean utility values,

$$\bar{V}_{mg} = \delta_m + \alpha \bar{\tau}_{ai} + \sum_t \gamma_t \theta_{pij,t} + \beta \bar{\tau}'_{ej} \quad (7.23)$$

and  $[\Sigma_{gg'}]_m$  is the covariance matrix associated with terminal travel times and representing the variability due to disaggregate trip-ends at origin and destination. Supposing that terminal travel times at origin and terminal travel times at destination are independent,

$$\Sigma_{gg'}^m = \alpha^2 \sigma_{ii'}^a + \beta^2 \sigma_{jj'}^e \quad (7.24)$$

In these equations,  $m$  counts  $a, p, e$  combinations of composite modes, and  $g$  counts  $i, j$  combinations of anchor points. Also,  $m'$  and  $g'$  correspond to  $a', p', e'$  and  $i', j'$  respectively.

### 4.3. Joint Model of Mode and Anchor Pair Choice:

The probability of choosing mode  $m$  between anchor pair  $g$  is given by:

$$\Pr m, g = \Pr \left[ \tilde{U}_{mg} > \max_{n \neq m; h \neq g} \tilde{U}_{nh} \right] \quad (7.25)$$

where,

$$\left[ \tilde{U}_{mg} \right] \sim \text{MVN} \left[ \bar{V}_{mg} \right], \left[ \Sigma_{gg'} \right]_m + \left[ \nu_{mm'} \right] \quad (7.26)$$

This is new expanded Multinomial Probit model, which can be solved using Clark's method within controlled error margins.

It is worth mentioning that if the mode choice model is GEV-based, appropriate scaling should be applied to  $\left[ \nu_{mm'} \right]$ , before assembling it to the origin-destination covariance matrices,  $\left[ \Sigma_{gg'} \right]_m$ .

# Chapter 8: Mode Choice in a Multimodal Network: Implementation with Application to Ile-de-France

## 1. Introduction

In this chapter, the aim is to implement the joint mode and anchor pair choice model with disaggregate treatment of trip-ends to the study of a specific demand segment. For this application, our study demand segment consists of commuters that come from single active households, who own at least one vehicle (see, Chapter 3).

Firstly, we estimate mode choice models based on the two Multimodal Path Enumeration Schemes I and II (MPES-I and MPES-II). We simulate level-of-service characteristics, according to the MPES-I and MPES-II. Then we use results to estimate discrete choice models, particularly with Multinomial and Nested Logit specifications.

Secondly, we add incorporate the explicit representation of space. We combine the mode choice model with a station choice layer to combine physical variability due to scatteredness of trip-ends over the space with behavioral variability due to unobserved (or unobservable) behavior of travelers. We demonstrate the model for an origin-destination relation.

The description of the travel demand is from the 2001 Paris Household Travel Survey. The description of the transportation supply is reconstructed using data from DRIEA (Highway and Public Transportation networks) and IGN (high-precision street network).

## 2. Reconstruction of Transportation Networks

We use three different networks to reconstruct a fully detailed representation of the Ile-de-France transportation supply. The Ile-de-France roadway and transit networks are reconstructed using data from DRIEA, which describe the two regional networks in their 2008 state. Street level network is from IGN's BD TOPO<sup>®</sup> database. These detailed data are required to represent terminal trip sections, realistically.

Transit access/egress legs, especially in case of slow modes, such as walk, are short span and usually do not extend outside zonal boundaries in a standard urban zoning system. As a result simulating level-of-services for these legs requires a high-resolution representation of local networks. Because the BD TOPO<sup>®</sup> database is a merely geographic one and does not provide characteristics such as free flow speed, capacity, etc. Therefore, we assign plausible walk, bike, and auto free flow speeds to different street types shown in the Table 8.1. Only for the walk mode, street directions are ignored. In addition, some street types are not permitted for some modes: these are

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designated by N/A. Street layer is connected to the highway layer at matching nodes to ensure the articulation between local and regional networks. Link travel times are calibrated based on the stated travel times from the commuters in the survey. It should be commented that the street and highway layers include many redundant links particularly corresponding to highways and semi-highways.

**Table 8.1. Free flow speed attributed to different road types in BD TOPO<sup>®</sup> network.**

Road Type	Walk	Bike	Auto
Highway ( <i>autoroute</i> )	N/A	N/A	20 Km/h, before access to highway network
Semi-Highway ( <i>quasi-autoroute</i> )	N/A	N/A	20 Km/h, before access to highway network
Dual carriageway ( <i>route à 2 chaussées</i> )	5 Km/h	20 Km/h	20 Km/h, before access to highway network
Single carriageway ( <i>route à 1 chaussée</i> )	5 Km/h	20 Km/h	20 Km/h, before access to highway network
Stone-paved road ( <i>route empierrée</i> )	5 Km/h	15 Km/h	N/A
Byway ( <i>chemin</i> )	5 Km/h	15 Km/h	N/A
Trail ( <i>sentier</i> )	5 Km/h	15 Km/h	N/A
Elevated path ( <i>escalier</i> )	5 Km/h	15 Km/h	N/A
Bikepath ( <i>piste cyclable</i> )	N/A	20 Km/h	N/A

### 3. Estimation of Mode Choice Models

For model estimation, we use MDC (multinomial discrete choice) procedure in SAS statistics package. It is capable of estimating Conditional Logit, Mixed Logit, Heteroscedastic Extreme-value, Nested Logit, and Multinomial Probit models. It uses Maximum Likelihood or Simulated Maximum Likelihood methods for estimation. We will test Conditional Logit and Nested Logit model specifications.

#### 3.1. Explanatory variables

We consider two families of explanatory variables. First, we use level of service characteristics to specify a mode choice model. Then we will introduce individual attributes to augment the explanatory power of the model. We

consider a linear-in-parameter utility function, which is identical for all mode alternatives except for an alternative specific constant.

For the auto mode, we consider the total physical travel time (AUTOT) as the only explanatory variable. For public transportations, we consider two ranges of variables: line-haul characteristic variables and feeder characteristic variables. In-vehicle travel time (IVT), Dwelling time (DWT), Initial wait time (IWT), Transfer wait time (XWT), Transfer walk time (XMT), and Number of transfers (NX) represent line-haul level-of-services. We also define two auxiliary variables: Line-haul time (LTH) equal to the sum of In-vehicle time and Dwelling time, and Total wait time (TWT) equal to the sum of Initial wait time and Transfer wait time.

As regards feeder mode characteristics, we distinguish between the Multimodal Path Enumeration Schemes I and II. In the MPES-I, Access time (ACCT) and Egress time (EGRT) represent feeder level-of-services. In the MPES-II, there is a particularity with regard to the Bus feeder mode. If the feeder mode is Bus, ACCT and EGRT represent the walk access to Bus stop. In addition, two more variables are defined at both ends. These include Access In-vehicle time (ACCIVT) and Access Initial wait time (ACCIWT) at home-end, and Egress In-vehicle time (EGRIVT) and Egress Initial wait time (EGRIWT) at work-end. We also define two auxiliary variables ACCGT and EGRGT, which represent generalized access and egress travel times.

Alternative specific constants are associated with transit modes; variable identifier is composed of "DUM" followed by the number of transit composite mode (e.g., DUM01, DUM02 ...).

As for individual attributes, we consider nine flag variables. EMPARK is 1 if a dedicated free parking place is available at work, or if workplace is outside Paris and Hauts-de-Seine (the two main business districts), in which case there is a good chance of finding a free place on street. SEXMAL is 1 if the traveler is a male. PTPASS is 1 if the traveler holds a public transportations pass. HFPARK is 1 if the traveler has access to free parking at home. INDCOL is 1 if the traveler is in individual housing (as opposed to collective housing), HZSECL is 1 if home is outside Paris. WZSECL is 1 if workplace is outside Paris, ICSP is 1 if commuter's socio-professional category is Managers and professional, Intermediate professions, or Employees; it is 0 if the commuter is in Farmers, Tradesmen, the self-employed and business owners, or Unskilled workers. IAGE is 1 if traveler is in 35 to 54 year old age range.

Individual attribute variables are added to the utility function of transit modes to influence their competitiveness against auto. Their coefficients are bound to be identical.

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### 3.2. Multimodal Path Enumeration Scheme I

Let us  $a \in 1: walk, 2: bike, 3: auto$  count access feeder modes,  $e \in 1: walk$  count egress feeder modes, and count main transit modes according to the following Table 8.2:

**Table 8.2. Main Transit Mode IDs.**

Main Transit Mode ID	Included Transit Components		
	Train	Metro	Bus
1	✓		
2		✓	
3			✓
4	✓	✓	
5	✓		✓
6		✓	✓
7	✓	✓	✓

We enumerate composite modes and assign to each mode a number,  $m$ , according to the following formula:

$$m = a + 3 p - 1 \quad (8.1)$$

Brut enumeration of composite modes will result in 21 potential transit composite modes. To these modes, we add auto as the 22th mode. Not all of these modes are practiced in reality. We use the observation database to rule out unobserved alternatives. Table 8.3 shows those mode IDs that are used by commuters of the study demand segment, according to the 2001 Paris Household Travel Survey. There are 14 effective mode alternatives.

The auto mode has the highest share with more than 72% of the trips. Among transit modes, those with Walk access have the highest share, followed by the auto access and bike access.

**Table 8.3. Effective modes after eliminating impractical transit chains (MPES-I).**

Mode ID	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	78	4.26	78	4.26
2	1	0.05	79	4.32
3	24	1.31	103	5.63
4	83	4.54	186	10.16
6	8	0.44	194	10.60
7	57	3.11	251	13.72
10	75	4.10	326	17.81
11	1	0.05	327	17.87
12	22	1.20	349	19.07
13	71	3.88	420	22.95
15	9	0.49	429	23.44
16	27	1.48	456	24.92
19	47	2.57	503	27.49
22	1327	72.51	<b>1830</b>	<b>100</b>

**Error! Not a valid bookmark self-reference.** summarizes the 13 effective transit composite modes in detail. These modes are considered for mode choice model estimation. These are observed among the 21 identified alternatives of the MPES-I, and the Auto mode is the 22nd mode.

**Table 8.4. Mode IDs in Multimodal Path Enumeration Scheme I.**

Mode ID	Access Mode			Main Transit Mode		
	Walk	Bike	Auto	Train	Metro	Bus
1	✓			✓		
2		✓		✓		
3			✓	✓		
4	✓				✓	
6			✓		✓	
7	✓					✓
10	✓			✓	✓	
11		✓		✓	✓	
12			✓	✓	✓	
13	✓			✓		✓
15			✓	✓		✓
16	✓				✓	✓
19	✓			✓	✓	✓

### 3.2.1. Multinomial Logit Specification

#### 3.2.1.1. Basic Model

In the basic model, we only include level-of-service explanatory variables. Table 8.5a shows the initial Multinomial Logit model estimation summary for the Multimodal Path Enumeration Scheme I, and Table 8.5b shows estimation results.

**Table 8.5a. Initial basic MNL model estimation summary (MPES-I).**

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<b>Model Fit Summary</b>	
Number of Observations	1542
Number of Cases	17336
Log Likelihood	-1401
Log Likelihood Null (LogL(0))	-3652
Maximum Absolute Gradient	1.40E-09
Number of Iterations	9
Optimization Method	Newton-Raphson
AIC	2846
Schwarz Criterion	2963

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Table 8.5b. Initial basic MNL model estimation results (MPES-I).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0557	0.0126	-4.43	<.0001
DWT	1	0.0194	0.0291	0.67	0.5044
IWT	1	-0.1271	0.0247	-5.14	<.0001
XWT	1	-0.1010	0.0198	-5.09	<.0001
XMT	1	-0.0508	0.0478	-1.06	0.2886
NX	1	-0.2252	0.1055	-2.14	0.0327
ACCT	1	-0.1293	0.009371	-13.79	<.0001
EGRT	1	-0.1223	0.0103	-11.86	<.0001
AUTOT	1	-0.1120	0.009659	-11.59	<.0001
DUM01	1	0.5817	0.2933	1.98	0.0474
DUM02	1	-5.2072	1.0317	-5.05	<.0001
DUM03	1	-2.0663	0.3294	-6.27	<.0001
DUM04	1	0.0931	0.2145	0.43	0.6644
DUM06	1	-3.5190	0.4230	-8.32	<.0001
DUM07	1	-1.3411	0.2221	-6.04	<.0001
DUM10	1	0.4099	0.2891	1.42	0.1563
DUM11	1	-5.1774	1.0314	-5.02	<.0001
DUM12	1	-2.0596	0.3281	-6.28	<.0001
DUM13	1	-0.3199	0.2867	-1.12	0.2645
DUM15	1	-3.1226	0.4143	-7.54	<.0001
DUM16	1	-1.4510	0.2928	-4.96	<.0001
DUM19	1	-0.4550	0.3263	-1.39	0.1631

Except for DWT and XMT, all level-of-service variable estimations are significant and of expected sign. DWT does not behave conveniently. The solution would be either to eliminate it or to combine it with IVT in LHT. The estimation log-likelihood for the model with only IVT remains -1401; it is equal to -1403 for the model with LHT. Moreover, in the model with only IVT, the t-test probability for NX increases from 0.033 to 0.043 whereas for the model with LHT it reaches 0.085. Finally, we choose to exclude DWT as it is neither significant nor of good sign.

The final model estimation is summarized in Table 8.6a, and Table 8.6b shows the estimation results:

**Table 8.6a. Final basic MNL model estimation summary (MPES-I).**

---

<b>Model Fit Summary</b>	
Number of Observations	1542
Number of Cases	17336
Log Likelihood	-1401
Log Likelihood Null (LogL(0))	-3652
Maximum Absolute Gradient	1.23E-09
Number of Iterations	9
Optimization Method	Newton-Raphson
AIC	2844
Schwarz Criterion	2956

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Table 8.6b. Final basic MNL model estimation results (MPES-I).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0502	0.009395	-5.34	<.0001
IWT	1	-0.1312	0.0240	-5.46	<.0001
XWT	1	-0.1044	0.0192	-5.43	<.0001
XMT	1	-0.0530	0.0477	-1.11	0.2664
NX	1	-0.2047	0.1009	-2.03	0.0425
ACCT	1	-0.1295	0.009375	-13.81	<.0001
EGRT	1	-0.1224	0.0103	-11.87	<.0001
AUTOT	1	-0.1111	0.009576	-11.60	<.0001
DUM01	1	0.6298	0.2846	2.21	0.0269
DUM02	1	-5.1626	1.0296	-5.01	<.0001
DUM03	1	-2.0206	0.3225	-6.27	<.0001
DUM04	1	0.1507	0.1962	0.77	0.4424
DUM06	1	-3.4667	0.4156	-8.34	<.0001
DUM07	1	-1.2909	0.2088	-6.18	<.0001
DUM10	1	0.4525	0.2823	1.60	0.1089
DUM11	1	-5.1405	1.0300	-4.99	<.0001
DUM12	1	-2.0230	0.3238	-6.25	<.0001
DUM13	1	-0.2711	0.2773	-0.98	0.3284
DUM15	1	-3.0785	0.4091	-7.53	<.0001
DUM16	1	-1.3867	0.2761	-5.02	<.0001
DUM19	1	-0.4119	0.3199	-1.29	0.1979

According to the estimation, the travel time in automobile is estimated 2.21 times costlier than the transit in-vehicle time. Initial wait and Transfer wait times are 2.61 and 2.08 times costlier than the transit in-vehicle time, respectively. Transfer walk time is only 1.06 times costlier than the transit in-vehicle time. Access and egress travel times are 2.58 and 2.44 times costlier than the transit in-vehicle time, respectively.

### 3.2.1.2. Enhanced Model

In the enhanced model, we add individual attributes as explanatory variables to the model. Table 8.7a shows the initial Multinomial Logit model estimation

summary for the Multimodal Path Enumeration Scheme I, and Table 8.7b shows estimation results.

**Table 8.7a. Initial enhanced MNL model estimation summary (MPES-I).**

<b>Model Fit Summary</b>	
Number of Observations	1453
Number of Cases	16370
Log Likelihood	-968.475
Log Likelihood Null (LogL(0))	-3445
Maximum Absolute Gradient	0.27673
Number of Iterations	153
Optimization Method	Dual Quasi-Newton
AIC	1995
Schwarz Criterion	2148

Table 8.7b. Initial enhanced MNL model estimation results (MPES-I).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0634	0.0129	-4.92	<.0001
IWT	1	-0.1082	0.0294	-3.68	0.0002
XWT	1	-0.0431	0.0241	-1.79	0.0737
XMT	1	-0.1036	0.0572	-1.81	0.0702
NX	1	-0.3921	0.1252	-3.13	0.0017
ACCT	1	-0.1347	0.008225	-16.38	<.0001
EGRT	1	-0.1149	0.0110	-10.42	<.0001
AUTOT	1	-0.0992	0.0137	-7.23	<.0001
DUM01	1	-0.8191	0.5519	-1.48	0.1377
DUM02	1	-8.5007	103.3579	-0.08	0.9345
DUM03	1	-3.5043	0.5960	-5.88	<.0001
DUM04	1	-1.2029	0.4899	-2.46	0.0141
DUM06	1	-5.1354	0.6155	-8.34	<.0001
DUM07	1	-2.2252	0.4923	-4.52	<.0001
DUM10	1	-0.8227	0.5512	-1.49	0.1356
DUM11	1	-6.6258	1.1248	-5.89	<.0001
DUM12	1	-3.4265	0.6015	-5.70	<.0001
DUM13	1	-1.7247	0.5410	-3.19	0.0014
DUM15	1	-4.3415	0.6217	-6.98	<.0001
DUM16	1	-2.6084	0.5449	-4.79	<.0001
DUM19	1	-1.7855	0.5752	-3.10	0.0019
EMPARK	1	-1.0168	0.2538	-4.01	<.0001
SEXMAL	1	-0.2967	0.2374	-1.25	0.2115
PTPASS	1	4.5120	0.2462	18.32	<.0001
HFPARK	1	-0.1235	0.2402	-0.51	0.6070
INDCOL	1	0.2462	0.3126	0.79	0.4310
HZSECL	1	0.6931	0.2818	2.46	0.0139
WZSECL	1	-0.6984	0.2694	-2.59	0.0095
ICSP	1	0.1280	0.3070	0.42	0.6768
IAGE	1	0.1471	0.2177	0.68	0.4993

The estimation of four of the individual attributes is insignificant: HFPARK, INDCOL, ICSP, and IAGE. By excluding these variables from the model, we obtain the final enhanced MNL model. The final MNL estimation is summarized in Table 8.8a, and Table 8.8b shows estimation results.

**Table 8.8a. Final enhanced MNL model estimation summary (MPES-I).**

<b>Model Fit Summary</b>	
Number of Observations	1542
Number of Cases	17336
Log Likelihood	-1034
Log Likelihood Null (LogL(0))	-3652
Maximum Absolute Gradient	0.47745
Number of Iterations	141
Optimization Method	Dual Quasi-Newton
AIC	2120
Schwarz Criterion	2259

Table 8.8b. Final enhanced MNL model estimation results (MPES-I).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0610	0.0124	-4.94	<.0001
IWT	1	-0.1135	0.0280	-4.05	<.0001
XWT	1	-0.0458	0.0231	-1.99	0.0470
XMT	1	-0.1124	0.0561	-2.00	0.0452
NX	1	-0.3790	0.1213	-3.12	0.0018
ACCT	1	-0.1361	0.008037	-16.93	<.0001
EGRT	1	-0.1147	0.0109	-10.56	<.0001
AUTOT	1	-0.0983	0.0130	-7.58	<.0001
DUM01	1	-0.4436	0.4217	-1.05	0.2929
DUM02	1	-6.3823	1.1782	-5.42	<.0001
DUM03	1	-3.1520	0.4770	-6.61	<.0001
DUM04	1	-0.8318	0.3363	-2.47	0.0134
DUM06	1	-4.6932	0.4904	-9.57	<.0001
DUM07	1	-1.9722	0.3466	-5.69	<.0001
DUM10	1	-0.4873	0.4202	-1.16	0.2462
DUM11	1	-6.1512	1.0679	-5.76	<.0001
DUM12	1	-3.0478	0.4806	-6.34	<.0001
DUM13	1	-1.3775	0.4174	-3.30	0.0010
DUM15	1	-4.0470	0.5141	-7.87	<.0001
DUM16	1	-2.3440	0.4138	-5.66	<.0001
DUM19	1	-1.4184	0.4532	-3.13	0.0017
EMPARK	1	-1.0276	0.2409	-4.27	<.0001
SEXMAL	1	-0.3036	0.2212	-1.37	0.1699
PTPASS	1	4.4641	0.2362	18.90	<.0001
HZSECL	1	0.6305	0.2627	2.40	0.0164
WZSECL	1	-0.7310	0.2576	-2.84	0.0045

By including individual attributes in the model, the log-likelihood increases significantly from -1401 to -1034. EMPARK and PTPASS variables are estimated significantly and their signs imply that, having a dedicated free parking place at destination effectively decreases the utility of transit modes compared to the auto mode, whereas holding a public transportation pass

does the exact opposite. Estimated coefficients for HZSECL and WZSECL imply that residing in Paris increases the utility of using public transportations against the auto mode, whereas working in Paris has the exact opposite effect. Finally, being a male also increases the disutility of using public transportations.

The travel time in automobile is estimated 1.61 times costlier than the transit in-vehicle time. Initial wait time is estimated 1.86 times costlier than the transit in-vehicle time, but the ratio for the Transfer wait time is 0.75, which is contrary to our expectation; nevertheless the variable estimation is not significant. Transfer walk time is estimated 1.84 times costlier than transit in-vehicle time and very close to the coefficient of the initial wait time. Access and Egress travel times are estimated 2.23 and 1.88 times costlier than the transit in-vehicle time.

### 3.2.2. Nested Logit Specification

The apparent similarity of transit composite modes, suggests that a Nested model specification may perform better. We test several different Nested structures. Table 8.9 shows model estimation summaries. Four structures are considered and tested. None of the four structures performs satisfactorily, as always one inclusive variable is greater than 1. Best performances however seems to come from the two last models where Auto mode is nested together with “Transit with auto access” alternatives.

Table 8.9. Nested Logit estimation summaries for different nested architectures (MPES-I).

Criterion	Architecture	LL	Inclusive parameter					
			No	DF	Est.	S.E.	t-V.	t-Pr.
(1) Transit + walk access/ (2) Transit + bike access/ (3) Transit + auto access/ (4) Auto/		-1393	IN1	1	1.21	0.12	10.47	<.0001
			IN2	1	0.56	0.31	1.82	0.0693
			IN3	1	0.89	0.13	6.89	<.0001
			IN4	0	1.19	.	.	.
(1) Transit + train in main mode / (2) Transit - train in main mode/ (3) Auto/		-1398	IN1	1	1.14	0.13	9.03	<.0001
			IN2	1	1.26	0.13	9.77	<.0001
			IN3	0	0.79	.	.	.
(1) Transit with walk access/ (2) Transit with bike access/ (3) Auto and Transit + auto access/		-1388	IN1	1	1.06	0.10	10.61	<.0001
			IN2	1	0.15	0.27	0.55	0.5807
			IN3	1	0.72	0.08	9.62	<.0001
(1) Transit + walk or bike access/ (2) Auto and Transit + auto access/		-1390	IN1	1	1.06	0.10	10.60	<.0001
			IN2	1	0.73	0.08	9.70	<.0001

### 3.2.2.1. *Enhanced Model*

In the enhanced Nested Logit model, we add individual attributes as explanatory variables to the model. We consider testing the third nested structure of the Table 8.9. Table 8.10a shows the initial Nested Logit model estimation summary based on the Multimodal Path Enumeration Scheme I, and Table 8.10b shows estimation results.

**Table 8.10a. Enhanced NL model estimation summary (MPES-I).**

<b>Model Fit Summary</b>	
Number of Observations	1542
Number of Cases	17336
Log Likelihood	-1023
Log Likelihood Null (LogL(0))	-3652
Maximum Absolute Gradient	0.3686
Number of Iterations	174
Optimization Method	Dual Quasi-Newton
AIC	2104
Schwarz Criterion	2259

Table 8.10b. Enhanced NL model estimation results (MPES-I).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0675	0.014	-4.81	<.0001
IWT	1	-0.1200	0.0307	-3.90	<.0001
XWT	1	-0.0404	0.0250	-1.62	0.1055
XMT	1	-0.1192	0.0584	-2.04	0.0411
NX	1	-0.3921	0.1298	-3.02	0.0025
ACCT	1	-0.1438	0.008645	-16.63	<.0001
EGRT	1	-0.1227	0.0115	-10.63	<.0001
AUTOT	1	-0.1369	0.0173	-7.91	<.0001
DUM01	1	-0.5613	0.4729	-1.19	0.2353
DUM02	1	-8.3812	50.4484	-0.17	0.8681
DUM03	1	-4.8180	0.6915	-6.97	<.0001
DUM04	1	-1.0929	0.3983	-2.74	0.0061
DUM06	1	-6.1505	0.5568	-11.05	<.0001
DUM07	1	-2.2940	0.4046	-5.67	<.0001
DUM10	1	-0.5895	0.4693	-1.26	0.2091
DUM11	1	-8.7821	33.4858	-0.26	0.7931
DUM12	1	-4.9191	0.7190	-6.84	<.0001
DUM13	1	-1.5574	0.4618	-3.37	0.0007
DUM15	1	-5.8367	0.7124	-8.19	<.0001
DUM16	1	-2.6182	0.4641	-5.64	<.0001
DUM19	1	-1.5605	0.4961	-3.15	0.0017
EMPARK	1	-0.9743	0.2759	-3.53	0.0004
SEXMAL	1	-0.2955	0.2479	-1.19	0.2331
PTPASS	1	5.0791	0.4687	10.84	<.0001
HZSECL	1	0.7140	0.2929	2.44	0.0148
WZSECL	1	-0.8027	0.2907	-2.76	0.0058
INC_L2C1	1	0.7949	0.0834	9.53	<.0001
INC_L2C2	1	0.6955	2.9432	0.24	0.8132
INC_L2C3	1	0.5162	0.1013	5.09	<.0001

The log-likelihood of the nested model improves significantly comparing to the similar Multinomial Logit model; it increases from -1034 to -1023. In addition,

all of the inclusive parameters are less than 1. Inclusive variables for “Transit with walk access” and “Transit with bike access” are close, suggesting that the two nests can be combined; however, the influence on estimation results is negligible.

The travel time in automobile is estimated twice as costly as the transit in-vehicle time. Initial wait time is estimated 1.78 times costlier than the transit in-vehicle time, but the ratio for the Transfer wait time is 0.55, which is contrary to our expectation. Access and Egress travel times are estimated 2.13 and 1.82 times more costly than the transit in-vehicle time.

Having “Transit with auto access” mode nested with Auto, suggests that when auto is used as an access mode, it actually dominates the whole composite mode chain. Here, we do not intend to draw such a quick conclusion, because there are factors such as the availability of a parking place at transit station, or parking search time at transit platform, that are not included in this model. Nevertheless, such a proposition merits to be investigated in more depth.

### 3.3. Multimodal Path Enumeration Scheme II

Let us  $a \in 1: walk, 2: bus, 3: bike, 4: auto$  count access feeder modes,  $e \in 1: walk, 2: bus$  count egress feeder modes, and  $p$  count main transit modes according to the Table 8.2. We enumerate composite modes and assign to each mode a number,  $m$ , according to the following formula:

$$m = a + 8(p - 1) + 4(e - 1) \quad (8.2)$$

Brut enumeration of composite modes will result in 56 potential composite transit modes. To these modes, we add Auto as the 57th mode. Not all of these modes are practiced in reality. We use the observation database to rule out unobserved alternatives.

Table 8.11 shows those mode IDs that are used by commuters of the study demand segment according to the 2001 Paris Household Travel Survey. This includes 23 effective mode alternatives. Table 8.12 summarizes the 22 effective transit composite modes in detail.

Table 8.11. Effective modes after eliminating impractical transit chains (MPES-II).

Mode ID	Frequency	Percent	Cumulative Frequency	Cumulative Percent
1	74	4.03	74	4.03
2	51	2.78	125	6.81
4	23	1.25	148	8.06
5	12	0.65	160	8.71
6	8	0.44	168	9.15
8	6	0.33	174	9.48
9	83	4.52	257	14.00
10	22	1.20	279	15.20
12	8	0.44	287	15.63
13	2	0.11	289	15.74
14	1	0.05	290	15.80
17	57	3.10	347	18.90
25	72	3.92	419	22.82
26	50	2.72	469	25.54
27	1	0.05	470	25.60
28	22	1.20	492	26.80
33	5	0.27	497	27.07
34	2	0.11	499	27.18
36	3	0.16	502	27.34
42	3	0.16	505	27.51
49	3	0.16	508	27.67
50	1	0.05	509	27.72
57	1327	72.28	<b>1836</b>	<b>100</b>

Table 8.12. Mode IDs in Multimodal Path Enumeration Scheme II.

Mode ID	Access Mode				Main Transit Mode			Egress Mode	
	Walk	Bus	Bike	Auto	Train	Metro	Bus	Walk	Bus
1	✓				✓			✓	
2		✓			✓			✓	
4				✓	✓			✓	
5	✓				✓				✓
6		✓			✓				✓
8				✓	✓				✓
9	✓					✓		✓	
10		✓				✓		✓	
12				✓		✓		✓	
13	✓					✓			✓
14		✓				✓			✓
17	✓						✓	✓	
25	✓				✓	✓		✓	
26		✓			✓	✓		✓	
27			✓		✓	✓		✓	
28				✓	✓	✓		✓	
33	✓				✓		✓	✓	
34		✓			✓		✓	✓	
36				✓	✓		✓	✓	
42		✓				✓	✓	✓	
49	✓				✓	✓	✓	✓	
50		✓			✓	✓	✓	✓	

### 3.3.1. Multinomial Logit Specification

#### 3.3.1.1. Basic Model

In the basic model, we include level-of-service explanatory variables only. DWT variable is also excluded because of its insignificance in the model estimations based on the MPES-I. The two variables ACCIVT and ACCIWT represent In-vehicle travel time and Initial wait time for the Bus access mode.

Normally ACCT represents access time to the main transit stations. However, if Bus is used as feeder mode, ACCT represents the time of access to the Bus stop. Table 8.13a shows the Multinomial Logit model estimation summary based on the Multimodal Path Enumeration Scheme II, and Table 8.13b shows estimation results.

**Table 8.13a. Final MNL model estimation summary (MPES-II).**

<b>Model Fit Summary</b>	
Number of Observations	1543
Number of Cases	25149
Log Likelihood	-1506
Log Likelihood Null (LogL(0))	-4112
Maximum Absolute Gradient	1.52E-06
Number of Iterations	8
Optimization Method	Newton-Raphson
AIC	3076
Schwarz Criterion	3247

Table 8.13b. Final MNL model estimation results (MPES-II).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0307	0.0101	-3.05	0.0023
IWT	1	-0.1076	0.0268	-4.01	<.0001
XWT	1	-0.0748	0.0220	-3.40	0.0007
XMT	1	-0.0917	0.0565	-1.62	0.1046
NX	1	-0.2455	0.1090	-2.25	0.0243
ACCT	1	-0.1037	0.008141	-12.74	<.0001
ACCIVT	1	-0.0230	0.0221	-1.04	0.2995
ACCIWT	1	-0.0328	0.0321	-1.02	0.3079
EGRGT	1	-0.1126	0.008739	-12.88	<.0001
AUTOT	1	-0.0797	0.007348	-10.84	<.0001
DUM01	1	0.1556	0.2886	0.54	0.5897
DUM02	1	-1.1358	0.3571	-3.18	0.0015
DUM04	1	-2.3791	0.3293	-7.23	<.0001
DUM05	1	-2.5774	0.3899	-6.61	<.0001
DUM06	1	-4.1872	0.6067	-6.90	<.0001
DUM08	1	-4.4349	0.4747	-9.34	<.0001
DUM09	1	0.0952	0.1934	0.49	0.6223
DUM10	1	-1.9208	0.3052	-6.29	<.0001
DUM12	1	-3.4647	0.4066	-8.52	<.0001
DUM13	1	-3.8571	0.7223	-5.34	<.0001
DUM14	1	-5.6460	1.0760	-5.25	<.0001
DUM17	1	-0.0297	0.2290	-0.13	0.8970
DUM25	1	0.0480	0.2820	0.17	0.8649
DUM26	1	-1.2294	0.3530	-3.48	0.0005
DUM27	1	-5.3751	1.0305	-5.22	<.0001
DUM28	1	-2.3584	0.3278	-7.19	<.0001
DUM33	1	-2.0041	0.5169	-3.88	0.0001
DUM34	1	-3.8267	0.7768	-4.93	<.0001
DUM36	1	-3.8431	0.6257	-6.14	<.0001
DUM42	1	-3.4918	0.6344	-5.50	<.0001
DUM49	1	-1.8159	0.6513	-2.79	0.0053
DUM50	1	-3.8459	1.0619	-3.62	0.0003

According to the estimation, the travel time in automobile is estimated 2.60 times costlier than the transit in-vehicle time. Initial wait and Transfer wait

times are 3.50 and 2.44 times costlier than the transit in-vehicle time, respectively.

Access travel time is estimated 3.38 more costly than transit in-vehicle travel time. It implies that where the access mode is Bus, the walk to the Bus stop is 4.51 times as costly as the Bus access in-vehicle time. In addition, the Bus access wait time is perceived about 1.43 costlier than the Bus access in-vehicle time. These proportions are used to calculate access and egress generalized time variables, ACCGT and EGRGT. Egress travel time therefore is estimated 3.67 times costlier than main transit in-vehicle time.

### 3.3.1.2. Enhanced Model

In the enhanced model, we add individual attributes as explanatory variables. Table 8.14a shows the Multinomial Logit estimation summary for the Multimodal Path Enumeration Scheme II, and Table 8.14b shows estimation results.

**Table 8.14a. Initial enhanced MNL model estimation summary (MPES-II).**

<b>Model Fit Summary</b>	
Number of Observations	1454
Number of Cases	23800
Log Likelihood	-1054
Log Likelihood Null (LogL(0))	-3885
Maximum Absolute Gradient	0.40757
Number of Iterations	195
Optimization Method	Dual Quasi-Newton
AIC	2186
Schwarz Criterion	2392

Table 8.14b. Initial enhanced MNL model estimation results (MPES-II).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0217	0.0137	-1.58	0.1139
IWT	1	-0.1072	0.0335	-3.20	0.0014
XWT	1	-0.0148	0.0270	-0.55	0.5849
XMT	1	-0.1311	0.0675	-1.94	0.0521
NX	1	-0.4487	0.1337	-3.36	0.0008
ACCGT	1	-0.1133	0.008049	-14.08	<.0001
EGRGT	1	-0.1106	0.008753	-12.64	<.0001
AUTOT	1	-0.0543	0.0108	-5.05	<.0001
DUM01	1	-0.9410	0.5494	-1.71	0.0868
DUM02	1	-2.2331	0.5507	-4.05	<.0001
DUM04	1	-3.4882	0.5929	-5.88	<.0001
DUM05	1	-3.6603	0.6124	-5.98	<.0001
DUM06	1	-5.0525	0.7026	-7.19	<.0001
DUM08	1	-5.4386	0.6699	-8.12	<.0001
DUM09	1	-1.0207	0.4897	-2.08	0.0371
DUM10	1	-3.0221	0.5268	-5.74	<.0001
DUM12	1	-4.7267	0.6080	-7.77	<.0001
DUM13	1	-5.5150	1.1219	-4.92	<.0001
DUM14	1	-6.2604	1.1306	-5.54	<.0001
DUM17	1	-0.9686	0.5018	-1.93	0.0536
DUM25	1	-0.9060	0.5378	-1.68	0.0921
DUM26	1	-2.3355	0.5505	-4.24	<.0001
DUM27	1	-6.4471	1.1197	-5.76	<.0001
DUM28	1	-3.4485	0.5852	-5.89	<.0001
DUM33	1	-3.9287	0.8827	-4.45	<.0001
DUM34	1	-4.8713	0.9279	-5.25	<.0001
DUM36	1	-5.1250	0.7892	-6.49	<.0001
DUM42	1	-4.5004	0.7556	-5.96	<.0001
DUM49	1	-2.8406	0.8325	-3.41	0.0006
DUM50	1	-4.8795	1.1374	-4.29	<.0001
EMPARK	1	-0.9104	0.2563	-3.55	0.0004
SEXMAL	1	-0.4230	0.2423	-1.75	0.0808
PTPASS	1	4.6238	0.2568	18.01	<.0001
HFPARK	1	-0.0123	0.2461	-0.05	0.9601
INDCOL	1	0.4549	0.3112	1.46	0.1438
HZSECL	1	0.5905	0.2789	2.12	0.0343
WZSECL	1	-0.7718	0.2718	-2.84	0.0045
ICSP	1	-0.0741	0.3191	-0.23	0.8163
IAGE	1	0.2623	0.2227	1.18	0.2390

Four of the individual attributes perform insignificantly: HFPARK, INDCOL, ICSP, and IAGE. By excluding these variables from the model, we obtain the final enhanced MNL model. The estimation is summarized in Table 8.15a, and Table 8.15b shows estimation results.

**Table 8.15a. Final enhanced MNL model estimation summary (MPES-II).**

<b>Model Fit Summary</b>	
Number of Observations	1543
Number of Cases	25149
Log Likelihood	-1142
Log Likelihood Null (LogL(0))	-4112
Maximum Absolute Gradient	0.64683
Number of Iterations	168
Optimization Method	Dual Quasi-Newton
AIC	2355
Schwarz Criterion	2542

Table 8.15b. Final enhanced MNL model estimation results (MPES-II).

Parameter	DF	Estimate	Standard Error	t Value	Approximate Pr >  t
IVT	1	-0.0267	0.0130	-2.06	0.0393
IWT	1	-0.0919	0.0323	-2.85	0.0044
XWT	1	-0.00882	0.0256	-0.34	0.7305
XMT	1	-0.1255	0.0651	-1.93	0.0540
NX	1	-0.4118	0.1276	-3.23	0.0012
ACCGT	1	-0.1117	0.007775	-14.36	<.0001
EGRGT	1	-0.1008	0.007884	-12.79	<.0001
AUTOT	1	-0.0584	0.0102	-5.73	<.0001
DUM01	1	-0.9132	0.4195	-2.18	0.0295
DUM02	1	-2.2595	0.4310	-5.24	<.0001
DUM04	1	-3.4508	0.4737	-7.28	<.0001
DUM05	1	-3.5671	0.5032	-7.09	<.0001
DUM06	1	-5.0570	0.6014	-8.41	<.0001
DUM08	1	-5.4276	0.5750	-9.44	<.0001
DUM09	1	-0.8058	0.3275	-2.46	0.0139
DUM10	1	-2.9151	0.3900	-7.47	<.0001
DUM12	1	-4.4198	0.4720	-9.36	<.0001
DUM13	1	-4.8370	0.7815	-6.19	<.0001
DUM14	1	-5.9029	1.0725	-5.50	<.0001
DUM17	1	-0.8718	0.3510	-2.48	0.0130
DUM25	1	-0.8813	0.4039	-2.18	0.0291
DUM26	1	-2.2562	0.4240	-5.32	<.0001
DUM27	1	-6.4123	1.0620	-6.04	<.0001
DUM28	1	-3.3462	0.4677	-7.15	<.0001
DUM33	1	-3.1229	0.6177	-5.06	<.0001
DUM34	1	-5.1237	0.8401	-6.10	<.0001
DUM36	1	-5.0121	0.7063	-7.10	<.0001
DUM42	1	-4.4387	0.6679	-6.65	<.0001
DUM49	1	-3.1768	0.7223	-4.40	<.0001
DUM50	1	-5.0368	1.1020	-4.57	<.0001
EMPARK	1	-0.9206	0.2427	-3.79	0.0001
SEXMAL	1	-0.4947	0.2245	-2.20	0.0275
PTPASS	1	4.5469	0.2436	18.66	<.0001
HZSECL	1	0.5681	0.2571	2.21	0.0271
WZSECL	1	-0.7550	0.2596	-2.91	0.0036

By including individual attributes in the model, the log-likelihood improves significantly from -1506 to -1142. EMPARK and PTPASS variables are estimated significantly and their signs imply that, having a dedicated free parking place at destination effectively decreases the utility of transit modes compared to the auto mode, whereas holding a public transportation pass does the exact opposite. Estimated coefficients for HZSECL and WZSECL imply that residing in Paris increases the utility of using public transportation against the auto mode, whereas working in Paris has the exact opposite effect. Finally, being a male also increases the disutility of using public transportation.

According to this estimation, the travel time in automobile is estimated 2.19 times costlier than the transit in-vehicle time. Initial wait time is estimated 3.44 times costlier than the transit in-vehicle time. However, the estimation of Transfer wait time is very insignificant. Access and Egress travel times are estimated 4.18 and 3.78 times costlier than the transit in-vehicle time.

### 3.3.2. Nested Logit Specification

The Nested Logit model specification by nesting according to access mode was estimated successfully for the MPES-I. Here, we try two nesting structures for the MPES-II. In the first nesting structure, four nests are defined. The three first nests regroup composite modes with Walk, Bus, and Bike or Auto access modes, respectively; the fourth nest includes composite modes with Bus egress mode (except when access mode is Auto). In the second nesting structure, three nests are defined regrouping composite modes with Walk, Bus, and Bike or Auto access modes, respectively. Auto main mode is also nested with “transit with auto access mode” alternatives.

None of the structures performs satisfactorily as always an inclusive parameter estimated is greater than 1 (Table 8.16)

Table 8.16. Nested Logit estimation summaries for different nesting architectures (MPES-II).

Criterion	Architecture	LL	Inclusive parameter					
			No	DF	Est.	S.E.	t-V.	t-Pr.
(1) Transit + walk access/ (2) Transit + bus access/ (3) Auto or Transit + bike or auto access/ (4) Transit + bus egress		-1139	IN1	1	0.97	0.09	11.20	<.0001
			IN2	1	1.08	0.12	8.70	<.0001
			IN3	1	0.82	0.17	4.88	<.0001
			IN4	1	0.86	0.19	4.57	<.0001
(1) Transit + walk access/ (2) Transit + bus access/ (3) Auto or Transit + bike or auto access/		-1398	IN1	1	0.93	0.08	11.03	<.0001
			IN2	1	1.06	0.13	8.43	<.0001
			IN3	0	0.76	0.17	4.61	<.0001

## 4. Mode Choice with Trip-end Disaggregation

So far, we identified mode choice sets based on two Multimodal Path Enumeration Schemes (MPES-I and MPES-II). We then specified and estimated different mode choice models. Multinomial and Nested Logit models based on the MPES-I, were estimated successfully. But, only Multinomial logit models were successfully estimated based on the MES-II, and estimation of Nested Logit models failed.

In this section, we add the explicit spatial dimension. We represent trip-ends explicitly and provide a stochastic disaggregate representation of the intrazonal space. The connection between the intrazonal space and the transportation network is provided by a number of transit anchor points.

For demonstration, we choose an origin-destination relation. The origin zone is situated at Outer suburbs, within the town of Noisy-le-Grand. The destination zone is at Paris, 5th district. At each side, we have identified four transit anchor points. At origin, “*Noisy – Champs*” and “*Noisy-le-Grand – Mont d’Est*”, on RER A, and “*Les Yvris – Noisy-le-Grand*” and “*Villiers-sur-Marne – Le Plessis-Tréville*”, on RER E, are identified as transit anchor points. At destination, “*Luxembourg*” and “*Port-Royal*”, on RER B, and “*Cardinal Lemoine*”, on Metro 10, and “*Censier – Daubenton*” on Metro 7, are identified as transit anchor points. Figure 8.1 shows origin and destination zones within the zoning system. Cross icons show all non-Bus transit stations (including SNCF, RER, and Metro stations) in the region. Red squares represent transit platforms that are identified as anchor nodes.

As for the mode choice model, we use the Multinomial Logit estimation based on the MPES-II, as summarized in the Table 8.15b.

### 4.1. Main Transit Mode Identification

Table 8.17 summarizes the anchor-to-anchor level-of-service characteristics for the selected pair of origin-destination zones. There are two main transit modes available between the two zones: “Train”, and “Train+Metro”. According to the Table 8.12, Train main mode corresponds to the composite modes 1, 2, 4, 5, 6, 8, where it is chained to the Walk, Bus, and Auto access modes, and the Walk and Bus egress modes. Similarly, “Train+Metro” main mode corresponds to composite modes 25, 26, 27, 28, where it is chained to the Walk, Bus, Bike, and Auto access modes and only the Walk egress mode. In the mode choice model with an implicit representation of space, including

transit stations, the mode choice set between the pair of zones would have been constituted of the 10 enumerated composite modes, as follows,

$$\left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \\ \text{Auto} \end{array} \right\} + \text{Train} + \left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \end{array} \right\}$$

$$\left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \\ \text{Bike} \\ \text{Auto} \end{array} \right\} + \text{Train+Metro} + \text{Walk}$$

In the mode choice with explicit representation of space, on the contrary, not only the structure of the composite mode is important, but also the physical configuration of transit platforms with respect to the intrazonal space is taken into account. According to the Table 8.17, the Train main mode is available from all the four origin stations to the two destination stations “*Luxembourg*” ( $C'_1$ ) and “*Port-Royal*” ( $C'_4$ ). Similarly, Train+Metro main mode is available from the all four origin stations to the two destination stations “*Cardinal Lemoine*” ( $C'_2$ ) and “*Censier – Daubenton*” ( $C'_3$ ). The joint mode and station choice model includes 80 different transit alternatives, as follows,

$$\left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \\ \text{Auto} \end{array} \right\} \times \left\{ \begin{array}{l} C_1 \\ C_2 \\ C_3 \\ C_4 \end{array} \right\} + \text{Train} + \left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \end{array} \right\} \times \left\{ \begin{array}{l} C'_1 \\ C'_4 \end{array} \right\}$$

$$\left\{ \begin{array}{l} \text{Walk} \\ \text{Bus} \\ \text{Bike} \\ \text{Auto} \end{array} \right\} \times \left\{ \begin{array}{l} C_1 \\ C_2 \\ C_3 \\ C_4 \end{array} \right\} + \text{Train+Metro} + \text{Walk} \times \left\{ \begin{array}{l} C'_2 \\ C'_3 \end{array} \right\}$$

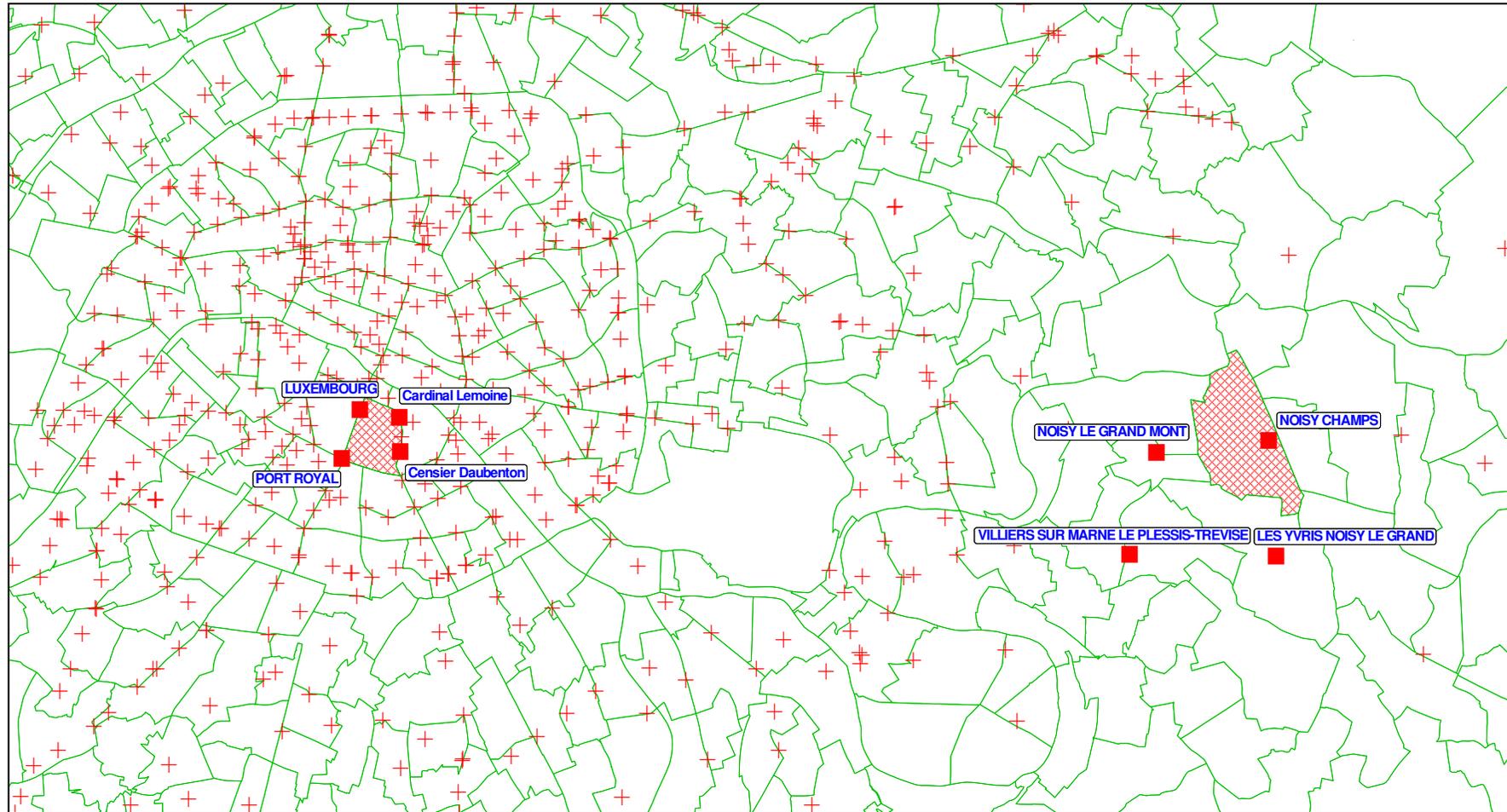


Figure 8.1. Origin-Destination pair of zones and transit anchor points.

Table 8.17. Anchor-to-anchor main transit modes and level-of-service characteristics.

Origin	Destination	Transit Mode	IVT (min)	DWT (min)	IWT (min)	XWT (min)	XMT (min)	NX
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_1$ Luxembourg	Train	20.70	5.25	7.50	7.50	0.00	1
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_2$ Cardinal Lemoine	Train-Metro	22.00	5.75	7.50	2.96	0.19	3
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_3$ Censier – Daubenton	Train-Metro	23.20	7.75	7.50	2.65	0.19	2
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_4$ Port-Royal	Train	21.80	6.00	7.50	7.50	0.00	1
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_1$ Luxembourg	Train	23.30	3.75	10.00	7.50	4.03	1
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_2$ Cardinal Lemoine	Train-Metro	29.00	7.00	10.00	2.08	3.20	2
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_3$ Censier – Daubenton	Train-Metro	30.20	7.25	10.00	2.65	2.25	2
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_4$ Port-Royal	Train	24.40	4.50	10.00	7.50	4.03	1
$C_3$ Noisy – Champs	$C'_1$ Luxembourg	Train	23.00	6.00	7.50	7.50	0.00	1
$C_3$ Noisy – Champs	$C'_2$ Cardinal Lemoine	Train-Metro	24.40	6.50	7.50	2.96	0.19	3
$C_3$ Noisy – Champs	$C'_3$ Censier – Daubenton	Train-Metro	25.50	8.50	7.50	2.65	0.19	2
$C_3$ Noisy – Champs	$C'_4$ Port-Royal	Train	24.10	6.75	7.50	7.50	0.00	1
$C_4$ Les Yvris – Noisy-le-Grand	$C'_1$ Luxembourg	Train	26.20	4.50	10.00	7.50	4.03	1
$C_4$ Les Yvris – Noisy-le-Grand	$C'_2$ Cardinal Lemoine	Train-Metro	31.90	7.75	10.00	2.08	3.20	2
$C_4$ Les Yvris – Noisy-le-Grand	$C'_3$ Censier – Daubenton	Train-Metro	33.10	8.00	10.00	2.65	2.25	2
$C_4$ Les Yvris – Noisy-le-Grand	$C'_4$ Port-Royal	Train	27.30	5.25	10.00	7.50	4.03	1

### 4.2. Stochastic Disaggregate Representation of Trip-ends

Figure 8.2 and Figure 8.3 show respectively the origin and the destination zones in detail. Black dots are street-ends, which represent the distribution of trip-ends within the zone schematically. Blue circles represent intrazonal Bus stops, which provide access to the four anchor points.

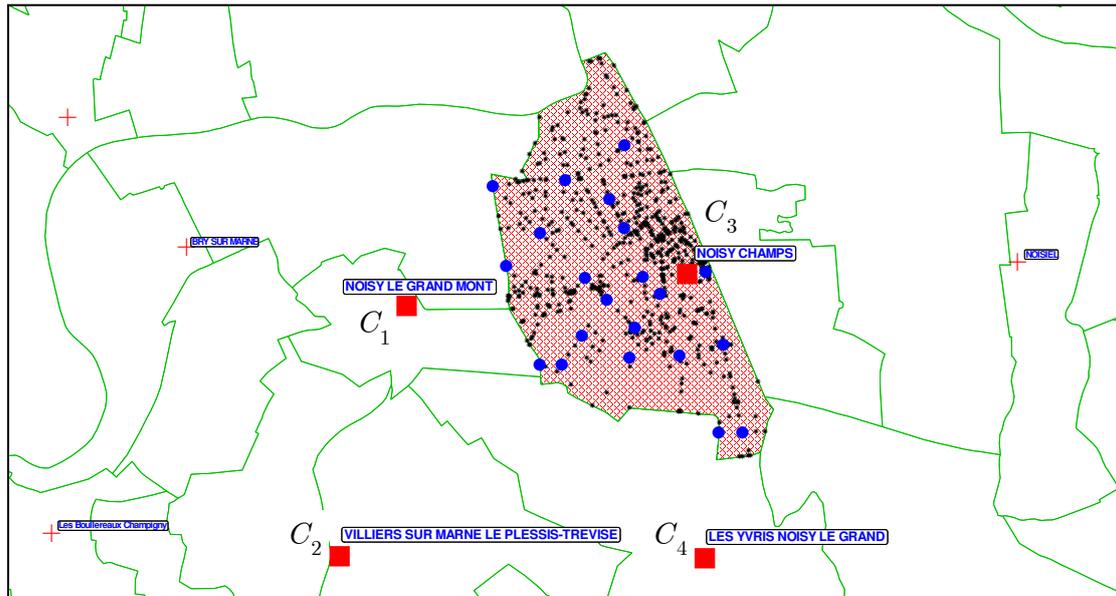


Figure 8.2. Origin zone at Outer suburbs, with transit anchors nodes, intrazonal bus stops, and schematic population distribution.

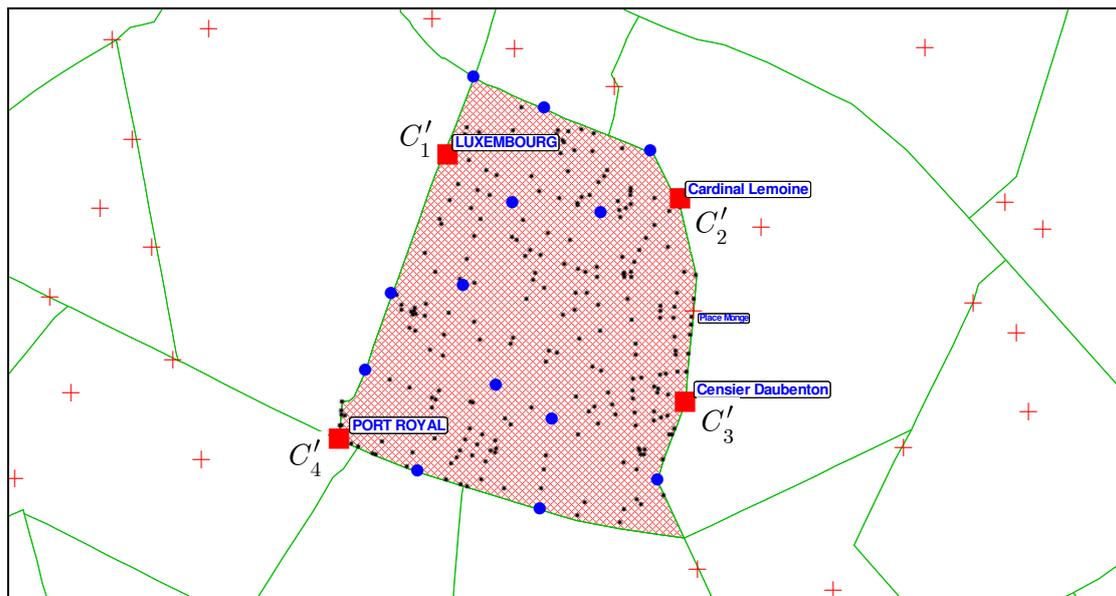


Figure 8.3. Destination zone at Paris, with transit anchors nodes, intrazonal bus stops, and schematic population distribution.

There are about 700 trip-ends at the origin zone versus 240 trip-ends at the destination zone. We suppose that the only source of variability at the intrazonal level is physical due to the dispersion of trip-ends in space. Therefore, modal access time vectors are uncoupled as described by the Equations 7.19 and 7.20. Therefore, by simulating the access time from each trip-end to each origin anchor point, and by each access feeder mode, we obtain the representative modal access time sample from which we draw statistical inferences required for a stochastic representation, including the mean time vector, and the covariance matrix.

In the particular case of this example, mean vectors and covariance matrices for the modal access time vectors are given as follows:

$$\left[ \bar{\tau}_i \right]_{walk} = \begin{bmatrix} 25.426 \\ 46.757 \\ 11.741 \\ 36.730 \end{bmatrix}, \quad \left[ \sigma_{ii'} \right]_{walk} = \begin{bmatrix} 37.943 & 26.631 & -7.476 & -5.850 \\ 26.631 & 38.497 & 0.241 & 32.249 \\ -7.476 & 0.241 & 40.803 & 24.368 \\ -5.850 & 32.249 & 24.368 & 77.916 \end{bmatrix}$$

$$\left[ \bar{\tau}_i \right]_{bus} = \begin{bmatrix} 8.127 \\ 11.878 \\ 6.024 \\ 7.673 \end{bmatrix}, \quad \left[ \sigma_{ii'} \right]_{bus} = \begin{bmatrix} 5.609 & 5.286 & 4.431 & 5.286 \\ 5.286 & 7.037 & 5.851 & 7.037 \\ 4.431 & 5.851 & 6.487 & 5.851 \\ 5.286 & 7.037 & 5.851 & 7.037 \end{bmatrix}$$

$$\left[ \bar{\tau}_i \right]_{bike} = \begin{bmatrix} 6.695 \\ 12.687 \\ 3.306 \\ 9.730 \end{bmatrix}, \quad \left[ \sigma_{ii'} \right]_{bike} = \begin{bmatrix} 2.827 & 1.958 & -0.399 & -0.167 \\ 1.958 & 2.736 & -0.001 & 2.462 \\ -0.399 & -0.001 & 2.837 & 1.911 \\ -0.167 & 2.462 & 1.911 & 5.995 \end{bmatrix}$$

$$\left[ \bar{\tau}_i \right]_{auto} = \begin{bmatrix} 6.284 \\ 10.868 \\ 3.821 \\ 10.098 \end{bmatrix}, \quad \left[ \sigma_{ii'} \right]_{auto} = \begin{bmatrix} 2.759 & 2.836 & 0.562 & 1.998 \\ 2.836 & 3.457 & 0.669 & 3.014 \\ 0.562 & 0.669 & 2.572 & 1.947 \\ 1.998 & 3.014 & 1.947 & 4.567 \end{bmatrix}$$

Similarly, mean vectors and covariance matrices for the modal egress time vectors are given as follows:

$$\begin{aligned} \left[ \bar{\tau}'_j \right]_{walk} &= \begin{bmatrix} 10.554 \\ 10.291 \\ 9.052 \\ 12.743 \end{bmatrix}, & \left[ \sigma'_{jj'} \right]_{walk} &= \begin{bmatrix} 18.983 & 8.783 & -9.340 & -3.401 \\ 8.783 & 26.936 & 11.440 & -24.144 \\ -9.340 & 11.440 & 21.249 & -13.138 \\ -3.401 & -24.144 & -13.138 & 25.824 \end{bmatrix} \\ \\ \left[ \bar{\tau}'_j \right]_{bus} &= \begin{bmatrix} 4.539 \\ 5.282 \\ 5.634 \\ 5.388 \end{bmatrix}, & \left[ \sigma'_{jj'} \right]_{bus} &= \begin{bmatrix} 2.359 & 1.632 & 1.298 & 2.428 \\ 1.632 & 2.004 & 1.099 & 0.991 \\ 1.298 & 1.099 & 2.112 & 1.671 \\ 2.428 & 0.991 & 1.671 & 3.696 \end{bmatrix} \end{aligned}$$

In the next step, we proceed by evaluating systematic utilities,  $\bar{V}_{mg}$ , according to the Equation 7.23. As there are 80 joint mode and anchor pair alternatives, it is inappropriate to reproduce all the values here. We only print out the 8 values corresponding to the “walk+Train+walk” mode, where  $g = 1 \dots 8$  counts members of the set of anchor pairs,  $C_1, C_2, C_3, C_4 \times C'_1, C'_4$  :

$$\left[ V_{g \in C_1, C_2, C_3, C_4 \times C'_1, C'_4} \right]_{m \equiv walk+Train+walk} = \begin{bmatrix} -1.917 \\ -2.167 \\ -5.104 \\ -5.354 \\ -0.449 \\ -0.699 \\ -4.062 \\ -4.312 \end{bmatrix}$$

In the composition of the utility function, we assume that EMPARK is 0 meaning that there is no dedicated parking place available at destination; SEXMAL is 1 for male commuters; PTPASS is 1 representing the behavior of public pass holders; HZSECL is 1 as the origin zone is not in Paris; and WZSECL is 0 as the workplace is in Paris. Nine other joint systematic utilities are calculated in similar way and assembled in a  $81 \times 1$  vector where the 81st line corresponds to the utility of the auto mode.

Finally, we evaluate origin-destination covariance matrices according to the Equation 7.24. Again, we only print out the first  $8 \times 8$  matrix corresponding

to the “walk+Train+walk” composite mode, where  $g = 1 \dots 8$  counts members of the set of anchor pairs,  $C_1, C_2, C_3, C_4 \times C'_1, C'_4$  :

$$\left[ \Sigma_{g,g' \in C_1, C_2, C_3, C_4 \times C'_1, C'_4} \right]_{m \equiv \text{walk+Train+walk}} = \begin{bmatrix} 0.666 & 0.439 & 0.525 & 0.298 & 0.100 & -0.128 & 0.120 & -0.108 \\ & 0.736 & 0.298 & 0.595 & -0.128 & 0.169 & -0.108 & 0.189 \\ & & 0.673 & 0.446 & 0.196 & -0.032 & 0.595 & 0.368 \\ & & & 0.743 & -0.032 & 0.265 & 0.368 & 0.665 \\ & & & & 0.702 & 0.475 & 0.497 & 0.270 \\ & & & & & 0.772 & 0.270 & 0.566 \\ & & & & & & 1.165 & 0.938 \\ & & & & & & & 1.235 \end{bmatrix}$$

Nine other origin-destination covariance matrices are calculated in a similar way. These are assembled in a  $81 \times 81$  matrix, where 81st rank corresponds to the auto mode.

In our, model, and according to the Equations 7.19 and 7.20, modal access and egress time vectors are characterized following Multivariate Normal distribution, representing physical source of variability. On the other hand, our mode choice models were specified and estimated as GEV-based Multinomial or Nested Logit models, representing behavioral source of variability. The combined model of mode and anchor point (i.e., station) choice is obtained by assembling the origin-destination covariance matrices  $\left[ \Sigma_{gg'} \right]_m$ , with the covariance matrix of modal utility functions,  $\left[ \nu_{mm'} \right]$ . Therefore, using the coefficients from the Multinomial Logit estimation for evaluating utilities in the combined model requires that the variance structure of the mode choice model be specified so that the choice probabilities form the equivalent Multinomial Probit model match those produced from the Multinomial Logit model. The covariance structure of the equivalent Multinomial Probit model should be homoscedastic with common variance of  $\pi^2/6^2 \simeq 2.71$  so that the origin-destination covariance matrices and the covariance matrix of modal utility functions are of the same scale. The model is solved using the Clark’s algorithm.

Figure 8.4 represents a test where Multinomial Logit and Multinomial Probit models are compared for evaluating choice probability for 10 alternatives. Systematic utility values are the same. The Multinomial Probit is solved using Clark’s method. Its covariance matrix is homoscedastic and the variance is

equal to  $\pi^2/6^2$ . The nearly perfect match between results from the two models approves correct scaling and the performance of Clark’s algorithm.

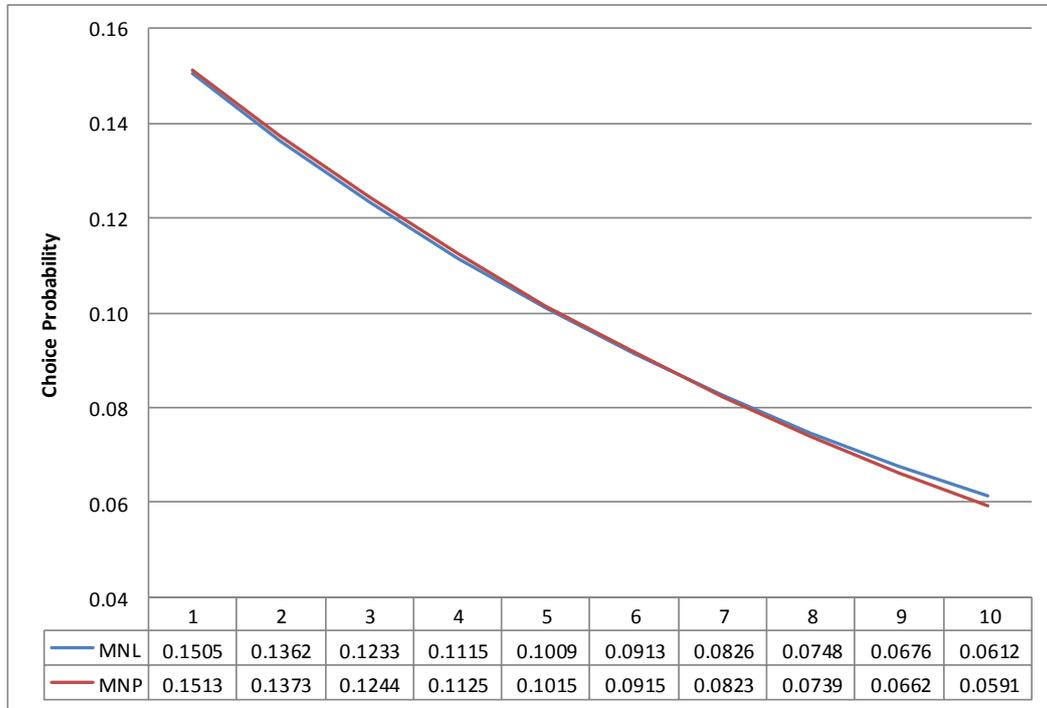


Figure 8.4. Multinomial Logit versus Multinomial Probit choice probabilities.

For the 81st mode which is the Auto, we do not consider a stochastic representation. However, it is also possible to consider an Auto itinerary as a composition of two intrazonal access and egress sections, and one interzonal main section. Then, one can apply the formulation of Chapter 5 in order to take into account of the variability due to disaggregate trip-ends. Auto and Transit anchor points should not be necessarily the same. Here we consider a mean Auto travel time between the origin and destination zones. In this network, we simulate mean Auto travel time constantly equal to 35 min, and focus on Transit modes.

Table 8.18 aggregates per composite mode. Walk + Train + Walk has the highest share. It is closely followed by Bus + Train + Walk, then Walk + Train+Metro + Walk and Bus + Train+Metro + Walk. The share of the Auto mode is very small and about 1.6%. This small share is mainly due to the PTPASS flag variable. By setting PTPASS to 0, for travelers with no public transportation pass, the share of Auto mode would increase to 61.7% for men and 51.8% for women.

**Table 8.18. The probability of choice of different composite modes.**

Mode ID	Mode Description	Probability
1	Walk + Train + Walk	0.287938
2	Bus + Train + Walk	0.218843
4	Auto + Train + Walk	0.058087
5	Walk + Train + Bus	0.026251
6	Bus + Train + Bus	0.008467
8	Auto + Train + Bus	0.005845
25	Walk + Train+Metro + Walk	0.195782
26	Bus + Train+Metro + Walk	0.143149
27	Bike + Train+Metro + Walk	0.000156
28	Auto + Train+Metro + Walk	0.039904
59	AUTO	0.015577

The 81 choice probabilities are aggregated for presentation. Table 8.19 aggregates choice probabilities per access mode. As expected, Walk is used in half of the cases, followed by Bus and Auto. Bike feeder mode has a negligible share.

**Table 8.19. Total share of out-going traffic per transit access feeder mode.**

Access feeder mode	Probability
Walk access	0.5099714
Bus access	0.3704596
Bike access	0.0001564
Auto access	0.1038360

Table 8.20 shows detailed anchor-to-anchor traffic shares. The highest share is between “*Noisy – Champs*” and “*Luxembourg*”, followed by “*Port-Royal*” and “*Censier – Daubenton*”.

Table 8.20. Pair of anchor points choice probabilities.

Origin Anchor	Destination Anchor	Probability
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_1$ Luxembourg	0.089925
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_2$ Cardinal Lemoine	0.032818
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_3$ Censier – Daubenton	0.061330
$C_1$ Noisy-le-Grand – Mont d'Est	$C'_4$ Port-Royal	0.069300
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_1$ Luxembourg	0.011147
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_2$ Cardinal Lemoine	0.006821
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_3$ Censier – Daubenton	0.008814
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	$C'_4$ Port-Royal	0.008231
$C_3$ Noisy – Champs	$C'_1$ Luxembourg	0.218218
$C_3$ Noisy – Champs	$C'_2$ Cardinal Lemoine	0.088502
$C_3$ Noisy – Champs	$C'_3$ Censier – Daubenton	0.152497
$C_3$ Noisy – Champs	$C'_4$ Port-Royal	0.173701
$C_4$ Les Yvris – Noisy-le-Grand	$C'_1$ Luxembourg	0.019972
$C_4$ Les Yvris – Noisy-le-Grand	$C'_2$ Cardinal Lemoine	0.012382
$C_4$ Les Yvris – Noisy-le-Grand	$C'_3$ Censier – Daubenton	0.015828
$C_4$ Les Yvris – Noisy-le-Grand	$C'_4$ Port-Royal	0.014938

Table 8.21 aggregates per origin anchor point. Intuitively, more than 63% of the public transportation traffic uses “*Noisy – Champs*” station. It is followed by 25% for “*Noisy-le-Grand – Mont d'Est*” and the two other stations together provide access to the destination for about 10% of commutes.

Table 8.21. Total out-going share of traffic from the origin anchor points.

Origin Anchor	Probability
$C_1$ Noisy-le-Grand – Mont d'Est	0.253373
$C_2$ Villiers-sur-Marne – Le Plessis-Tréville	0.035013
$C_3$ Noisy – Champs	0.632918
$C_4$ Les Yvris – Noisy-le-Grand	0.063120

Table 8.22 aggregates per destination anchor point. All of the four anchor points contribute effectively to receiving the traffic.

**Table 8.22. Total in-coming share of traffic to the destination anchor points.**

Destination Anchor	Probability
$C'_1$ Luxembourg	0.339262
$C'_2$ Cardinal Lemoine	0.140523
$C'_3$ Censier – Daubenton	0.238469
$C'_4$ Port-Royal	0.266169

## 5. Conclusion

In this chapter, firstly, we estimated Multinomial and Nested logit models for the MPES-I and MPES-II. For the MPES-I, Multinomial and Nested Logit models were estimated successfully. For the MPES-II, only a Multinomial Logit model was estimated. Although, the goodness-of-fit, measured in terms of log-likelihood, that was achieved for the MPES-II is worse than that of the MPES-I, the Multinomial Logit model based on the MPES-II is quite essential for implementing a mode choice model with disaggregate treatment of trip-ends. Otherwise, the number of required anchor points in the model increases to exceedingly high amounts, due to the predominant number of Bus stops, which should be explicitly represented.

Secondly, we implemented the mode choice model with desegregate treatment of trip-ends for one pair of origin-destination zones. The example included the entire modeling procedure. The use of Clark's approximate method provided the model with computational efficiency. Its numerical error is expected to be limited, because even though the rank of the resultant matrix is generally big, its structure is sparse and very close to diagonal.

In this example, for the sake of simplicity in demonstration, we have assumed that all access/egress modes, especially Walk, are accessible all over the zone area. This is not generally true, and sub-zoning may be required in order to respect modal catchment areas. The procedure can be generalized and implemented for any number of zones however there are complexities that should be addressed with regard to the choice of anchor points. In dense areas such as Paris, the availability of long-range feeder modes, such as Auto, Bike or Bus, makes farther stations accessible to the traveler. Therefore, the

number of potential anchor points increases. However, the methodology can be applied satisfactorily to regions with simpler public transportations system.

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# Conclusion

This research addressed the domain of transportation demand modeling and particularly the mode choice problem. It proceeded through a systemic analysis of the process of mode choice decision making, and then concentrated on improving the route and mode choice modeling by providing a stochastic disaggregate spatial representation framework.

In route choice, we investigated the similarities among route alternatives due to the geometry of the local space. It is due to a geometric constraint that one cannot change his distance from one anchor point without changing his distance from all other anchor points. Therefore, from the point of view of a disaggregate traveler, randomly-situated in the local space, terminal route sections are necessarily interdependent. In addition, the variability of the terminal travel time was *physically measurable*. This led to a stochastic traffic assignment model with disaggregate representation of trip-ends and compared its results with a classic assignment model.

In mode choice, we were able to combine two sources of variability. The variability in mode choice behavior, due to unobserved determinants, was combined with the physical variability introduced by the random physical position of the disaggregate traveler. The result was a joint mode and route choice model. Therefore the model was capable of addressing two aspects simultaneously: on one hand, the multimodal structure of complex transit itineraries with feeder and main legs was represented in full explicit precision; on the other hand, trip-ends at origin and destination were disaggregate and scattered over the local space.

In this section we point out some of the main conclusions of this research and suggest some directions for future research.

## 1. Transportation Demand Modeling

We addressed the four-step architecture as an important innovation, which brought a systemic approach to the modeling of mobility behavior. Conventional demand models have generally identified four steps including: trip generation (decision whether to make a trip), trip distribution (decision of

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destination), mode choice (decision of transportation mode), and assignment (decision itinerary). However, it is not the number of the steps nor the nature of those that are conventionally implemented in demand models that draw our interest, but the very concept of considering the human decision process as a system of interdependent task-specified components, which deal with different aspects of mobility. The four-step approach has captured the mainstream of transportation demand modeling and has survived the test of time thanks to its strong systemic foundation.

## 1.1. Travel Decision Making Determinants

From our point of view, travel decisions are made depending on two factors: the behavioral factor, which addresses the decision-making behavior of individuals; and the physical factor, which determines conditions and situations in which the traveler decides. Development of demand modeling paradigms has followed two lines of improvement, accordingly:

### 1.1.1. Main Behavioral Aspects

On the behavioral side, models have evolved and improved from their aggregate trip-based origins – where trips are considered as independent movements in space and time – to the-state-of-the-art activity-based models. Aggregate trip-based models are very limited in their interpretation of travel “behavior” on a cause-and-consequence basis, and function mostly based on correlations and regressions.

Part of this incompetence is due to their aggregate representation of travel demand. Travelers’ of different socio-professional categories with different attributes and travel purposes, do reason differently. Travel demand models are predominantly based on microeconomic theory, which postulates that human decisions are made in such a way to maximize the perceived utility. Such models cannot lead to a consistent interpretation of travel behavior unless applied to people with similar decision-making mindset. Disaggregate trip-based models have been able to alleviate this problem.

Although demand segmentation and the use of random coefficient discrete choice models improved the representation of the travel demand, trip-based models were still limited by their treatment of trips as very independent. It has been a known fact that some travel decisions are correlated strongly among trips within a tour. Probably the most important travel decision in this regard, is the choice of transportation mode. This led to the development of the tour- and activity-based modeling paradigms.

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Activity-based models, on the contrary, recognize that travel is a secondary activity and is derived from the need to participate in activities or access services. In the activity-based paradigm, the modeling process starts by representing individual's daily activity program and scheduling activities within the limited time and spatial span of the day. Travel is only made in order to relate different activity places. By focusing on the daily activity program these models are capable of giving a much incorporating behavioral aspects that are due to intra-household interactions.

### 1.1.2. Main Physical Aspects

On the physical side, with regard to mode choice, we were able to identify two trends that go hand-in-hand:

The first trend concentrates on ameliorating the representation of composite alternatives. In public transportations, especially not exclusively, it is often the case that a number of modes are involved in making a single trip. One can at least distinguish between feeder modes and main modes: the former regards modes such as walk, bike, or auto driver or passenger, which may be used to access transit stations; the latter regards actual transit services that can be accessed at transit stations. Demand models have improved well in this area and many applied models are capable of taking in to account, though to different extents, the composite nature of transit modes.

The second trend concentrates on improving the disaggregate representation of the local space. Travelers' access to different modes of transportation is conditioned by the precise location of both trip-ends in space. Within the same zone, the ease of access to nearby highway entrance or a transit platform is likely to affect the perceived utility of auto or transit modes. Aggregate centroid-based spatial representations are far from being able to incorporate such effects explicitly. On the other hand disaggregate representation of the physical space has been generally overlooked and except for agent-based microsimulation models, applied demand modeling is still based on centroid-based representations of space.

## 2. Stochastic Disaggregate Traffic Assignment to a Monomodal Network

We started addressing the spatial disaggregation problem by concentrating on a monomodal framework. In the second part of the dissertation we have first studied the disaggregate representation of individuals in space from a statistical point of view, and introduced a concrete approach for measuring

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the amount of information loss due to aggregation (cf. Chapter 4). This measure was used later to provide an estimation of the amount of information loss in traffic assignment to the highway network of the Greater Paris Area due centroid-based spatial representation (cf. Chapter 6).

Then we developed a model of traffic assignment to a monomodal network with a stochastic disaggregate representation of trip-ends (cf. Chapter 5). The model was successfully implemented and used for traffic assignment to the highway network of Ile-de-France. By comparing the results from the stochastic assignment model and a classic centroid-based assignment model, we concluded that information loss due to aggregation could reach 10% to 20% of the total variance in suburbs where zone sizes are relatively big and population distribution is relatively sparse.

### 3. Stochastic Disaggregate Traffic Assignment to a Multimodal Network

In the third and final part we focused on disaggregate mode choice modeling in a multimodal network system. The aim was to develop a stochastic model of trip-end disaggregation for traffic assignment to multimodal networks. A systematic analysis of the different aspects of traveling in a multimodal transportation network shed light on a number of major points and raised important questions.

Firstly, we distinguished between access, main, and egress sections of a multimodal itinerary. Each section of the itinerary was considered as a modal leg, and transit platforms separated access, main, and egress modal legs. We proposed two transit mode identification schemes, namely Multimodal Path Enumeration Scheme I and II (MPES-I and MPES-II), and identified access, main, and egress modes based on the observations from the 2001 Paris Household Travel Survey. One Auto alternative was added as the private travel mode. As regards feeder sections, MPES-I identified Walk, Bike, and Auto access modes at origin and Walk egress mode at destination; whereas MPES-II added Bus as a possible feeder mode at both ends. As regards the main transit section, the transit network of Ile-de-France is radial with a hierarchical structure: Train dominates over long regional distances; Metro is mostly used for medium range trips across Paris and Bus is for short distances. We identified 7 main transit modes reflecting the hierarchical structure of the Parisian network.

Secondly, we specified and estimated a number of mode choice models for both enumeration schemes. For MPES-I, Multinomial and Nested Logit models were estimated successfully. For MPES-II, only a Multinomial Logit

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model was satisfactorily estimated; different nested structures were tried but none was found satisfactory.

Thirdly, we developed a mode choice model with disaggregate treatment of trip-ends. The model considered an explicit representation of transit platforms as anchor points and combined two sources of variability. The first source is “behavioral” representing the variability in the mode choice behavior, due to unobserved behavioral factors. The second source is “physical” and deals with the variability of terminal travel times, due to the dispersion of disaggregate trip-ends within space. Therefore, for any given pair of origin-destination zones, the model was capable of evaluating the probability of the joint choice of the composite travel mode (i.e., combination of access, main, and egress modes) and the pair of transit stations that were used for accessing the network at origin and destination.

## 4. Future Research Directions

Different aspects of this work can be investigated in more depth. We briefly discuss some of the main directions that can be subject for a future research:

1. Scrutinizing some of the practical assumptions: Some of the areas that can be improved based on the current work include:
    - a. The abstraction of main transit chains into the aforementioned 7 combinations should be investigated in more depth. In this regard, it is important to devise a methodology that can be applied effectively to different modeling contexts other than the Paris area.
    - b. The identification of anchor points requires further research to propose an optimal way for determining anchor points on highway and transit networks.
    - c. The composition of the modal utility functions can be improved by including more individual attributes and demand segments as well as by including characteristics such as the existence of a parking place at the access transit station, which are expected to have a major impact on the propensity to use an auto access mode.
    - d. The identification of feeder modes can be ameliorated by including new feeder modes such as public bike at origin and destination.
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- e. The algorithm for station-to-station enumeration of transit itineraries can be improved to consider flexible search criteria (e.g., paths with least number of transfers) and to cover more than the shortest modal path.
  2. Accounting for similarities among interzonal routes: Route alternatives that share common sections are more likely to be considered similar by the traveler. The similarity between two such route alternatives is considered by most authors proportional to the relative length of the common section. Specific discrete choice models such as Path Size Logit or C-Logit are proposed to account for similarities among route alternatives. Examples of Cross Nested Logit, Paired Combinatorial Logit or Probit with Logit Kernel models are also specified for route choice contexts. In this dissertation we assumed that anchor-to-anchor interzonal travel times are deterministic and independent. Investigating the case of correlated anchor-to-anchor travel times can be a subject for further research.
  3. Intrazonal covariance structure: Terminal times between the anchor points and the intrazonal space are characterized as a multivariate random vector. We supposed that the terminal times are dependent and differently distributed within the same zone but independent between the origin and destination zones. This hypothesis needs more investigation to determine the situations where it can be held and where it should be revised. In such cases, the covariance matrix is not purely physical, i.e., measurable based on physical coordinates.
  4. Integration of the choice of destination: The mode and route joint choice model with disaggregate spatial representation, should be integrated with other modeling stages in order to contribute to an applied travel demand model. This particularly concerns the destination choice model for non-mandatory trip purposes. Many applied models nowadays implement the mode and destination choice as a joint decision. Further research should be directed to explore how the choice of destination can be integrated with the proposed methodological approach for the joint mode and route choice.
  5. Tour-based approach: We have modeled the choice of the travel mode at the level of single trip. This can be applied to modeling mode choice for two-leg round trips, but when it comes to more complex travel patterns, a tour-based mode choice model is required. Further research is required to extend the proposed methodological approach to a tour-based framework.
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## Appendix A:

# Derivation of the Generalized Moments of the Normal Distribution

Normal probability density function and the normal cumulative probability function are defined as functions of the mean and the standard deviation in the following way:

$$\phi_i(x; \mu_i, \sigma_i) = \frac{1}{\sqrt{2\pi}\sigma_i} \exp\left[-\frac{(x - \mu_i)^2}{2\sigma_i^2}\right]$$

The corresponding cumulative distribution function is given by:

$$\Phi_i(x; \mu_i, \sigma_i) = \int_{-\infty}^x \phi_i(t; \mu_i, \sigma_i) dt = \frac{1}{2} \left[ 1 + \operatorname{erf}\left(\frac{x - \mu_i}{\sqrt{2}\sigma_i}\right) \right]$$

We define the first order moment,  $\mu_i^*$ , and the second order moment,  $\sigma_i^{*2}$ , of a normal probability density function over the interval  $[-\infty, a]$  which are given by (Here, detailed developments are suppressed for simplicity):

$$\mu_i^* = \int_{-\infty}^a x \phi_i(x; \mu_i, \sigma_i) dx = \mu_i \Phi_i(a) - \sigma_i^2 \phi_i(a) \quad (\text{A.1})$$

$$\left[\sigma_i^*\right]^2 = \int_{-\infty}^a x^2 \phi_i(x; \mu_i, \sigma_i) dx = \mu_i^2 \Phi_i(a) - \sigma_i^2 \mu_i \phi_i(a) + \sigma_i^2 \phi_i(a) \quad (\text{A.2})$$

We study a particular random variable distributed normally following two normal density functions  $\phi_1(x)$  and  $\phi_2(x)$  in two distinct but equal sized subpopulations. From the union between the two preceding equal sized subpopulations, a population is constructed in which the random variable follows the probability density function  $\omega(x)$  defined as:

$$\omega(x) = \frac{1}{2} \phi_1(x) + \frac{1}{2} \phi_2(x) \quad (\text{see Eq. 4.17})$$

We study the optimal domain decomposition strategy for breaking the entire population into two subpopulations with maximum inter-class variance being conserved. We suppose breaking the domain at  $\Gamma: x = a$ . So the first subpopulation spreads over the interval  $-\infty, a$  and the second subpopulation spreads over the interval  $a, +\infty$ . The population proportion in the two subpopulation are denoted by  $p_1$  and  $p_2$ , and are defined as follows (For the sake of readability from now on we denote where necessary a given function  $f$  at  $a$  by  $f^a$ ):

$$p_1 = \int_{-\infty}^a \omega(x) dx = \int_{-\infty}^a \left[ \frac{1}{2} \phi_1(x) + \frac{1}{2} \phi_2(x) \right] dx = \frac{1}{2} \Phi_1^a + \frac{1}{2} \Phi_2^a \quad (\text{A.3})$$

$$p_2 = 1 - p_1 = \frac{1}{2} (1 - \Phi_1^a) + \frac{1}{2} (1 - \Phi_2^a) \quad (\text{A.4})$$

Now the mean value in the first subpopulation,  $m_1$ , is given by:

$$m_1 = \frac{\int_{-\infty}^a x \omega(x) dx}{\int_{-\infty}^a \omega(x) dx} = \frac{\int_{-\infty}^a x \left[ \frac{1}{2} \phi_1(x) + \frac{1}{2} \phi_2(x) \right] dx}{\int_{-\infty}^a \left[ \frac{1}{2} \phi_1(x) + \frac{1}{2} \phi_2(x) \right] dx} = \frac{\mu_1^* + \mu_2^*}{\Phi_1^a + \Phi_2^a} \quad (\text{A.5})$$

Which, substituting for the first order moments  $\mu_1^*$  and  $\mu_2^*$ , yields:

$$m_1 = \frac{\left[ \mu_1 \Phi_1^a - \sigma_1^2 \phi_1^a \right] + \left[ \mu_2 \Phi_2^a - \sigma_2^2 \phi_2^a \right]}{\Phi_1^a + \Phi_2^a} \quad (\text{A.6})$$

The mean value in the second subpopulation,  $m_2$ , is given in a similar way:

$$m_2 = \frac{\int_a^{+\infty} x \omega(x) dx}{\int_a^{+\infty} \omega(x) dx} = \frac{\frac{1}{2} (\mu_1 + \mu_2) - \int_{-\infty}^a x \omega(x) dx}{1 - \int_{-\infty}^a \omega(x) dx} = \frac{\mu_1 - \mu_1^* + \mu_2 - \mu_2^*}{1 - \Phi_1^a + 1 - \Phi_2^a} \quad (\text{A.7})$$

Which, substituting for the first order moments  $\mu_1^*$  and  $\mu_2^*$ , is reduced to:

$$m_2 = \frac{\left[ \mu_1 (1 - \Phi_1^a) + \sigma_1^2 \phi_1^a \right] + \left[ \mu_2 (1 - \Phi_2^a) + \sigma_2^2 \phi_2^a \right]}{1 - \Phi_1^a + 1 - \Phi_2^a} \quad (\text{A.8})$$

In the next step, we define variances over the two subpopulations. Over the first subpopulation the random variable variance  $s_1^2$  is defined as:

$$s_1^2 = \frac{\int_{-\infty}^a (x - m_1)^2 \omega(x) dx}{\int_{-\infty}^a \omega(x) dx} = \frac{\int_{-\infty}^a x^2 \omega(x) dx}{\int_{-\infty}^a \omega(x) dx} - m_1^2 = \frac{\sigma_1^{*2} + \sigma_2^{*2}}{\Phi_1^a + \Phi_2^a} - m_1^2 \quad (\text{A.9})$$

Which, substituting for the second order moments  $\sigma_1^*$  and  $\sigma_2^*$ , yields:

$$s_1^2 = \frac{\left[ \mu_1^2 + \sigma_1^2 \Phi_1^a - \sigma_1^2 \mu_1 + a \phi_1^a \right] + \left[ \mu_2^2 + \sigma_2^2 \Phi_2^a - \sigma_2^2 \mu_2 + a \phi_2^a \right]}{\Phi_1^a + \Phi_2^a} - m_1^2 \quad (\text{A.10})$$

For the second subpopulation, the variance  $s_2^2$  is defined in a similar way:

$$s_2^2 = \frac{\int_a^{+\infty} (x - m_2)^2 \omega(x) dx}{\int_a^{+\infty} \omega(x) dx} = \frac{\int_a^{+\infty} x^2 \omega(x) dx}{1 - \int_{-\infty}^a \omega(x) dx} - m_2^2 \quad (\text{A.11})$$

Given that:

$$\int_{-\infty}^{+\infty} x^2 \omega(x) dx = \int_{-\infty}^{+\infty} x^2 \left[ \frac{1}{2} \phi_1(x) + \frac{1}{2} \phi_2(x) \right] dx = \frac{1}{2} \mu_1^2 + \sigma_1^2 + \frac{1}{2} \mu_2^2 + \sigma_2^2 \quad (\text{A.12})$$

the second subpopulation variance is expressed by:

$$s_2^2 = \frac{\left[ \mu_1^2 + \sigma_1^2 - \sigma_1^{*2} \right] + \left[ \mu_2^2 + \sigma_2^2 - \sigma_2^{*2} \right]}{1 - \Phi_1^a + 1 - \Phi_2^a} - m_2^2 \quad (\text{A.13})$$

which, substituting for the second order moments  $\sigma_1^*$  and  $\sigma_2^*$ , yields:

$$s_2^2 = \frac{\left[ \mu_1^2 + \sigma_1^2 (1 - \Phi_1^a) + \sigma_1^2 \mu_1 + a \phi_1^a \right] + \left[ \mu_2^2 + \sigma_2^2 (1 - \Phi_2^a) + \sigma_2^2 \mu_2 + a \phi_2^a \right]}{1 - \Phi_1^a + 1 - \Phi_2^a} - m_2^2 \quad (\text{A.14})$$

The optimal domain decomposition program determines  $\Gamma(a)$  such that the interclass variance captured in terms of the difference between the intra-class means is maximized so that the maximum amount of the information is conserved which otherwise would have been lost as intra-class variances due to the application of aggregate methods.

The optimal decomposition program is expressed by:

$$\max_a : s_{12} = p_1 p_2 (m_1 - m_2)^2 \quad (\text{A.15})$$

This inter-class variance maximization program is solved numerically.

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## Appendix B: Integrating Location Statistics over Polygon Surface

We can define an optimization program with the interzonal variance of the spatial localization to be maximized as its objective function. In the most general case with  $J$  subzones, the optimization program should search for  $J - 1$  boundary curves that minimize the expected value of intrazonal variances and maximize the interzonal variance, using the calculus of variations; this is excessively burdensome for a metropolitan size area. Nevertheless, regarding the fact that zone boundaries are defined as polygons we develop the formulation applicable to the search of linear piecewise separating boundaries. The centroid point for the  $n$ th sub-zone is given by the following:

$$C^n = \frac{1}{A^n} \iint_{\Omega^n} \begin{pmatrix} x \\ y \end{pmatrix} d\Omega \quad , \quad A^n = \iint_{\Omega^n} d\Omega \quad (\text{B.1})$$

where  $\Omega^n \subset Z$  represents the  $n$ th sub-zone of the zone  $Z$  (capital zeta). The problem is now to integrate over the surface of the sub-zone and to evaluate their total area. From the Green's theorem for a Cartesian coordinate system, we have:

$$\iint_{\Omega} \left( \frac{\partial F}{\partial x} - \frac{\partial G}{\partial y} \right) d\Omega = \oint_{\Gamma} F dy + G dx \quad (\text{B.2})$$

where  $\Gamma$  represents the boundary of the sub-zone. First for integrating the total area we consider the following  $F$  and  $G$  :

$$\begin{aligned} \frac{\partial F}{\partial x} = \frac{1}{2} & \Rightarrow F = \frac{1}{2}x \\ -\frac{\partial G}{\partial y} = \frac{1}{2} & G = -\frac{1}{2}y \end{aligned} \quad (\text{B.3})$$


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Substituting in the Equation B.2 we have:

$$\iint_{\Omega^n} d\Omega = \frac{1}{2} \oint_{\Gamma^n} xdy - \frac{1}{2} \oint_{\Gamma^n} ydx \quad (\text{B.4})$$

We suppose that zones are in the form of polygons with linear piecewise boundaries. Consequently, the entire boundary can be decomposed into the union of boundary lines:

$$\Gamma^n = \bigcup_{i=1}^{I^n} \Gamma_i^n \quad ; \quad \Gamma_i^n : \quad x_i, y_i \quad ; \quad x_{i+1}, y_{i+1} \quad (\text{B.5})$$

where  $\Gamma_i^n$  are mutually exclusive and collectively exhaustive boundary lines, and  $I^n$  is the number of sides of the polygon. The Equation B.4 now can be reformulated into the following form:

$$A^n = \iint_{\Omega^n} d\Omega = \frac{1}{2} \sum_{i=1}^{I^n} \left\{ \int_{y_i}^{y_{i+1}} xdy - \int_{x_i}^{x_{i+1}} ydx \right\} \quad (\text{B.6})$$

The integrals over boundary lines are given by:

$$\begin{aligned} \int_{y_i}^{y_{i+1}} xdy &= \frac{1}{2} x_{i+1} + x_i \quad y_{i+1} - y_i \\ \int_{x_i}^{x_{i+1}} ydx &= \frac{1}{2} y_{i+1} + y_i \quad x_{i+1} - x_i \end{aligned} \quad (\text{B.7})$$

Thus by substituting, expanding and simplifying we obtain:

$$\begin{aligned} A^n &= \frac{1}{2} \sum_{i=1}^{n_r} \left\{ \frac{1}{2} x_{i+1} + x_i \quad y_{i+1} - y_i - \frac{1}{2} y_{i+1} + y_i \quad x_{i+1} - x_i \right\} \\ &= \frac{1}{2} \sum_{i=1}^{n_r} x_i y_{i+1} - x_{i+1} y_i \end{aligned} \quad (\text{B.8})$$

Second for integrating for the first moment of surface we propose the following  $F$  and  $G$  :

$$\begin{aligned} \frac{\partial F}{\partial x} &= \begin{pmatrix} x \\ 0 \end{pmatrix} & \Rightarrow & F = \frac{1}{2} \begin{pmatrix} x^2 \\ 0 \end{pmatrix} \\ -\frac{\partial G}{\partial y} &= \begin{pmatrix} 0 \\ y \end{pmatrix} & & G = -\frac{1}{2} \begin{pmatrix} 0 \\ y^2 \end{pmatrix} \end{aligned} \quad (\text{B.9})$$

Substituting in the Equation B.2 the centroid coordinates are given by integrating over the boundary:

$$C^n = \frac{1}{A^n} \oint_{\Gamma^n} \left[ \frac{1}{2} \begin{pmatrix} x^2 \\ 0 \end{pmatrix} dy - \frac{1}{2} \begin{pmatrix} 0 \\ y^2 \end{pmatrix} dx \right] = \frac{1}{2A^n} \oint_{\Gamma^n} \begin{pmatrix} x^2 \\ 0 \end{pmatrix} dy - \frac{1}{2A^n} \oint_{\Gamma^n} \begin{pmatrix} 0 \\ y^2 \end{pmatrix} dx \quad (\text{B.10})$$

or,

$$\begin{aligned} C_x^n &= \frac{1}{2A^n} \oint_{\Gamma^n} x^2 dy \\ C_y^n &= \frac{-1}{2A^n} \oint_{\Gamma^n} y^2 dx \end{aligned} \quad (\text{B.11})$$

By integrating over a piecewise linear boundary, the coordinates of the centroid for a polygon are given by the following equations:

$$\begin{aligned} C_x^n &= \frac{1}{2A^n} \sum_{i=1}^{I_n} \frac{1}{3} \frac{y_{i+1} - y_i}{x_{i+1} - x_i} x_{i+1}^3 - x_i^3 \\ C_y^n &= \frac{-1}{2A^n} \sum_{i=1}^{I_n} \frac{1}{3} \frac{x_{i+1} - x_i}{y_{i+1} - y_i} y_{i+1}^3 - y_i^3 \end{aligned} \quad (\text{B.12})$$

By expanding and simplifying these equations, the final form of the centroid coordinates is given by:

$$\begin{aligned} C_x^n &= \frac{1}{6A^n} \sum_{i=1}^{I_n} x_{i+1} + x_i \quad x_i y_{i+1} - x_{i+1} y_i \\ C_y^n &= \frac{-1}{6A^n} \sum_{i=1}^{I_n} y_{i+1} + y_i \quad y_i x_{i+1} - y_{i+1} x_i \end{aligned} \quad (\text{B.13})$$

## Appendix C:

# Integrating Terminal Distance over Polygon Surface

The mean Manhattan distance is given by:

$$\bar{\lambda} = \mathbb{E}[\tilde{\lambda}] = \frac{1}{A} \iint_{\Omega} |x - x_C| + |y - y_C| d\Omega \quad , \quad A = \iint_{\Omega} d\Omega \quad (\text{C.1})$$

where  $\Omega \subset Z$  represents the populated areas of the zone  $Z$  (capital zeta), and  $x_C, y_C$  are coordinates of an anchor of the zone. The problem is now to integrate the distance measure over the surface of the intrazonal residence/activity regions and to evaluate their total area. From the Green's theorem for a Cartesian coordinate system, we have:

$$\iint_{\Omega} \left( \frac{\partial F}{\partial x} + \frac{\partial G}{\partial y} \right) d\Omega = \oint_{\Gamma} F dy - G dx \quad (\text{C.2})$$

where  $\Gamma$  represents the boundary of the intrazonal residence/activity regions. First for integrating the total area we consider the following  $F$  and  $G$  :

$$\begin{aligned} \frac{\partial F}{\partial x} = \frac{1}{2} & \Rightarrow F = \frac{1}{2} x \\ \frac{\partial G}{\partial y} = \frac{1}{2} & G = \frac{1}{2} y \end{aligned} \quad (\text{C.3})$$

Substituting in the Equation C.2 we have:

$$\iint_{\Omega} d\Omega = \frac{1}{2} \oint_{\Gamma} x dy - \frac{1}{2} \oint_{\Gamma} y dx \quad (\text{C.4})$$

We suppose that zones are in the form of polygons with linear piecewise boundaries. Consequently, the entire boundary can be decomposed into the union of boundary lines:

$$\Gamma = \bigcup_{i=1}^{n_r} \Gamma_i \quad ; \quad \Gamma_i : \quad x_i, y_i \quad ; \quad x_{i+1}, y_{i+1} \quad (C.5)$$

where  $\Gamma_i$  are mutually exclusive and collectively exhaustive boundary lines, and  $n_r$  is the number of sides of the polygon. The Equation C.4 now can be reformulated into the following form:

$$A = \iint_{\Omega} d\Omega = \frac{1}{2} \sum_{i=1}^{n_r} \left\{ \int_{y_i}^{y_{i+1}} x dy - \int_{x_i}^{x_{i+1}} y dx \right\} \quad (C.6)$$

The integrals over boundary lines are given by:

$$\begin{aligned} \int_{y_i}^{y_{i+1}} x dy &= \frac{1}{2} x_{i+1} + x_i \quad y_{i+1} - y_i \\ \int_{x_i}^{x_{i+1}} y dx &= \frac{1}{2} y_{i+1} + y_i \quad x_{i+1} - x_i \end{aligned} \quad (C.7)$$

Thus,

$$\begin{aligned} A &= \frac{1}{2} \sum_{i=1}^{n_r} \left\{ \frac{1}{2} x_{i+1} + x_i \quad y_{i+1} - y_i - \frac{1}{2} y_{i+1} + y_i \quad x_{i+1} - x_i \right\} \\ &= \frac{1}{2} \sum_{i=1}^{n_r} x_i y_{i+1} - x_{i+1} y_i \end{aligned} \quad (C.8)$$

Second for integrating the Manhattan distance, we propose the following  $F$  and  $G$ :

$$\begin{aligned} \frac{\partial F}{\partial x} = |x - x_C| &\quad \Rightarrow \quad F = \frac{1}{2} x - x_C \quad |x - x_C| \\ \frac{\partial G}{\partial y} = |y - y_C| &\quad \quad \quad G = \frac{1}{2} y - y_C \quad |y - y_C| \end{aligned} \quad (C.9)$$

Substituting in the Equation C.2 we have:

$$\begin{aligned} \iint_{\Omega} |x - x_C| + |y - y_C| \quad d\Omega &= \frac{1}{2} \oint_{\Gamma} x - x_C \quad |x - x_C| \quad dy \\ &\quad - \frac{1}{2} \oint_{\Gamma} y - y_C \quad |y - y_C| \quad dx \end{aligned} \quad (C.10)$$

The Equation C.10 now can be reformulated into the following form:

$$\begin{aligned} & \iint_{\Omega} |x - x_C| + |y - y_C| d\Omega = \\ & = \frac{1}{2} \sum_{i=1}^{n_r} \left\{ \int_{y_i}^{y_{i+1}} |x - x_C| dy - \int_{x_i}^{x_{i+1}} |y - y_C| dx \right\} \end{aligned} \quad (\text{C.11})$$

The integrals over boundary lines are given by:

$$\begin{aligned} & \int_{y_i}^{y_{i+1}} |x - x_C| dy = \\ & = \frac{1}{3} \frac{x_{i+1} - x_i}{y_{i+1} - y_i} \left[ |y_{i+1} - y_C|^2 |y_{i+1} - y_C| - |y_i - y_C|^2 |y_i - y_C| \right] \end{aligned} \quad (\text{C.12a})$$

$$\begin{aligned} & \int_{x_i}^{x_{i+1}} |y - y_C| dx = \\ & = \frac{1}{3} \frac{y_{i+1} - y_i}{x_{i+1} - x_i} \left[ |x_{i+1} - x_C|^2 |x_{i+1} - x_C| - |x_i - x_C|^2 |x_i - x_C| \right] \end{aligned} \quad (\text{C.12b})$$

Thus:

$$\begin{aligned} \bar{\lambda} & = \frac{1}{6A} \sum_{i=1}^I \frac{x_{i+1} - x_i}{y_{i+1} - y_i} \left[ |y_{i+1} - y_C|^2 |y_{i+1} - y_C| - |y_i - y_C|^2 |y_i - y_C| \right] \\ & \quad - \frac{1}{6A} \sum_{i=1}^I \frac{y_{i+1} - y_i}{x_{i+1} - x_i} \left[ |x_{i+1} - x_C|^2 |x_{i+1} - x_C| - |x_i - x_C|^2 |x_i - x_C| \right] \end{aligned} \quad (\text{C.13})$$

Now we turn attention to the variance-covariance matrix of the Manhattan distance measure. By definition, the variance-covariance matrix is given by:

$$\begin{aligned} \sigma_{ij} & = \text{cov}[\tilde{\lambda}_i, \tilde{\lambda}_j] \\ & = \frac{1}{A} \iint_{\Omega} |x - x_{C^i}| + |y - y_{C^i}| - \bar{\lambda}_i \quad |x - x_{C^j}| + |y - y_{C^j}| - \bar{\lambda}_j d\Omega \end{aligned} \quad (\text{C.14})$$

By expanding the integrant, we propose the following association:

$$\begin{aligned} \frac{\partial F}{\partial x} & = |y - y_{C^i}| |y - y_{C^j}| + |x - x_{C^i}| |y - y_{C^j}| \\ & \quad - \bar{\lambda}_i |x - x_{C^j}| - \bar{\lambda}_j |x - x_{C^i}| + \bar{\lambda}_i \bar{\lambda}_j \end{aligned} \quad (\text{C.15a})$$

$$\frac{\partial G}{\partial y} = \left| x - x_{C^i} \right| \left| x - x_{C^j} \right| + \left| y - y_{C^i} \right| \left| x - x_{C^j} \right| - \bar{\lambda}_i \left| y - y_{C^j} \right| - \bar{\lambda}_j \left| y - y_{C^i} \right| \tag{C.15b}$$

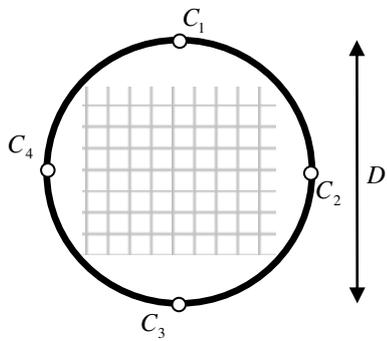
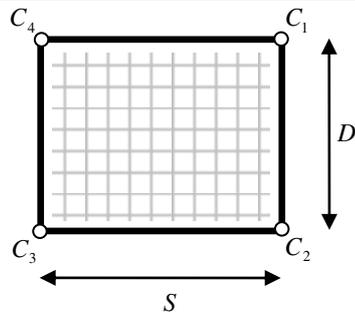
Therefore the two functions  $F$  and  $G$  are given by:

$$F = \left| y - y_{C^i} \right| \left| y - y_{C^j} \right| x + \frac{1}{2} \left| x - x_{C^i} \right| \left| y - y_{C^j} \right| x - x_{C^i} - \bar{\lambda}_i \left| y - y_{C^j} \right| x - \bar{\lambda}_j \left| y - y_{C^i} \right| x + \bar{\lambda}_i \bar{\lambda}_j x \tag{C.16a}$$

$$G = \left| x - x_{C^i} \right| \left| x - x_{C^j} \right| y - \frac{1}{2} \left| y - y_{C^i} \right| \left| x - x_{C^j} \right| y - y_{C^i} + \bar{\lambda}_i \left| x - x_{C^j} \right| y + \bar{\lambda}_j \left| x - x_{C^i} \right| y \tag{C.16b}$$

Contrary to the case of the mean of the Manhattan distance measure, the analytical solution of the right-hand side integral in the Equation C.14 does not yield a convenient closed-form result and should be evaluated numerically. Table C.i recapitulates intrazonal diffusion distance statistics for circular (polygon with infinite sides) and rectangular shapes.

**Table C.i. Intrazonal Manhattan distance statistics.**

Intrazonal geometry	Manhattan distance statistics
	$\mu = \left( 1 + \frac{4}{3\pi} \right) \frac{D}{2}$ $\sigma_1^2 = \left( \frac{1}{2} - \frac{16}{9\pi^2} \right) \frac{D^2}{4}$ $\sigma_{12} = \left( \frac{1}{2\pi} - \frac{16}{9\pi^2} \right) \frac{D^2}{4}$ $\sigma_{13} = - \left( \frac{16}{9\pi^2} \right) \frac{D^2}{4}$
	$\mu = \frac{S + D}{2}$ $\sigma_1^2 = \frac{S^2 + D^2}{12}$ $\sigma_{12} = \frac{S^2 - D^2}{12}$ $\sigma_{13} = - \frac{S^2 + D^2}{12}$



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