# Revenue Management for transport service providers in Physical Internet : freight carriers as case

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# Revenue Management for transport service providers in Physical Internet: freight carriers as case

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# Abstract

Although the freight transport plays vital role in the economic sector and the freight transport demand is increasing, there are still challenges for the carriers in the freight market to keep and improve their revenue. To respond to the challenges, Revenue Management (RM) and Physical Internet (PI) are adopted as the solution in this thesis. RM is a method, which is originated from airline industry, to maximize the revenue. PI is a fully interconnected, open, dynamic logistics system aiming to develop an open global interconnected logistics networks to increase the logistics efficiency and sustainability. This thesis investigates the application of RM in PI to improve the revenue of less-than-truckload (LTL) carriers.

The application of RM in PI is studied based on four research questions in RM, i.e. pricing, capacity control, forecasting, and bundle pricing. In addition, for each research question, an experimental study is conducted to evaluate the feasibility and performance of the proposed optimization models corresponded to each question. The results provide the carriers managerial implications and constructive guidance to make decisions to optimize their revenue at several levels, considering different situations and scenarios.

Overall, this research investigates the Revenue Management from the point of view of LTL carriers operating in a highly dynamic environment like Physical Internet. The work in this research gives a general and systematical sight to the application of RM in a dynamic network of road freight transport. The achievements of this thesis give a basis for the future in-depth study on the revenue problem in a dynamic environment.

Keywords: Revenue Management, Physical Internet, Freight transport, Dynamic pricing, Auction

# Résumé

Bien que le transport de marchandises joue un rôle essentiel dans le secteur économique et que la demande de transport de marchandises augmente, les transporteurs sur le marché du fret ont encore du mal à maintenir et à améliorer leurs revenus. Pour répondre aux défis, Revenue Management (RM) et l'Internet Physique (PI) sont adoptés comme solution dans cette thèse. RM est une méthode, issue de l'industrie du transport aérien, qui permet de maximiser les revenus. PI est un système logistique entièrement interconnecté, ouvert et dynamique visant à développer des réseaux logistiques mondiaux interconnectés ouverts afin d'accroître l'efficacité et la durabilité de la logistique. Cette thèse examine l'application de RM dans PI pour améliorer les revenus des transporteurs de chargement partiel.

L'application de RM dans PI est étudiée à partir de quatre questions de recherche sur RM : la tarification, le contrôle de capacité, les prévisions et la tarification groupée. De plus, pour chaque question de recherche, une étude expérimentale est menée pour évaluer la faisabilité et les performances des modèles d'optimisation proposés correspondant à chaque question. Les résultats fournissent aux transporteurs des implications en termes de gestion et des conseils constructifs leur permettant d'optimiser leurs revenus à plusieurs niveaux, en tenant compte de situations et de scénarios différents.

Dans l'ensemble, cette recherche examine Revenue Management du point des transporteurs de chargement partiel opérant dans un environnement très dynamique tel que l'Internet Physique. Les travaux de cette recherche donnent un aperçu général et systématique de l'application de Revenue Management dans un réseau dynamique de transport de marchandises par route. Les réalisations de cette thèse fournissent une base pour la future étude approfondie sur le problème des revenus dans un environnement dynamique.

Mots Clés: Revenue Management, Internet Physique, transport de fret, Tarification dynamique, enchères

# La description

Le transport de marchandises est une activité essentielle de la logistique, qui consiste à transporter des marchandises et des cargaisons d’un lieu à un autre. Sur le marché du fret, il existe trois acteurs fondamentaux (expéditeurs, transporteurs, intermédiaires) et quatre modes principaux (routier, ferroviaire, aérien et maritime). Tous les différents acteurs et modes de transport ont des caractéristiques différentes. L'objectif de cette thèse est sur les transporteurs dans le transport de marchandises par route.

Dans le secteur économique, le transport de marchandises représente une part importante de l'économie, représentant environ 5% du GDP en Europe. De plus, le transport routier de marchandises est le mode de transport de marchandises intérieur le plus utilisé en raison de la flexibilité et de la capacité de fournir des services porte à porte. Par exemple, 88% du volume de transport de fret intérieur en France en 2013 provient du transport routier. Ce qui rend le fret routier plus important, c'est que la demande de fret routier continue d'augmenter en raison de la mondialisation croissante du commerce et de la croissance économique. Cependant, les transporteurs sur le marché du transport de marchandises sont confrontés à de sérieux défis pour maintenir et améliorer leurs revenus. Les défis pourraient être classés en trois facteurs principaux, à savoir la faible marge, le coût de fret accru et en particulier la concurrence intense. Premièrement, la marge des opérateurs de transport routier est très faible, autour de 4% ou en dessous de 4% dans de nombreux pays et régions. En outre, l'augmentation du coût du fret rend encore plus difficile l'amélioration de la marge. Plus grave, la concurrence sur le marché du transport de marchandises est plus vive à trois niveaux, parmi les pays et les régions, parmi les divers modes de transport et parmi les nombreux transporteurs et prestataires de services logistiques.

Pour relever les défis, certaines solutions possibles pourraient être adoptées pour améliorer les revenus du transporteur directement ou indirectement. Les nouvelles technologies, par exemple véhicule avancé et carburant moins cher, sont des solutions pour réduire les coûts de transport, augmentant ainsi la marge. Nouvelles méthodes de fonctionnement, par exemple la gestion de flotte et le routage des véhicules constituent un autre ensemble de solutions permettant de réduire les coûts d'exploitation. Un mécanisme d'approvisionnement efficace pourrait également améliorer l'efficacité des opérations, optimisant ainsi le prix et contrôlant les coûts. En outre, des organisations et systèmes logistiques efficaces pourraient également accroître l'efficacité du transport et réduire les coûts grâce à une demande plus structurée. Ainsi, les transporteurs pourraient tirer parti d’un système logistique novateur pour améliorer leurs revenus. Enfin, Revenue Management est une autre méthode bien connue pour améliorer les revenus des transporteurs. La gestion des revenus est utilisée pour réagir aux fluctuations du marché et améliorer les revenus de l’entreprise. Dans cette thèse, un système logistique innovant et Revenue Management sont adoptés pour résoudre le problème d'optimisation des revenus.

Pour le système logistique innovant, cette thèse a sélectionné un nouveau concept d'interconnexion de réseaux logistiques, appelé l’Internet Physique (PI). PI vise à développer un système logistique mondial ouvert et interconnecté afin d’accroître l’efficacité et la durabilité de la logistique. Le principe de PI consiste à interconnecter les réseaux logistiques indépendants via des ressources accessibles, la normalisation des interfaces et des protocoles, des conteneurs intelligents, etc., afin d'améliorer l'intégration, la coordination et le partage des ressources. Précisément, dans cette thèse, nous étudierons comment appliquer la gestion des revenus dans un réseau dynamique tel que PI, où la demande est concentrée sur des hubs afin d’améliorer les revenus de l’opérateur. Nous devons mentionner ici que les opérations de chargement partiel (LTL) sont étudiées dans cette thèse parce que les demandes, conteneurs et boîtes, dans PI sont pour la plupart chargement partiel. Cette thèse étudiera l'application de Revenue Management dans ce contexte à travers quatre sections: tarification, contrôle de la capacité, prévision et tarification à la volée.

Le problème de la recherche dans cette thèse est le problème de Revenue Management pour les transporteurs de chargement partiel dans l’Internet Physique. Plus précisément, cette recherche vise à répondre aux questions de recherche suivantes:

Question de recherche 1 (RQ1): comment les transporteurs déterminent-ils le prix de l'offre pour les demandes de chargement partiel (LTL) dans l’Internet Physique afin d'améliorer leurs revenus?

Question de recherche 2 (QR 2): comment les transporteurs sélectionnent-ils les demandes avec différentes destinations et quantités à transporter?

Question de recherche 3 (RQ3): comment la prévision pourrait-elle affecter la tarification et la décision de sélection des demandes dans l'Internet Physique?

Question de recherche 4 (RQ4): comment les transporteurs déterminent-ils le prix de l'offre pour le paquet de demandes dans l'Internet Physique?

Les objectifs de cette recherche peuvent être résumés comme suit:

1) Étudiez l'application de Revenue Management dans un réseau de transport dynamique tel que l'Internet Physique, afin de proposer une solution permettant d'améliorer les revenus des opérateurs.

2) Élaborer un modèle de tarification permettant aux opérateurs de choisir le prix optimal des enchères qui permettrait d'optimiser les revenus.

3) Développer un modèle de sélection des demandes pour aider les opérateurs à sélectionner les demandes les plus rentables face aux différentes demandes.

4) Modélisez la prévision des demandes dans les modèles de tarification et de sélection des demandes afin d'étudier l'influence des futures demandes possibles sur la décision en cours.

5) Développer le modèle de tarification pour le groupe de demandes dans la situation où les opérateurs doivent proposer des demandes de groupe pour soumissionner.

6) Analyser la faisabilité et la performance des modèles proposés basés sur une organisation l'Internet Physique ou de grands concentrateurs.

Nous pensons que cette recherche et ses résultats fourniront des implications en termes de gestion et des outils d'aide à la décision pour les entreprises de camionnage actives sur des marchés dynamiques LTL comme PI environnement et qui recherchent de nouvelles solutions pour améliorer leurs revenus.

Afin de répondre aux questions de recherche proposées, nous avons adopté la méthodologie de recherche suivante.

Tout d'abord, nous présentons le contexte de la recherche et la portée de cette thèse à travers une revue de la littérature.

1) Au début, nous avons procédé à une analyse documentaire du transport de marchandises dans le cadre de la logistique afin de cerner l'importance du transport de marchandises pour l'économie et les difficultés actuelles en matière de recettes sur le marché du transport de marchandises du point de vue du transporteur.

2) Ensuite, les solutions au sein des littératures et pratiques existantes pour répondre aux problèmes de revenus et les résoudre, sont discutées. Parmi les différentes solutions, nous avons sélectionné Revenue Management et un concept innovant d'interconnexion de réseaux logistiques récemment proposé: l'Internet Physique comme contexte de recherche.

3) Ensuite, la revue de la littérature de Revenue Management et l'Internet Physique est effectuée respectivement. Les applications de RM dans divers secteurs, et en particulier dans le transport de marchandises, sont généralement présentées dans le but de rechercher le potentiel d'application de RM dans PI. Pendant ce temps, la recherche existante sur PI est examinée afin d'identifier son potentiel d'amélioration de l'efficience et de l'efficacité de la logistique.

Après l'introduction du contexte de recherche, le problème de recherche et les quatre questions de recherche dans PI sont proposés. Ensuite, dans l'étape suivante, nous étudions les questions une par une. La méthodologie utilisée pour enquêter sur chaque question est indiquée ci-dessous.

1) Dans un premier temps, une revue de la littérature relative à la question discutée est menée afin de comprendre les problèmes et les limites actuelles pour étudier la question de la recherche en général et dans le contexte de PI. Cette étape nous offre la possibilité de traiter nos recherches.

2) Ensuite, pour résoudre les questions de recherche, un modèle d'optimisation correspondant à chaque question est développé. Les modèles des quatre questions de recherche sont liés et pourraient être utilisés dans différentes situations.

3) Enfin, une étude numérique est menée pour évaluer et vérifier la faisabilité et la performance du modèle pour chaque question de recherche. Les facteurs susceptibles d'influencer les décisions font également l'objet d'une enquête. Les résultats de l'optimisation pourraient fournir des directives et des outils pour la prise de décision.

Le reste de cette thèse est organisé comme suit:

Le chapitre 2 présente le problème de revenus auquel les transporteurs sont confrontés sur le marché du transport de marchandises. Premièrement, nous discutons de l'importance du transport de marchandises pour l'économie. Ensuite, les défis pour les opérateurs de gérer leurs revenus sont présentés et les leviers possibles sont discutés. Après avoir introduit le problème des recettes dans le transport de marchandises, le Revenue Management et l'Internet Physique sont présentés respectivement à partir de la définition, des caractéristiques et des applications. Enfin, le problème de recherche, les questions de recherche et la méthodologie associée utilisée dans cette thèse sont discutés.

Le chapitre 3 examine le problème de la prise de décision en matière de tarification dynamique dans le contexte de l'Internet Physique (PI). Dans un environnement dynamique et stochastique tel que PI, l'un des principaux soucis des transporteurs est de savoir comment proposer des prix pour les demandes afin de maximiser leurs revenus. Ce dernier est déterminé par le prix proposé et la probabilité de gagner la demande à ce prix. Ce chapitre propose un modèle de tarification dynamique en réponse à un mécanisme d'enchères visant à optimiser le prix des offres du transporteur. Une étude expérimentale est menée dans laquelle deux stratégies de tarification sont proposées et évaluées: un prix d'offre unique (un prix unique pour toutes les demandes d'une même période d'enchères) et un prix d'enchère variable (prix pour chaque demande d'une seule période d'enchères). Trois facteurs d'influence sont également étudiés: le nombre de demandes, la capacité du transporteur et le coût. Les résultats expérimentaux fournissent des conclusions intéressantes et des lignes directrices utiles pour les opérateurs en ce qui concerne les décisions de tarification dans les hubs PI.

Le chapitre 4 étend la situation à une jambe du chapitre 3 à multi-jambes et examine un problème de tarification et de sélection des demandes de chargement partiel (LTL) afin d'optimiser les revenus du transporteur dans l'Internet Physique (PI). Dans un hub confronté à de nombreuses demandes différentes, le transporteur doit sélectionner un (ou plusieurs) type (s) de demandes d'intérêt à soumissionner et, dans l'intervalle, décider du prix de l'offre afin de maximiser son profit. Deux scénarios sont étudiés, à savoir un transporteur à pleine capacité ou un transporteur avec des charges avec des destinations connues. Pour chaque scénario, un modèle de programmation entier basé sur un modèle de tarification dynamique multi-jambes est proposé pour résoudre le problème de sélection de demande et le problème de tarification simultanément. Une étude informatique est menée pour démontrer la faisabilité des modèles.

Le chapitre 5 étend la demande de transport du chapitre 3 à plusieurs périodes d'enchères et la quantité de demande statique dans les hubs suivants du chapitre 4 à une quantité stochastique. Dans ce chapitre, un modèle de tarification dynamique pour plusieurs périodes est développé. Ce modèle pourrait aider les transporteurs qui resteraient dans un hub à participer à plusieurs enchères pour déterminer le prix optimal des enchères pour chaque période. De plus, le modèle de sélection des demandes associé à un modèle de prévision stochastique est proposé. De plus, nous étudions comment l'incertitude des prévisions influencerait le bénéfice attendu.

Le chapitre 6 considère le réseau dans lequel il n'y a pas beaucoup de demandes sur les voies. Cela signifie qu'il n'y aura pas assez de demandes pour occuper la capacité des transporteurs LTL. Face à une telle situation, les transporteurs devraient envisager de regrouper leurs demandes pour accroître l'utilité de leur capacité de transport. Ce chapitre propose un modèle de programmation mixte non linéaire à nombres entiers (MINLP) pour résoudre le problème de la tarification de l'offre groupée des transporteurs LTL. Le problème de la tarification d'un ensemble concerne la génération et la tarification de l'ensemble. En outre, le modèle résout entre-temps un problème d'enlèvement et de livraison dynamique (PDP). Une méthode générale d'analyse des données historiques pour obtenir les informations utilisées dans le modèle est également proposée. Enfin, un processus d'analyse basé sur les données réelles est présenté et une étude numérique est construite pour évaluer la faisabilité du modèle proposé.

Le chapitre 7 conclut cette thèse, indique les limites des travaux présentés et propose des perspectives de recherche.

# Contents

# List of Figures

# List of Tables

# Chapter 1. General introduction

## 1.1 Research context

Freight transport is an essential activity in logistics, which is the process of transporting goods and cargos from one location to another. In freight market, there are three fundamental actors (shippers, carriers, intermediaries) and four main modes (road, rail, air, and water). All the various actors and transport modes have different characteristics. The focus of this thesis is on the carriers in road freight transport.

In the economy sector, freight transport is a significant part of the economy, which is around 5% of the GDP in Europe. Moreover, road freight transport is the most dominant inland freight transport mode due to the flexibility and capability to provide door-to-door services. For example, 88% of the inland freight transport volume in France in 2013 is from road transport (Savy 2015). What makes the road freight more important is that the road freight demand is still increasing because of the increasing globalized trade and economic growth. However, the carriers in freight transport market are confronted with serious challenges to keep and improve their revenue. The challenges could be classified as three main factors, i.e. the low margin, the increased freight cost and particularly the intense competition. First, the margin of road transport operators is very low, which is around or below 4% in many countries and regions. Besides, the increased freight cost makes it even more difficult to improve the margin. More seriously, the competition in the freight transport market is more and more fierce at three levels, among the countries and regions, among the various transport modes, and among the abundant carriers and logistics services providers.

To respond to the challenges, some possible solutions could be adopted to improve the carrier's revenue directly or indirectly. The new technologies, e.g. advanced vehicle and cheaper fuel, are solutions to decrease the transport cost thereby increase the margin. New operation methods, e.g. fleet management and vehicle routing, are another set of solutions to decrease the operation cost. An efficient procurement mechanism could also improve the operation efficiency, thereby optimize the price, and control the costs. Moreover, efficient logistics organizations and systems could also increase the transport efficiency and decrease the costs with a more structured demand. Thus, carriers could take advantage of innovative logistics system to improve their revenue. At last, Revenue Management is another well-known method to improve the revenue of carriers. Revenue Management is used to respond to the market fluctuation and improve the firm's revenue. In this thesis, an innovative logistics system and Revenue Management are adopted to solve the revenue optimization problem.

For the innovative logistics system, this thesis selected a new concept of interconnection of logistics networks, named Physical Internet (PI). The PI aims to develop an open global interconnected logistics system to increase the logistics efficiency and sustainability (Ballot, Montreuil et al. 2014). The principle of the PI is to interconnect the independent logistic networks through accessible resources, standardization of interfaces and protocols, smart containers, etc., thereby improve the integration, coordination and sharing of resources. Precisely, in this thesis, we will study how to apply the revenue management in a dynamic network like PI where the demand is concentrated on hubs to improve the carrier's revenue. We need to mention here that the less-than-truckload (LTL) operations are studied in this thesis because the requests, containers and boxes, in PI are mostly less-than-truckload. This thesis will investigate the application of Revenue Management in this context through four sections: pricing, capacity control, forecasting, and bundle pricing.

## 1.2 Research questions and objectives

The research problem in this thesis is Revenue Management problem for less-than-truckload freight transport carriers in Physical Internet. More precisely, this research aims to answer the following research questions:

Research question 1 (RQ1): how do carriers decide the bidding price for less-than-truckload (LTL) requests in Physical Internet to improve their revenue?

Research question 2 (RQ2): how do carriers select the requests with various destinations and quantity to transport?

Research question 3 (RQ3): how could the forecasting affect the pricing and requests selection decision in Physical Internet?

Research question 4 (RQ4): how do carriers decide the bidding price for request bundle in Physical Internet?

The objectives of this research can be summarized as follows:

7) Investigate the application of Revenue Management in a dynamic transport network like Physical Internet to provide a possible solution to improve the revenue of carriers.

8) Develop pricing model for carriers to decide the optimal bidding price that could optimize the revenue.

9) Develop request selection model to help carriers select the most profitable requests when facing various requests.

10) Model the request forecasting into the pricing and request selection models to study the influence of future possible requests to current decision.

11) Develop the pricing model for the bundle of requests in the situation where carriers need to propose a bundle requests to bid.

12) Analyze the feasibility and performance of the proposed models based on Physical Internet organization or large hubs.

We believe that this research and the results will provide managerial implications and decision making tools to trucking companies who operate in dynamic LTL markets like PI environment and who are seeking new solutions to improve their revenue.

## 1.3 Research methodology

In order to answer the proposed research questions, we have adopted the following research methodology.

First, we introduce the research context and the scope of this thesis through literature reviewing.

4) At the beginning, we conducted a literature review of freight transport in the frame of logistics to identify the importance of freight transport to the economy and the current challenges to the revenue in the freight transport market from the carrier's perspective.

5) Then, the solutions within the existing literatures and practices to respond to and to overcome the revenue problems are discussed. Among the various solutions, we select Revenue Management and a recently proposed innovative concept of interconnection of logistics networks – Physical Internet as our research context.

6) Next, the literature review of Revenue Management and Physical Internet are conducted respectively. The applications of Revenue Management to various industries and especially to freight transport are presented generally to seek the potential of applying RM in PI. Meanwhile, the existing research on PI is reviewed to identify the potential of PI to the improvement of efficiency and effectiveness of logistics.

After the introduction of the research context, the research problem and the four research questions in PI are proposed. Then in the next step, we study the questions one by one. The methodology used to the investigation of each question is listed below.

4) As a first step, a literature review related to the question discussed is conducted to understand the issues and the current limits to study the research question generally and in the PI context. This step provides the possibility for us to process our research.

5) Then, to solve the research questions, a corresponding optimization model to each question is developed. The models for the four research questions are linked and could be used in different situations.

6) Finally, a numerical study is conducted to evaluate and verify the feasibility and the performance of the model for each research question. The factors that could influence the decisions are also investigated. The optimization results could provide decision-making guidelines and tools.

## 1.4 Structure of the thesis

The rest of this dissertation is organized as follows:

Chapter 2 introduces the revenue problem that carriers confront in the freight transport market. First, we discuss the importance of freight transport for the economy. Then the challenges for carriers to manage their revenue are presented and the possible levers are discussed. After introducing the revenue problem in freight transport, the Revenue Management and Physical Internet are presented respectively from the definition, characteristics and applications. At last, the research problem, research questions, and the related methodology used in this thesis are discussed.

Chapter 3 investigates the less-than-truckload dynamic pricing decision-making problem in the context of the Physical Internet (PI). In a dynamic, stochastic environment like PI, a major concern for carriers is how to propose prices for requests to maximize their revenue. The latter is determined by the proposed price and the probability of winning the request at that price. This chapter proposes a dynamic pricing model as a response to an auction mechanism to optimize the carrier's bidding price. An experimental study is conducted in which two pricing strategies are proposed and assessed: a unique bidding price (one unique price for all requests in a single auction period), and a variable bidding price (price for each request in a single auction period). Three influencing factors are also investigated: quantity of requests, carrier capacity, and cost. The experimental results provide insightful conclusions and useful guidelines for carriers regarding pricing decisions in PI-hubs.

Chapter 4 extends the one-leg situation in chapter 3 to multi-legs and investigates a less-than-truckload (LTL) request pricing and selection problem to optimize carrier's revenue in Physical Internet (PI). In a hub, being faced with many different requests, carrier needs to select one (or several) type of requests of interest to bid and meanwhile decides the bidding price to maximize his profit. Two scenarios are investigated, i.e. carrier with full capacity, or carrier with loads with known destinations. For each scenario, an integer programming model based on a multi-legs dynamic pricing model is proposed to solve the request selection problem and pricing problem simultaneously. A computational study is conducted to demonstrate the feasibility of the models.

Chapter 5 extends the transport request in Chapter 3 to multiple auction periods and the static request quantity in the next hubs in Chapter 4 to a stochastic quantity. In this chapter, a dynamic pricing model for multi-periods is developed. This model could help carriers who would stay in a hub to participate several auctions to decide the optimal bidding price in each period. Moreover, the request selection model combined with a stochastic forecasting model is proposed. In addition, how the uncertainty of forecasting would influence the expected profit is studied.

Chapter 6 considers the network in which there are not much requests on the lanes. This means there will not be enough requests to fill the capacity of LTL carriers. Facing with such a situation, carriers should consider request bundling to increase the utility of their transport capacity. This chapter propose a mixed integer nonlinear programming (MINLP) model for the bundle pricing problem of LTL carrier. The bundle pricing problem consists of bundle generation and pricing for the bundle. In addition, the model solves a dynamic pickup and delivery problem (PDP) meanwhile. A general method to analyze the historical data to obtain the information used in the model is also proposed. At last, an analysis process based on actual data is presented and a numerical study is constructed to evaluate the feasibility of the proposed model.

Chapter 7 concludes this dissertation, indicates the limits of the works presented and proposes perspectives for further research.

# Chapter 2. The revenue problem of carriers in freight transport market

The objective of this chapter is to introduce the revenue problem that carriers confront in the freight transport market. First, we discuss the importance of freight transport to the economy. Then the challenge for carriers to keep their revenue is presented and the possible levers are discussed. In this thesis, we study how to improve the carriers' revenue through applying Revenue Management in a new logistics organization that is Physical Internet. Therefore, after introducing the revenue problem in freight transport, the Revenue Management and Physical Internet are presented respectively from the definition, characteristics and applications. At last, the research problem, research questions, and the related methodology used in this thesis are discussed.

## 2.1 Introduce the revenue problem of carriers in freight transport

### 2.1.1 Freight transport and its importance

#### 2.1.1.1 The definition and components of freight transport

*The definition*

As an essential activity in logistics, freight transport is the physical process of moving goods from locations where they are sourced to locations where they are demanded using transport means (e.g. trucks, trains) and transport infrastructures (e.g. roads, railways) (Goldsby, Iyengar et al. 2014, Bektas 2017).

*The actors*

There are three fundamental actors taking part in the freight transport: shippers, carriers, and intermediaries.

- Shippers: shippers normally propose the demand for freight transport, i.e. generate the demand to transport goods. Shippers need to decide whether to transport the goods by themselves or outsourcing the freight transport to carriers or intermediaries, through considering the availability and characteristics of the services provided on the market (e.g. price, quality).

- Carriers: carriers offer the transport services to shippers. On one hand, carrier could offer a vehicle or a fleet to a particular shipper with a customized service. On the other hand, carrier could accept transport demands from different customers and consolidate these freight goods in the same vehicle to transport.
- Intermediaries: an intermediary organization could be a freight forwarder, who manages the shipments of shippers by contracting one or several carriers. They provide services for shippers who do not own a fleet and do not want to make the planning decision neither. The freight forwarders always work closely with shippers and carriers.

In this thesis, we chose the point of view of carrier to process our research. Because carrier is the main actor providing transport services while facing with low margin. The reasoning will be further discussed in section 2.1.2.

*The modes*

There are different means to transport freight and each mean is called a mode of transport. Based on the type of vehicle used and the relevant infrastructures, there are five main modes, which are road, rail, water, air, and pipeline. A brief description of road, rail, air, and water transport are presented here, as they have different specific characteristics.

Road: Road transportation has been the most common and widely used mode of inland freight transport. This is mainly due to the fact that the road transport is relatively fast, flexible, reliable, and often available. According to Goldsby, Iyengar et al. (2014), road transportation uses a wide variety of vehicles or means, such as trucks, vans, cars, or motorcycles. Among these means, truck is the primary mean to move shipment of a single-pallet size to several pallets.

Based on the volume, the trucking market could be segmented to full-truckload (also called truckload) and less-than-truckload. Truckload (TL) carriers mainly (but not necessarily) transport large volumes of freight, and move freight from the origin location to the destination directly without any intermediate stops. This means TL carriers dedicate a truck to just one customer for an O-D movement. Less-than-truckload (LTL) carriers specialize in smaller volumes of freight and they sell the capacity of one truck to multiple shippers. This means LTL carriers need to collect the freights from multiple shippers’ location and deliver them to different locations.

Rail: Rail transportation could offer efficient long-haul transportation services with very large volumes. Comparing with road transport, a single rail boxcar can carry almost three times the weight of a typical truck. Boxcars are usually grouped in large numbers to form a train. This make the train efficient to transport goods. However, the lack of flexibility and the strict (O,D) decrease the attractiveness from the point of view of economy and environment. Besides, the bulk transportation can only be shared with multiple shippers.

Air: Originally, air transportation is for passengers, but most airlines also transport freight in regular passengers' flight with dedicated cargo. All-cargo carriers and some integrated carriers, such as DHL, FedEx, could also provide the air transportation service. The main goods transported with airlines are always time sensitive or have quite high value.

Water: Transportation by water could occur on the seas and on the inland waterways like rivers. Sea or maritime transport is the major mode of transporting a large majority of international goods. It is economical and suitable for transporting goods that are not time sensitive. Inland water transportation is a mean to move goods among cities inland on the lakes or rivers. However, obviously, the viability of water transportation is largely depending on the location. In addition, the maritime shipping uses shared capacity with containers.

#### 2.1.1.2 The importance of freight transport to logistics and economy

The logistics makes a significant contribution to the economy, which could be represented by the percentage that the logistics costs occupy the nation's GDP (Gross domestic product). As shown in Figure 2. 1, logistics costs amount to approximately 13% of the GDP in Europe and 8.5% in US. This share is even greater in less developed countries, e.g. the logistics costs in Asia are approximately 17% of the GDP. Besides, ALICE (2016) presented that logistics account for 10% to 15% of the final cost of finished goods in the EU manufacturing and service sectors. All these data show that logistics is a key enabling sector for the economy, not only to the GDP but also to the industries business.

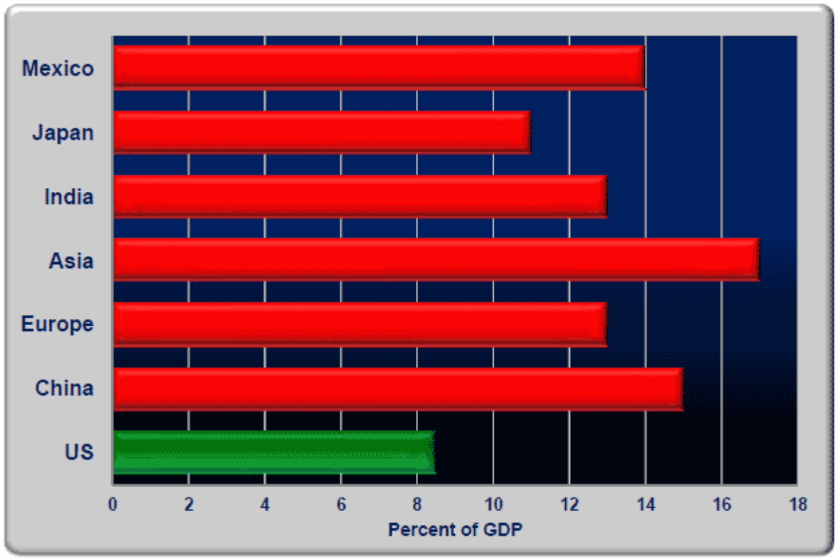



Figure 2. 1 Logistics costs as a percentage of GPD (2013 State of Logistics Report from CSCMP)

As a key activity in logistics, freight transport is a fundamental sector for the economy. Goldsby, Iyengar et al. (2014) show that around 62% of total logistics cost was spent on transportation in US and the transportation represents 5.4% of the U.S.GDP. Similarly in Europe, the freight transport industry accounts for about 5% of the GDP[1]. Moreover, Figure 2. 2 presents that the growth of GDP is correlated with the growth in freight transport. During the decades, freight transport demands has tended to grow rapidly coupled with growth of GDP in Europe. In other words, freight transport is an important part and a cornerstone in the growth of the economy.

[1] https://ec.europa.eu/jrc/en/research-topic/transport-sector-economic-analysis

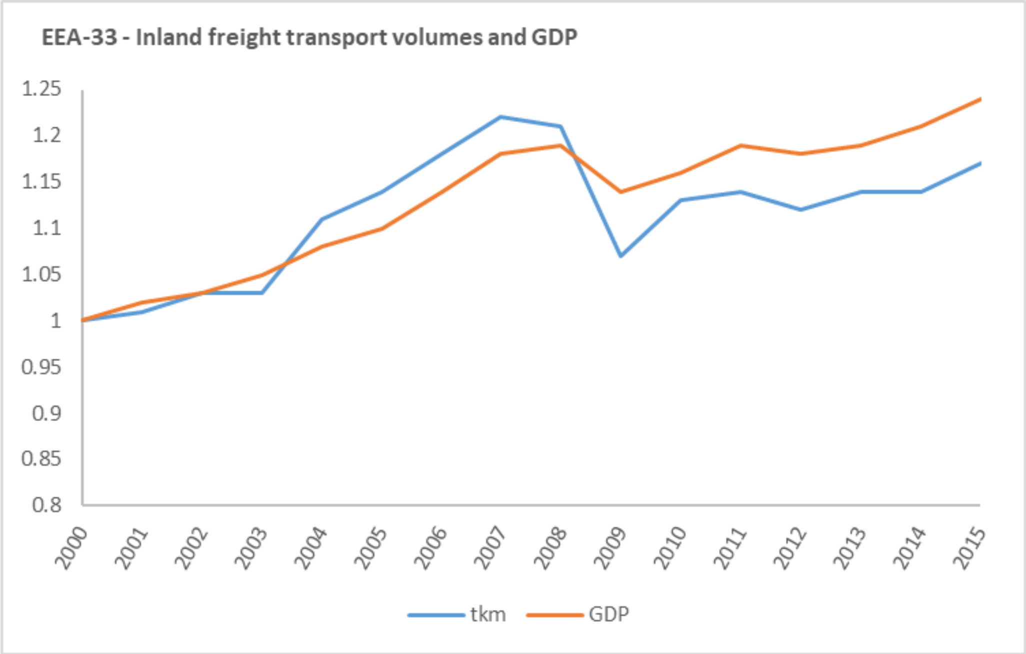



Figure 2. 2 Growth of inland freight transport volumes and GDP in EEA-33 (from European Environment Agency)

Among the freight transport modes, road transport is the most dominant inland freight transport mode in t.km. Savy (2015) states that 88% of the inland freight transport volume in France in 2013 are from road transport. As Figure 2. 3 shows, road freight accounts for 73% of all inland freight in the EU in 2010. And the same situation occurs in USA according to Goldsby, Iyengar et al. (2014). When considering the maritime transport, road freight still has the most volumes based on Figure 2. 4. Moreover, according to European Commission (2017), road freight transport produced an annual turnover of more than €300 billion and almost 3 million jobs (1.3% of total EU employment) in 2014, which shows that road freight transport is a dominant economic sector. The road freight transport can connect the production, distribution and consumption due to the flexibility and capability to provide door-to-door services (IRU 2016). Therefore, in this thesis, our study will focus on the road freight transport.

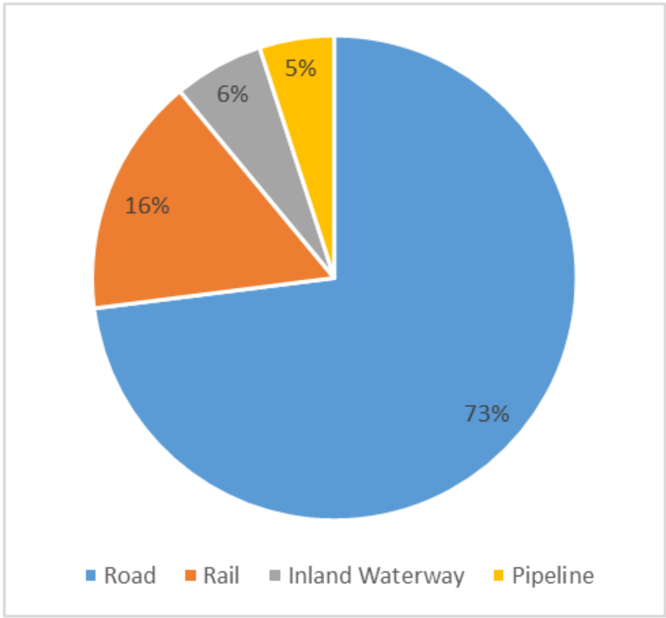



Figure 2. 3 Percentage mode share of EU inland freight movements by ton-km (AECOM 2014)

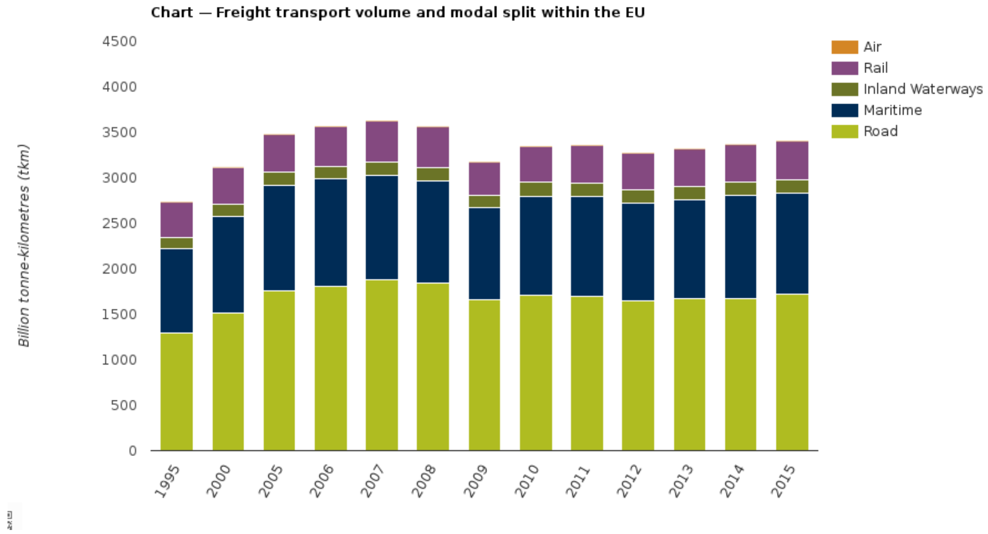



Figure 2. 4 Freight transport volume of different modes within EU (from European Environment Agency)

### 2.1.2 The challenge on revenue of carriers in freight transportation market

Along with the increasing demands of globalized trade and growing economic, the freight transport demand is also increasing. According to the statistics from Eurostat[2], European road freight transport increased by 4.5 % in 2016 compared with 2015 in terms of ton-kilometers (tkm). TechNavio (2017) forecasts the road freight transportation market in Europe to grow at a CAGR (Compound Annual Growth Rate) of 2.68% during the period 2017-2021. Despite the development of the freight transport industry, the freight carriers still face with some challenges and the freight transport performance remains insufficient. Except the challenge to meet the environment sustainability requirements, e.g. the reduction of $CO_2$ emission, we focus on the challenge for carriers to keep and improve their revenue. Figure 2. 5 shows a revenue change of several major truckload carriers in US and Canada between 2015 and 2016. We can see that most firms have a very slight increasing, but still several carriers experienced a significant decline.

2016 Revenue, including fuel surcharges. *In millions of US dollars.*

| RANK | CARRIER NAME | 2015 REVENUE | 2016 REVENUE | PERCENT CHANGE | PUBLIC/ PRIVATE |
|---|---|---|---|---|---|
| 1 | **FEDEX FREIGHT** | $5,745 | $5,936 | 3.3% | Public |
| 2 | **XPO LOGISTICS** | $3,525 | $3,445 | -2.3% | Public |
| 3 | **OLD DOMINION FREIGHT LINE** | $2,893 | $2,936 | 1.5% | Public |
| 4 | **YRC FREIGHT** | $3,033 | $2,923 | -3.6% | Public |
| 5 | **UPS FREIGHT** | $2,479 | $2,384 | -3.8% | Public |
| 6 | **ESTES EXPRESS LINES** | $2,135 | $2,155 | 0.9% | Private |
| 7 | **ABF FREIGHT SYSTEM** | $1,870 | $1,870 | 0.0% | Public |
| 8 | **R+L CARRIERS** | $1,429 | $1,452 | 1.6% | Private |
| 9 | **SAIA MOTOR FREIGHT LINE** | $1,221 | $1,218 | -0.2% | Public |
| 10 | **HOLLAND** | $1,044 | $1,046 | 0.2% | Public |
| 11 | **SOUTHEASTERN FREIGHT LINES** | $1,031 | $1,043 | 1.1% | Private |
| 12 | **AVERITT EXPRESS** | $702 | $717 | 2.2% | Private |
| 13 | **CENTRAL TRANSPORT INTERNATIONAL** | $675 | $703 | 4.3% | Private |
| 14 | **TRANSFORCE** | $692 | $602 | -13.0% | Public |
| 15 | **AAA COOPER TRANSPORTATION** | $513 | $518 | 1.0% | Private |

Figure 2. 5 The revenue change of major LTL carriers in US&Canada in 2016[3]

[2] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Road_freight_transport_statistics#European_road_freight_transport_growths_for_the_fourth_consecutive_year_in_2016

[3] http://jindel.com/wp-content/uploads/IndustryData/2017_Top%2050%20US%20and%20Canadian%20LTL%20Carriers_JOC_August%202017.pdf

In this section, we will classify the revenue challenges as three factors: the low margin, the increased freight cost, and particularly the intense competition.

*Low Margin*

Logistics is a low margin activity in many countries and regions. For example, the margin is around 4 percent in UK (FTA 2016). Moreover, as the UK's fifth largest employer, road transport operator's profit margins increased just slightly from 3% in 2014 to 4% in 2015. The big European road transport operators are earning EBIT (Earnings before Interest and Taxes) margins between 1-4%, which is well below their aspirations[4] of 8.5%. Figure 2. 6 shows the margins of five big European road transport companies in 2017. In Australia, the freight transport industry also faces the margins pressures, with the fact that the average net profit margins had fallen to 3% in 2014 (Hodgson 2014). Simon-Kucher (2017) presents that the margins of North American companies are about 3-5%.

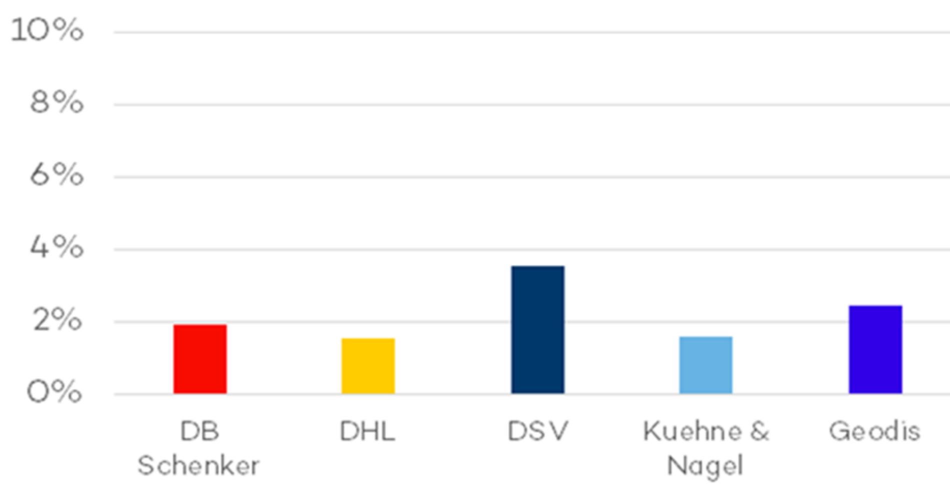



Figure 2. 6 Margins of big European road transport companies in 2017 (Source: Company financial reports, TNX Logistics)

*Increased Freight Cost*

In the freight market, various companies are confronted with different customers, which will influence the price through affecting request transport distance, weight or volume. Considering the

[4] https://www.tnx-logistics.com/blog/2018/03/15/how-profitable-is-european-road-transport.html

complexity, only the individual cost elements are considered. Six elements are primarily discussed in European Commission (2015), which are personnel costs (mainly the driver costs), fuel costs, investment-related costs (interests, leasing, depreciation costs), taxes and insurance, administration costs, other variable costs (maintenance, road tolls etc.). Because of the rise of personnel costs and fuel costs, the freight transport cost is increasing. European Commission (2015) reports that the freight transport cost has increased between 2006 and 2012 in Europe. Separately, 19% increasing in road transport, 13% increasing in rail transport, 18% increasing in inland waterway transport, 19% increasing in sea and 23% increasing in air transport.

In order to cope with the rise of the costs, the transport service providers may offer higher price. However, the higher price might decrease the attraction to the customers. Besides, the increasing price in the freight transport market will also influence the prices in others markets which depend on the freight service. Thus, it is a challengeable task for carriers to decide the profitable price to sustain and improve their profit when facing with the increased transport cost.

*Intense Competition*

As we have seen, the importance and demand of freight transport has grown but at the same time, the competition in the market has become more and more fierce. Along with the growth of global trade economies, the European logistics service providers (LSP) are facing intense competition within and outside Europe (European Commission 2015). EU-15 (Western Europe) Member States experienced a strong reduction in tkm from 2008 to 2016, particularly for international transport, due to the competition from EU-13 (Eastern Europe) Member States. For example, Belgium saw a 7% decrease on the share of international road freight transport between 2008 and 2016 (De Wispelaere and Pacolet 2018). This means the market in EU-15 Member States is eroded, which will make the competition within the market more intense as the resource is decreasing.

In addition, there is also significant competition among the various freight transport modes (North 2018). For example, the competition between road freight and rail freight. The competition in the less-than-truckload (LTL) segment has been increasing while the market has been shrinking. Because the traditional LTL market share has been eroded by Full-truckload (FTL) market and by package/courier market (Prokop 2014).

Moreover, at the small end of the market, such as road freight, courier and express services, there are generally low barriers to entry. This generates a high number of competitors in these logistics sectors (European Commission 2015). For example, based on the statistics of AECOM (2014), the top 10 third-party logistics providers (3PLs) in Europe only have a market share of 5%. Besides, some firms or platforms have adopted auction mechanism to sell the transport requests. This will make the price even lower, which also makes the competition fiercer.

We could find that freight transport market, particularly road freight, is a highly competitive and low-margin business. Besides, considering the increasing freight costs, it is much difficult for the freight carriers to maintain and even improve their revenue. Thus, the carriers should pay more attention on their revenue issues. Therefore, in this thesis, our research objective will be helping carriers to keep and improve their revenue.

### 2.1.3 Possible solutions to the revenue problem in freight transport

To respond to the challenges presented in previous section, we study the possible solutions to the revenue problem of carriers in freight transport. However, it is worth noting that there are few researches investigating the revenue problem and the relative solutions currently. The solutions discussed in this section are not just the methods to improve the revenue directly, but also some levers that could influence the revenue indirectly, for example, the strategies to decrease the transport cost or increase the competitiveness. The levers to improve the carrier's revenue are classified as five categories for the discussion here: (1) new technology; (2) new operation method; (3) efficient allocation mechanism; (4) innovative logistics organization; (5) revenue management method.

*New technology*

The technologies mentioned here mainly refer to the physical technologies, which could improve the transport efficiency or decrease the freight costs. For example, the more advanced vehicle and cheaper fuel could be two kinds of new technologies used to decrease the transport cost. New trucks' average consumption of fuel has decreased by 40% during the last 40 years[5].

[5] https://www.iru.org/what-we-do/advocacy/environment

Adopting advanced freight related technologies could be a solution to the revenue problem. Nevertheless, this is not in our research scope.

*New operation method*

Freight carriers also could adopt some advanced operation methods to decrease the operation cost. Fleet management is a well-studied area, which could improve the efficiency, productivity and reduce the overall transport costs for the transportation companies. For example the studies proposed by (King and Topaloglu 2007, Topaloglu and Powell 2007). Besides, there are a lot researches about vehicle routing problem (VRP), which could optimize the routes for a fleet of vehicles used to deliver goods to customers. The VRP has the main objectives of minimizing the overall transport cost and minimizing the number used to serve the customers (Adelman 2004, Mes, Heijden et al. 2006, Liu, Jiang et al. 2010, Aras, Aksen et al. 2011, Ehmke and Mattfeld 2012).

*Efficient procurement mechanism*

Freight transportation service procurement (FTSP) studies how to match shippers' transportation needs and carriers' capacities. This problem involves prices setting, costs and capacity controlling, and so on. Obviously, an efficient FTSP mechanism could improve the revenue from both optimizing the price and control the costs. Lafkihi, Pan et al. (2017) review the research on procurement mechanisms of freight transportation services and identify the trends and gaps between practice and research. Many other researchers also investigate the efficient FTSP mechanisms e.g. Caplice and Sheffi (2003), Garrido (2007), Xu and Huang (2013), Yan, Xu et al. (2016) and Song and Regan (2003).

*Innovative logistics organization*

An efficient logistics system could also help to improve the revenue through increasing the transport efficiency and decreasing the costs. There are more and more researches developing the innovative logistics organizations. Transport collaboration, either vertically or horizontally, is one of the most discussed model. With collaboration, the actors could share the distribution resources, transport orders, inventories, and so on. Thus, the costs of administration, inventory and transport will be reduced due to the centralized purchasing and consolidation. Several relative research could be found in Berger and Bierwirth (2010), Dai and Chen (2011), Hernández, Peeta et al. (2011), Özener, Ergun et al. (2011), Xu (2013), Dai, Chen et al. (2014), Vanovermeire, Sörensen et al. (2014), Xu, Huang et al. (2016). More particularly, horizontal collaboration, or logistics pooling is a recent solution for freight transport collaboration model (Corbett and Rajaram 2006, Pan, Ballot et al. 2014). Besides, crowdsourcing transport is a new logistics concept, which considers outsource the transport tasks to people with a private car who willing to earn extra money (Estellés-Arolas and González-Ladrón-De-Guevara 2012, Mladenow, Bauer et al. 2015, Chen, Pan et al. 2017). More recently, an innovative interconnection of logistics networks, named Physical Internet (PI), has been investigated in (Ballot, Montreuil et al. 2014). The objective of PI is to develop an open global interconnected logistics systems to increase the logistics efficiency and sustainability (Montreuil 2011, Montreuil, Meller et al. 2013, Sarraj, Ballot et al. 2014, Pan, Ballot et al. 2017).

*Revenue management method*

As to the solution of improving revenue directly, Revenue Management (RM) is one of the most developed method. RM could be used to respond to the market fluctuation and improve the firm's revenue, through the levers of pricing, capacity control, forecasting and overbooking, etc. RM has been applied in various industries and gain satisfactory performance. The example applications could be found in Pak and Piersma (2002), Boyd and Bilegan (2003), Koide and Ishii (2005), Amaruchkul, Cooper et al. (2007), Lee, Chew et al. (2009), Crevier, Cordeau et al. (2012), Cleophas (2017).

Among all these levers, firstly based on our interest, we will adopt revenue management and innovative logistics organization to study the revenue problem. In other words, we will study how to apply the revenue management in an innovative logistics system, which is the Physical Internet in this thesis. In the next two sections, we will review the Revenue Management and Physical Internet, separately.

# 2.2 Revenue Management

## 2.2.1 What is Revenue Management?

### 2.2.1.1 Definition of Revenue Management

Firstly, began in the airline industry, the aim of Revenue Management (RM, also named Yield Management at first) is to maximize the overall revenue for company. Along with the development of Revenue Management from the origin airline industry to the current various industries, different definitions of RM were proposed. For instance, as one of the earliest leading users of revenue management, American Airlines defined the objective of revenue management as “to maximize passenger revenue by selling the right seats to the right customers at the right time” (Weatherford and Bodily 1992). According to Kimes (2000), in brief, revenue management can be defined as the method to allocate the right capacity to the right customer at the right time for the right price. In Cleophas, Yeoman et al. (2011), the revenue management was simply described as the art of selling products to the right customers at the right prices.

Ng (2013) reviewed a number of definitions of revenue management in different industries and concluded three key concepts about revenue management: (1) The objective of revenue management is to increase or maximize the revenue. (2) The objective could be achieved using demand management and resource management techniques. These techniques control the pricing and inventory, which decide where and when to sell, to whom, and at what price (Talluri and Van Ryzin 2006). (3) Revenue management uses rigorous methods and analysis to make the demand and resource management.

In this thesis, we focus on the freight transport industry and freight carriers. For the freight carriers in freight transport industry, the product for selling is the transport capacity and the customers are shippers who have requests need to be transported to different destinations. Thus, the revenue management in this research could be defined as follows:

Revenue management is the method and technique to maximize the freight carrier’s revenue by allocating transport capacity to the right transport requests at an optimal price.

#### 2.2.1.2 The research problems of revenue management

In the research of revenue management, there are several major research problems. In McGill and Van Ryzin (1999), the authors discussed four key research areas – forecasting, overbooking, seat inventory control, and pricing. However, it should be noted that these four research problems are mainly from the airline industry, especially seat inventory control. Also in Chiang, Chen et al. (2006), the authors categorized revenue management problems into four research areas: pricing, capacity control, overbooking, and forecasting. We could found that there is a delicate difference between the research areas discussed in the two references mentioned above. It is seat inventory control and capacity control separately. This is mainly because seat inventory control is from the airline industry. In airline industry, the product to sell is the finite seat in the flight. But with the development of revenue management in other industries, the term of "seat inventory control" is not appropriate. Because in other industries, they sell other products with finite inventory or capacity, for example the finite hotel rooms in hospitality industry. Therefore, "capacity control" is more generic. In this thesis, we will use the term of "capacity control". Besides, in both Chiang, Chen et al. (2006) and Talluri and Van Ryzin (2006), auction was discussed as a research area of revenue management. In this thesis, auction is not just a specific type of pricing strategy (Chiang, Chen et al. 2006), but also a strategy to allocate the transport requests to carriers in a spot market. In this section, we will introduce these five research areas in general – pricing, capacity control, forecasting, overbooking, and auction.

*Pricing*

The objective of pricing is mainly to find the optimal pricing strategy to maximize the revenue of seller with the finite resources (Bitran and Caldentey 2003). In other words, pricing is to study how to decide the prices for various customers based on the seller's status, including the remaining resources and the remaining time before the expiration of the product. Pricing policies has increasingly become a fundamental operation approach for manufacturing and service companies (Bitran and Caldentey 2003). We could find that the prices in revenue management change over time and vary for different customers. Therefore, the pricing in revenue management also could be defined as dynamic pricing, which is an active research field and meanwhile the main research area in this thesis.

Pricing is a strategy that uses prices as the primary variables to manage the demand from customers. In terms of current business practice, firms are confronted with dynamic and fluctuating market in which the demand is uncertain. Thus, firms should study how to estimate the uncertain demand and determine the price dynamically with scientific methods to maximize their revenues (Talluri and Van Ryzin 2006). Huefner (2015) introduced several general approaches to setting prices, cost-based pricing, market-based pricing, and value-based pricing. In this thesis, we chose market-based pricing considering selling prices of competitors, which will be studied in chapter 3.

*Capacity control*

Capacity control study how to allocate the capacity of resources to various demands from different customer groups. The objective is also to maximize the expected revenue of sellers. As discussed above, capacity control could be referred to as seat inventory control in the airline industry. Originally, in order to decrease the number of empty seats, the airline firms sell a limited number of seats with a discount price several weeks or months in advance (Barz and Waldmann 2007). The airline firms must decide how many seats they should allocate to discount price and how many they should save for the passengers who would pay full price. This is seat inventory control in brief. In other industries, the capacity could be the inventory of other resources, for example, the hotel rooms in hospitality industry, the cargo capacity in freight transport industry. The simple single-resource capacity control and more complicated network capacity control were introduced in many references. Single-resource could be referred to as the seats in a single-leg flight in the airline industry. The network capacity control study how to allocate the capacity when customers require a bundle of different resources. The bundle of resources could be, for example, several connecting flights in the airline industry or multi-day rentals in the rental car industry (Chiang, Chen et al. 2006).

*Forecasting*

Forecasting is a critical part of revenue management and an important component of planning for the firms. The forecasting accuracy directly influence the quality of other revenue management decisions, such as pricing, capacity control, or overbooking (Chiang, Chen et al. 2006). In revenue management, several quantities need to be forecasted, such as the future demand, possible market price and the capacity. What need to notice is that RM forecasting does not just estimate a single number (so-called point estimate), such as the number of seats demand at a day on a specific flight in the future. Because the point estimate is not accurate enough. The uncertainty in predicting future outcomes must be accounted in statistical level (Talluri and Van Ryzin 2006). Besides, RM forecasting tasks also need to undertake the issues of the type of forecasting method, the data collection and the accuracy of forecast.

*Overbooking*

Overbooking has the longest research history of any of the components of the revenue management problem, especially in airline industry (McGill and Van Ryzin 1999). There are significant cancellations in a reservation-based system, for example, almost 50% of reservations result in cancellations or no-shows and about 15% of all seats are unsold in the airline industry. Overbooking is concerned with increasing the capacity utilization. The objective of overbooking is to find an optimal overbooking level to maximize the expected revenue by minimizing the risk of denied service (Chiang, Chen et al. 2006). In other words, overbooking needs to balance the potential risks of denied services and the profits of increased sales. Thus, overbooking depends on the forecasting of the probability distribution of the number of future demands.

*Auction*

Auctions is a relatively new way to dynamically adjust prices. An auction is a mechanism differs from a typical posted-price mechanism, in which customers are the ones who offer a price they are willing to pay and the firm then decides which bids to accept. While in auction mechanism, in brief, customers post their prices for a resource (e.g. the flight seats) and the resource will be allocated to the customer under a winning determination mechanism. Auction will be introduced as a request allocation method in section 2.3.

### 2.2.2 The applications of Revenue Management in various industries

In practice, revenue management means setting prices according to predicted demand levels and capacity levels to attract different customers. Obviously, revenue management could not be appropriate for all kinds of industries. Kimes (2000) presents the conditions and characteristics to apply revenue management as following.

Related fixed capacity: revenue management is appropriate for capacity-constrained firms, for example, airline firms with limited seats on a specific flight.

Predictable and time-variable demand: demand could be the reservation of the resources from customers. These demands vary by time of year or time of day or even time of hour. The firms should forecast the tile-related demands to make effective pricing and capacity allocation decisions. For example, the demand for seats on a flight varies from weekdays to weekends.

Perishable inventory: the resource in capacity-constrained firms is time-related, such as the seats on a specific flight are only valuable in a specific period and this kind of resource cannot be stored if they are not sold.

Large fixed costs and low variable costs: this kind of cost structure could give the firms higher pricing flexibility to adapt to the fluctuation of demand.

Revenue management has been studied and applied in a wide variety of industries. Chiang, Chen et al. (2006) and Cleophas, Yeoman et al. (2011) both summarized the industries that adopt revenue management. The main applications of RM are presented in Table 2. 1. In this section, we will not review all the industries, we just simply overview the three major traditional applications of revenue management, airlines, hotels and rental car industries. The objective of this section is to present how the RM works in industries.

Table 2. 1 The application of revenue management in industries (Chiang, Chen et al. 2006)

| | Industries |
|---|---|
| Traditional industries | Airlines, Hotels, Rental business (car, other equipment) |
| Non-traditional industries | Hospitality organizations:<br>Restaurants, Cruise lines and ferry lines, Casinos, Resort, Theaters and sports events |
| | Transportation-related industries:<br>Air cargo, Freight, Passenger railways, Boat, Natural gas, petroleum storage and transmission |
| | Others:<br>Retailing, Manufacturing, Broadcasting and media |

*Airlines*

Airline industry is among the first to introduce and adopt revenue management. The customers of airlines include both individual travelers and groups. The individual travelers are segmented into business customers and leisure customers. The travel groups are also various, such as cruise lines and tour operators (Talluri and Van Ryzin 2006). All these different customers have various purposes and preferences that are going to be discussed below.

For the business travelers, they are time-sensitive but price-insensitive normally. What is more important for them is the schedule convenience or booking/cancellation flexibility. In contrast, price is not their primary consideration because the employers always pay for their travel expenses. Besides, business travelers always travel during the weekdays and normally avoid the peaks around holidays.

On the other hand, for leisure travelers, they care more about the price other than the time. Because they always pay for themselves. Thus, find a good price, leisure travelers could modify their travel date and schedule flexibly. Moreover, they could buy the tickets many days ahead of the departure of the flight to get a good deal. To be contrary to the business travelers, leisure travelers always travel during the weekend and the holidays.

However, the description of the two kinds of travelers is general. There are also many specific situations, for example, some high-income leisure travelers might do not care much about the price while some self-employed business travelers are more price-sensitive. Therefore, in general, various preferences for schedules, routings, and prices exist among the different travelers. Even not to mention the various requirements from different groups and also the uncertain cancellations and no-shows. All these make the airlines market very fluctuating and dynamic.

In response to the dynamic market, the airlines adopt several practices, such as providing different fare classes of tickets, adjusting prices based on the demand, and selling more tickets in case of cancellations and no-shows (Chiang, Chen et al. 2006).

For the various fare classes of tickets, Pak and Piersma (2002) presented that the seats on a flight could be segmented not just by the business class or economy class, but also other various conditions, e.g. basically the cancellation options.

For the pricing of the various classes of seats on a flight, discount prices are offered to various classes of customers. The airlines decide the discounts according to a combination of different conditions. For example purchased how many days before the departure of flight, the leaving and return date (weekday or weekend), whether it is changeable or refundable, and what kind of itinerary this ticket is involved in (Talluri and Van Ryzin 2006). The pricing problem for airlines has been studied widely. For example, Botimer and Belobaba (1999) studied e a new model of fare product differentiation which can be used to optimize the fare product price level. Zhang and Cooper (2009) used Markov decision process to decide the price for multiple substitutable flights between the same origin and destination dynamically. Anjos, Cheng et al. (2004) described the one-way price optimization considering the buying behavior of customers.

*Hotels*

Being similar to airlines industry, hotels also face with various customers with different preferences for the time and duration of stay, room types and prices. Hotels always provide different discount rate packages for the periods of low occupancy. For example, how long it is booked before the stay date, is it is changeable and refundable, and if the breakfast is included. The overbooking policy is also used to avoid the cancellation and no-shows (Huyton and Thomas 2000). There have been many studies about the revenue management in hotel industry. These are some examples below.

Koide and Ishii (2005) studied the hotel rooms allocation problem. In this paper, the early discount and the overbooking was considered in the model to optimize the room allocation decision. In Zhang and Weatherford (2016), the dynamic pricing problem and the application in the hotel industries was investigated. The overbooking problem was also specifically studied in Hadjinicola and Panayi (1997). This paper investigated the problem of whether to apply the overbooking policy at the hotel level or at the tour-operator level. Bitran and Mondschein (1995) developed optimization models and relative heuristics algorithm to make the optimal policies for renting hotel rooms. Baker and Collier (2003) studied and evaluated a new price setting method with various cases in the hotel industry.

*Car Rental*

A car rental company rents cars for short periods ranging from hours to several weeks. The customers in rental car industry also have various preferences, including the date and location to pick/return the car, the driving distance limitation included in the basic fare, the type of insurance. In response to these differences, the firms provide various combinations of rental conditions, for example, car type, insurance options, pickup and drop-off location, advance purchase limitation, and rental length (Talluri and Van Ryzin 2006). Accordingly, the firms adjust prices for these combinations. Besides, the firms need to decide whether to accept the booking based on the rental length. For example, a one-day rental during the holiday might be rejected because this booking could interrupt a demand from a customer who wants to rent a car for the whole holiday.

Geraghty and Johnson (1997) studied and described how the revenue management improve the National Car Rental through capacity management, pricing, and reservation control. Fink and Reiners (2006) provided a logistics management approach to improve the profits of the car rental business. Li and Pang (2017) investigated the booking control problem in car rental revenue management. Similarly, the capacity allocation. i.e. capacity management of the rental business was also studied in Savin, Cohen et al. (2005).

### 2.2.3 The application of revenue management in freight transport industry

In the section 2.2.1, we introduced the conditions to apply revenue management and reviewed the application of RM in three major traditional industries. In this survey, we focus on the freight transport industry, and the application of RM in freight industry will be discussed specifically in this section. Five modes of freight transport will be reviewed, air cargo, railway, maritime, road, and intermodal.

*Air cargo*

Compared with airlines industry, the application of RM in freight is relatively new. Moreover, most of the study in this area is on air cargo. The selling product in air cargo is the remaining transport capacity on a flight after satisfying the baggage transport demand from passengers. There are also some cargo aircrafts that are normally used to transport freight.

Air cargo revenue management is more complex than airline passenger revenue management. Kasilingam (1997) and Talluri and Van Ryzin (2006) both presented the differences between air cargo RM and airline passenger RM. The cargo capacity depends on the expected number of passengers and their registered baggage. Also, the capacity is limited both by the weight and the volume. Budiarto, Putro et al. (2018) reviewed existing theories and researches about air cargo RM. Then the author found new research opportunities through the study on the gap between theory and practice. Amaruchkul, Cooper et al. (2007) discussed the single-leg air-cargo revenue management and developed an MDP model to compute the optimal decision. While Huang and Lu (2015) studied the network revenue management of air cargo by formulating a multi-dimension dynamic programing model. Huang and Chang (2010) and Hoffmann (2013) both focused on the algorithm to solve the air cargo RM problem. Levin, Nediak et al. (2012) and Moussawi-Haidar (2014) presented the capacity control problem of cargo RM, which is how to allocate the capacity to allotment contracts or spot market. The implementation of RM in an air-cargo industry organization, KLM, was also presented in Slager and Kapteijns (2004)

*Other freight transport modes*

In addition to air cargo, there are also other freight industries, railway, maritime (shipping), road (trucking), and intermodal. These industries also have fixed capacity and large fixed costs. Also, freight transport is confronted with customers with different service level requirements. For example, the time-sensitive customers and the price-sensitive customers. These make freight transport industry a natural candidate for RM methods (Talluri and Van Ryzin 2006). However, there are few researches about the RM in these freight transport areas, because the firms always sell their capacity with long-term contracts. Nevertheless, in spot market, RM has significant business and we still found some relative researches.

In railway freight, Armstrong and Meissner (2010) reviewed the literatures and models of RM in rail freight. Crevier, Cordeau et al. (2012) integrated the operations planning and revenue management for rail freight carrier through developing a new model with pricing decisions and network planning policies. Kraft (2002) developed a new method to maximize profits through solving a car scheduling process considering the customer needs and possible train capacity. Rao (1978) developed a demand forecasting model for the national railway freight industry in Canada. Bilegan, Brotcorne et al. (2015) studied a demand acceptance model to dynamically allocate the rail capacity with the objective of maximizing the revenue of the company. The overbooking problem in railway freight industry was studied using a dynamic programming model in Feng, Zhang et al. (2015). Harker and Hong (1994) presented a track pricing problem to create the ideal track utilization schedule considering the capacity management.

For maritime freight transport, Maragos (1994) studied the revenue management in liner shipping firstly. Lee, Chew et al. (2009) proposed a stochastic dynamic programming model for a single-leg liner shipping revenue management problem considering the optimal allocation of containers. Ting* and Tzeng (2004) proposed a RM model for liner shipping carriers and also an integer programming model for a slot allocation problem. Bu, Xu et al. (2008) and Uğurlu, Coşgun et al. (2012) investigated the dynamic pricing problem with a dynamic programming method for sea-cargo carriers. Wang, Wang et al. (2015) particularly studied the itineraries optimization problem with a bi-level optimization model.

There are also some studies about RM in intermodal freight transport. Wang, Bilegan et al. (2016) investigated the capacity allocation problem in the network level by developing a RM model. Similarly, Wang, Wang et al. (2017) studied the dynamic resource allocation problem in intermodal freight transport with a Markov decision process model. The pricing problem was studied in Di and Hualong (2012) and Li, Lin et al. (2015). The former one proposed a dynamic pricing model while the latter reference adopted a cost-plus-pricing strategy. Luo, Gao et al. (2015) studied how to apply dynamic forecasting in the RM in intermodal transport. Especially, how the dynamic forecasting influences the capacity leasing and demand acceptance decision.

As to the revenue management in road freight transport, there are few specific studies. Most studies focus on the pricing problem in full-truckload (FTL) or less-than-truckload (LTL) transport. For example, in Figliozzi, Mahmassani et al. (2007), the author studied how to decide the price for a dynamic vehicle routing problem under the revenue management frame. Toptal and Bingöl (2011) analyzed the pricing problem for transportation of a truckload carrier considering the competitor's and retailer's behavior. More discussion of the pricing problem will be presented in the chapter 3.

Overall, we could find that Revenue Management has been adopted in various industries to improve the firms' revenue. However, in the freight transport industry, the application of RM is still based on the traditional logistics organizations. In an innovative logistics organization, it is essential to study how to apply the RM when facing with new characteristics. In the next section, a new concept of logistics network, which is Physical Internet, will be presented.

# 2.3 Physical internet

## 2.3.1 What is Physical Internet?

### 2.3.1.1 The origin and definition of physical internet

The Physical Internet (PI) was proposed in response to the existed unsustainable prospects and limits of current logistics system (Ballot, Montreuil et al. 2014). The main unsustainable prospects are the costly goods flow and the growing greenhouse gas emission. On the other hand, the primary limit of current logistics system is the fragmentation of networks belonged to specific companies, which limits the inventory degree and the load factor of trucks. These issues make the current logistics organization inefficient.

The Physical Internet was inspired by the metaphor of Digital Internet (Ballot, Montreuil et al. 2014, Sarraj, Ballot et al. 2014). Digital Internet means the interconnection of computer networks. In digital internet, the computer networks are interconnected through "routers" using intermediate protocol (TCP/IP), see Figure 2. 7. The data packets with standardized characteristics such as size and structure are transited between the neighboring computer networks. With the digital internet, people have been highly interconnected and can send digital messages very effectively.

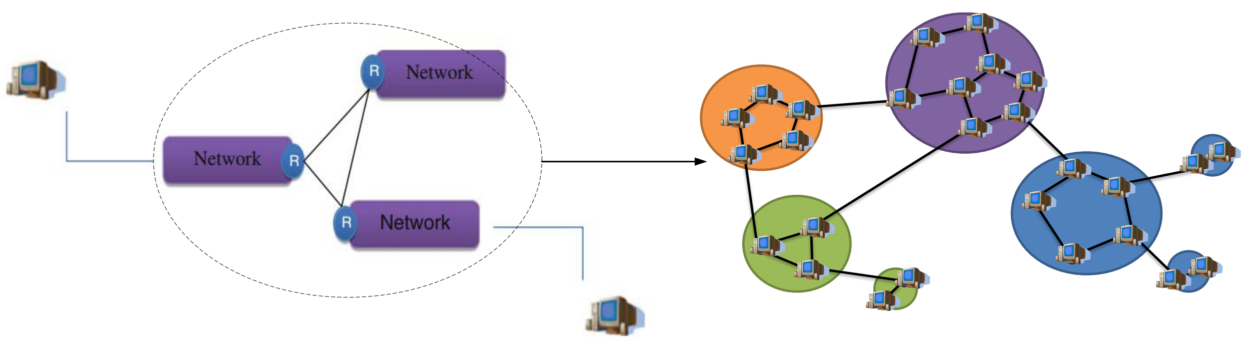



Figure 2. 7 The interconnection of computer networks in Digital Internet (Sarraj, Ballot et al. 2014)

Thus, the central idea of Physical Internet is the interconnection of logistics networks, which is shown in Figure 2. 8. The Physical Internet was defined as follows in Ballot, Montreuil et al. (2014).

*"The Physical Internet is a global logistics system based on the interconnection of logistics networks by a standardized set of collaboration protocols, modular containers and smart interfaces for increased efficiency and sustainability."*

In detail, the PI is an open logistics system consisted of different existing logistics networks. These networks are interconnected through PI-hubs with standardized protocols. In the PI-hubs, products are encapsulated in modular PI containers, just like the data packets in Digital Internet, to be transported among PI-hubs. In any PI-hubs, shippers can post the goods to ship and carriers can exchange their goods in hand. The sharing of this open system could make the collaboration in logistics more efficient.

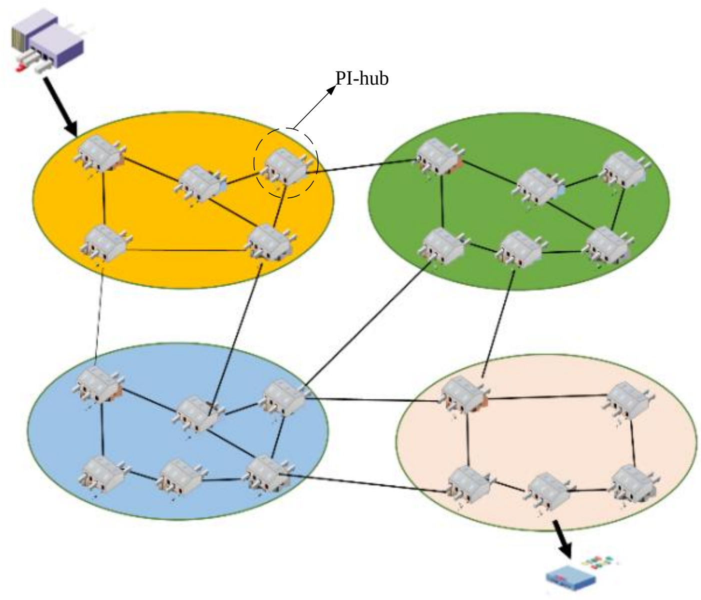



Figure 2. 8 The interconnection of logistics networks in Physical Internet (Yang 2016)

#### 2.3.1.2 The freight transport in PI

Ballot, Montreuil et al. (2014) discussed the differences between current logistics and physical internet in several points. The difference related to transport is shown in Table 2. 2.

Table 2. 2 Differences related to transport between current logistics and the Physical Internet

| Function | Current logistics | Physical Internet |
|---|---|---|
| Shipping | Goods | Containers |
| Network | Specific services | Network of open and shared networks |
| Trip | Logistics service | Dynamic routing |
| Capacity management | Private | Market-based |

Based on these new features of physical internet, we could conclude the major characteristics of freight transport in PI.

(1) Frequent flows: the PI is open and shared, so various users, including shippers and carriers, post and exchange the request to transport their goods in hand. This will bring very frequent

requests allocation and reallocation activities. Then the flows in PI could be very large and frequent, as the market is very open and dynamic.

(2) Stochastic requests: because of the various shippers from different industries and carriers with various O-Ds in PI, the transport requests will arrive with stochastic sizes and destinations.

(3) Dynamic decisions: here we focus on the decision of carriers, because shippers just need to post transport requests and choose or be allocated a carrier under the allocation mechanism.

- Routing decision: the requests in PI is stochastic and carrier can exchange their requests in hand. Thus, the carriers need to decide their routes dynamically according to the requests they get.
- Pricing decision: similarly, facing with the stochastic requests and dynamic route, the cost to transport a request is dynamic. Therefore, the carrier should propose different price for the various requests according to the possible route.
- Capacity management decision: according to discussion above, the various request could influence the route and the price, which will bring different revenue. Thus, carriers should allocate their limit transport capacity to these requests dynamically considering the possible revenue.

### 2.3.2 The research scope and related works of PI

Since the research of Physical Internet was pioneered in 2009, there have been numerous studies carried out on various scientific issues. Pan, Ballot et al. (2017) reviewed the studies in four key categories: conceptual research, assessment research, solutions design and validation research. In the conceptual research, the definition of Physical Internet, key PI components and the implementation of PI was discussed (Montreuil 2011, Montreuil, Meller et al. 2013, Ballot, Montreuil et al. 2014, Sarraj, Ballot et al. 2014). The assessment research investigate how the PI could improve the logistics efficiency and sustainability through analytical, optimization and/or simulation methods (Ballot, Sarraj et al. 2012, Sarraj, Ballot et al. 2014).

The study in this thesis obviously belongs to the solutions design issue, which we will focus on. This research issue focuses on developing the methodologies and technologies to apply the PI in industries.

Firstly, the design of PI components was discussed. For example, Ballot, Gobet et al. (2012) designed the Physical Internet transport network. The PI container is also an important research area and has been addressed in several literatures (Lin, Meller et al. 2014, Gazzard and Montreuil 2015, Landschützer, Ehrentraut et al. 2015, Sallez, Pan et al. 2016). Besides, there are some researches about the design of PI facilities and material handling systems (Montreuil, Meller et al. 2010, Ballot, Montreuil et al. 2012, Meller, Montreuil et al. 2012, Montreuil, Meller et al. 2013).

Another area in solutions design research is the methodologies, models to derive the planning, and operations decisions in PI. For example, Sarraj, Ballot et al. (2014) discussed the transportation protocols in PI. Chen, Pan et al. (2017) proposed a crowed sourcing solution using taxis inspired by PI. Qiao, Pan et al. (2016), Qiao, Pan et al. (2017) developed a dynamic pricing model and request selection model for transport service providers in PI. Pan, Nigrelli et al. (2015), Yang, Pan et al. (2016) discussed the inventory management problem in PI and (Yang, Pan et al. 2016, Yang, Pan et al. 2017) introduced the impact of PI on resilience in inventory and transport.

Moreover, in confronted with the frequent request flows in PI-hubs, the design of mechanism to allocate the requests efficiently is very important. Xu (2013) proposed a mechanism design model for transport service procurement, in which the auction mechanism was introduced. Kong, Chen et al. (2016) firstly discussed the scheduling solution under auction mechanism in PI. In brief, the process of using auction to allocate requests in PI could be described as follows, also see an example in Figure 2. 9.

Step1. At the beginning of an auction period, users submit their transport requests into a request pool managed by the auctioneer. Each request is encapsulated in a container with standardized sizes.

Step2. Then the participators could propose a price to bid for their interested requests. There are three main kinds of auction here: (1) forward auction: the shipper propose the bidding price;

(2) reverse auction; the carrier propose the bidding price; (3) double auction: both shippers and carriers submit the bidding price.

Step3. After receiving all the bidding prices, the requests will be allocated to the winners according to a specific winner determination strategy (WDP).

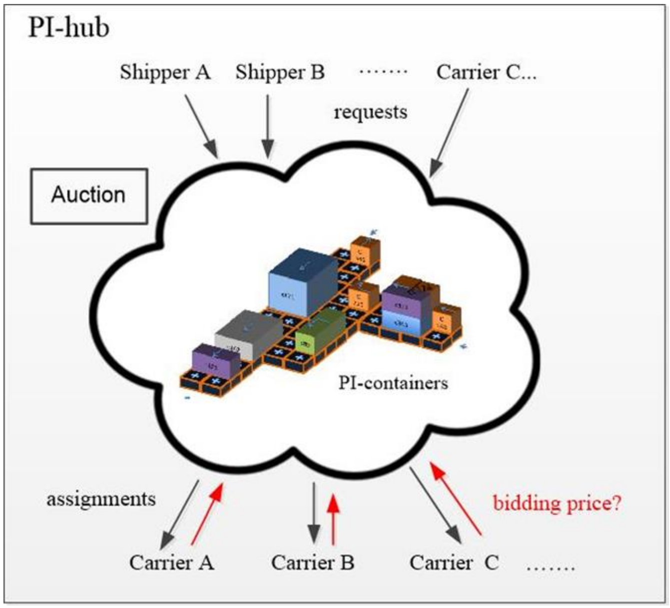



Figure 2. 9 Using auction mechanism to allocate requests in PI

Obviously, if PI adopts auction mechanism to allocate the requests, it will be one of the foremost challenges for carriers to be able to decide the optimal bidding price. Meanwhile this is one of the main objectives of this thesis.

The Physical Internet has gain increasing attention from academies and industries. The research result so far can show that PI could improve the performance of logistics in several aspects. For example, according to the research from Yang (2016), PI can reduce dramatically inventory holding cost with the same service level to shops. Sarraj (2013) shows that PI can reduce up to 35% of actual transportation cost through the optimization of truckload transport and the integration of different transportation models.

Overall, Physical Internet research is still in its infancy stage. The current research investigating the efficiency of PI are mostly focus on the sustainability to environment. Few researches discuss the improvement of PI on the transport cost. We have not found any research that are focus on the actors' revenue directly. Thus, it is significant to study the revenue problem for the actors in PI. The research problem and questions will be discussed in the next section.

## 2.4 Research problem, questions and methodology

### 2.4.1 Research problem and questions

Based on the review in section 2.2 and section 2.3, we could find that:

(1) The application of revenue management in freight transportation has not been studied as widely as the application in passenger transportation. But still, these researches indicated the potential that RM could improve the revenue of the freight service providers. However, the current application of RM remains in the traditional logistics organizations.

(2) As a new organization of logistics, the Physical Internet has the potential to improve the performance of logistics in many aspects, such as reducing the transport cost through increasing the transport efficiency and load factor. Because of the high level of collaboration and interconnection in PI, there are many differences between the traditional logistics network and PI. Thus, studies about PI in many areas are required. Besides, the freight transport market is becoming more and more dynamic. Therefore, it is significant and worthwhile to study the application of Revenue Management in a dynamic environment like Physical Internet.

In this thesis, the research problem could be defined as "Revenue Management problem for less-than-truckload (LTL) freight transport carriers in Physical Internet". Which means, we will study how to improve the revenue of freight transport carriers through applying the Revenue Management method in a new logistics organization of Physical Internet, where many transport requests are available at a given location. The focus of this thesis is LTL carriers, because the requests in PI are mostly less-than-truckload.

According to the review about RM, we know that there are several research topics related to RM. Considering the characteristics of PI, we will define and determine the research questions based on three topics: pricing, capacity control, forecasting.

Research question 1 (RQ1): How do carriers decide the bidding price for less-than-truckload (LTL) requests in Physical Internet? As we adopt reverse-auction mechanism to allocate the requests, carriers need to post a price to bid for the requests. This question is to study how to help carriers decide the bidding price.

Research question 2 (RQ2): How do carriers select the requests with various destinations and quantity to transport? Capacity control in freight transportation means how to allocate the transport capacity to the right requests, so the capacity control problem could also be the request selection problem.

Research question 3 (RQ3): How could the forecasting affect the pricing and requests selection decision in Physical Internet? This question is to study whether the pricing and request selection decision will be different considering the future situation or not. In addition, how the forecasting uncertainty could influence the decisions.

Research question 4 (RQ4): How do carriers decide the bidding price for request bundle in Physical Internet? The study of this question aims to help the carrier decide which requests to be bundled and with what bidding price.

### 2.4.2 Research Methodology

Before presenting the methodology, to better illustrate the complexity of the problem, we firstly introduce the dynamic environment for transport requests in PI-hubs as shown in Figure 2. 10. At one PI-hub, there are various requests. These requests have different origins/destinations (O-D), different quantities, and different sizes of the container. Moreover, all the requests arrive at the hub at different auction periods stochastically.

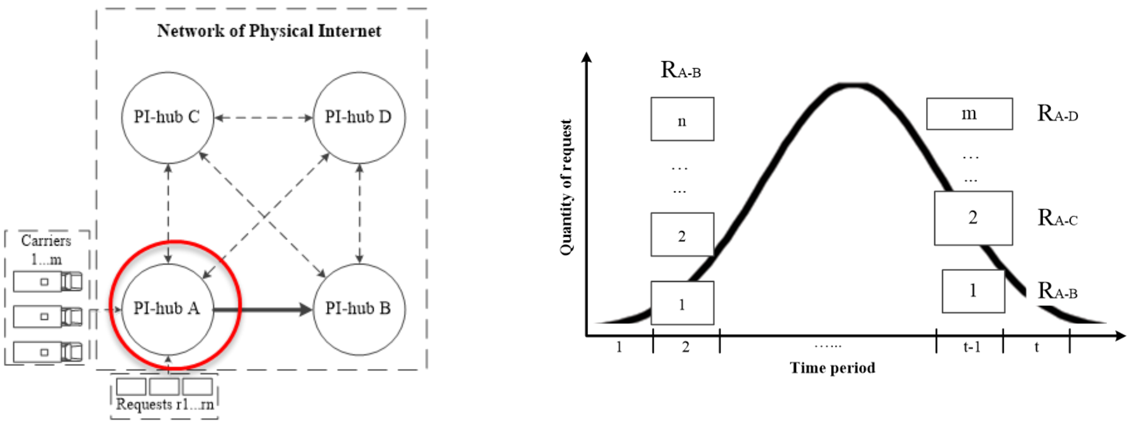



Figure 2. 10 The flow of requests in PI-hub

This dynamic situation makes it very complicated to study our research questions. In this thesis, we will conduct the research from the simplest to the most complex situation, step by step. We could see from Table 2. 3, each research question, or scenario is corresponding to a real-life situation, which is adapted to the different interest from carriers. Thus, we could determine the methodology to study the research questions as follows, and the connection between chapters is shown in Figure 2. 11:

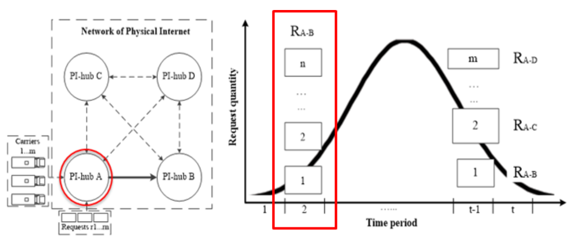
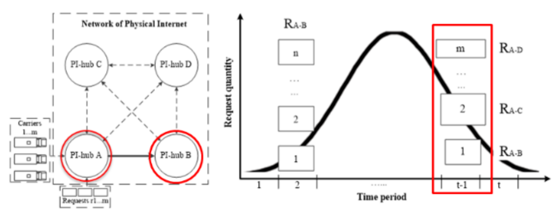
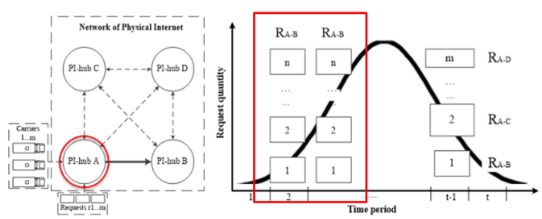
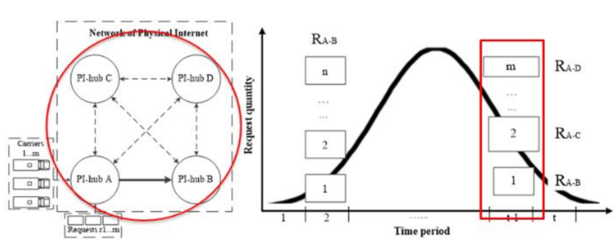
(1) We start developing the pricing strategy and model (RQ1) with the simplest situation. In this situation, we just consider the same request with the same O-D in one auction period in one hub. This question will be studied in Chapter 3, in which a review of related works about the pricing in freight transportation will be conducted.

(2) Based on the pricing model of RQ1, RQ2 could extend the situation to different requests with various O-Ds in one auction period and one hub. Thus, the request selection problem need to be solved through an optimization model. Chapter 4 is focusing on the request selection problem. The literatures related to request selection in freight transportation will be reviewed in Chapter 4.

(3) The forecasting problem of RQ3 will be addressed in Chapter 5. A more complex and extended situation will be conducted, in which the requests with various O-Ds in different auction periods and hubs will be considered. Therefore, in order to make appropriate decision, the carrier should forecast the request information in the next auction periods or next hubs. Similarly, the works about forecasting in RM will be presented in Chapter 5.

(4) At last, a composite situation will be investigated in Chapter 6. We will study the requests bundle problem with bundle pricing and selection (RQ4). Moreover, we will also develop a data statistics process related to our research to provide the essential information we need, for example the relation between market transport price and request quantity of a freight firm.

Table 2. 3 The situation corresponding to each research question

| Research question | Request situation | Carrier interest |
|---|---|---|
| RQ 1 |  | • Same request<br>• One auction period<br>• One hub |
| RQ 2 |  | • Different requests<br>• One auction period<br>• One hub |
| RQ 3 |  | • Different requests<br>• Several auction periods<br>• Different hubs |
| RQ 4 |  | • Different requests<br>• One auction period<br>• Hubs in the network<br>• Bundle of requests |

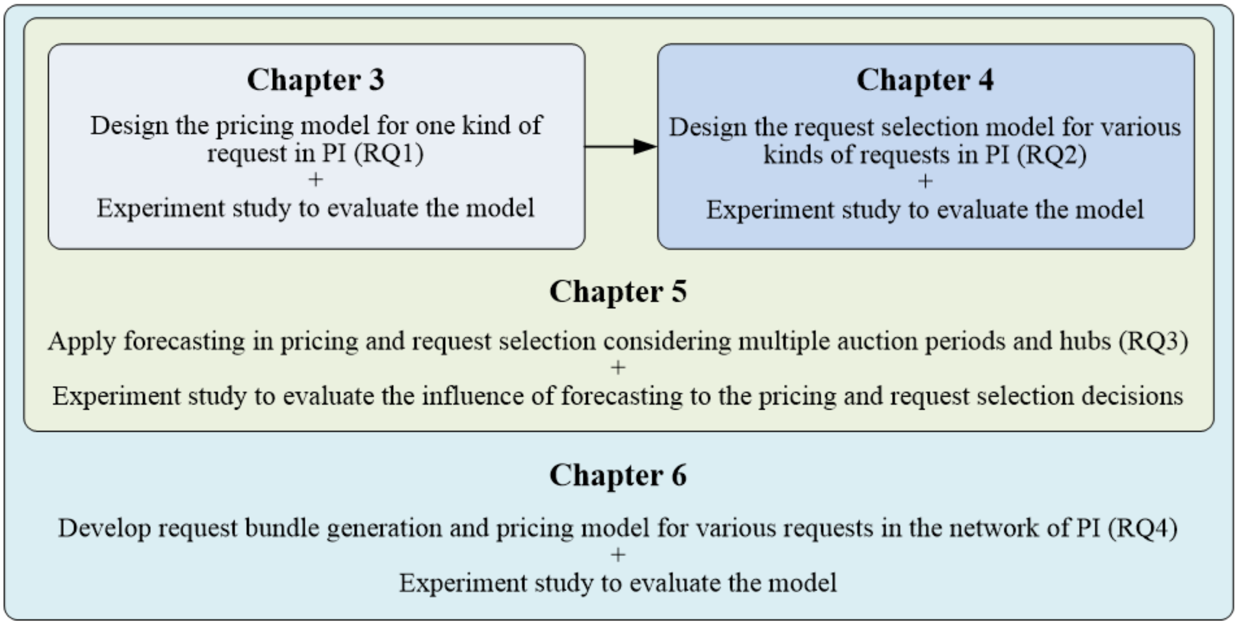



Figure 2. 11 Overview of research questions and the chapters

# Chapter 3. Dynamic Pricing of one-leg one-period same-unit request for Less-than-truckload Carrier in Physical Internet

According to the discussion in Chapter 2, pricing is one of the basic research problems in Revenue Management. This chapter studies the dynamic pricing problem of the simplest situation, which is one-leg one-period same-unit problem. One-leg means carriers only bid for the requests on the same route (i.e. same O-D hubs) in one auction period. While one-period means carriers just participate one auction period and do not consider the situation of the next period. Besides, we also assume all the requests have the same unit (same size). The problem considering requests with different sizes will be studied in the bundle pricing in Chapter 6.

The dynamic pricing problem in this chapter is a less-than-truckload dynamic pricing (LTLDP) decision-making problem in the context of the Physical Internet (PI) specifically. As introduced in Chapter 2, the PI can be seen as the interconnection of logistics networks via open PI-hubs. In terms of transport, PI-hubs can be considered as spot freight markets where LTL requests with different volumes/destinations continuously arrive over time and only remain for short periods. Carriers can bid for these requests using short-term contracts. In a dynamic, stochastic environment like this, a major concern for carriers is how to propose prices for requests to maximise their revenue. The latter is determined by the proposed price and the probability of winning the request at that price. This chapter proposes a dynamic pricing model based on an auction mechanism to optimise the carrier's bid price. An experimental study was conducted in which two pricing strategies were proposed and assessed: a unique bidding price (one unique price for all requests at an auction), and a variable bidding price (price for each request at an auction). Three influencing factors were also investigated: quantity of requests, carrier capacity, and cost. The experimental results provide insightful conclusions and useful guidelines for carriers regarding pricing decisions in PI-hubs.

## 3.1 Introduction

In the freight transport industry, a carrier's pricing decision involves choosing the right prices for transport requests in order to maximise his profit with a limited capacity. This is known as price-based revenue management (Ting and Tzeng 2004, Talluri and Van Ryzin 2006). A transport request can be defined simply as a request to transport an object from point A to point B. In a dynamic environment, where transport requests with different volumes and/or destinations arrive over time, carriers can adjust their pricing policies within a given time, taking into account the status and the arrival of requests in real time (fill rate, capacity constraints, departure time, etc.) to maximise their expected profits. The problem is known as a dynamic pricing decision problem (Lin 2006, Talluri and Van Ryzin 2006). Examples include the air cargo industry where cargo tariffs can be adjusted according to a flight's real-time fill rate prior to the scheduled departure. Another well-known example is ticket pricing strategies in the airline industry (Talluri and Van Ryzin 2006).

This chapter introduces and investigates a decision-making problem consisting of less-than-truckload dynamic pricing (LTLDP) in a specific context - the Physical Internet (PI) - and will be called PI-LTLDP hereinafter. As introduced in Chapter 2, PI can be referred to as the interconnection of logistics networks via open logistics hubs, i.e. PI-hubs where shippers procure transport services and carriers offer transport services. In particular, carriers in a hub can also exchange in-hand requests to improve transport efficiency (Montreuil 2011, Ballot, Montreuil et al. 2014, Mervis 2014). In other words, either the shipper (e.g. retailer or manufacturer) or the carrier can submit transport requests in PI-hubs. Accordingly, a PI-hub can be thought of as a spot freight market, where less-than-truckload (LTL) transport requests with different volumes and/or different destinations continuously arrive over time and remain for only short periods. The transport requests in PI-hubs are therefore very dynamic and stochastic. Carriers can propose a price to win the spot requests using short-term contracts. Once prices have been submitted, requests will be optimally allocated to carriers according to the proposed prices. An auction mechanism is one of the most efficient solutions to the request allocation problem (Huang and Xu 2013, Xu and Huang 2013, Kuyzu, Akyol et al. 2015). However, research on the LTL dynamic (bid) pricing problem for carriers in the Physical Internet is very limited.

The PI-LTLDP problem is different to the dynamic pricing problem in the liner shipping or air cargo shipping industries. Firstly, the departure time and even the destination of a given truck in a PI-hub are not scheduled but depend on its fill rate, delivery time constraints, and the delivery route of the request, whereas liner shipping or air cargo services are generally scheduled for a specific departure time and destination. In addition, the pricing mechanism of each industry is different. In the liner shipping industry, shipping companies are often cartelized to avoid price competition, as they claim it would lead to destructive competition that would undermine the stability of global trade (Munari 2012). Liner shipping prices are, therefore, usually stable. The air cargo market is very competitive, so companies usually sell their capacity through a common selling format called allotment. Shippers propose freight with a price and airlines just decide to accept or not (Kasilingam 1997). The selling process may begin a few months prior to the departure time, and price negotiations may take place. Obviously, the allotment mechanism is not applicable in PI-hubs due to the short period of time requests remain available and the many requests-to-many carriers allocation problem.

The PI-LTLDP problem is also new to the traditional pricing problems in road freight transport, in both the TL and the LTL industry. In the truckload (TL) industry, carriers may consider some factors to adjust the price (or bid) for a request, for example asymmetric requests in a truck's round-trip (Zhou and Lee 2009), daily scheduling (Mes and Van der Heijden 2007), real-time request learning and forecasting (Lin 2006), competitor behaviour (Toptal and Bingöl 2011), or synergy between lanes of long-term contracts and spot contracts (Kuyzu, Akyol et al. 2015). However, fill rate or request size is not taken into account. In the LTL industry, to the best of our knowledge, research focusing on the LTL pricing problem itself is very limited and even less focuses on dynamic and stochastic LTL pricing. We only found a few studies dealing with the auction-based bid price optimisation problem for deterministic demands (Douma, Schuur et al. 2006, Dai and Chen 2011, Wang and Kopfer 2011). The main reason is that, as per current practices, LTL carriers offer fixed-cost services such as €/palette or €/kg. Dynamic pricing is not among their main concerns. Moreover, the auction mechanism is not widely applied and only a few examples can be found, e.g. Leanlogistics and Transplace. However, it is clear that traditional pricing models and mechanisms are fundamentally challenged in a PI environment since the interconnection of fragmented freight markets enabled by PI will increase the competition between freight carriers. As a result, novel dynamic pricing models are necessary for LTL carriers in PI.

To study the dynamic pricing models used for LTL carriers in PI, several challenges should be solved. First, the Physical Internet (PI) is a new form of logistics. The pricing problem in PI has never been discussed before, so the first challenge will be defining the pricing characteristics in

PI. Second, PI is a highly interconnected network, which makes the environment very dynamic and stochastic. The pricing problem in such an environment has been rarely studied before.

The aim of this chapter is to study the PI-LTLDP problem and to contribute to the relevant literature. First, we characterise the PI-LTLDP problem and illustrate its novelty compared with other pricing problems in freight transport in the literature. Second, we propose a pricing model based on a dynamic programming approach, the aim of which is to optimise the carriers' price and to maximise their global profits in a PI-hub. Third, through an experimental study, we employ the proposed model to investigate the impacts of different pricing strategies and some influencing factors on the carrier's profits. Two strategies and three factors are proposed and investigated.

This chapter is organised as follows. After the introduction, section 3.2 presents a brief literature review of the PI concept, and related pricing problems and models in freight transport in order to identify the research gap. Section 3.3 describes the PI-LTLDP problem, which is formulated in section 3.4. An experimental study with the results and discussion is presented in section 3.5. Finally, section 3.6 concludes the contributions of this part of work and identifies some research prospects.

# 3.2 Related Works

## 3.2.1 Road freight transport in The Physical Internet

As defined in (Ballot, Montreuil et al. 2014), the Physical Internet (PI) is a global interconnected logistics system that connects logistics networks together. Its main objective is to make freight transport more efficient and sustainable (Montreuil 2011, Montreuil, Meller et al. 2013). PI creates a collaborative transport network by developing standardised, modular containers, common protocols and tools, and shared transport and technological assets (Mervis 2014).

The discussion now focuses on road freight transport in PI. According to the PI philosophy, goods are firstly encapsulated in standard, modular containers, named PI-containers, which can be of different sizes (Lin, Meller et al. 2014). One or several carriers then transport these containers from hub to hub to the destination. The hubs in PI, or PI-hubs (Sarraj, Ballot et al. 2014), are open to shippers or carriers, which means that shippers or carriers may freely join or leave any hub. In each PI-hub, there are plenty of containers to be transported, of which the size and/or destination can vary. Each container represents a transport request submitted by a shipper or a carrier to exchange requests with other carriers. Conversely, there are also numerous carriers offering transport capacity. They can propose a price to win the requests they are interested in using short-term contracts. The auction mechanism is a solution to match carriers with requests in PI-hubs (Huang and Xu 2013, Xu and Huang 2013). Carriers can obtain some of these containers by participating in several auctions. It can be assumed that the carrier will be interested in determining an optimal auction price to maximise their profit. This is the so-called carrier pricing problem. The characteristics of the pricing problem of road freight transport in PI for carriers and for requests are as follows.

*Three main pricing characteristics from the carriers' perspective:*

- Pricing decisions are sequential for a given carrier, which means the current decision will affect the status of the next auction in the current hub, as the carrier's capacity and waiting time are finite.

- The capacity for a given carrier is finite: although a carrier may have more than one vehicle, their capacity would be finite.

- The waiting time in a hub for a given carrier is finite: carriers can wait in a PI-hub for requests to improve the fill rate. In theory, the waiting time can be finite – a maximum waiting time is given – or infinite, by waiting until the truck is full. We argue that the first setting is more reasonable in PI because a carrier can easily move to another hub if the waiting time is too long. In addition, a carrier may have to leave for at least two reasons: full capacity reached or scheduled departure time.

*Three main pricing characteristics from the perspective of requests:*

- LTL: most of the transport requests in a PI-hub are LTL requests, and are encapsulated in standard and modular PI-containers (Lin, Meller et al. 2014).

- Stochastic: requests arriving at a PI-hub may have some stochastic features such as arrival or departure time, size, destination, and scheduled lane (routing).

- Bundle: requests arriving at a PI-hub may be in large quantities and in the form of bundles. This means that the carrier can bid for several requests in a single auction.

In this context, each PI-hub is actually a many-requests-to-many-carriers LTL spot market, with dynamic and stochastic LTL requests arriving over time. The carriers' pricing decisions, therefore, become very dynamic and difficult to make. As the openness of the PI market will also increase pricing competition between carriers, a novel pricing model for carriers is appealing.

### 3.2.2 Dynamic Pricing in Different Transport Industries

Since there is very little research on dynamic pricing in LTL transport in the literature, the review here has been extended to other sectors concerned by the dynamic pricing problem, such as air cargo, liner shipping, railway freight, and FTL transport.

As we mentioned previously, with the allotment mechanism (Kasilingam 1997), air cargo carriers just need to decide whether to accept the shipment at a price given by the shippers. The authors in (Amaruchkul, Cooper et al. 2007) studied this problem by considering a single-leg flight of which the goal was to maximise the expected profits by finding an accept or reject policy for requests with a proposed price. The author presented a Markov decision process to solve this problem. He used a value function to represent the maximum expected revenue that could be obtained from time t until the time of departure, which was computed recursively. Similarly, in (Huang and Chang 2010), the authors also solved a similar problem with dynamic programming using different approximating algorithms. However, these two papers focus mainly on overbooking and capacity management, not dynamic pricing.

As we discussed above, in the liner shipping industry, there is no price competition in order to avoid destructive competition. It is one of the peculiarities of the sector (Munari 2012). However, the pricing problem in maritime passenger transport is similar to the pricing problem in LTL freight transport, as well as some pricing models. In (Uğurlu, Coşgun et al. 2012) and (Coşgun, Ekinci et al. 2014), the authors discussed the dynamic pricing problem faced by maritime transport service providers selling seats to consumers. Using probabilistic dynamic programming, they found the optimal prices under different conditions, for example, weather or time.

Railway freight transport is also similar to LTL freight transport because of the finite capacity. Reference (Kraft 2002) used a bid price approach to solve a capacity-constrained railway scheduling problem. To maximise the revenue, the author presented a train segment-pricing model in which the prices were pre-established. Reference (Crevier, Cordeau et al. 2012) studied the revenue management for carriers in rail freight transport. The authors proposed a mathematical method including pricing decisions. With a determinate request, this method provides an optimal set of prices and a set of equipment that maximise the profit.

Some research has also investigated the pricing problem in intermodal transport. In (Di and Hualong 2012), the authors discussed the dynamic pricing problem with uncertain conditions in container sea-rail intermodal transport. In addition to slot allocation in the contract market, the author considers the dynamic pricing problem in the free sale market. The optimal price was decided according to the forecast of the future requests, using an equation to indicate the relation between the request and the price. In (Li, Lin et al. 2015), a cost-plus pricing strategy is presented for intermodal freight transport services with determinate requests. This strategy aimed to minimize the total delivery cost, which includes storage, transfer, and subcontracting costs. The price can then be decided by adding targeted profit margins to the minimal cost.

The pricing strategies in the transport industries mentioned above do not rely on an auction mechanism. The latter has been studied more often in the road transport industry. However, only a few relevant papers focusing on pricing decisions can be found in the TL transport sector, and even fewer in the LTL sector. Opportunity costs are the most studied in TL pricing. Here, opportunity costs are used to describe the influence of current decisions (bidding price) on the future status. For example, opportunity costs can describe the loss in expected future revenue due to fulfilling a new request. Reference (Figliozzi, Mahmassani et al. 2006) presents a method to calculate the opportunity cost in sequential TL requests auctions. The author considers opportunity costs in the context of a dynamic routing problem modelled in a stochastic simulation framework. Based on this research, reference (Figliozzi, Mahmassani et al. 2007) studied the carrier pricing strategy for the dynamic vehicle routing problem. Similarly, reference (Mes, Heijden et al. 2006) discussed the pricing strategy of vehicle agents when deciding whether to insert a new request in a current task sequence while considering the opportunity cost. Besides, opportunity costs could also be used in scheduling decisions (Mes and Van der Heijden 2007). In the LTL pricing literature, reference (Douma, Schuur et al. 2006) is the working paper the most related to our study. In this paper, the authors present how the carrier should dynamically decide on the price of loads to maximise carrier profit. They considered a single-leg problem, i.e. request from point *i* to *j*. A vehicle travels from *i* to *j* and waits *t* time units at most. In every time unit, a vehicle bids for one load if there is a load arriving. This method decides the price according to the remaining capacity and the time left before departure.

A comparison of pricing problems between different transport models in some studies is given in Table 3. 1.

Table 3. 1 Comparison of the pricing problem between different transport models (S-single; M-multiple; D-dynamic; F-fixed; St-stochastic; De-determinate; Y-yes; N-no; Fi-finite; IF-infinite)

| Modal | Carrier | | | | | Requests | | | Study |
|---|---|---|---|---|---|---|---|---|---|
| | Pricing | Auction | Route | Time period | Capacity | Cost | Number | Type | |
| Air Cargo | \ | N | S | M | Fi | D | St | M | (Amaruchkul, Cooper et al. 2007) |
| | \ | N | S | M | Fi | D | St | M | (Huang and Chang 2010) |
| Maritime passenger transport | D | N | S | M | Fi | D | St | S | (Uğurlu, Coşgun et al. 2012) |
| | D | N | S | M | Fi | D | St | S | (Coşgun, Ekinci et al. 2014) |
| Rail freight | \ | N | M | S | Fi | D | St | M | (Kraft 2002) |
| | D | N | M | S | Fi | F | De | M | (Crevier, Cordeau et al. 2012) |
| Intermodal transport | D | N | S | M | Fi | \ | St | S | (Di and Hualong 2012) |
| | D | N | S | S | Fi | F | De | S | (Li, Lin et al. 2015) |
| TL | D | Y | M | M | IF | D | De | S | (Figliozzi, Mahmassani et al. 2006) |
| | D | Y | M | M | IF | D | St | S | (Figliozzi, Mahmassani et al. 2007) |
| | D | Y | M | M | IF | D | St | S | (Mes, Heijden et al. 2006) |
| | D | Y | M | M | IF | D | St | S | (Mes and Van der Heijden 2007) |
| LTL | D | Y | S | M | Fi | \ | St | S | (Douma, Schuur et al. 2006) |
| PI-LTLDP | D | Y | S | S | Fi | F | St | S | This study |

Overall, the novelty of the PI-LTLDP problem with regard to the relevant literature can be justified from several aspects. Firstly, pricing decisions in PI are mostly concerned with LTL shipping, where carriers are constrained by both capacity and time. It is more complex than TL shipping. Secondly, in a PI-hub, pricing decisions are made using an auction mechanism. Although the auction mechanism has already been studied in the freight transport industry, there is very little research focusing on the pricing problem in the LTL industry, and even less in maritime, rail, and air transport. Thirdly, most of the research studied single-leg transport problems. However, pricing in a PI-hub should take into account routing of either the request or the carrier at network level. Due to the above novelties of the pricing problem in PI, we were unable to find a similar study or model that could be applied to our research and therefore, a novel dynamic pricing model is needed.

## 3.3 The Definition of PI-LTLDP Problem

The Physical Internet consists of numerous interconnected hubs, as indexed from A to D in Fig. 1, for example. In each hub, there are shippers (or carriers) that offer transport requests encapsulated in containers, e.g. $r_1 \ldots r_n$ in PI-hub A. Carriers $1 \ldots m$, providers of transport services, participate in a sequence of auctions to win these requests, taking into account their capacity constraint (finite capacity) and, possibly, time before departure (time-finite). We assume that the auction mechanism is employed here to allocate $n$ requests to $m$ carriers. In this context, the problem studied in this chapter is how a carrier should determine a bidding price for requests to maximise the expected profit according to the present situation, such as request quantity and size, remaining capacity, and time left before departure. This is called the PI-LTLDP problem.

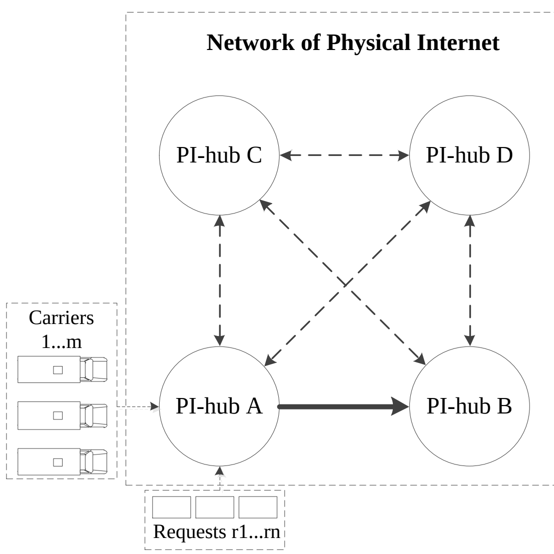



Figure 3. 1 A simple PI network with n requests and m carriers at Hub A

In the first part of this research, and to simplify the problem, this chapter focuses on a single hub in the network and considers a capacity-finite one-leg and one-period same-unit PI-LTLDP problem. One-leg transport means a carrier (vehicle) only considers requests from hub A to hub B, see Figure 3. 1, and not the complete route of the requests or the carrier. As stated in 3.2.1, a carrier's waiting time in a hub is finite and it could be any length of time, 1 hour for example. The carrier needs to decide on a price for all requests that arrive within that hour. This is called one (decision) period problem in this chapter. Nevertheless, it can be extended to multi-periods to study the impact of waiting time on pricing decisions. It is also worth noting that in this chapter we do not consider requests in bundles, because we just consider the same size requests. Therefore, a given carrier bids for requests one by one.

In this context, we firstly aim to investigate the impact of different pricing strategies on carrier profit. Accordingly, two pricing strategies are proposed and studied here.

*Unique bidding price:* the carrier submits one unique optimal price $x^*$ for all requests at an auction;

*Variable bidding price:* the carrier submits a set of bidding prices $\{x_{dr}\}^*$ for each request $r$ according to the vehicle status (remaining capacity and requests) at an auction. These two strategies will be investigated and compared in the experimental study.

Besides the pricing strategy, it is also important to analyse the factors that could significantly influence the optimal pricing decision. To this end, the following three factors were identified and independently studied in the experimental study.

*Quantity of requests:* since the total (or estimated) number of requests that arrive within each period can be different, the carrier could be faced with some extreme scenarios, e.g. from very few to numerous requests to bid for. The optimal pricing decision should also be adjusted. By considering this factor, we can study, in a given hub, how the number of requests impacts a carrier's pricing decision and expected profit with a fixed capacity – capacity of a truck for example.

*Carrier capacity:* if a carrier can assign more than one truck to a hub, they can adjust the total capacity and pricing policy according to the estimated number of requests in the hub. By investigating this factor, we aim to answer the following question: in a given hub, if the number of requests can be estimated, what is the optimal decision for allocating capacity and bidding price for a carrier.

*Carrier's actual transport cost:* in real-world situations, only the carrier knows the actual cost of transport, e.g. €/ton or /km. The carrier may want to estimate how the variation in cost will affect the price, without knowing the others' costs. The following question could be of interest to carriers: in a deterministic environment, if their cost changes (either increases or decreases), what is the impact on the pricing decision, and most importantly on the expected profit.

# 3.4 Modelling

## 3.4.1 Assumptions

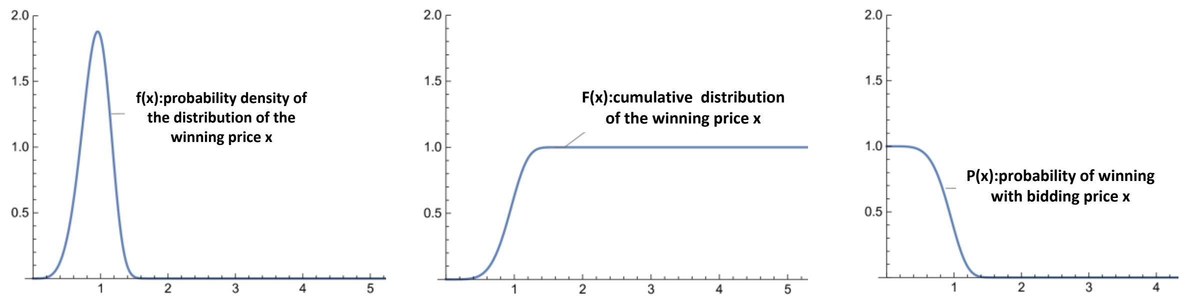
As said previously, this chapter studies a capacity-finite one-leg one-period and same unit PI-LTLDP problem. We propose some assumptions, which are shown below:

1. Auction Mechanism: (1) we adopted a first-price sealed-bid auction mechanism as discussed in (Kuyzu, Akyol et al. 2015); (2) a carrier bids for all the requests one by one within a single auction period, but with no bids on bundles of requests; (3) each auction is independent of the other auctions or other carriers.

2. As it is a one-leg transport problem (from A to B), the complete route of the requests or carrier is not considered.

3. Probability of winning with a given price. If historical data on the winning prices (the lowest price) for each request were somehow available (the data from all previous auctions, for example), it would be possible to develop a distribution function of the winning prices and then deduce the probability of winning with a given price. In (Kuyzu, Akyol et al. 2015), the authors modelled the distribution of winning prices as a uniform, normal, or empirical probability distribution. According to the experimental results, the normal distribution and the empirical distribution performed well. However, due to a lack of data, the empirical distribution is not applicable to our study. Moreover, in practice, carriers would never submit a negative price, so normal distribution is also excluded. Here, we assume that the winning prices are distributed according to a Weibull

distribution because based on our knowledge, and confirmed by (Douma, Schuur et al. 2006), this distribution corresponds well to current carriers' pricing strategies. Reference (Douma, Schuur et al. 2006) also infers that this distribution can be used to present the independent auction mechanism in the chapter. Furthermore, according to the authors' conclusions, we can assume that $\lambda$ is 1 and $k$ is 5, as illustrated in Figure 3. 2.a. The $\lambda$ is set as 1, because the average transport price for a pallet is 1€/km in practical industry. Based on the latter, the distribution function of the winning prices and the probability function of winning with a given price can be determined (b and c, respectively, in Figure 3. 2).




a. probability density of the distribution of the winning price x

b. cumulative distribution of the winning price x

c. probability of winning with bidding price x

Figure 3. 2 Probability of winning expressed as a Weibull Distribution

4. The valuation of the cost for a given request varies independently for each carrier i.e. private auction value (Klemperer 1999). Therefore, when a carrier determines or adjusts their pricing strategy, the other carriers-competitors do not immediately follow suit and their pricing strategy remains unchanged. This also means that the Weibull distribution function proposed in assumption 3 is always valid. Strategic pricing interactions between carriers can be examined through the "learning" process, but this is not within the scope of the study in this chapter.

5. The capacity of a vehicle is defined as $D$ units. As a carrier may have $n \geqslant 1$ vehicles, the total capacity is $n*D$.

6. All requests are encapsulated in PI-containers of unique, standard size, i.e. a homogeneous size of 1 unit.

7. The cost of fulfilling a request is fixed for the carrier.

### 3.4.2 Notations and Model

*Parameters:*

*r*: requests remaining in the auction period. We assume that a vehicle can bid n times at most if there are n requests during the auction period, so $r = n, n\text{-}1, \cdots, 1$.

*p(x)*: the winning probability to a given bid price x in an auction. Based on assumption 3, we have $p(x) = e^{-(\frac{x}{\lambda})^k}, with\ \lambda = 1, k = 5$

*D*: capacity of a vehicle.

*c*: the cost of fulfilling a request.

$d_r$: the vehicle status, defined according to the remaining capacity when bidding for r requests.

$V_r(d_r)$: the expected maximum profit at state $d_r$.

$V_r$: the maximum expected profit during an auction period.

*X*: the bid prices set, i.e., rang of prices to be tested in the model, and X= [0, 2] here.

*Variable:*

Strategy 1: Unique price

*x*: bid price given by the carrier for a request during each auction period. In particular, the optimal bid price determined by the model is noted as $x^*$ and $x^* \in X$.

Strategy 2: Variable price

$x_{dr}$: bid price given by the carrier for each request *r* for each status during an auction period.

$\{x_1, x_2, \ldots, x_{m-1}, x_m\}$: set of bid prices given for requests during each auction period. $m = dr$: present status number. The optimal set of bid prices is noted as $\{x_1, x_2, \ldots, x_{m-1}, x_m\}^*$.

*Dynamic Programming Model:*

As the PI-LTLDP problem concerns sequential auctions, i.e. the decision in the present status will affect the future status, we propose the following dynamic programming (DP) model to solve this problem:

Strategy 1: Unique price – carrier submit just one price to bid for all requests in one period.

$$V_r(d_r) = \max_{x\in X}\left[p(x)\cdot[x-c+V_{r+1}(d_r-1)] + \left(1-p(x)\right)\cdot V_{r+1}(d_r)\right],\ r = 1,2,\dots n-1,n \tag{3.1}$$

Strategy 2: Variable price – carrier submit a new price when bid for each request.

$$V_r(d_r) = \max_{x_{dr}\in X}\ \left[p(x_{dr})\cdot[x_{dr}-c+V_{r+1}(d_r-1)] + \left(1-p(x_{dr})\right)\cdot V_{r+1}(d_r)\right],\ r = 1,2,\dots n-1,n \tag{3.2}$$

And considering the boundary condition (3.3):

$$V_r(d_r) = 0, if\ d_r \le 0\ OR\ r \ge n+1 \tag{3.3}$$

Then the optimal bidding price $x^*$ and the set of bidding prices $\{x_1, x_2,\dots, x_{m-1}, x_m\}^*$ for all the requests can be found through (3.4) (3.5),

$$x^* = arg\max_{x\in X}[p(x)\cdot[x-c+V_{r+1}(d_r-1)] + (1-p(x))\cdot V_{r+1}(d_r)],\ r = 1,2,\dots n-1,n \tag{3.4}$$

$$\{x_1,x_2,\dots,x_{m-1},x_m\}^* = arg\max_{x_{dr}\in X}\ \left[p(x_{dr})\cdot[x_{dr}-c+V_{r+1}(d_r-1)] + \left(1-p(x_{dr})\right)\cdot V_{r+1}(d_r)\right],\ r = 1,2,\dots n-1,n \tag{3.5}$$

The expected maximum profit will be:

$$\mathrm{V_r} = \max[V_r(d_r)],\ r = 1,2,\dots n \tag{3.6}$$

Functions (3.1) and (3.2) are recursive functions that calculate the carrier's expected maximum profit when they bid for $r$ requests using price $x$ or $x_r$ with a remaining capacity of $d_r$. When the carrier wins a request its capacity will be minus 1, otherwise the capacity does not change. The difference between (3.1) and (3.2) is the bidding price. In function (3.1), there is just one price $x$ in the entire period, while in function (3.2), there is one price $x_{dr}$ in each state $d_r$. According to the boundary condition (3.3), the expected profit will be 0 when the capacity is sold out or there are no more requests to bid for. Functions (3.4), (3.5) and (3.6) present the optimal pricing decision $x^*$ or $\{x_1, x_2\dots x_{m-1}, x_m\}^*$ and the resulting expected maximum profit $V_r$.

## 3.5 Experimental Study

An experimental study was designed to evaluate the performance of the model developed, as well as to investigate the two strategies proposed and the three influencing factors identified. The experiment was studied based on optimization with Mathematica 10.4, under the environment of Windows 10. Two scenarios corresponding to the strategies are proposed.

*Scenario 1: Unique Price.* In this scenario, it is assumed that the carrier bids the same price for each request. The optimisation result is the optimal bidding price $x^*$.

*Scenario 2: Variable Price.* In this scenario, the carrier bids different prices for each request according to their status, i.e. the remaining capacity or the remaining number of requests. The optimisation result is a set of optimal bidding prices $\{x_{dr}\}^*$ for each request $r$ for each status.

In each scenario, the three influencing factors - quantity of requests, capacity, cost - are studied separately. The value of each factor varied independently over a given range, as presented in Table 3. 2. In all cases, the value of the bid price was increased from 0 to 2 in 0.1 increments, i.e. $x$=0, 0.1, 0.2….2.

Table 3. 2 Input data (r-requests quantity; D-carrier capacity; c-carrier cost)

| **Investigating Factors** | **Request quantity** | **Carrier capacity** | **Carrier cost** |
|---|---|---|---|
| F1-request quantity | $5\leq r \leq 1000$, Step=5 | $D$=20 | $c$=0.5 |
| F2-carrier capacity | $r$=200 | $1\leq D \leq 241$, Step=3 | $c$=0.5 |
| F3-carrier cost | $r$=200 | $D$=20 | $0.1\leq c \leq 1.5$, Step=0.05 |

### 3.5.1 Results and discussion: scenario 1

In this scenario, the carrier just bids one unique price for all the requests within one auction period. The distribution of the expected profit and the optimal bid price according to the variation of the three factors are shown in Figure 3. 3.

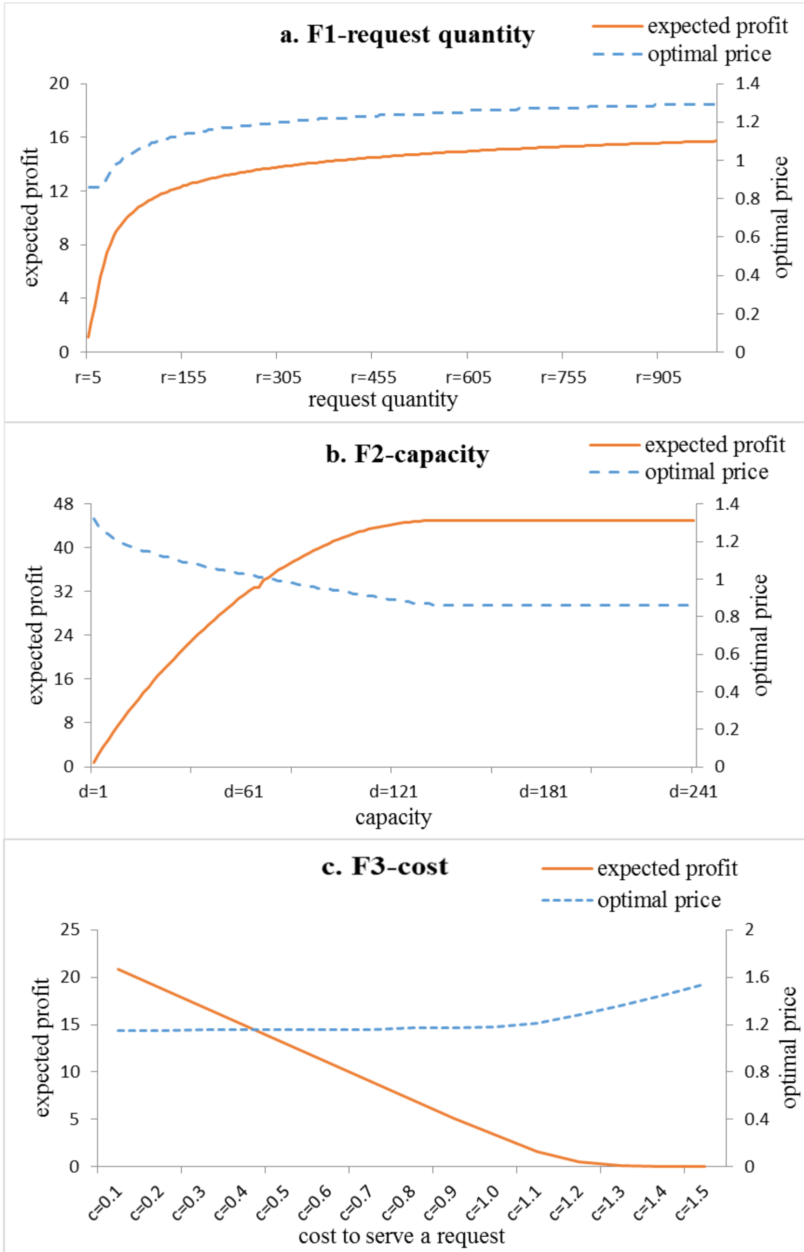



Figure 3. 3 Expected profit and optimal bid price for scenario1

As shown in Figure 3. 3, the expected profit and the optimal bidding price in different conditions can be calculated using our model. In other words, the model can be used as a decision-making tool for carriers. Furthermore, some conclusions can be drawn regarding the impact of the different factors on optimal pricing decisions.

Quantity of requests: for a given carrier, the expected profit $V_r$ and the optimal bidding price $x*$ increase together with the number of requests $r$. However, the rate of increase decreases, dropping dramatically after $r$=125. This result is helpful for carriers with a fixed capacity in PI, e.g. $D$=20. If they knew (or could estimate) the number of requests in each PI-hub, they would be able to select the PI-hubs with the highest rate of profit increase.

Carrier capacity: the capacity $D$ of a carrier has a different impact on the profit and the price, i.e. when the capacity increases, the profit increases and the price decreases. However, beyond a certain point, both the profit and price stay the same. We repeated the experiment with a different number of requests, i.e. $r$ = 20, 100, 200, 300, and 400. The conclusion was the same for all the scenarios. In addition, the critical point was always close to the quantity of requests, $r$. This can be explained by the fact that if $r<D$, the dynamic program will stop once all the requests have been auctioned, see Function (3). This discovery can help carriers decide how many vehicles they need to allocate to cope with different numbers of estimated requests. For example, when there are 200 requests, the turning point is at $d$=137. Therefore, a carrier just needs to allocate 137 units of capacity to the main PI-hub during this auction period. Consequently, their profit and price will be 45 and 0.86, respectively.

Transport cost: the optimal bidding price $x^*$ increases concomitantly with the increasing transport cost $c$, while the profit $V_r$ decreases. The conclusion remained the same when we repeated the experiment with a different number of requests (i.e. $r$ = 20, 100, 200, 300, and 400). The results can help carriers analyse the impact of the variation in their actual costs on the expected profits and pricing strategy. For example, if a carrier in a given hub adopts some new technologies to reduce their transport costs, they could adjust their pricing strategy and estimate the increase in expected profit using the model in order to assess the profitability.

## 3.5.2 Results and discussion: scenario 2

In this scenario, the carrier bids one price for each request according to their status (remaining capacity and requests). A set of optimal bid prices is thus given for each capacity and number of requests (e.g. $D$=20, $r$=50, $c$=0.5). The variation in expected profit according to the three factors, as well as the comparison between the expected profits for the two strategies, is shown in Figure 3. 4. The optimal bid prices for a capacity of 20, 50 requests, and a transport cost of 0.5 are shown in Figure 3. 5. Each point in the figure represents the optimal price for a given status. Both the three-dimensional and the lateral views are provided to describe the variations in price. All the prices can be found in the Appendix 1.

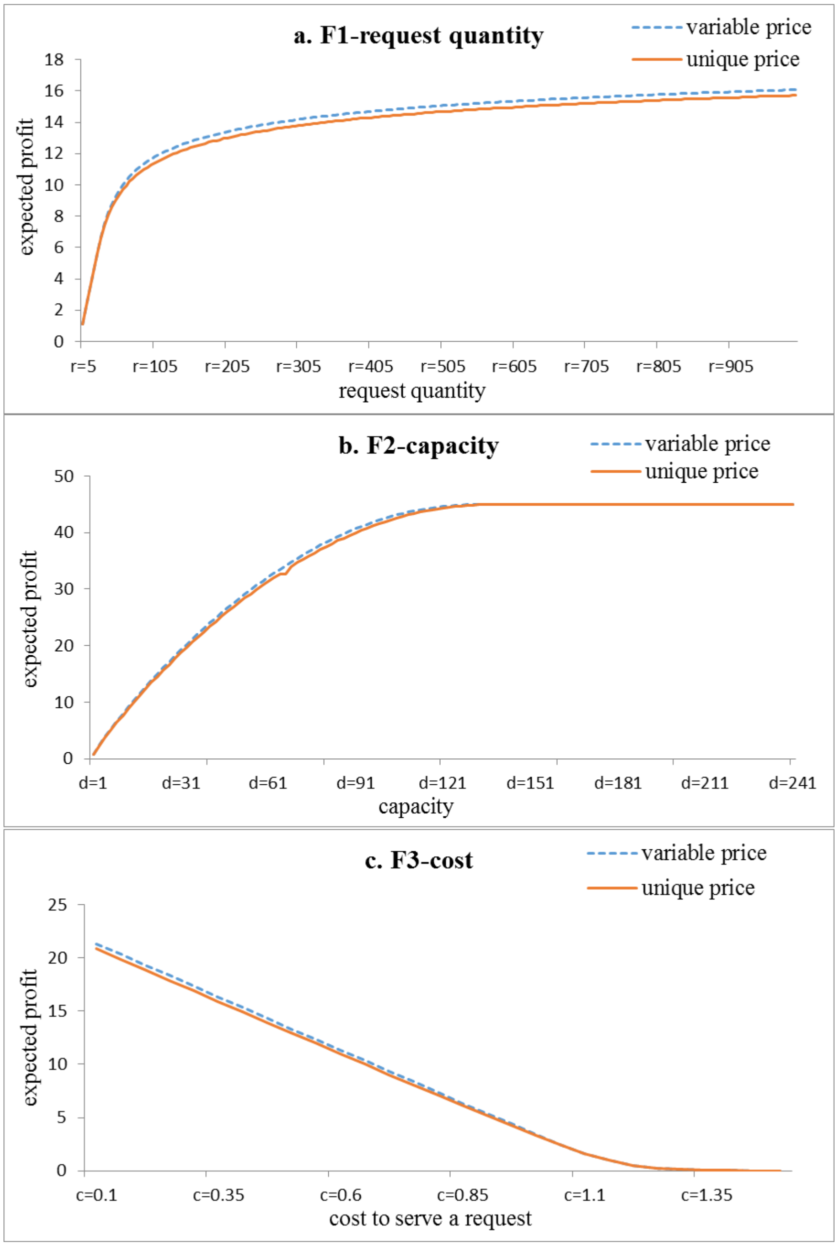



Figure 3. 4 Expected profit for scenario2 and scenario1

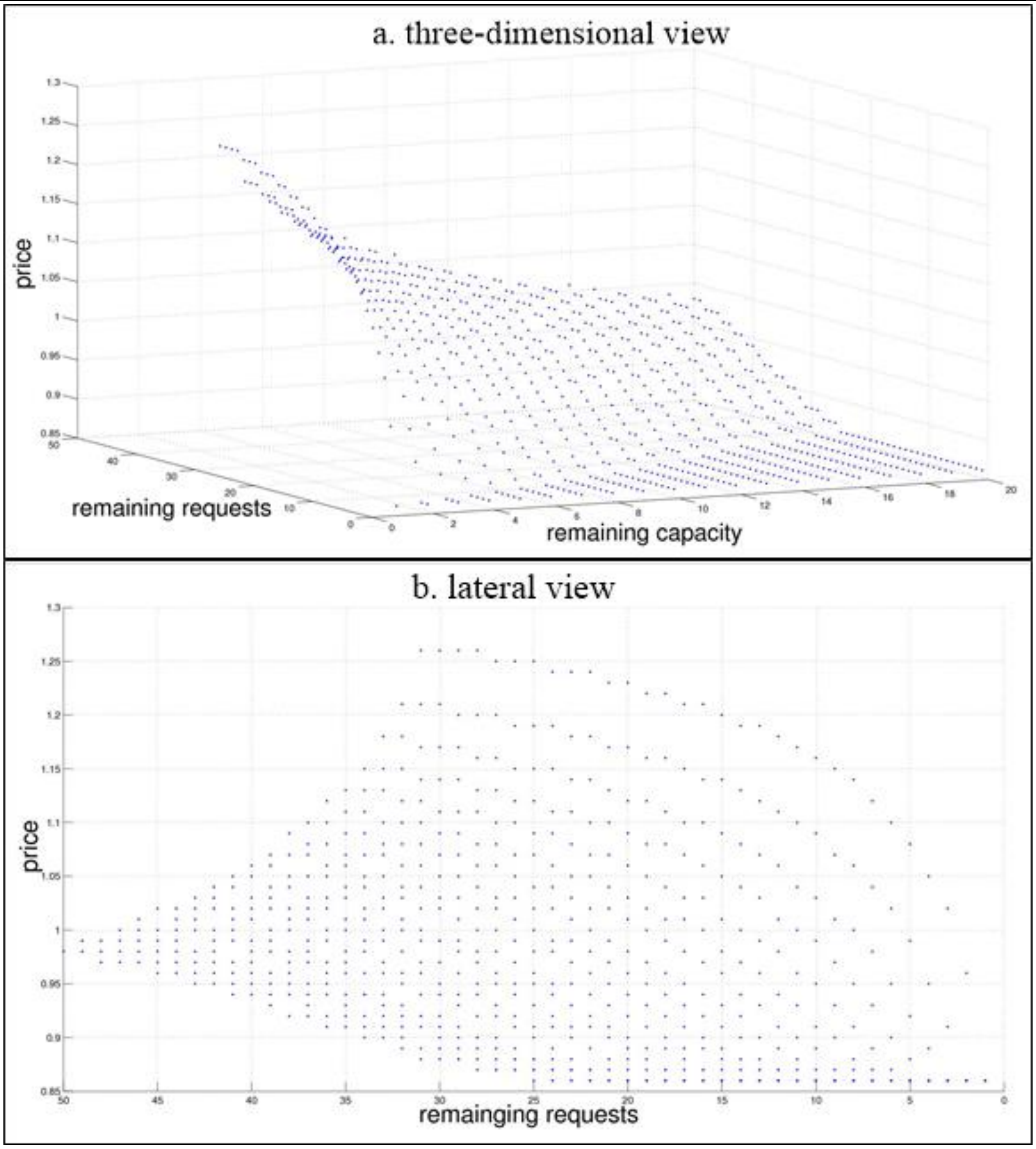



Figure 3. 5 Set of optimal prices with r=50, D=20, c=0,5

In terms of expected profit, according to Figure 3. 4, the evolution of the variable price and the unique price is almost the same when the variations in the three factors are taken into consideration. In addition, in all cases, the variable price strategy only just outperformed the unique price strategy. As a variable price strategy is much more complicated to apply in real-life situations due to the price adjustment after each auction, the performance of the unique price strategy is good and could be more attractive in some real-life cases.

Figure 3. 5.a presents the distribution of the optimal prices in three-dimensional. With regard to optimal price decisions, from Figure 3. 5.b and the Appendix 1, we can see that the optimal bid price – every point in the figure – can vary for each status. When bidding for the first request, the capacity of the carrier is maximal (20), therefore, there is only one optimal price: 0.98. When bidding for the second request, the carrier's remaining capacity can be either 19 if it won the first request or 20 otherwise. Respectively, the carrier has two optimal prices: 0.99 or 0.98. The decision depends on the output of the first auction being on time. When the quantity of requests remaining to be auctioned is less than the carrier's full capacity, the optimal prices begin to converge. Finally, only one optimal price is submitted for the last request, which is 0.86. Fig.5.b can be considered as an optimal price decision tree for carriers. This result is similar to the conclusion in scenario 1. However, as the number of requests decreases, the price converges to the same price because there are fewer requests than the remaining capacity.

## 3.6 Conclusion

This research introduces and analyses the less-than-truckload dynamic pricing problem in the Physical Internet, the PI-LTLDP problem. First, this chapter focuses on a single hub in the network and considers a capacity-finite one-leg and one-period PI-LTLDP problem. A dynamic programming model to calculate the optimal bidding price and expected profit was derived. Then, based on this model, the impact of three influencing factors - quantity of requests, carrier capacity, and transport cost - on the optimal result was estimated using two scenarios: a unique price strategy and a variable price strategy. LTL carriers in PI can use this model as a decision-making tool to determine their optimal price and thus optimise their profits.

In real-life environment, (1) when a carrier arrives at a PI-hub, he could know the cumulative request quantity now. Thus according to his capacity, he could choose an optimal bidding price to bid all the requests based on the calculation results of the model if he adopts strategy of Unique price; or he could give a price when bid for each request according to his current capacity based on the calculation results if he adopts strategy of variable price. (2) before a carrier departs, he could forecast the request quantity of several PI-hubs that he could pass. According to the forecasting results and the calculation results of the pricing model, he could choose one hub that will make his profit maximum. (3) carrier also could collect and analyse the real data of bidding price to update the winning probability.

In summary, this chapter contributes significantly to research on pricing in freight transport, as well as to research on the Physical Internet. Firstly, the study introduced and defined the PI-LTLDP problem, which is different to and more complex than the traditional pricing problem in the freight transport industry, and so a new problem has been identified and investigated. Secondly, this chapter also contributed to research relating to pricing policies in the LTL transport industry, for which the literature is currently very limited. Finally, this chapter presents the first research on the pricing problem in the Physical Internet. The decision-making tool proposed, as well as the conclusions from the experimental study, will provide some useful guidelines for future research. And also, the study in this chapter provide the basis to study more complex problem in the next step.

In the next step, this research could be extended to encompass three characteristics of the Physical Internet – auctioning time, route of request and carrier, and request size. The auctioning time concerns the pricing problem over multiple auction periods, where the price may also be adjusted over time and not just the capacity as in this chapter. Moreover, the one-leg problem could also be extended to the entire Physical Internet, taking into consideration the route of requests and carriers, as well as transport synergies. Dimensional pricing is also another line of research to be investigated, where requests could be of a homogeneous size, from small to big, such as TL for example. The pricing decision taking into account all the characteristics of PI will be much more complex. And besides, how to apply the pricing strategies, model and experiment results into the real environment is also a problem to research.

# Chapter 4. Request pricing and selection in the network of Physical Internet

In the previous chapter 3, the dynamic pricing problem was studied in a simple situation, in which the one-leg one-period same unit requests are considered. This model could be adopted when a carrier has one determinate unchangeable route and faces requests with the same size. But if a carrier has no determinate route and faces with different kinds of requests going to different destinations, the previous model needs to be extended to multi-legs. Carriers need to decide the bidding price for different requests and also decide which requests to transport.

Thus, this chapter extends the one-leg situation in chapter 3 to multi-legs and investigates a less-than-truckload (LTL) request pricing and selection problem to optimize carrier's revenue in Physical Internet (PI). In a hub, many types of LTL requests with different volume and route arrive continually and are allocated to carriers frequently. LTL carriers can bid for these requests through participating several auctions. Being faced with many different requests, carrier needs to select one (or several) type of requests of interest to bid and meanwhile decides the bidding price to maximize his profit. Two scenarios are investigated, i.e. carrier with full capacity, or carrier with loads with known destination. For each scenario, an integer programming model based on a multi-legs dynamic pricing model is proposed to solve the request selection problem and pricing problem simultaneously. A computational study is conducted to demonstrate the feasibility of the models.

## 4.1 Introduction

From the point of view of carriers in freight transport, the request selection problem consists in selecting and pricing the most profitable requests (demands of transport service) at the original depot, for long-haul direct routes or for multiple pickup and delivery routes. A transport request can be defined simply as a request to transport an object from one location to another. They sometime also need to determine the price to bid for the requests, namly the pricing problem. The request selection plays vital role to optimize carrier's revenue. It is particularly obvious considering the fierce competition in transport market, according to the fact that the top 10 third party logistics providers (3PLs) in Europe can only have a market share of 5% (AECOM 2014). In the LTL industry, during the past decades, the LTL segment has been faced with increased competition and shrinking market, which is due to the fact that the LTL market share has been eroded by Full-truckload (FTL) market and by package/courier market (Prokop 2014). Here, the LTL market is operated by LTL trucking companies who handle pallet-size LTL shipments, e.g., *FedEx Freight*, *YRC Freight*, and the package/courier market concerns small-size shipments handled by parcel shipping companies, e.g., *FedEx Express*, *UPS*. According to the definition of the European Commission (2015), the LTL segment transports goods weighing between 30 kg and 2 to 3 tons while the courier segment covers shipments weighing less than 31 kg. Considering the importance, it is essential for logistics providers to pay more attention on their revenue management in current competitive environment. The problem is thus of significance to investigate.

This chapter introduces and investigates a transport request selection problem for less-than-truckload (LTL) carriers based on dynamic pricing in Physical Internet. The requests in PI-hubs are mostly LTL requests with different destination and volume (or quantity) arrive over time (Ballot, Montreuil et al. 2014, Sarraj, Ballot et al. 2014, Qiao, Pan et al. 2016). Carriers propose price to win the requests and then the requests will be allocated to carriers optimally (to the lowest price for example). Auction mechanism is one of the most efficient solution to allocate the requests in PI-hub (Huang and Xu 2013, Xu and Huang 2013, Kuyzu, Akyol et al. 2015). Moreover, the allocation process in PI-hub is very dynamic and stochastic. As a result, carrier should propose different, or dynamic prices to different requests to maximize his profit.

Request selection problem mainly appears in the areas of collaborative transportation. For example (Berger and Bierwirth 2010) and (Xu, Huang et al. 2016), both papers discussed how to select their requests in hand to exchange. Antoher two related references are (Liu, Jiang et al. 2010) and (Li, Rong et al. 2015), who studied the request selection problem in the truckload collaboration area. The former aims to minimize carrier’s total costs via combining different requests in a route. The later aims to maximize carrier’s profit after outsourcing or sourcing some requests, based on a fixed but not dynamic pricing strategy. Indeed, the literature has rarely paid attention to LTL request selection problem, especially considering dynamic pricing.

More precisely, this chapter aims to study how to select requests for LTL carriers to bid in a PI-hub taking into consideration upcoming requests in the following hubs based on dynamic pricing. The dynamic pricing in PI has been studied in (Qiao, Pan et al. 2016), in which dynamic pricing decision for one-leg and single-sized LTL requests in a hub was investigated. The objective is to optimize carriers' price and to maximize their global profits in a PI-hub. In this chapter, we extend the one-leg situation to multi-legs. In a given PI-hub, a carrier is confronted with many requests of varying quantity and destination. To maximize profits, we assume that the carrier takes into account the situation at the next hub (quantity and destination of requests) when selecting and pricing requests. Because, once requests are selected, the next destination he will pass is also decided. Backhaul is a typical example. It is called multi-legs decision here. It means we extend the pricing problem for one single route in Qiao, Pan et al. (2016) to pricing for different routes, which is the request selection problem. For that, based on a dynamic pricing model, we propose two integer programming models for two different scenarios to select the request to bid for, in order to maximize the carrier's profit. The first one considers a full capacity carrier (without load and destination). The other one considers a partially loaded carrier with a determinate destination. By that, this chapter aims to provide decision-making models for carriers' request selection decisions in PI-hubs, and to investigate which factors will influence the request selection decision.

This chapter is organized as follows. After the introduction, section 4.2 presents a brief literature review of the related research in order to identify the research gap and research interest. Section 4.3 describes the request selection problem in PI, which is formulated in section 4.4. A computational study with the results is presented in section 4.5. Finally, section 4.6 concludes the contributions of this work and identifies some research prospects.

# 4.2 Related Works

In the freight transport literature, request selection has been particularly studied in the area of transport collaboration. For example, how to select several requests that carrier received from customers to be subcontracted to other carriers (see Berger and Bierwirth (2010) and Xu, Huang et al. (2016)). Two references relevant to the problem investigated this paper can be found. In Liu, Jiang et al. (2010), the authors presented the task selection and routing problem for TL carriers in collaborative transportation. The objective is to minimize the total cost when a carrier serves the requests. According to their model, the carrier just needs to decide which requests to fulfil and which to outsource to external carriers but does not need to decide on the price of the request. In Li, Rong et al. (2015), the author focused on the request selection and exchange problem between carriers in collaborative transportation. Carriers need to select requests for outsourcing and sourcing with the objective of maximizing their profit. Auction-based exchange of requests with the objective of maximizing the overall profit was also introduced. However, we are unable to use either of these methods to solve our problem directly. First, they did not focus on request pricing. They solve the fleet management problem when the TL request is selected. Second, the environment they researched is static and they did not consider the future situation after request selection. It is very different to the environment of PI-hub that is very dynamic and stochastic.

Another problem, which is relative to request selection in freight transport, is traveling salesman problem with profits (TSPP). As stated in (Feillet, Dejax et al. 2005), TSPP is a generalization of the traveling salesman problem (TSP) and each vertex is associated with a profit. There are two objectives in this problem, optimize the collected profit and the travel cost meanwhile. According to the way the two objectives are addressed, TSPP can be divided into three categories: profit tour problems (PTP), orienteering problems (OP), and prize collecting TSPs (PCTSP). In (Balas 1989), the third category problem was studied. This reference solved a routing problem. This problem is still not the same with our problem. The profit in TSPP is related to vertex, while in PI, the profit is related to a request, i.e. the route.

Several research related to vehicle routing problem (VRP) with profit are also related. In (Figliozzi, Mahmassani et al. 2007), the TSPP was generalized to a dynamic environment. The author studied the pricing problem for truckload carrier using auction mechanism. In this reference, there is no request selection, but a vehicle routing problem considering maximize carrier's profit. In reference (Aras, Aksen et al. 2011), the author studied the reverse logistics problem. The problem discussed in this reference can also be seen as an extension of TSPP, except that vehicles need to pay the customers when visit them. Reference (Ichoua, Gendreau et al. 2006) studied how to exploit information about future events to improve the fleet management of vehicles. The objective is to minimize the total cost to serve the possible requests. It solved the problem that if to accept or how to allocate the new arriving requests to the vehicles the firm owns. This is not a request selection problem actually. The reference (Thomas and White Iii 2004) studied the similar fleet management problem when facing possible requests, but this reference considered the revenue to serve the request. In the context of the VRP, the pickup and delivery problem (PDP) is also related to request selection, see Berbeglia, Cordeau et al. (2007) who provide a survey of static

PDPs and the methods used. Gansterer, Küçüktepe et al. (2017) investigate the multi-vehicle profitable PDP in which LTL paired pickup and delivery requests are selected with the objective of maximizing the total profit the carrier can collect from the requests fulfilled. Moreover, each request provides a fixed revenue. Likewise, the dial-a-ride problem is similar to the PDP. Egan and Jakob (2016) propose a mechanism to optimize the scheduling, routing and passenger pricing of on-demand services, which highlights the key role of provider profit in allocating resources.

Overall, the literature is very limited to the request selection problem for LTL carriers in a dynamic environment like PI. Here, we conclude the characteristics of LTL request selection problem in PI. First, in a stochastic and dynamic environment such as PI, the number and route of requests vary from hub to hub. Different requests could bring the carrier different profits. So, carriers should pay more attention to how to select requests due to limited capacity, which is new research problem to traditional transport networks. Second, the carrier's route will depend on the requests selected in PI. But this is quite different with the classical VRP. The VRP focuses on how to minimize transport costs based on known demands (sometimes with known price), while the request selection problem in PI aims to maximize revenue based on a dynamic pricing decision. This chapter aims to contribute to the literature of PI and request selection, by investigating the new research problem.

## 4.3 Request selection problem definition

The Physical Internet consists of a number of interconnected PI-hubs for freight flow transit. In each hub, shippers can submit transport requests for which carriers can provide transport services. A transport request can be defined as $r^{v}_{ij}$, where $v$ is the volume, $i$ is the origin, and $j$ is the destination. We assume that the quantity of requests is huge at the hub and that they will be allocated to carriers via auction mechanism. This means carriers have to participate in a sequence of auctions to win the requests, taking into account their constraints of capacity (capacity-finite) and time to departure (time-finite). We define the requests with the same route $(i,j)$ as one type of request $R_{ij}$. In a PI-hub, there will be many different types of requests with different quantity. The transportation cost and the carrier's expected profit associated with each type could be very different. In this context, we could assume that the carrier will adopt a dynamic pricing strategy to maximize his profit.

This chapter focuses on how a carrier should select the request type to bid for and decide on the bidding price to maximize his profit. To simplify the problem, it is assumed that request type bundling is not considered which means a carrier just chooses one type of request to bid for and bids for requests one by one. When selecting the request type $R_{ij}$, the carrier needs to consider the upcoming requests at destination $j$ in order to improve total revenue. The result will be the request types that the carrier should bid for and also a route consisting of several PI-hubs that will give the carrier the most profit. This is the request selection problem based on dynamic pricing in PI.

In general, there are two kinds of carriers: a full-capacity carrier with no determinate destination and a loaded carrier with a determinate destination. They are respectively discussed by two scenarios.

*Scenario1: Full-capacity carrier with no determinate destination*

In this scenario, we study the request selection for full-capacity carrier who has no request in hand and has a full capacity. Full-capacity carrier has no determinate destinations which depend on the requests he wins.

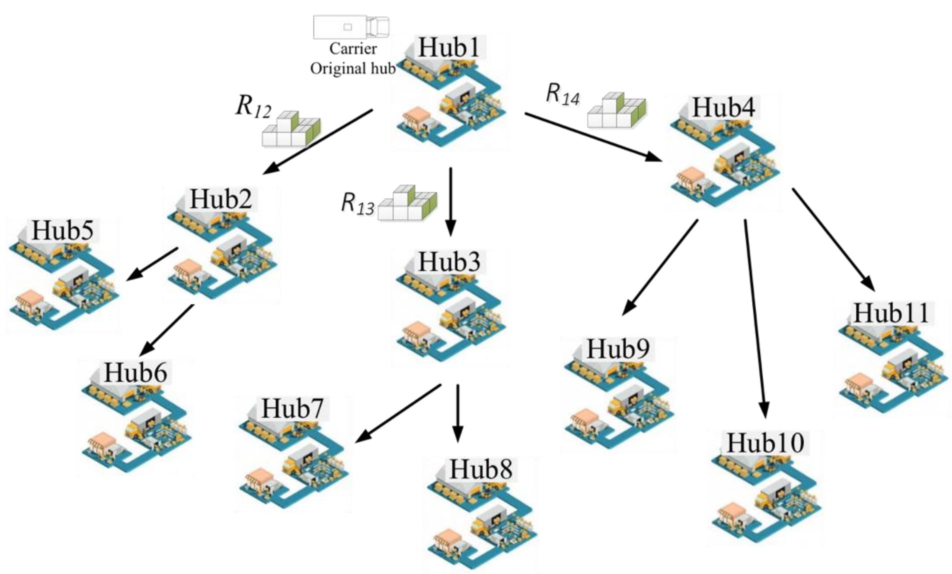



Figure 4. 1 Illustration of Scenario 1

Taking the simple transport network in Figure 4. 1 as an example, let $G = (H, A)$ represents this network, where $i \in H$ is the hub and $(i,j) \in A$ is the route between two hubs. A full-capacity carrier arrives at a PI-hub where there are several types of requests $R_{ij}$ $(R_{12}, R_{13}, R_{14})$ with different quantities $N_{ij}$. The carrier must choose one type of request to bid for and at the same time decide on the bidding price to maximize his expected profit. When making the decision, the carrier should consider upcoming requests at the hub the requests currently selected will take them to. Without losing generality, we just consider the hub one-step ahead, i.e. the hub that the carrier will go to next and not the hub the carrier might go to after the next hub. Thus here, the carrier just needs to consider the requests in hub2, hub3, and hub4. For example, if the carrier selects request $R_{12}$, he should consider if the requests in hub2 can provide a greater profit. As a result, the carrier will choose a route that provides the greatest expected profit, e.g. hub1→hub2→hub6.

*Scenario2: Loaded carrier with determinate destination*

Contrary to a full-capacity carrier, a loaded carrier has already acquired some requests and thus has a determinate destination to go to deliver the requests in hand. If these requests cannot fill the carrier's whole capacity, the carrier could travel to other hubs to collect some requests on the way to the destination hub, with the objective of maximizing the fill rate and profit.

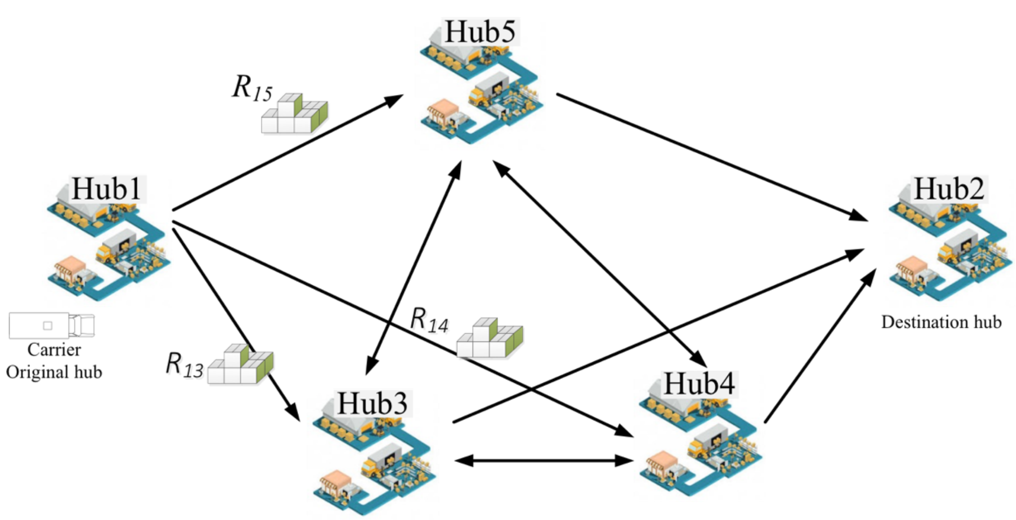



Figure 4. 2 Illustration of Scenario 2

Some intermediary hubs, e.g., hub3, hub4, and hub5 in Figure 4. 2, are located along the carrier's route to the destination hub (hub2). The quantity of requests from one hub to another is different and, in addition, $N_{ij}$ and $N_{ji}$ are different. The carrier needs to decide which hubs to travel through and which type of requests to bid for in each hub. Finally, the carrier will choose the most profitable route consisting of several intermediary hubs to travel to and also the order, e.g., hub1→hub3→hub4→hub2 or hub1→hub4→hub3→hub2.

In this context, we also studied which factors are significant to the request selection decision. To this end, two factors were identified and studied independently in an experimental study.

*Request quantity*: the number of different types of request determines the maximum number of auction periods that the carrier can participate in. According to Qiao, Pan et al. (2016), the number of requests for one route will influence the carrier's expected profit, and therefore the request selected. In this paper, we will investigate if this conclusion is still tenable in a network.

*Route distance*: the distance will decide the transport cost for carriers, which is closely related to the average price of the requests along this route. Thus, whether the route distance can influence the request selection decision by influencing the price of requests should be studied.

# 4.4 Modelling

## 4.4.1 Notations and Methodology

The following notations and methodology in Figure 4. 3 was used to describe and model the problem.

Parameters:

$r$: the index of requests remaining in the auction period. We assume that a vehicle can bid $n$ times at most if there are $n$ requests during the auction period, so $r = n, n\text{-}1, \cdots, 1$.

$S$: the capacity of a vehicle which is assumed as 20 *units* in the experiment study. We also assume the request in this paper has the uniform size of one *unit*.

$(i,j)$: the route of one type of request.

$Dis_{ij}$: the distance from hub $i$ to hub $j$.

$C_u$: unit cost, i.e. the cost to deliver a uniform size request in unit distance, here $C_u=1€/km$.

$C_{ij}$: the cost of fulfilling a request in route $(i,j)$, i.e. $C_{ij}=C_u*Dis_{ij}$.

$N_{ij}$: request quantity (number) from hub $i$ to hub $j$.

$(s_r,n,c)$: the vehicle status, defined according to the remaining capacity $s_r$ when bidding for r requests, the total requests quantity $n$ to bid and the travel cost $c$.

$p(x)$: the probability of winning with a given bid price $x$ at an auction. Based on (Qiao, Pan et al. 2016), we have $p(x) = e^{-(\frac{x}{\lambda})^k}$. We assume that the average price $\lambda = 1.1 * c$, which comes from the practical operation in the market and $k$=5.

$V_r(d_r,n,c)$: the expected maximum profit for one type of request with the status $(s_r,n,c)$.

$V_{ij}(S)$: the maximum expected profit for carrier to bid request with route $(i,j)$.

$A$: the set of routes of requests, $(i,j) \in A$. $(O,D)$ represents the original hub and the destination hub. In particular, we define that N represents all hubs, and $N^-$ represents the middle hubs (hubs except the O, D), i.e. $N^- \cup O \cup D = N$.

$X$: the set of bid prices, i.e. range of prices to be tested in the model.

Variable:

$x$: bid price given by the carrier for a request during each auction period. In particular, the optimal bid price determined by the model is noted as $x^*$ and $x^* \in X$.

$x_{ij}$: the binary variable, set to one if carrier select request from hub $i$ to hub $j$, and $i \neq j$.

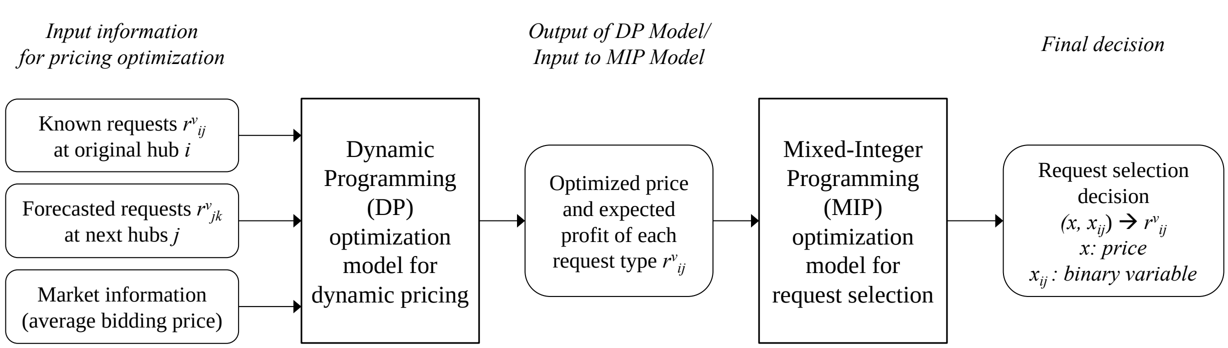



Figure 4. 3 Modelling Methodology

## 4.4.2 Dynamic pricing model

We extended the one-leg pricing model in (Qiao, Pan et al. 2016) to multi-legs. The main difference is that the different travel costs associated with the route are considered in the model. The multi-leg dynamic pricing model is presented below.

$$V_r(s_r, n, c) = \max_{x \in X}\left[p(x) * [x - c + V_{r+1}(s_r - 1, n, c)] + \left(1 - p(x)\right) * V_{r+1}(s_r, n, c)\right], r = 1, \dots, n \quad (4.1)$$

$$V_r(s_r, n, c) = 0, if\ d_r \leq 0\ OR\ r > n \quad (4.2)$$

$$x^* = arg \max_{x \in X}\left[p(x) * [x - c + V_{r+1}(s_r - 1, n, c)] + \left(1 - p(x)\right) * V_{r+1}(s_r, n, c)\right],\ r = 1,2, \dots n - 1, n \quad (4.3)$$

$$V_{ij}(S) = V_1\left(S, N_{ij}, c_{ij}\right) \quad (4.4)$$

Function (4.1) is a recursive function to calculate the carrier's maximum expected profit when bidding for $r$ requests using price $x$ with a remaining capacity of $s_r$ and travel cost $c$. When the carrier wins a request its capacity will be minus 1, otherwise, the capacity does not change. Function (4.2) is the boundary condition representing the expected profit which is 0 when the capacity is sold out or there are no more requests to bid for. Function (4.3) presents the optimal bidding price $x^*$. Finally, function (4.4) is used to calculate the maximum expected profit $V_{ij}$ obtained with the request on route *(i,j)*.

## 4.4.3 Request selection model for scenario 1

Based on the dynamic pricing model above, an integer programming (IP) model to select request for carrier is given as (4.5)-(4.8). This model is constructed according to the idea of maximum expected profit:

Objective:

$$Max \sum_{(i,j) \epsilon A} V_{ij}(S) * x_{ij} \quad (4.5)$$

Constraints:

$$x_{ij} - \sum_{(j,k) \in A} x_{jk} \geq 0, (i,j) \in A \quad (4.6)$$

$$\sum_{(i,j) \in A} x_{ij} \leq 1,\ i \in N \quad (4.7)$$

$$x_{ij} \in \{0,1\}, (i,j) \in A \tag{4.8}$$

The objective function (4.5) maximizes the carrier's total expected profit after selecting one type of request to bid for. Constraint (4.6) ensures that information relating to upcoming requests in the next hub will only be considered if the request going to this hub is selected. Constraint (4.7) ensures only one type of request can be selected in one hub.

### 4.4.4 Request selection model for scenario 2

Similar to 4.4.3, an integer programming (IP) model to select requests for the loaded carrier is formulated below.

Objective:

$$Max \sum_{(i,j)\epsilon A} V_{ij}(S) * x_{ij} - \left(\sum_{(i,j)\epsilon A} Dis_{ij} * x_{ij} - Dis_{OD}\right) * N_{OD} * C_u \tag{4.9}$$

Constraints:

$$\sum_{(i,j)\in A} x_{ij} - \sum_{(j,k)\in A} x_{jk} = 0, j \in N^- \tag{4.10}$$

$$\sum_{(i,j)\in A} x_{ij} \leq 1,\ i \in N^- \tag{4.11}$$

$$\sum_{(O,j)\in A} x_{Oj} = 1 \tag{4.12}$$

$$\sum_{(i,D)\in A} x_{iD} = 1 \tag{4.13}$$

$$\sum_{i\in N^*} \sum_{j\in N^*} x_{ij} \leq |N^*| - 1, N^* \subseteq N^- \tag{4.14}$$

$$x_{ij} \in \{0,1\}, (i,j) \in A \tag{4.15}$$

Function (4.9) maximizes the carrier's expected profit after selecting the intermediary hubs to go through. The first term represents the total expected profit gained from passing through the intermediary hubs. The second term calculates the detour cost for loaded requests in hand where $N_{OD}$ is the number of loaded requests. Constraint (4.10) imposes a balance in each hub, i.e. if the carrier travels to a hub it must leave from this hub, except for the hubs of origin and destination. Constraint (4.11) ensures only one type of request can be selected in one hub. Constraints (4.12) and (4.13) ensure that for the hubs of origin and destination, only one type of request goes out and in. Finally, constraint (4.14) avoids the situation where a carrier goes back and forth between two hubs.

## 4.5 Computational study

At first, an experiment was designed to investigate the influence of two factors discussed in 4.3. Next, a computational study was proposed to illustrate and evaluate the performance of the models developed. For the two scenarios described in 4.3, two examples were used to test the models separately. All the illustrations were running on Mathematica 10.4 under the environment of Windows 10 on a DELL of Model Inspiron 15 (5000) with 16 GB of RAM.

### 4.5.1 Investigation of Influencing Factors

Without losing generality, this experiment was designed based on the simplified networks shown in Figure 4.1. As discussed in 4.3, the number of requests and the route distance are two factors that might influence the request selection decision. We studied the influence of the factors separately. The quantity for each request type was randomized over four levels (5-50, 51-100, 101-150, 151-200) and each distance was randomized over three levels (20-100km, 200-300km, 400-500km). Three groups of experiments have been conducted. The input data and results are presented in Table 4. 1, Table 4. 2 and Table 4. 3.

- The first group using the input data in Table 4. 1, which gives the same distance but different quantities of each type of request over four levels, was used to study how the number of requests influences request selection. We observed that the route that maximizes the carrier's expected profit always has the highest total number of requests. However, the route with the lowest total number of requests minimizes the profit. This result shows that the carrier should select the route with the most requests if the travel distance is the same. Nevertheless, the difference between maximal and minimal expected profit decreases as the request quantity increases.

- The second group based on the data in Table 4. 2 was used to study the influence of the travel distance on request selection. The results show that the longest route maximizes the carrier's expected profit, which can be explained by our assumption that the travel cost was the distance multiplied by a fixed unit cost, and the average market price was

1.1*the travel cost, and so the expected profit will increase as the distance increases. If the number of different requests is the same, the carrier should select the one with the longest distance.

- In the third group, we mixed the input data from the previous two tests (see Table 4. 3). Compared with the results of group1 and group2, the results of group3 prove that in request selection, the number of requests and the travel distance influence the decision simultaneously. An optimization model is, therefore, essential to help carriers select the request.

Table 4. 1 Same distance, different number over four levels

| Rang of Random Quantity | Input data (distance is 50km for all routes) | | | | | | | | | | Output Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | request quantity | | | | | | | | | | Solution of maximal expected profit | | Solution of minimal expected profit | |
| | $R_{12}$ | $R_{13}$ | $R_{14}$ | $R_{25}$ | $R_{26}$ | $R_{37}$ | $R_{38}$ | $R_{49}$ | $R_{4-10}$ | $R_{4-11}$ | route | profit | route | profit |
| (5-50) | 40 | 13 | 27 | 50 | 39 | 30 | 36 | 8 | 48 | 5 | 1-2-5 | 195 | 1-4-11 | 69 |
| (51-100) | 91 | 98 | 63 | 83 | 76 | 82 | 100 | 85 | 83 | 58 | 1-3-8 | 386 | 1-4-11 | 261 |
| (101-150) | 124 | 137 | 138 | 124 | 106 | 124 | 146 | 148 | 102 | 111 | 1-4-9 | 475 | 1-2-6 | 422 |
| (151-200) | 172 | 189 | 171 | 167 | 195 | 192 | 190 | 156 | 158 | 179 | 1-3-7 | 538 | 1-4-9 | 505 |

Table 4. 2 Same number, different distance over three levels

| Rang of Random Distance (km) | Input data (request quantity is 100 for all hubs) | | | | | | | | | | Output Results | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | route distance | | | | | | | | | | Solution of maximal expected profit | | Solution of minimal expected profit | |
| | $D_{12}$ | $D_{13}$ | $D_{14}$ | $D_{25}$ | $D_{26}$ | $D_{37}$ | $D_{38}$ | $D_{49}$ | $D_{4-10}$ | $D_{4-11}$ | route | profit | route | profit |
| (20-100) | 83 | 79 | 67 | 93 | 21 | 36 | 39 | 92 | 91 | 20 | 1-2-5 | 686 | 1-4-11 | 341 |
| (200-300) | 220 | 292 | 246 | 203 | 291 | 249 | 289 | 271 | 202 | 294 | 1-3-8 | 2262 | 1-2-5 | 1647 |
| (400-500) | 438 | 422 | 479 | 427 | 444 | 476 | 444 | 439 | 498 | 453 | 1-4-10 | 3803 | 1-2-5 | 3370 |

Table 4. 3 Different number, different distance over mixed levels

| | QL1:5-50 | | QL2:51-100 | | QL3:101-150 | | QL4:151-200 | |
|---|---|---|---|---|---|---|---|---|
| | max | min | max | min | max | min | max | min |
| DL1: | 1-2-5 | 1-4-11 | 1-2-5 | 1-4-11 | 1-2-5 | 1-4-11 | 1-2-5 | 1-4-11 |
| 20-100 | 347 | 83 | 621 | 234 | 780 | 399 | 908 | 456 |
| DL2: | 1-2-6 | 1-4-11 | 1-3-8 | 1-4-10 | 1-3-8 | 1-2-5 | 1-3-8 | 1-2-5 |
| 200-300 | 879 | 354 | 2247 | 1363 | 2752 | 1872 | 3138 | 2181 |
| DL3: | 1-2-5 | 1-4-11 | 1-3-8 | 1-4-11 | 1-4-9 | 1-2-6 | 1-4-10 | 1-2-5 |
| 400-500 | 1695 | 662 | 3351 | 2442 | 4371 | 3733 | 4965 | 4461 |

## 4.5.2 Illustration of the Models

This section aims to demonstrate the feasibility of our request selection models. The two scenarios are studied here (full-capacity carrier vs loaded carrier). All the experiments in this paper are run on Mathematica 10.4 under Windows 10 on a DELL Inspiron 15 (5000) with 16 GB of RAM. We use the function Maximize in Mathematica to solve the problems, which can solve any linear (integer) programming problem thanks to the solvers developed by Mathematica. In our cases, the average CPU times are around 1 minute and 16 minutes for the two scenarios, respectively.

*Scenario 1: Full-capacity carrier with no determinate destination*

Based on the network in Figure 4. 1, the distance, average request quantity on each route is given in Table 4. 4. The measurement units are *KM* for distance and *unit* for request quantity.

Table 4. 4 Input Data for scenario 1

| **Route** | **Distance** | **Average Request Quantity** | **Route** | **Distance** | **Average Request Quantity** |
|---|---|---|---|---|---|
| 1->2 | 165 | 13 | 3->7 | 163 | 14 |
| 1->3 | 150 | 32 | 3->8 | 176 | 26 |
| 1->4 | 104 | 30 | 4->9 | 83 | 33 |
| 2->5 | 97 | 23 | 4->10 | 126 | 31 |
| 2->6 | 346 | 32 | 4->11 | 54 | 25 |

Based on the input data in Table 4. 4 and the model proposed, the computation result shows that carrier should select requests 1->2 in hub1, and also the optimized route is 1->2->6. Accordingly, the maximum expected profit is 576 and the optimal bidding price for request 1->2 is 193.

According to the result, we can found that even though there are not much requests 1->2, but request 2->6 with much quantity and high price can give more possible future profit. So carrier should select request 1->2 and go to hub2.

*Scenario 2: Loaded carrier with determinate destination*

In this scenario, as shown in Figure 4. 2, it is interconnected between hub3, hub4 and hub5. Three tests with [10, 4, 1] loaded requests $N_{OD}$ are made to evaluate if the loaded request quantity could influence the request selection decision in this scenario.

Table 4. 5 Input Data for scenario 2

| **Route** | **Distance** | **Average Request Quantity** | **Route** | **Distance** | **Average Request Quantity** |
|---|---|---|---|---|---|
| 1->3 | 104 | 30 | 4->2 | 193 | 15 |
| 1->4 | 150 | 32 | 4->3 | 125 | 31 |
| 1->5 | 165 | 13 | 4->5 | 267 | 13 |
| 3->2 | 36 | 32 | 5->2 | 98 | 31 |
| 3->4 | 125 | 25 | 5->3 | 100 | 27 |
| 3->5 | 100 | 18 | 5->4 | 267 | 25 |

According to the input data in Table 4. 5 and the model proposed, three optimal decisions are given based on three tests:

(1) 10 loaded requests: optimal route 1->2 with extra profit of 0. This means carrier should go to destination directly without selecting requests in hub1. Because the detour cost for the loaded requests is more than any profit he can get from the intermediary hubs.

(2) 4 loaded requests: optimal route 1->3->2 with extra profit of 72. We can found that loaded request quantity could influence the request selection decision by affecting the detour cost.

(3) 1 loaded request: optimal route 1->4->3->2 with extra profit of 228. This extreme example shows that carrier could go to as many as intermediary hubs if the extra profit can cover the detour cost.

## 4.6 Conclusion

This chapter introduces and investigates the LTL request pricing and selection problem considering upcoming requests in PI with the aim of optimizing LTL carrier revenue. First, we proposed a revenue optimization model based on a dynamic pricing model and IP optimization models to help the carrier select the best LTL requests. Second, we qualitatively studied the influence of the transport factors on pricing and selection decision. The feasibility of the proposed model is demonstrated through a computational study. Two scenarios considering full-capacity carrier and partially loaded carrier are proposed and studied.

This chapter also contributes to revenue optimization for LTL carriers in PI based on dynamic pricing and request selection. First, the chapter develops the dynamic pricing model for multi-leg requests, which can be used as a decision-making tool for selecting requests. The pricing model can maximize the revenue gained from each type of request. This model has extended the research on dynamic pricing in LTL transport as well as in PI. Next, this chapter introduces and studies the request selection problem in a stochastic environment such as PI, which has been studied very little up to now. The request selection model is used to help the carrier select the most profitable requests to maximize total revenue. Overall, the dynamic pricing and request selection models provide carriers with guidelines to make decisions to optimize revenue.

One main limitation of this work is that the request quantity considered in each PI-hub is static. But in fact, the quantity might change very quickly. Because transportation is a very dynamic and stochastic environment, the allocation of request in PI-hubs is very frequent. In the next, we will study the request selection problem in a dynamic situation, i.e. the request quantity in each hub is not static but stochastic. The request selection problem will be associated with forecasting problem in the network of PI. Besides, the optimization models could be extended for bundles of requests for different routes. In our future research, we aim to study the request pricing and selection problem taking request bundles into consideration. The problem could be extended to request pricing and selection in the vehicle routing problem.

# Chapter 5. Forecasting problem in dynamic request pricing and request selection in Physical Internet

This chapter extends the transport request in Chapter 3 to multiple auction periods and the static request quantity in the next hubs to a stochastic quantity. In this chapter, a dynamic pricing model for multi-periods is developed. This model could help carriers who would stay in a hub to participate several auctions to decide the optimal bidding price in each period. Moreover, the request selection model combined with a stochastic forecasting model is proposed. In addition, how the uncertainty of forecasting would influence the expected profit is studied.

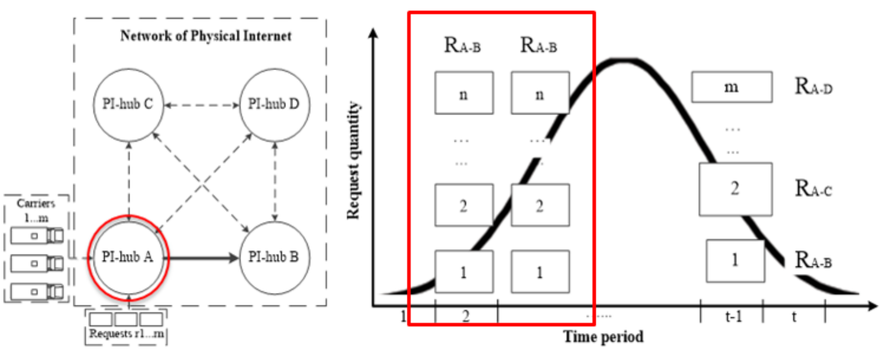
## 5.1 Introduction

At the most basic level, forecasting is refer to the point estimate, which just determine a single number for the forecasting item, such as the number of seats demanded on a specific flight. However, the forecasting in RM is much more complex than this. According to Helve (2015), in general, the forecasting could be classified as: macro-level (aggregated forecasts, e.g. total industry level demand), micro-level (disaggregated forecasts, e.g. demand of passenger for a particular train), choice modeling (forecasts of individual behavior, e.g. individual's choice between transport modes). Moreover, a forecast should be explained with an inherent uncertainty in predicting the future demand. As presented in Talluri and Van Ryzin (2006), the forecasting results are used as the input of optimization models, which aim to make the optimal RM decisions, such as pricing and capacity control. In addition, RM is normally adopted to respond to the market fluctuation, which indicates that the future demand is always stochastic. Therefore, it is essential to forecast the demand as a distribution with a complete probability distribution or parameters for the assumed distribution. What we need to note is that the forecast is not just about the future demand, but also the future capacity and the market price. With a good forecasting, carriers could make more accurate RM decisions, dynamic pricing and request selection decision in this thesis. How the forecasting could influence the decision making will be the forecasting problem discussed in this chapter.

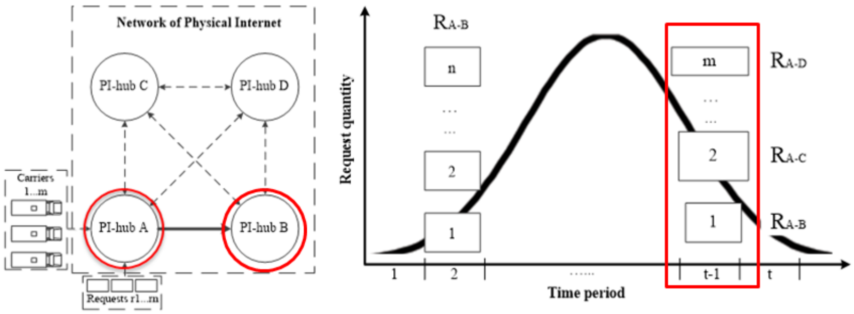
Forecasting is an important part in Revenue Management, especially in a dynamic market. The performance of other RM components depends on the quality of forecasting. For example, the capacity allocation, overbooking, and pricing decisions are made based on the forecasting result of the future demand, market price, and so on. In Pölt (1998), it is presented that 20% of reduction of forecast error can bring 1% increase in revenue generated from the RM system. There have been a number of researches about the forecasting problem in Revenue Management. Luo, Gao et al. (2015) investigate how to use dynamic forecasting to optimize the revenue in intermodal transportation. Zaki (2000) summarize the forecasting in airline revenue management. Helve (2015) study the forecasting of demand from passenger in railway revenue management while Rao (1978) present the similar demand forecasting problem in railway freight industry. There are some studies about the forecasting in supply chain. For example, Ali, Babai et al. (2017) present a simple Downstream Demand Inference (DDI) strategy for those supply chains without information sharing. The DDI strategy could help users to forecast the consumer demand mathematically. Murray, Agard et al. (2015) forecast the supply chain demand through segmenting the customers into number of clusters with similar demand behavior.

Besides, in the road traffic sector, the forecasting method has been applied widely. For instance, Chen and Grant-Muller (2001) propose and discuss the potential application of neural networks algorithm in the short-term traffic flow forecasting of motorway. Chrobok, Kaumann et al. (2004) investigate two methods of short-term traffic forecasting, which are based on 2 years of real data. The application of forecasting in freight transport is also significant, because the freight transport demand fluctuate frequently over space and time (Garrido and Mahmassani 2000). Chow, Yang et al. (2010) review the current freight forecasting models and advances. Moreover, the authors present the future development of forecasting with data using. Petri, Fusco et al. (2014) propose a new freight demand forecasting model driven by data and based on Bayesian Network. In Fite, Don Taylor et al. (2002), the freight demand forecasting in truckload (TL) industry is discussed. The air cargo demand forecasting is investigated by Suryani, Chou et al. (2012), in which a system dynamics simulation model is developed. Nuzzolo and Comi (2014) present the demand forecasting in urban freight and propose a mixed modelling approach comprising quantity, delivery and vehicle. All these researches show that an appropriate forecasting method could improve the operational efficiency in the transport system and help the actor in the system to produce effective RM decisions.

Instead of studying the method of forecasting, in this thesis and this chapter, we combine the forecasting with the previous proposed dynamic pricing and requests selection models. The objective of this chapter is to investigate how the forecasting would influence the decision-making in Revenue Management. This chapter extend the request type to multi-legs, several auction periods, and different hubs, as shown in Figure 5. 1. In chapter 3, we develop the dynamic pricing model based on the simplest request with the same lanes in one hub and single auction period. Then in chapter 4, based on the previous pricing model, the request selection model is proposed for various requests with different lanes in one hub and one auction period. In this chapter, the request in the next latter auction periods and the next hubs will be considered. In other words, we will consider the current requests and the future requests in the following auction periods and hubs, when making the pricing and request selection decisions. Thus, the forecasting should be combined in the decision model, because the future requests might influence the current decision of carriers, e.g. if the carrier pretend to save the capacity to the more profitable requests which are probably coming. Based on the models in chapter 3 and chapter 4, this chapter will propose a dynamic pricing model considering the request in the next auction periods and a request selection model combining with a stochastic forecasting model. Two questions are going to be investigated: (1) how the forecasting in next auction periods influence the pricing decision; (2) how the forecasting uncertainty influence the decision-making.




a. request in several auction periods




b. various request in next hubs

Figure 5. 1 The type of request in forecasting problem

Some other researches propose to consider demand forecasting in request selection. Ichoua, Gendreau et al. (2006) present how to exploit information about future events to improve vehicle fleet management with the objective of minimizing the total cost to fulfil the possible requests. It solved vehicle dispatching problem rather than request selection problem. Thomas and White Iii (2004) propose a similar fleet management problem while considered the revenue to fulfil the request. Figliozzi, Mahmassani et al. (2007) forecast possible transport requests associated with an incoming probability for each. Some dynamic pricing research also studied how to forecast future customer demands to improve pricing decisions. For example, Lin (2006) develop a real-time learning method to better forecast future customer numbers over a time horizon, and thus to adjust the pricing decision dynamically in real time. Some other research assumes that customers/demands arrive according to a discrete or continuous probability distribution (Gallego and Van Ryzin 1994, Chatwin 2000). The main objective of these studies is to determine how to make dynamic pricing decisions based on the forecasting result. Differently, in this chapter we are interested in pricing and selecting requests according to the forecasting result of the future demand in the next auction periods or the next hubs. Moreover, we also discuss how the uncertainty of the forecasting can influence the decision.

This chapter is organized as follows. Section 5.2 describe the forecasting problem in this thesis. Section 5.3 formulate the forecasting problem in dynamic pricing considering several auction periods. Similarly, section 5.4 modelling the forecasting problem in request selection. In section 5.5, we construct a field study to investigate how the forecasting of the requests in next auction periods could influence the pricing decision, and how the forecasting uncertainty could affect the future expected profit and the request selection decision. Finally, section 5.6 concludes the contributions of this work and identifies some research prospects.

# 5.2 Forecasting problem description

## 5.2.1 Forecasting in the dynamic pricing

In chapter 3, the dynamic pricing problem in one auction period is studied. However, in some situations, carriers might participate several auctions to try to take more requests. Here, we will consider the pricing problem with multi-periods and still one type of request. As shown in Figure 5. 2, the waiting time of a carrier in one PI-hub can be divided into *m* periods, e.g. $t_1$, $t_2$, …, $t_{m-1}$, $t_m$. Each period can be seen as an auction period, and carrier bid for all requests arriving during that period. Carrier could forecast the possible request numbers during each period, e.g. $n_1$, $n_2$, …, $n_{m-1}$, $n_m$. At the first period, a carrier will give a bidding price $p_{1d}$ according to his full capacity *D*, the known requests number $n_1$, and the possible requests number of the following periods. Because the future request number could influence the carrier's current pricing decision. For example, if the request number in the next period is huge, the carrier might want to save the capacity for the next auction period, as we know that more requests bring more profit from chapter 3.

It is also worth noting that from period $t_2$, the capacity will be not *D*, but decided by the auction results in the previous periods. In other words, the remaining capacity in the latter periods rely on how many requests carrier got in the previous periods. In each period from $t_2$, carrier will have *D* kinds of possible remaining capacity, i.e. *1, 2, …, D*. Carrier need to decide the bidding price according to the remaining capacity, so there will be *D* possible prices in each period, e.g. $p_{21}$, $p_{22}$, …, $p_{m1}$ in period $t_2$.

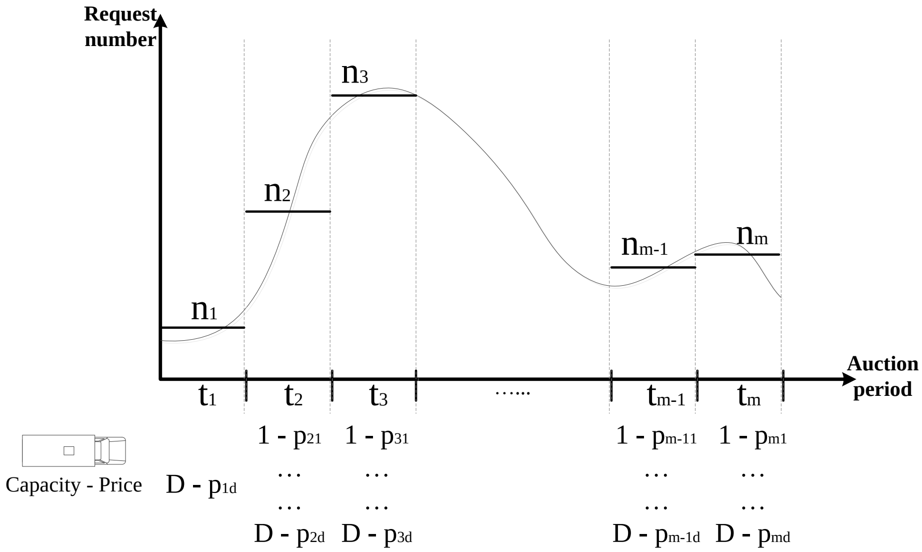



Figure 5. 2 Auction periods division in the PI-hub

In this context, we aim to give a pricing guide according to the carrier's remaining capacity, forecasting requests number, and the auction period the carrier is in. Another objective is to investigate how the future possible requests influence the current pricing decision. In addition, to simplify the problem, we adopt the unique price strategy proposed in chapter 3, i.e. carrier submits one unique optimal price to bid for all requests in each auction period.

### 5.2.2 Forecasting in the request selection

In chapter 4, we present the request selection problem, in which the request number in the next hubs is considered. The objective of chapter 4 is mainly provide a request selection guide and study what factors would influence the decision. We assume the request number as a known constant in previous request selection model. However, in reality, the market is fluctuant, which means the carrier could not know the exact number of the request before arriving at the next hubs. Figure 5. 3 could show the distribution of the requests in the next hubs.

In this chapter, we will modelling the future request in the next hubs as a stochastic distribution. Moreover, we will evaluate whether and how the forecasting uncertainty could influence the request selection decision. The forecasting uncertainty here is the request quantity distribution at a given time, which means the dispersion of the historical request quantity, also known as the distribution variance. In real transportation hubs, there are a huge number of requests and the distribution uncertainty of the number of different types of requests is variable. Two types of requests with the same average quantity might have very different uncertainties, e.g., the average quantity is 100 for both but one ranges from 90 to 110 and the other from 60 to 130. By considering this factor, we discuss whether and in which situations the forecasting uncertainty can influence the request selection decision.

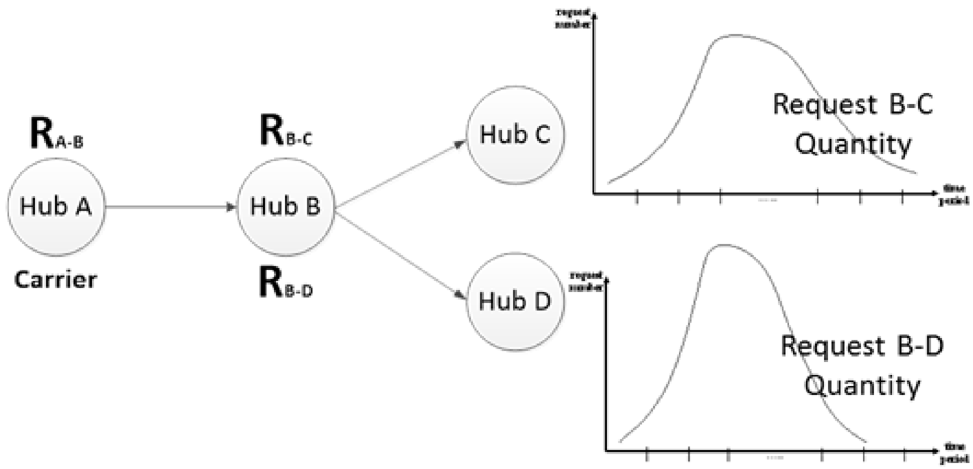



Figure 5. 3 Requests distribution in the next hubs

# 5.3 Model formulation of the forecasting in the dynamic pricing

## 5.3.1 Notations

*Parameters:*

*r[t]*: requests remaining in auction period t. As presented in chapter 3, we assume that a vehicle can bid n times at most if there are n requests during the auction period, so *r[t] = n, n-1, ···, 1*.

*p(x)*: the probability of winning with a given bid price x in an auction. We have $p(x) = e^{-(\frac{x}{\lambda})^k}, with\ \lambda = 1, k = 5$

*Pw(r,x,i)*: the probability that carrier could win *i* requests with a bid price *x* when facing *r* requests in total. We assume the winning request number in one auction period is distributed following a Binomial Distribution.

*D*: the capacity of a vehicle.

*c*: the cost of fulfilling a request.

T: the number of auction periods carrier will participate.

*(d,t)*: the vehicle status, defined according to the remaining capacity *d* when carrier is in auction period *t*.

*V(d,r,x)*: the expected maximum profit in one auction period with *d* remaining capacity, *r* requests and a bidding price *x*.

*VT(d,t)*: the expected maximum profit when carrier is in status *(d,t).*

*X*: the set of bid prices, i.e. range of prices to be tested in the model, and *X* = [0, 2] here.

*Variable:*

$x_{dt}$: bid price given by the carrier for a request at state *(d,t)*. In particular, the optimal bid price for each state determined by the model is noted as $x_{dt}$*.

## 5.3.2 Model of dynamic pricing considering several auction periods

Same with the PI-LTLDP problem discussed in chapter 3, the pricing problem considering several auction periods also concerns sequential auctions, i.e. the decision in the present status will affect the future status. Moreover, the pricing decision will influence the capacity remained for the next auction periods. Thus, we propose the following dynamic programming (DP) model to solve this problem:

Equation (5.1) is used to calculate the expected maximum profit of status (d,r,x) in auction period *t*.

$$V(d,r[t],x) = p(x)\cdot[x-c+V(d-1,r[t]+1,x)] + \big(1-p(x)\big)\cdot V(d,r[t]+1,x),\ r[t] = 1,2,\ldots n-1,n \qquad (5.1)$$

Equation (5.2) presents the probability to win i requests in one period.

$$Pw(r,x,i) = \binom{r}{i}p(x)^i(1-p(x))^{(r-i)},\ i = 0,1,\ldots,r-1,r \qquad (5.2)$$

The expected maximum profit in the state of (d,t) could be calculated through (5.3).

$$VT(d,t) = \max_{x_{dt}\in X}\left[V(d,r[t],x_{dt}) + \sum_{i=0}^{i=d} Pw(r[t],x_{dt},i)\cdot VT(d-i,t+1)\right],\ r = 1,\dots n-1,n \tag{5.3}$$

Boundary conditions are given by (5.4) and (5.5)

$$V(d,r[t],x) = 0, \text{if d} \le 0\ OR\ r[t] \ge n+1 \tag{5.4}$$

$$VT(d,t) = 0, \text{if d} \le 0\ OR\ t \ge T+1 \tag{5.5}$$

Then the optimal bidding price $x_{dt}*$ for the state of (d,t) can be found through (5.6).

$$x^* = arg \max_{x_{dt}\in X}\left[V(d,r[t],x_{dt}) + \sum_{i=0}^{i=d} Pw(r[t],x_{dt},i)\cdot VT(d-i,t+1)\right],\ r = 1,\dots n-1,n \tag{5.6}$$

Function (5.1) is a recursive function that calculate the carrier's expected maximum profit when they bid for *r[t]* requests using price *x* with a remaining capacity of *d*. Function (5.3) is a recursive function based on the auction period to calculate the maximum profit when carrier is in auction period *t* and with remaining capacity *d*. According to the boundary condition (5.4) and (5.5), the profit will be 0 when capacity is sold out, or there are no requests, or the waiting time is finish. The expected maximum profit in the whole waiting time will be *VT (D, 1).*

# 5.4 Model formulation of the forecasting in the request selection

## 5.4.1 Notations

The model here is proposed as an extension of the request selection model in chapter 4. The following notations were used to describe the extended model. Most of the notations appeared in chapter 4 are not presented again.

$N_{ij}$: request quantity (number) from hub *i* to hub *j*, of which the forecasted quantity is assumed as a Normal Distribution.

$A$: the set of routes of requests, $(i,j) \in A$. $(O,D)$ represents the original hub and the destination hub.

$VF_{ij}(S)$: the maximum expected profit for carrier to bid request with route $(i,j)$ and forecasting quantity.

$f_{ij}(x)$: the density function of the forecasted request quantity.

$P_{ij}(N_{ij} \leqslant k)$: the probability that no more than k requests arrive.

Variable:

$x_{ij}$: the binary variable, set to one if carrier select request from hub $i$ to hub $j$, and $i \neq j$.

### 5.4.2 Request selection model considering forecasting

However, in reality, the carrier is not able to accurately know how many requests there will be when he arrives at the following hubs after a period of travel. The carrier can just use the historical data to estimate the possible number of requests, which is normally given as a probability distribution.

Following some similar studies (Kuyumcu and Garcia-Diaz 2000, Helve 2015, Hassani, Silva et al. 2017), in this research we also use Normal Distribution to model the request quantity distribution in the following hubs. We assume the distribution of the quantity $N_{ij}$ of requests $R_{ij}$ is Normal Distribution $N(\mu_{ij},\sigma_{ij}^2)$ with the following density function,

$$f_{ij}(x) = \frac{1}{\sqrt{2\pi}\sigma_{ij}} e^{-\frac{(x-\mu_{ij})^2}{2\sigma_{ij}{}^2}} \tag{5.7}$$

So the probability that no more than k requests arrive will be,

$$P_{ij}\left(N_{ij} \leq k\right) = \int_{-\infty}^{k} f_{ij}(x)\, dx = \frac{1}{\sqrt{2\pi}\sigma_{ij}} \int_{-\infty}^{k} e^{-\frac{(x-\mu_{ij})^2}{2\sigma_{ij}{}^2}}\, dx \tag{5.8}$$

Equation (4.4) to calculate the expected profit from request $R_{ij}$ will be transformed to:

$$VF_{ij}(S) = \int_0^N V_1(S,k,c_{ij}) f_{ij}(k) dk \tag{5.9}$$

where *N* is a large number and *k* is the possible number of requests. But this integration formula has a dynamic programming function inside, which makes the equation very complex to solve. To simplify the calculation and without loss of generality, we approximate the continuous probability with a discrete probability; that is, we calculate the probability that *k* requests arrive as follows,

$$P_{ij}\left(N_{ij} = k\right) = P_{ij}(k) = P_{ij}\left(N_{ij} \leq k + 0.5\right) - P_{ij}\left(N_{ij} \leq k - 0.5\right) \tag{5.10}$$

Then equation (5.9) can be transformed to:

$$VF_{ij}(S) = \sum_0^N P_{ij}(k) V_1(S, k, c_{ij}) \tag{5.11}$$

As the number of requests in the current hub is already known, when calculating the total expected profit, the carrier just needs to consider the predicted number of requests in the following hubs. So, the objective functions (4.5) and (4.9) become:

$$Max \sum_{(i,j)\epsilon A_O} V_{ij}(S) * x_{ij} + \sum_{(i,j)\epsilon A_{O-}} VF_{ij}(S) * x_{ij} \tag{5.12}$$

$$Max \sum_{(i,j)\epsilon A_O} V_{ij}(S) * x_{ij} + \sum_{(i,j)\epsilon A_{O-}} VF_{ij}(S) * x_{ij} - \left(\sum_{(i,j)\epsilon A} Dis_{ij} * x_{ij} - Dis_{OD}\right) * N_{OD} * C_u \tag{5.13}$$

Where $A_O$ represents the routes departing from the original hub and $A_{O\text{-}}$ represents the other routes in the network. All the constraints (4.6)-(4.8) and (4.10)-(4.15) stay the same because the predicted number of requests just changes the way in which the expected profit of each type of request is calculated.

## 5.5 Experiment study

In this section, an experiment study is designed to evaluate the performance of the proposed models. Firstly, we qualitatively investigate the influence of forecasting to the pricing decision when considering several auction periods. Then, we study how the forecasting uncertainty, i.e. the fluctuation of market, could affect the expected profit. At last, we add uncertainty to each average request quantity of the input data in 4.5.2 and use new input data to evaluate the extended request selection model in this chapter. All the experiments in this chapter were run on Mathematica 10.4 under Windows 10 on a DELL of Model Inspiron 15 (5000) with 16 GB of RAM.

### 5.5.1 The influence of the forecasting to the dynamic pricing decision

This experiment aims to study the influence of the request quantity in the following auction periods to the current pricing decision. Thus, we assume the quantity of forecasted future request to be a static number. Three auctions periods with three different request quantity are considered. Moreover, there will be 6 scenarios according to the different que of the three quantity, which is presented in Table 5. 1. Besides, the vehicle capacity and transport cost is assumed as 20 and 0.5, which are the same as in Chapter 3.

Table 5. 1 Input data and scenarios for the experiment study 5.5.1

| Scenario | Request quantity in each Auction Period (AP) | | |
|---|---|---|---|
| | AP1 | AP2 | AP3 |
| S1 | 50 | 100 | 150 |
| S2 | 50 | 150 | 100 |
| S3 | 100 | 150 | 50 |
| S4 | 100 | 50 | 150 |
| S5 | 150 | 100 | 50 |
| S6 | 150 | 50 | 100 |

As presented above, we adopt unique price strategy here, which means there only one biding price for one pair of request quantity and remaining capacity, i.e. one price $x$ for one status *(d,t)*. Table 5. 2 presents part of the results obtained based on model proposed in 5.3.2, while the complete results could be found in in Appendix 2. The results shows the optimal bidding price corresponding to each possible status *(d,t)*. For example, in the second auction period of scenario 1, the status will be (15,100) if there are 15 units capacity left after the first auction period and the corresponding optimal price is 1.22. We also should note that the capacity is full in the first auction period which is period that carrier just arrives. Besides, Table 5. 2 also present the optimal price when not considering several auction periods, which is calculated through the model proposed in 3.4.2. This price is given for each status *(d,r)* and without influence from the future requests.

From the results and the comparing between the two strategies, considering several auction periods or not, we found that the future request could influence the current pricing decision. For example, let us see the status (8,100) that is highlighted in red in Table 5. 2. When there are 150 requests coming, the bid price is 1.27. The price will decrease to 1.23 when the following request quantity is 50. When does not consider the future request, the price is lower which is 1.17. This is because the capacity should be saved to earn more profit when there are a lot requests coming, while in contrary, the capacity should be sold as much as possible with a lower price. Moreover, when in the last auction period, the bid price should be the same as the price when does not consider the future request. Because there are no future requests in both these two strategies, which could be evidenced by the result in yellow for example.

Table 5. 2 Optimal bidding prices for each status

| Capacity | Optimal bidding price | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Considering several auction periods | | | | | | Not considering several auction periods | | |
| | Scenario 1 | | | Scenario 5 | | | | | |
| | 50 | 100 | 150 | 150 | 100 | 50 | 50 | 100 | 150 |
| 1 | \ | 1.37 | 1.3 | \ | 1.34 | 1.22 | 1.22 | 1.27 | 1.3 |
| 2 | \ | 1.34 | 1.28 | \ | 1.31 | 1.19 | 1.19 | 1.25 | 1.28 |
| 3 | \ | 1.33 | 1.26 | \ | 1.29 | 1.17 | 1.17 | 1.23 | 1.26 |
| 4 | \ | 1.31 | 1.25 | \ | 1.27 | 1.15 | 1.15 | 1.21 | 1.25 |
| 5 | \ | 1.3 | 1.23 | \ | 1.26 | 1.14 | 1.14 | 1.2 | 1.23 |
| 6 | \ | 1.29 | 1.22 | \ | 1.25 | 1.12 | 1.12 | 1.19 | 1.22 |
| 7 | \ | 1.28 | 1.21 | \ | 1.24 | 1.11 | 1.11 | 1.18 | 1.21 |
| 8 | \ | 1.27 | 1.2 | \ | 1.23 | 1.09 | 1.09 | 1.17 | 1.2 |
| 9 | \ | 1.26 | 1.2 | \ | 1.22 | 1.08 | 1.08 | 1.16 | 1.2 |
| 10 | \ | 1.25 | 1.19 | \ | 1.21 | 1.07 | 1.07 | 1.15 | 1.19 |
| 11 | \ | 1.24 | 1.18 | \ | 1.2 | 1.06 | 1.06 | 1.14 | 1.18 |
| 12 | \ | 1.24 | 1.17 | \ | 1.19 | 1.05 | 1.05 | 1.13 | 1.17 |
| 13 | \ | 1.23 | 1.17 | \ | 1.19 | 1.04 | 1.04 | 1.13 | 1.17 |
| 14 | \ | 1.23 | 1.16 | \ | 1.18 | 1.03 | 1.03 | 1.12 | 1.16 |
| 15 | \ | 1.22 | 1.16 | \ | 1.17 | 1.02 | 1.02 | 1.11 | 1.16 |
| 16 | \ | 1.21 | 1.15 | \ | 1.17 | 1.01 | 1.01 | 1.1 | 1.15 |
| 17 | \ | 1.21 | 1.14 | \ | 1.16 | 1 | 1 | 1.1 | 1.14 |
| 18 | \ | 1.2 | 1.14 | \ | 1.16 | 0.99 | 0.99 | 1.09 | 1.14 |
| 19 | \ | 1.2 | 1.13 | \ | 1.15 | 0.98 | 0.98 | 1.09 | 1.13 |
| 20 | 1.21 | 1.19 | 1.13 | 1.22 | 1.14 | 0.98 | 0.98 | 1.08 | 1.13 |

We also calculate the expected profit in each scenario and the strategy without considering several auction periods. The profit is shown in Table 5. 3. In the case of this chapter, we could found the profit between each scenario is similar. While the profit considering the future request is higher than the profit without considering the influence from the coming requests. This result gives a sight that it will be profitable to consider the future request in a dynamic market.

Table 5. 3 Expected profit for each scenario

| | S1 | S2 | S3 | S4 | S5 | S6 |
|---|---|---|---|---|---|---|
| Considering several auction periods | 13.9 | 14.0 | 14.0 | 13.9 | 14.0 | 14.0 |
| Not considering several auction periods | 9.9 | 9.9 | 11.7 | 11.6 | 12.6 | 12.6 |

## 5.5.2 The influence of forecasting uncertainty to the expected profit

In this section, we investigate the influence of forecasting uncertainty on the expected profit. Forecasting uncertainty is defined as the dispersion of the request quantity historical data, which can also be represented by the request quantity distribution variance. When the average number of requests $\mu$ is determinate, we calculate the variance as follows: (1) as Figure 5. 4 shows, we assume 98% of the quantity are distributed in the range [$\mu$*(1-x), $\mu$*(1+x)], where $0<x<1$; (2) based on the symmetrical features of Normal Distribution, we obtain the variance $\sigma^2$ through solving the equation $P(\mu * (1 + x)) = 0.99$, where P is the cumulative distribution function.

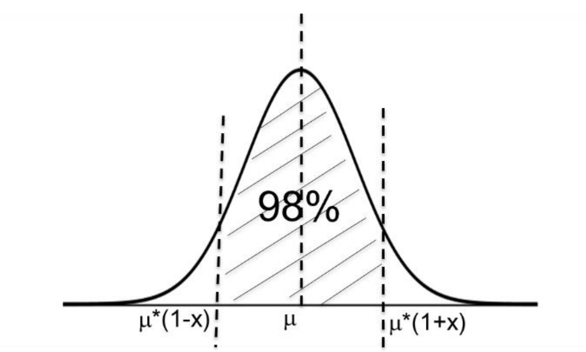



Figure 5. 4 Request quantity distribution function

Without loss of generality, we could just take one type of request, e.g., $R_{BC}$ in Figure 5. 3, to qualitatively study how forecasting uncertainty influences the expected profit based on equation (5.11). In this experiment, we considered 9 dispersion degrees, that is $x$ changes from 0.1 to 0.9 in increments of 0.1. In addition, we conducted the test at different average levels of request quantity and route distance. The average number of requests increased from 10 to 200 in increments of 10 while the route distance varied from 10 to 400 in increments of 10. We thus obtained 7200 sets of input data of which the output is the expected profit. Some of the results are shown in Figure 5. 5 and Figure 5. 6.

As shown in Figure 5. 5 and Figure 5. 6, we can observe that when the average number of requests and the route distance stay the same, the smaller the uncertainty generates a higher expected profit. This can be concluded by the negative linear correlation ($R^2$>0.9 in most cases). But, the influence of the uncertainty on the expected profit varies according to the levels of request quantities and route distances.

(1) Same route distance: as the average number of requests increases, the expected profit increases very fast, but the rate of increase begins to decrease and drops dramatically after a quantity. We can see from the bottom half of Figure 5. 5, the negative linear correlation becomes more significant along with the increase of request quantity. This means, at the beginning, the uncertainty does not influence the expected profit significantly, which results in no matter how the uncertainty changes, a greater number of requests always gives a higher profit and should be selected. While as the average number of requests increases, the uncertainty has more significant influence on the profit and can influence the request selection. For example, 190 requests with an uncertainty of 0.3 produce a greater profit than 200 requests with an uncertainty of 0.9, so the carrier should select the request with the quantity of 190. This result can help the carrier to decide whether to take the forecasting uncertainty into consideration when making decisions.

(2) Same number of requests: with the increasing of route distance, the expected profit increases linearly based on the assumption about the relation between average price and transport cost in 4.4.1. But being same with the conclusion above, the uncertainty influences the expected profit significantly and can influence the request selection when the distance is long, which can be found from Figure 5. 6.

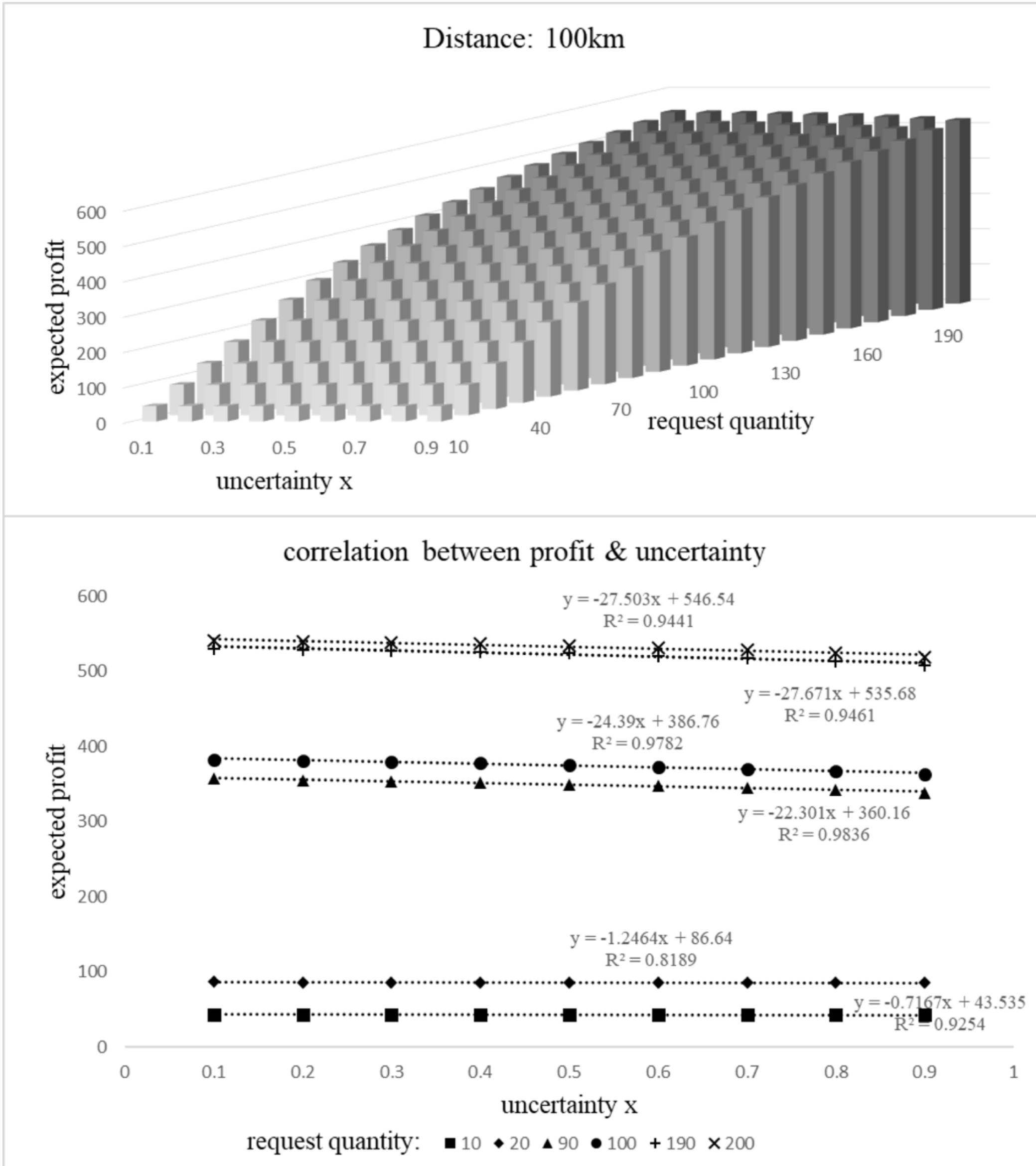



Figure 5. 5 Expected profit over a distance of 100 km

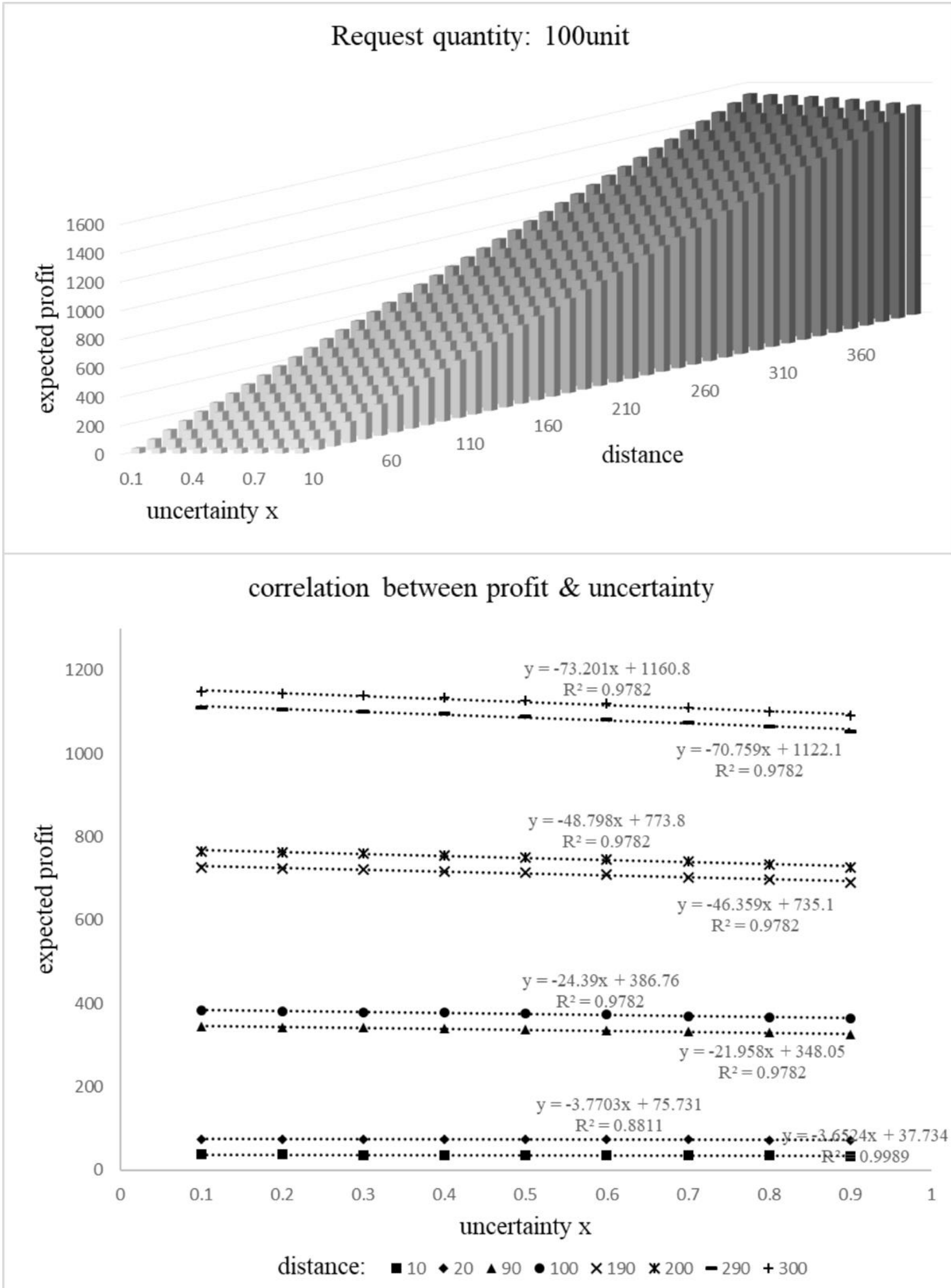



Figure 5. 6 Expected profit over request quantity of 100 unit

# 5.6 Conclusion

This chapter present and investigate the forecasting problem for LTL carriers in the dynamic pricing and request selection decisions making process in PI. First, we extend the dynamic pricing problem in one auction period to several auction periods. Thus, carrier need to forecast the request quantity in the next periods and make the pricing decision. The influence of the future requests to the pricing decision is studied. Second, we consider a stochastic forecasting in the request selection model and investigate the impact of forecasting uncertainty on revenue optimization.

This chapter contributes to the research of forecasting of Revenue Management in Physical Internet. First, this chapter develop the multi-periods dynamic pricing model, for carriers who would like to wait in a hub for several auction periods. This model could help them to decide the optimal bidding price according to the upcoming requests. Second, how forecasting and forecasting uncertainty could influence request selection is also a new problem in PI. By learning this problem, we can illustrate the sensitivity of request selection decisions to forecasting uncertainty. This study could give a guideline to carrier about whether to consider the forecasting uncertainty or not.

However, due to the lack of appropriate real data, we did not study the method to do the forecasting. We just assumed the fluctuation of request in the market. How to do the forecasting should be a future work in the next steps.

# Chapter 6. Bundle pricing of LTL freight transport requests based on historical data analysis in Physical Internet

In the previous chapters, we discuss how to decide the bidding price and how to select the profitable request in a network with abundant requests. In this chapter, we consider the network in which there are not enough requests on the lanes. This means there will not be enough requests to fill the capacity of LTL carriers. Facing with such a situation, carriers should consider request bundling to increase the utility of their transport capacity. This chapter propose a mixed integer nonlinear programming (MINLP) model for the bundle pricing problem of LTL carrier. The bundle pricing problem consists of bundle generation and pricing for the bundle. In addition, the model solves a dynamic pickup and delivery problem (PDP). We also present a general method to analyze the historical data to obtain the information used in the model. At last, an analysis process based on an actual data is presented and a numerical study is constructed to evaluate the feasibility of the proposed model.

## 6.1 Introduction

In marketing, bundling refers to combine the individual products or services in a package to sell it with a different price (mostly a lower price than the sum of the prices of the individual bundle components). Bundling is a strategy applied in many industries, for example, the “meal menu” includes separate food items in fast food industry; the vacation packages consisting of airfare, hotel and car rental offered by travel aggregators (Fuerderer, Herrmann et al. 2013). In freight transport, from the perspective of carriers, the bundling of freight transport requests means accepting or submitting a package of loads which have inter synergies on the transport pathways. One simple example is the bundle of requests on the go-and-return path. If the requests are allocated with auction mechanism, especially the combinatorial auction (CA), carriers could submit their bids to the auctioneer for a bundle of requests that they want to transport in a pool of various requests. As a result, carrier might win all the requests in the bundle or loss them all. Carriers need to solve a bid generation problem (BGP), in which there are two issues of bundle generation and bundle pricing (Sheffi 2004, Yan, Ma et al. 2018). First, the bundle of bidding requests needs to be determined from all the potential bundles. Second, carrier must decide the bidding price for this bundle considering both the benefits and the probability to win this bundle. These two issues compose the bundle pricing problem in this chapter.

From the aspect of economies of scope, request bundling has significant meanings to the carriers (Sheffi 2004). First, appropriate bundles could avoid some possible empty movement of the vehicles through bundling the requests on the go and return path. Such as in Figure 6. 1.a, carrier bundle the request of A-B and B-A together to remove the empty travel. Second, for truckload (TL) carriers, bundling the requests could increase the utility of their transport networks. We could see the example on Figure 6. 1.b, through bundling the request of A-B and C-A, TL carrier could reduce the empty movement and increase the utility of the network. Besides, for less-than-truckload (LTL) carriers that we focus on in this thesis, they could make full use of their capacities to optimize the loading rate. On Figure 6. 1.c, the LTL carrier could bundle the two requests of C-A into one vehicle, which efficiently improves the loading rate.

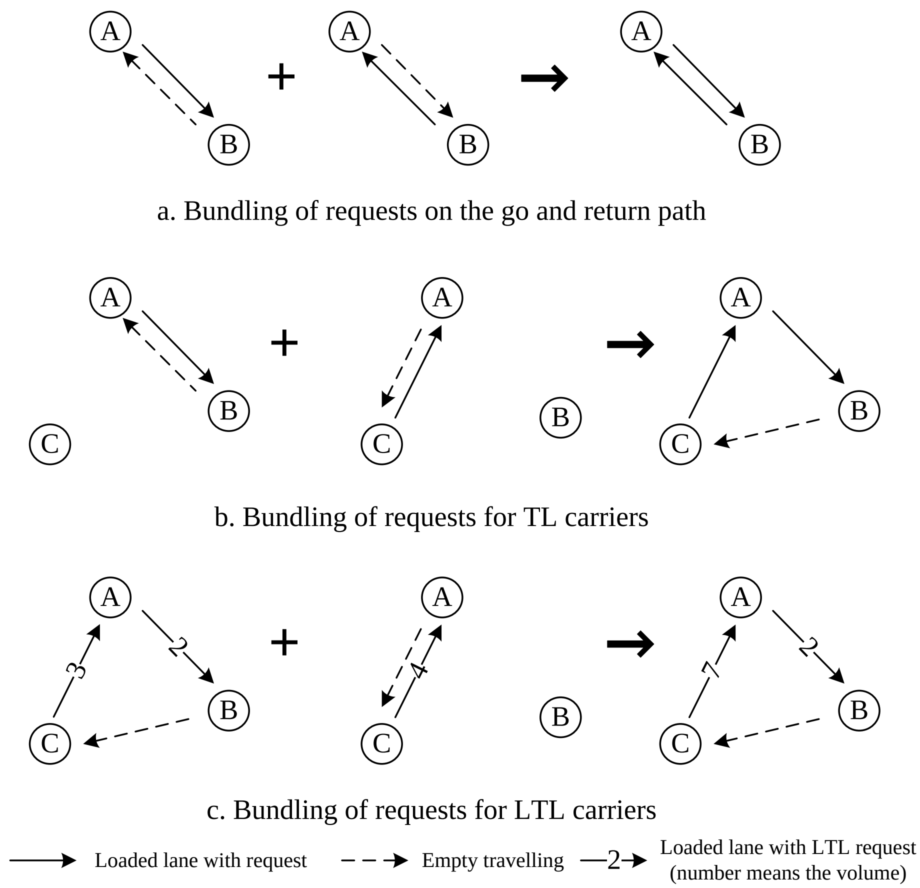



Figure 6. 1 The economies of scope of request bundling (Sheffi 2004)

The pricing for the bundle is another problem that carriers need to consider, especially when they adopt the auction mechanism. The price for a bundle is difficult to determine due to various factors to consider (Banciu and Ødegaard 2016). First, the different requests have various characteristics, such as various volume and lane. It is difficult to determine the value when several requests are bundled together. Second, it is not easy to know the valuation of the shipper to the bundle. This could affect the probability to sell the bundle to shippers. Obviously, a higher price could bring more profit but more likely losing the business. While the lower price could win the business with higher probability but might lose potential profit.

The bundle generation and pricing in freight transport have been studied mostly in Combinatorial Auction (CA). For example, Sheffi (2004) and Song and Regan (2003) introduce the application of CA in the procurement of transportation services. Wang and Xia (2005) present the bid generation problem in the transportation service procurement. However, most of these researches are focused on full truckload. There has been little research focused on the bundle pricing for the LTL carriers. Ackermann, Ewe et al. (2011) investigate that the CA could improve the usefulness of LTL carriers. Mesa-Arango and Ukkusuri (2013) discuss the development of consolidated bids that is suitable for LTL operations. Therefore, it has significant meaning to study the bundle pricing for LTL transport requests.

In the previous chapters, we focus on the lanes that have abundant requests. Thus, the request bundling is not needed. In this chapter, we will study the routes that are not very busy, i.e. there are not so many requests on these routes. In such a situation, for the sake of economies of scale and scope, it is essential for carriers to bid for a bundle of requests. This chapter introduces and investigates the bundle pricing problem on the legs with small quantity requests for LTL carriers in Physical Internet. We need to mention that there could be many possible requests in the future in PI. Thus the carrier should consider the influence of the requests in the next hubs when making the bundle pricing decision. A mixed integer non-linear programming (MINLP) model, which integrates the bundle generation and pricing problem together, is developed to generate the optimal request bundle and the optimal bidding price to maximize the revenue of carrier.

More precisely, to increase the loading rate and the revenue, carrier could bundle the small number of requests on several legs together and submit this bundle as a bid. Two main decisions need to make, bundle generation and bundle pricing. Carrier should select the most profitable requests as a bundle that satisfy the constraints of routes and vehicle capacity. However, the profit from the request bundle depends on the transport cost and the bidding price. Therefore, these two decisions could not be solved separately and require an integrated model. In order to get the transport cost, the transport route and the request quantity on each lane should be determined. Therefore, a pickup and delivery vehicle routing problem (PDVRP) considering the future possible requests on the route needs to be solved. The proposed MINLP model in this chapter could solve bundle generation, bundle pricing and PDP at the same time. Besides, in the model, we consider two scenarios based on whether the requests could be split or not. In this chapter, we also propose a method to get the function to calculate the unit price based on the real data. The objective of this chapter is to provide a decision-making model to help carriers make the request bundle pricing decision in the network of Physical Internet.

The rest of this chapter is organized as follows. Section 6.2 is dedicated to a review of literatures in three areas: bundle generation, bid construction in Combinatorial Auction, and LTL pickup and delivery problem. The bundle pricing problem in PI is described in section 6.3. In section 6.4, we formulate the bundle pricing model and present the data analysis method. A numerical study is conducted to evaluate the feasibility of the proposed model in section 6.5. At last, section 6.6 concludes the achievements of this chapter and also proposes some future research perspectives.

## 6.2 Related works to bundle pricing

Bundle pricing is studied mostly in the bid generation problem (BGP) in combinatorial auction in the procurement transportation services. Wang and Xia (2005) examine the BGP for full truckload (TL) carriers. The bundle is generated through solving a generic vehicle routing problem with the objective of minimizing the total transportation cost. Moreover, the pricing problem for the bundle is not studied in this paper. Similarly, Song and Regan (2003) propose a simulation model to study the bid construction and the benefits of CA for the carriers. The price for the bundle is calculated based on a cost plus model. In Song and Regan (2005), optimization based strategies and approximation algorithms are developed to generate the bids for TL carriers. The objective is to minimize the total empty movement cost. Chang (2009) proposes a decision support model for the bid generation problem that TL carriers face with in one-shot combinatorial auctions. He formulates the problem as a synergetic minimum cost of network flow problem, which is solved with a column generation approach. The focus of this paper is on the various transport cost but not the price. An, Elmaghraby et al. (2005) study the bundle evaluation based on pairwise synergies and develop bundling strategies for profitable bundle generation. The price for the bundle is decided according to the bundle value and a fixed profit margin. And the bundle value is linearly in the bundle size and the pricing is static. Lee, Kwon et al. (2007) construct the bid for TL carriers in CA with the objective of maximizing the profit by solving a fleet management problem. The approach considers optimally trading off the repositioning costs of vehicles and the rewards associated with servicing lanes. The price for the new flow is ask price that is decided by auctioneer and is fixed.

In the references above, the bundle price is not considered as a decision variable that could influence the request bundle result. They usually decide the price based on the transport cost or the ask prices suggested by the auctioneer. It is rare to formulate the bundle price as a decision variable. Triki, Oprea et al. (2014) propose a probabilistic optimization model to deal with the bid generation problem in CA. The bundle generation and pricing problem are integrated together in the model, in which the auction clearing prices are modeled as normally distributed random variables. Ergun, Kuyzu et al. (2007) and Kuyzu, Akyol et al. (2015) investigate the bid price optimization problem aiming to maximize the TL carrier's expected profit in simultaneous auctions. The competitor's lowest price is assumed as different probability distribution to study the different effect.

All the research discussed above are on the TL transport. We could find that the bundle pricing considering bundle generation and pricing for the bundle together in the TL transport industry is not studied widely, which is even less in LTL transport. Mesa-Arango and Ukkusuri (2013) present a m-PDVRP (multi-commodity one-to-one pickup-and-delivery vehicle routing problem) model to generate the bundles that could minimize the total system traversing cost. The numerical results show that the nonconsolidated bids (TL transport) are dominated by the consolidated bids (bundle of requests in LTL transport). What we need to notice is that the demand considered in the model is deterministic and the pricing problem is not studied. In Mesa-Arango and Ukkusuri (2016), the stochastic demand for the LTL carriers in CA is considered. A bidding advisory model for LTL-CA with stochastic demand and unused capacity is proposed to maximize the total expected profit.

The unitary price for the lanes in the bid is constrained to the shippers' lowest reservation price of the bundled lanes, which is assumed known. Dai, Chen et al. (2014) provide a price-setting mechanism to reduce the complexity of the BGP in CA. With this approach, the BGP for carriers has been transformed to a request selection problem based on the prices set by auctioneer.

More recently, Yan, Ma et al. (2018) propose a mixed integer programming model to solve the transportation service procurement bid construction problem from the LTL carriers and shippers perspectives. The objective of the model is to maximize the expected profit of bidder (carrier) considering the probability of winning the bid and to minimize the total costs of shipper. Besides, the bundle price given by the bidder (carrier) is modeled as a decision variable and is influenced by the winning probability, which is decided by both the shipper's cost and the competitor's price.

There are also few references studying the method of bundle generation in CA independently not considering the pricing for the bundles. Gansterer and Hartl (2018) present a method to generate a reduced set of offered bundles from the auctioneer's perspective to maximize the total coalition profit. The authors develop a proxy method to assess the attractiveness of the bundles to the carriers. In Gansterer and Hartl (2016), the CA-based bundle generation problem is presented from the LTL carrier's viewpoint. Different request evaluation strategies are proposed to help carriers decide the bundle of requests to outsource. Triki (2016) also investigates how the carrier should select the bundle of requests to bid in CA. An optimization approach using the location techniques is developed to generate the bundles with maximum synergy among the bundle's requests and between the auctioned and pre-existing requests.

Due to the few studies on the less-than-truckload bundle pricing, including bundle generation and pricing for the bundle, we also review the bundle problem and strategies in other industries other than truckload transport. For example, Banciu and Ødegaard (2016) analyze the pricing problem for a bundle of products when the valuation of a bundle's components are dependent on each other. The dependence among the consumers' reservation prices for the products is modeled using copula theory. Moreover, the optimal prices are derived under three predominant bundling strategies. The focus of this paper is not on the bundle generation. Wu, Hitt et al. (2008) develop a nonlinear mixed-integer programming model to determine which bundle sizes to offer and with what prices for the information goods. Briskorn, Jørnsten et al. (2016) propose a new pricing scheme for the product bundle in CA, which consider the bundle size rather than just use the linear prices for items.

In addition, as discussed in section 6.1, a PDVRP for the LTL carrier should be solved to generate the transport cost and the requests quantity on each lane. Thus, the research of PDVRP is also reviewed in this section. Berbeglia, Cordeau et al. (2010) give a survey of the dynamic pickup and delivery problems, which means the items should be collected and delivered in real-time. The survey shows the research on dynamic pickup and delivery problems has increased significantly during the recent years. Gribkovskaia, Halskau sr et al. (2007) present a single vehicle routing problem with pickups and deliveries. A mixed integer linear programming model is developed to produce the route which minimizes the transport cost. Yanik and Bozkaya (2014) study a capacitated multiple-pickup single-delivery vehicle routing problem with multi-vehicles and time windows. The objective is also minimizing the total cost including transport cost and fixed cost of a vehicle. In Psaraftis (2011), the dynamic programming solutions are used to solve a multi-commodity, capacitated pickup and delivery problems. Two cases, single-vehicle and two-vehicles, are discussed. The optimal value function is the minimum possible total cost.

Most of the PDVRPs are aiming to minimize the total transport cost, but there are still some research with objectives of maximizing the profit of carriers. For example, Gansterer, Küçüktepe et al. (2017) present a multi-vehicles profitable pickup and delivery problem, which aims to maximize the total profit by subduing the transport cost. The revenue from customers is fixed, thus there is no pricing problem here. In Yan, Ma et al. (2018), the bid construction model could also solve a PDVRP with the objective of maximizing the profit of carriers. The problem in this paper is very similar to the bundle pricing problem in this thesis. However, there are still several differences. First, the PDVRP presented in this paper is a one-to-one type problem, while it is a many-to-many problem in this thesis. Second, the multi-vehicles fleet management problem is the focus of this paper, while we consider the one vehicle routing problem, in which the vehicle capacity is a strict constraint.

Overall, we find that the research about the bundle pricing, including bundle generation and pricing for the bundle is very limited in the less-than-truckload transport. However it is very dynamic and a new research topic. Moreover, the bundle pricing problem studied in this chapter contributes to the literature with several novelties. First, the bundle pricing decision is made dynamically according to the future possible requests in the network. Second, the optimization model is integrated with data analysis model. In other words, the data analysis could provide the essential input for the optimization model.

## 6.3 Bundle pricing problem description

The Physical Internet (PI) is a highly open and interconnected network of logistics networks. As discussed in the previous chapters, the request flow in PI is quite abundant and frequent. In such a network, carrier does not need to bundle the requests, because it is easy to fulfill the capacity of the vehicle. However, there still might be not many requests on some lanes during some specific periods. When facing with this situation, carrier could consider bundling the current known requests on different lanes together to increase the fill rate of the vehicle and to get more profit in this chapter, we consider a single-vehicle carrier. Carrier could win the interested request bundle through participating the auction, which could be combinatorial auction. Thus, the bundle pricing problem for the LTL carrier in this chapter could be defined as follow:

When there are not enough requests to fulfill the LTL carrier's transport capacity in the logistics network, carrier should decide to bundle the request on which lanes and with what bidding price to maximize the expected profit.

The number of potential bundles of request grows exponentially along with the increasing of the request number. For example, if there *n* requests posted, carrier could have $2^n$-1 different bundles of request to choose. When the requests on one lane must be transported by one carrier, which means the requests on each lane cannot be split, the request bundle is equal to the bundle of different lanes. If there are *n* hubs in the network, there will be $m = n*(n-1)$ lanes, which will produce $2^m$-1 bundles of lanes. When the requests on each lane could be transported by different carriers, the number of potential bundles will be much more. Therefore, the bundle pricing problem for LTL carrier is a NP-hard problem.

Specifically, three decisions need to be made with the objective of maximizing the total expected profit. Figure 6. 2 presents a sample of request flow.

1) Bundle generation: We assume carrier departure from the current hub and return to the same hub. There are requests posted on some lanes with total quantity that could be noted as qij, for example the eight lanes denoted with solid arrow in Figure 6. 2. Carrier could select the interested requests to bundle considering the constraints. One of the most strict constraint is the vehicle capacity, e.g. if the bundle includes $r_{23}$ and $r_{24}$, the loaded requests quantity will be $q_{23} + q_{24}$, which could not exceed the vehicle capacity.

2) Vehicle routing: After determining the bundle of requests, the route to deliver the requests should also be decided. The vehicle routing problem here is a many-to-many pickup and delivery problem, because each hub in the network could be the original and destination of request. Moreover, the route to deliver the same bundle could be different. For example, in Figure 6. 2, if the bundle is $(r_{23}, r_{24})$, the route of carrier could be 1-2-3-4-1, or 1-2-4-3-1. The different route induces different transport cost through influencing the total travel distance and the loaded request quantity on each lane.

3) Pricing for the bundle: The pricing decision is made to produce the bidding price for the bundle. Two factors should be considered. One is the characteristics of the bundle including the route. The main characteristics need to consider are the loaded request quantity on each lane and the total travel cost. The other factor is the competitors' behavior, which will affect the winning probability of carrier's bidding price.

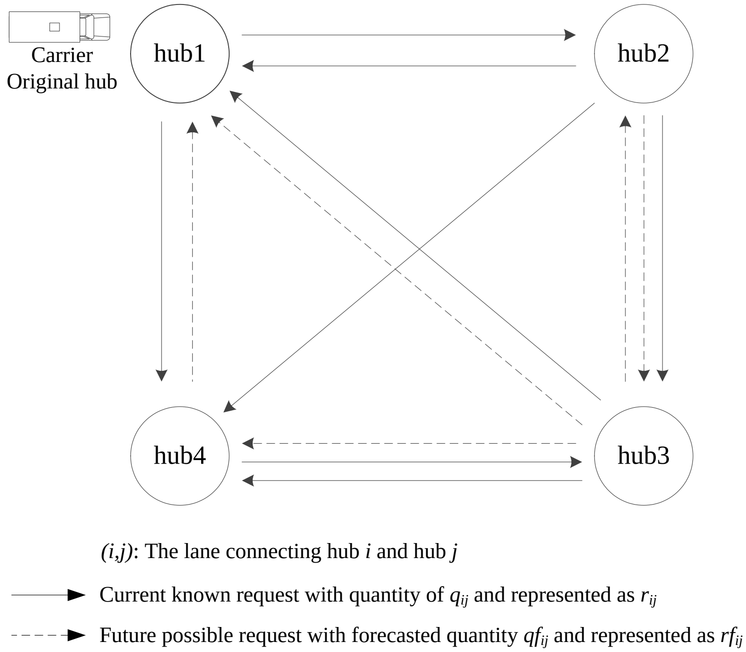



Figure 6. 2 Request flow in the bundle pricing problem

When making the three decisions above, carrier should take the future possible request $rf_{ij}$ into consideration, which is denoted with dotted arrow in Figure 6. 2. The future request might influence the bundle and routing decision, which are the basis of the pricing. (1) The future possible request with a forecasted quantity $qf_{ij}$ might affect the bundle decision, because the carrier might prefer save more capacities for the future requests if they could bring higher possible profit. (2) The carrier might choose the route that could cover the lanes with profitable future requests. For example, when the bundle is $(r_{23}, r_{24})$, carrier might select the route 1-2-3-4-1 rather than 1-2-4-3-1, because $rf_{34}$ and $rf_{41}$ might give higher future possible profit.

In this context, we investigate two scenarios considering whether the known request on each lane could be split or not.

1) *Scenario1: the known requests could not be split*

The known requests on one lane cannot be split, because the requests on the lane might come from the same shippers, who does not want their requests be delivered by different carrier. This means carrier could not just bundle part of the requests on one lane. The quantity $q_{ij}$ of the request on one lane should be all put in the bundle or none.

*2) Scenario2:the known requests could be split*

The known requests on one lane could be split when the requests on one lane are from various shippers. And the requests could be delivered by different carriers. Thus, carrier could just bundle part of the requests, which means the quantity picked in the bundle $qp_{ij}$ could be less than $q_{ij}$. Without loss of generality, we assume each request have the same unit size.

The bundle pricing decision aims to provide the request bundle with an optimal vehicle route and optimal bidding price for the LTL carrier to maximize the total expected profit. Meanwhile, the future possible profit from the possible requests in the next hubs on the route should be considered. Several assumptions should be highlighted here. (1) We consider a single-vehicle problem, which means the transport capacity is equal to the vehicle capacity. (2) We assume the requests are homogeneous and have a uniform size of one *unit* in this chapter. Thus, the total size of the requests with quantity $q_{ij}$ on one lane is $q_{ij}$ *units*. (3) Each hub could be visited at most once. The carrier will departure from the current hub and return to the same one. (4) Carrier just submit one request bundle to the auctioneer.

# 6.4 Formulation of the bundle pricing

## 6.4.1 Notations and Methodology

The notations to be used are listed as follows.

Parameters:

$(i,j)$: the lane connecting hub $i$ and hub $j$.

$V_{fij}$: expected profit from the forecasted request on lane $(i,j)$.

$V_b$: expected profit from the bundle of known requests.

$P_b(x, p)$: wining probability of a given bundle price $x$ according to the market reference price $p$

$N$: the number of hubs, including the depot hub $O$. Besides $N^{o-}$ represents the hubs except $O$

$A$: the set of request routes, $(i,j) \in A$.

$q_{ij}$: total known request quantity on lane $(i,j)$.

$qf_{ij}$: forecasted quantity for the future possible request on lane *(i,j)*.

$S$: vehicle capacity, here $S$ is assumed to be *33 units*.

$c_e$: empty unit cost, which means the cost that an empty vehicle travels *1km*, here $c_e=1€/km$.

$c_u$: load unit cost, which is the cost to deliver one *unit* request on *1km*, here $c_u=0.2€/unit\cdot km$.

$d_{ij}$: the travel distance on lane *(i,j)*.

$Q_{aij}$: the annual request quantity on lane *(i,j)*.

Variables:

$Q_i$: loaded request quantity when carrier leaves hub $i$.

$S_{ij}$: vehicle remaining capacity on lane *(i,j)* for the future possible request.

$t_i$: the time when carrier arrives at hub $i$.

$p_{ij}$: market price for total loaded requests on lane *(i,j)*.

$p_{uij}$: unit price (i.e. the price to deliver one unit request on one km) for request on lane *(i,j)*.

$p_b$: market price for the request bundle, which is assumed as the summation of the market price of the loaded requests on each lane.

$c_b$: total cost to transport the bundle of request, including the empty cost.

Decision variables:

$x_{ij}$: binary variable, 1 if lane *(i,j)* is covered by the vehicle otherwise 0.

$x_b$: the bidding price for the request bundle. We focus on the carrier's profit, so the price for each request is not calculated. Shippers can calculate the price of each request according to several existing methods, e.g. the Shapley value allocation method.

*Scenario1:*

$y_{ij}$: binary variable, 1 if all the requests on lane *(i,j)* are picked in the bundle, otherwise 0.

*Scenario2:*

$z_{ij}$: binary variable, 1 if the request on lane *(i,j)* is picked in the bundle, otherwise 0.

*$qp_{ij}$*: the total picked up request quantity in the bundle on lane *(i,j)*.

The methodology to formulate the bundle decision problem is shown as Figure 6. 3. The pricing model for the future possible requests is not independent, but is integrated in the bundle pricing model.

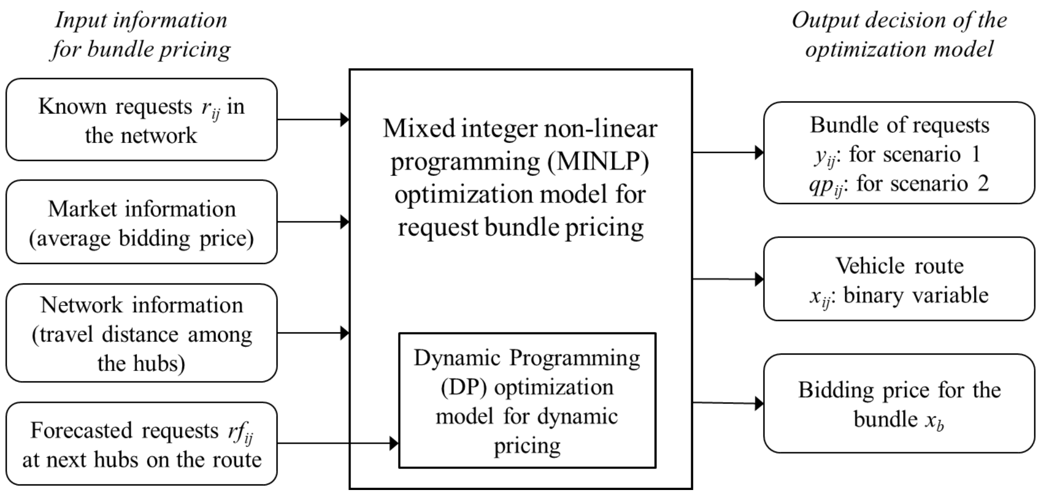



Figure 6. 3 Methodology to formulate the bundle pricing problem

## 6.4.2 Dynamic pricing model for the future possible request

In Chapter 4, we extend the one-leg pricing model in Qiao, Pan et al. (2016) to multi-legs. In this chapter, we also extend the one-leg pricing model to decide the expected profit from the future possible requests. The main differences are: (1) the different travel costs associated with the route are considered in the model; (2) the remaining capacity for the future requests depends on the bundle of the known requests and the vehicle route. The dynamic pricing model for the future possible request is presented below.

$$V^r{}_{fij}(s_r, n) = \max_{x \in X}\left[p(x) * \left[x - c_u * d_{ij} + V^{r+1}{}_{fij}(s_r - 1, n)\right] + \left(1 - p(x)\right) * V^{r+1}{}_{fij}(s_r, n)\right], r = 1, \dots, n \quad (6.1.1)$$

$$V^r{}_{fij}(s_r, n) = 0, if\ s_r \leq 0\ OR\ r > n \quad (6.1.2)$$

$$V_{fij}\left(S_{ij}, qf_{ij}\right) = V^1{}_{fij}\left(S_{ij}, qf_{ij}\right) \quad (6.1.3)$$

Function (6.1.1) is a recursive function to calculate the carrier's maximum expected profit when bidding for $r$ requests using price $x$ with a remaining capacity of $s_r$. When the carrier wins a request, its capacity is minus one, otherwise, the actual capacity does not change. Besides $n$ represents the total request quantity. Function (6.1.2) is the boundary condition representing the expected profit, which is 0 when the capacity is sold out or there are no more requests to bid for. Finally, function (6.1.3) is used to calculate the maximum expected profit $V_{fij}$ obtained with the forecasted request on lane *(i,j)*.

### 6.4.3 Bundle pricing model

With the objective to maximize the carrier's total expected profit, the optimal bundle pricing model is given as follows.

Objective:

$$Max\ \sum_{i\in N}\sum_{j\in N}\left[V_{fij}\left(S_{ij}, qf_{ij}\right)\right] * x_{ij} + V_b(x_b) \tag{6.2.1}$$

Constraints:

$$V_b(x_b) = (x_b - c_b) * P_b(x_b, p_b) \tag{6.2.2}$$

$$P_b(x_b, p_b) = e^{-(x_b/p_b)^5} \tag{6.2.3}$$

$$c_b = \sum_i \sum_j \left(Max[Q_i, 0] * c_u * d_{ij} * x_{ij} + Max[1 - Q_i, 0] * c_e * d_{ij} * x_{ij}\right), (i,j) \in A \tag{6.2.4}$$

$$p_{ij} = \left(q_{ij} \| qp_{ij}\right) * p_{uij} * d_{ij}, (i,j) \in A \tag{6.2.5}$$

$$p_b = \sum_i \sum_j p_{ij} * (y_{ij} \| z_{ij}), (i,j) \in A \tag{6.2.6}$$

$$p_{uij} = a * x^b * y^c * z^d, x = load\ quantity\ \left(q_{ij}/qp_{ij}\right), y = lane\ distance\ \left(d_{ij}\right), z = annual\ request\ quantity\ on\ the\ lane\ \left(Q_{aij}\right), (i,j) \in A \tag{6.2.7}$$

$$\sum_{j\in N} x_{ij} \le 1, (i,j) \in A \tag{6.2.8}$$

$$\sum_{i\in N} x_{ih} - \sum_{j\in N} x_{hj} = 0, h \in N^{o-} \tag{6.2.9}$$

$$\sum_{i\in N^{o-}} x_{io} = 1 \tag{6.2.10}$$

$$\sum_{j\in N^{o-}} x_{oj} = 1 \tag{6.2.11}$$

$$t_i + x_{ij} - M * \left(1 - x_{ij}\right) \le t_j, (i,j) \in A \tag{6.2.12}$$

$$0 < t_i < N + 2, i \in N \tag{6.2.13}$$

*Scenario1:*

$$0 \le y_{ij} \le \left(\sum_{h\in N} x_{hj} \,\&\&\, \sum_{k\in N} x_{ik}\right), (i,j) \in A \tag{6.2.14-1}$$

$$Q_o = \sum_{j\in N^{o-}} q_{oj} * y_{oj}, (i,j) \in A \tag{6.2.15-1}$$

$$Q_j = \sum_{i\in N}[x_{ij} * \left(Q_i + \sum_{k\in N} q_{jk} * y_{jk} - \sum_{h\in N} q_{hj} * y_{hj}\right)], i \ne j, j \in N \tag{6.2.16-1}$$

$$y_{ij} * \left(t_j - t_i\right) \ge 0, (i,j) \in A \tag{6.2.17-1}$$

*Scenario2:*

$$0 \le z_{ij} \le \left(\sum_{h\in N} x_{hj} \,\&\&\, \sum_{k\in N} x_{ik}\right), (i,j) \in A \tag{6.2.14-2}$$

$$0 \le qp_{ij} \le \sum q_{ij} * z_{ij}, (i,j) \in A \tag{6.2.15-2}$$

$$Q_o = \sum_{j\in N^{o-}} qp_{oj} \tag{6.2.16-2}$$

$$Q_j = \sum_{i\in N}[x_{ij} * \left(Q_i + \sum_{k\in N} qp_{jk} - \sum_{h\in N} qp_{hj}\right)], i \ne j, j \in N \tag{6.2.17-2}$$

$$z_{ij} * \left(t_j - t_i\right) \ge 0, j \in N \tag{6.2.18-2}$$

*Scenario1&2:*

$$0 \le Q_i \le S, i \in N \tag{6.2.19}$$

$$S_{ij} = (S - Q_i) * x_{ij}, j \in N \tag{6.2.20}$$

$$x_{ij}, y_{ij}, z_{ij} \in \{0,1\}, (i,j) \in A \tag{6.2.21}$$

$$qp_{ij}, t_i, Q_i, S_{ij} \in Integers, i \in N, (i,j) \in A \tag{6.2.22}$$

$$x_b \in \{0, \infty\} \tag{6.2.23}$$

The objective function (6.2.1) maximizes the carrier's total expected profit and consists of the profit from the bundle of known requests and the future possible requests. The function (6.2.2) is used to calculate the expected profit from the bundle of known requests. The function (6.2.3) calculates the winning probability of the bidding price $x_b$ for the bundle, which is assumed as a Weibull distribution (Qiao, Pan et al. 2016). The equation (6.2.4) is used to calculate the total cost to transport the request bundle consists of the loaded travel cost and empty travel cost. The market price for to transport the requests on lane *(i,j)* without bundling is calculated with equation (6.2.5). The equation (6.2.6) is developed to calculate the market price for the bundle of known requests. The function (6.2.7) is used to get the unit market price for the request on lane *(i,j)*. This function is obtained through analyzing the historical data, which will be discussed in 6.5.1.

The constraint (6.2.8) ensures that each hub could be visited at most once. The constraint (6.2.9) imposes a balance in each hub, i.e. if the carrier travels to a hub, he must leave from this hub. $N^{o-}$ represents the hubs in the network except the depot hub. The constraints (6.2.10) and (6.2.11) make sure the carrier must departure from the depot hub and return to the same hub. The constraint (6.2.12) ensures the carrier arrives at hub $j$ after visiting the hub $i$ if lane $(i,j)$ is covered by the vehicle route. The constraint (6.2.13) limits the value range of $t_i$.

The constraints (6.2.14-1) and (6.2.14-2) ensure that the request on lane $(i,j)$ could only be bundled when there are lanes leave hub $i$ and lanes go to hub $j$ on the vehicle route. Which means carrier must visit both hub $i$ and hub $j$. Moreover, hub $j$ must be visited after hub $i$. The constraint (6.2.15-2) ensures the picked request quantity not more than the total requests on lane $(i,j)$ if it is bundled in scenario 2. The equations (6.2.15-1) and (6.2.16-2) are used to calculate the loaded request quantity when carrier leaves depot hub $o$. Relatively, the equations (6.2.16-1) and (6.2.17-2) are used to calculate the loaded request quantity when carrier leaves hub $j$. The constraints (6.2.17-1) and (6.2.18-2) make sure the request on lane $(i,j)$ could only be bundled when hub $j$ is visited after hub $i$.

The constraint (6.2.19) ensure the loaded request quantity do not exceed the vehicle capacity. The equation (6.2.20) is used to calculate the remaining capacity for the future possible requests on each lane. The constraints (6.2.21), (6.2.22) and (6.2.23) are for binary variables, integer variables and real variable.

### 6.4.4 Data analysis method

In the current spot LTL transport market, the transport price is normally decided base on a static price table (see the example of Figure 6. 4). We could find the price per km or per truck is different according to the transport distance. As we know, some firms also change their price based on the volume of the request. However, in a highly dynamic market, the static pricing strategy cannot deal with the fluctuation of the market. We need to change the pricing strategy dynamically according to the historical data.

| kilometer_mini | kilometer_max | price for one truck | price for one km |
|---|---|---|---|
| 1 | 30 | 161 | 161 (sell with one truck price) |
| 31 | 50 | 161 | 3.30 |
| 51 | 75 | 165 | 2.10 |
| 76 | 100 | 158 | 1.85 |
| 101 | 125 | 185 | 1.79 |
| 126 | 150 | 223 | 1.70 |
| 151 | 175 | 254 | 1.51 |
| 176 | 200 | 265 | 1.46 |
| 201 | 250 | 292 | 1.35 |
| 251 | 300 | 338 | 1.23 |

Figure 6. 4 Sample of static price table in spot LTL transport market

In the bundle pricing problem discussed here, an important parameter we need to know is the market unit transport price, which is the price to transport one unit request on one km. In order to obtain the function to calculate the unit price based on the historical data, we present a general method to analyze the data, see Figure 6. 5. What need to note is that this method is general but might need a little modification according to the different type of data.

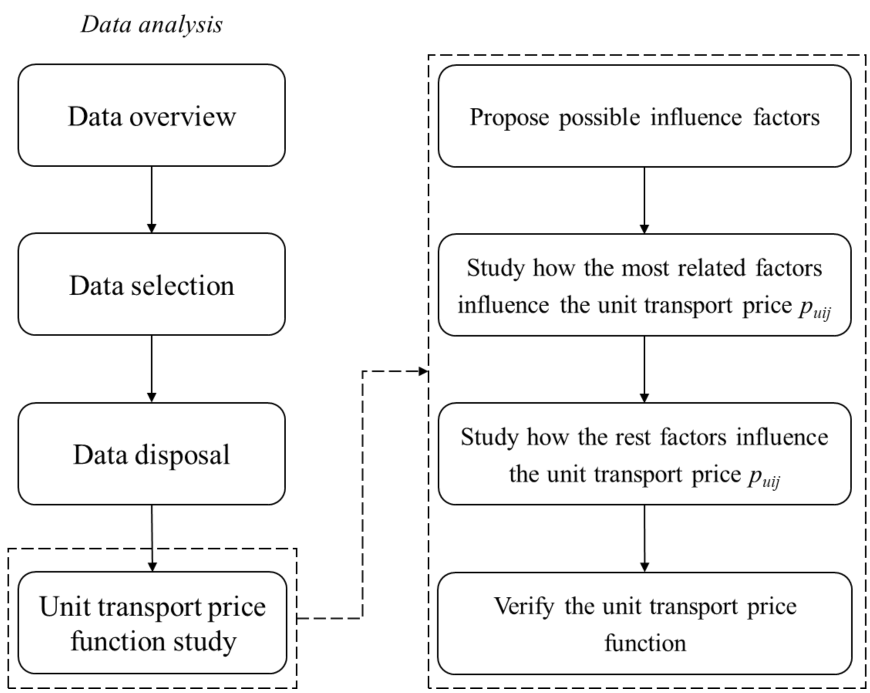



Figure 6. 5 General data analysis process

Step1: Data overview

At the beginning, the data should be surveyed in general. We should know what kinds of information the data has, for example, the total request quantity and total lanes.

Step2: Data selection

Normally, there are various items in the data. We should select the items that are useful for the calculation of the unit transport price. Two basic works need to be done. First, if the data consists of the items from different market, we need to extract the spot market items out. Second, in the data, there are always some aberrant items. These outlier data need to be eliminated. Besides, carriers could select the items according to their needs, for example selecting the items on their interested lanes or during their interested periods.

Step3: Data disposal

In this step, carrier need to process the data to get more implied information. Because the original data might do not provide the information needed, for example the distance of each lane. As our experience, the unit price is always not given, so the carriers need to calculate the unit transport price for each request based on the total volume and the travel distance.

Step4: Unit transport price function study

After the needed data is prepared, carrier could start to study the general mathematic function to calculate the unit transport price. The statistics methods could be used here, for example the linear regression, the nonlinear regression and the variance analysis.

(1) Propose the possible influence factors to the unit price, i.e. the possible variables of the function. For example the request volume, the travel distance, the delivery date and so on.

(2) Starting with the most possible related factors, such as the request volume and travel distance, analyze the correlation between factors and the unit price. If they are correlated, study how the factors influence the price. i.e. what is the function between the unit price and these factors.

(3) According to the function obtained in the last step, study whether and how the rest factors influence the price one by one.

(4) Apply the obtained influence factors to different data segments to verify the unit transport price function.

## 6.5 Numerical study

In this chapter, at first, an analysis based on the historical data of a logistics company we work with is processed to determine the unit transport price function. Second, a numerical study based on assumption is conducted to evaluate the feasibility of the proposed bundle pricing model.

### 6.5.1 Determination of the unit transport function

Based on the proposed method in 6.4.4, we obtain the unit transport price function through analyzing one year historical data from a transport company in France. The experiment is run with Microsoft excel, Mathematica 10.4 and Microsoft Access under Windows 10 on a DELL Inspiron 15 (5000) with 16 GB of RAM. The analysis process and results are summarized as follows.

(1) We propose five possible influence factors: request volume ($X_1$), travel distance ($X_2$), various clients ($X_3$), delivery date ($X_4$), and annual request quantity on the lane ($X_5$). The unit transport price is represented with $Y$ here.

(2) As presented in 6.4.4, the request volume ($x_1$) and the travel distance ($x_2$) are the parameters that firms use to decide the transport price. Thus, we start from these two factors. The result is listed in Table 6. 1.

Table 6. 1 Influence of request volume and travel distance to the unit transport price

| Model | Method | Statistics Result | |
|---|---|---|---|
| | | P-value | $R^2$-coefficient of determination |
| $Y = a + b_1*X_1 + b_2*X_2$ | linear regression | 0 | 0.065 |
| $Ln(Y) = a + b_1*ln(X_1) + b_2*ln(X_2)$ | linear regression | 0 | 0.55 |

According to the result, we could find both these two models are statistics significant (p-value is 0) but the first one is very weak on the linear relation ($R^2$ is 0.065, which means just 6.5% of the data could be explained by this function). Thus, we accept that the relation between $y$ and $X_1$, $X_2$ is exponentially, i.e. $Y = a_1 * X_1^{b1} * X_2^{b2}$.

(3) The influence of the rest three factors is studied and the result are listed in Table 6. 2. We could find the client has significant influence on the price. But because the client is not a fixed parameter, we do not consider it in the function. The delivery date has no significant influence on the price (p-value is larger than 0.1). The annual request quantity also has an exponent relation with the unit price (61% of the total data could be explained with the exponent function).

Table 6. 2 Influence of client, delivery date, and annual request quantity to the unit transport price

| Factor | Model | Method | Statistics Result | |
|---|---|---|---|---|
| | | | P-value | $R^2$-coefficient of determination |
| $X_3$ | | one factor variance analysis | 1.21E-32 | |
| $X_4$ | | one factor variance analysis | 0.13 > 0.10 | |
| $X_5$ | $Ln(Y) = a + b_1*ln(X_1) + b_2*ln(X_2) + b_5*ln(X_5)$ | linear regression | 0 | 0.61 |

(4) Based on the result previous, the unit transport function is $Y = a_1 * X_1^{b1} * X_2^{b2} * X_5^{b5}$. To verify this function, we apply it in three data segments based on the request volume. The result in Table 6. 3 proves that this function is acceptable. When request volume is in the medium level (8-24) and high level (25-33), the $R^2$ is 0.79 and 0.78 respectively. This means that around 78% of the data in these two segments could be explained by the exponent function, which is acceptable. In the small request volume segment (1-7), 58% of the data could match the function, which is also not bad. But we should notice that when the request volume is very small, the carrier might sell the capacity with a higher price. Thus, the unit price function is also acceptable in the small request volume segment.

Table 6. 3 Verification of the unit transport price function

| Request volume | Model | Method | Statistics Result | |
|---|---|---|---|---|
| | | | P-value | $R^2$-coefficient of determination |
| (1-7) | $Ln(Y) = a + b_1*ln(X_1) + b_2*ln(X_2) + b_5*ln(X_5)$ | linear regression | 0 | 0.58 |
| (8-24) | $Ln(Y) = a + b_1*ln(X_1) + b_2*ln(X_2) + b_5*ln(X_5)$ | linear regression | 0 | 0.79 |
| (25-33) | $Ln(Y) = a + b_1*ln(X_1) + b_2*ln(X_2) + b_5*ln(X_5)$ | linear regression | 0 | 0.78 |

In this chapter, the request volume is equal to the request quantity on each lane, because of the assumption of one-unit size. Therefore, the unit price $p_{uij}$ for request on lane $(i,j)$ could be modeled as equation (6.2.7). This function is also conform to the reality, as we know.

## 6.5.2 Evaluation of the bundle pricing model

A numerical study is designed in order to evaluate the bundle pricing model and demonstrate its feasibility. All the experiments in this section are run in Mathematica 10.4 under Windows 10 on a DELL Inspiron 15 (5000) with 16 GB of RAM. We use the function *NMaximize* with *SimulatedAnnealing* method in Mathematica to solve the problems, which can solve the linear and nonlinear programming problem thanks to the solvers developed by Mathematica.

### 6.5.2.1 Test instances

In this section, we consider a complete connected network with three hubs, which means every two hubs are connected to each other. What need to note is that the unit transport price $p_{uij}$ is assumed as $0.3€/unit·km$. Because we do not have appropriate actual data to conduct the complete numerical study, so the input data is assumed. Moreover, the transport cost is a private information of the carrier. Thus, it is difficult to determine the parameters of the unit transport price function corresponding to the assumed input data. Therefore, without loss of generality, the unit transport price is assumed as a constant here.

We generate 8 test instances according to (i) quantity of the known requests, (ii) distance of the lanes, (iii) whether considering the future requests, (iiii) quantity of the future possible requests. Table 6. 4 displays the specific data of each instance. The quantity of known requests are randomly generated in the small size range [5,10] and large size range [15,20]. Moreover, Ins3, Ins4, Ins7 and Ins8 do not consider the future requests when making the bundle pricing decision.

Table 6. 4 Test instances for the bundle pricing model

| | | Instance | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Ins1 | Ins2 | Ins3 | Ins4 | Ins5 | Ins6 | Ins7 | Ins8 |
| Quantity of known requests | $q_{12}$ | 10 | 10 | 10 | 10 | 17 | 17 | 17 | 17 |
| | $q_{13}$ | 10 | 10 | 10 | 10 | 17 | 17 | 17 | 17 |
| | $q_{21}$ | 10 | 10 | 10 | 10 | 18 | 18 | 18 | 18 |
| | $q_{23}$ | 8 | 8 | 8 | 8 | 20 | 20 | 20 | 20 |
| | $q_{31}$ | 7 | 7 | 7 | 7 | 19 | 19 | 19 | 19 |
| | $q_{32}$ | 6 | 6 | 6 | 6 | 17 | 17 | 17 | 17 |
| Quantity of future requests | $qf_{12}$ | 0 | 0 | | | 0 | 0 | | |
| | $qf_{13}$ | 0 | 0 | | | 0 | 0 | | |
| | $qf_{21}$ | 150 | 70 | | | 150 | 70 | | |
| | $qf_{23}$ | 70 | 150 | | | 70 | 150 | | |
| | $qf_{31}$ | 0 | 0 | | | 0 | 0 | | |
| | $qf_{32}$ | 0 | 0 | | | 0 | 0 | | |
| Distance of lanes | $d_{12}$ | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| | $d_{13}$ | 40 | 40 | 40 | 40 | 40 | 40 | 40 | 40 |
| | $d_{23}$ | 40 | 40 | 40 | 10 | 40 | 40 | 40 | 10 |

### 6.5.2.2 Results and discussions

The two scenarios are studied here (no split request vs. split request) with each test instance. The results are shown in Table 6. 5, which gives the decision variables (the bundled requests, the optimal bidding price, the vehicle route) and the optimization objective (the maximal expected profit). For example, according to the result of Ins2 in Scenario1, the carrier should bundle the request on lanes (1,2), (2,3) and (3,1) together and travel on the route 1-2-3-1. With the optimal bidding price of 267, the carrier could gain the expected profit of 96. As to the Ins2 in Scenario2, carrier could bundle 10 requests on lane (1,2), 6 requests on lane (2,3), and 7 requests on lane (3,1) together. The delivery route will be 1-2-3-1. The optimal bidding price and expected profit are 247 and 94 respectively.

Table 6. 5 Numerical results for the two scenarios

| | | Instance | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Ins1 | Ins2 | Ins3 | Ins4 | Ins5 | Ins6 | Ins7 | Ins8 |
| Scenario1: The known requests could not be split | $y_{12}$ | 1 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| | $y_{13}$ | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | $y_{21}$ | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | $y_{23}$ | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 |
| | $y_{31}$ | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 1 |
| | $y_{32}$ | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 |
| | *Route* | 1-2-1 | 1-2-3-1 | 1-3-2-1 | 1-3-2-1 | 1-3-2-1 | 1-2-3-1 | 1-2-3-1 | 1-2-3-1 |
| | *Price* $x_b$ | 220 | 267 | 279 | 436 | 567 | 622 | 613 | 448 |
| | *Expected profit* | 78 | 96 | 54 | 53 | 128 | 128 | 101 | 74 |
| Scenario2: The known requests could be split | $qp_{12}$ | 9 | 10 | 0 | 9 | 0 | 15 | 16 | 17 |
| | $qp_{13}$ | 0 | 0 | 9 | 10 | 14 | 0 | 0 | 15 |
| | $qp_{21}$ | 10 | 0 | 8 | 9 | 17 | 0 | 0 | 15 |
| | $qp_{23}$ | 0 | 6 | 0 | 0 | 0 | 17 | 20 | 4 |
| | $qp_{31}$ | 0 | 7 | 0 | 6 | 0 | 19 | 19 | 19 |
| | $qp_{32}$ | 0 | 0 | 5 | 6 | 17 | 0 | 0 | 0 |
| | *Route* | 1-2-1 | 1-2-3-1 | 1-3-2-1 | 1-3-2-1 | 1-3-2-1 | 1-2-3-1 | 1-2-3-1 | 1-2-3-1 |
| | *Price* $x_b$ | 209 | 247 | 234 | 401 | 536 | 555 | 595 | 756 |
| | *Expected profit* | 77 | 94 | 47 | 50 | 123 | 126 | 99 | 85 |

About the numerical results, some conclusions are given as follows.

(1) *The future requests influence the current bundle pricing decision*. This conclusion is the same in both two scenarios. Comparing Ins1 and Ins3, we could find that the route and the request bundle are different when considering the future possible requests. When there are more possible requests on lane (2,1) that could bring more possible profit, carrier will arrange the route covering this lane. The results of Ins1 and Ins2 enhance this conclusion. When there are more future requests on lane (2,3), the optimal route changes from 1-2-1 to 1-2-3-1 that covers lane (2,3). The same conclusion could be made based on the results of Ins5, Ins6 and Ins7.

(2) *The lane distance could influence the bundle decision*. In our bundle pricing model, The lane distance could directly influence the market price to the request and also the

transport cost. Then the bundle pricing decision will be affected indirectly. See the results in Ins1, Ins2 and Ins3, we find there is not detour for the requests in the bundle. However, when change the distance of lane (2,3) from 40 to 10 in Ins4, more requests are bundled with detour. For example, the request (1,3) is not bundled in Ins2 but is bundled in Ins4. Because, in the Ins2, the detour cost for request (1,3) is more than the profit it could bring. So more capacity are saved to the future requests. The results of Ins5 – Ins8 enhance this conclusion.

(3) *Splitting the requests on one lane or not influences the bundle pricing decision*. Comparing Ins4 and Ins8, we find that the bundle pricing decisions in two scenarios are different with the large quantity request. Obviously, because the total quantity of the requests on two lanes exceeds the vehicle capacity. For example, the request (1,2) and request (1,3) in Ins8 could not be transported in one vehicle at the same time. Thus, there will be some unused capacity when the request could not be split. While is the request could be split, carrier could just take some extra requests on other lanes to fill up the capacity to obtain more profit. However, when the request quantity on each lane are not large, the optimal decision in two scenarios are the same. Because the capacity is enough for all the requests.

Overall, the proposed bundle pricing model in this chapter is feasible to generate the optimal decision, including the request bundle and bidding price. In other words, the model can be used as a decision-making tool for carriers when the requests need to be bundled to optimize the profit.

## 6.6 Conclusion

This chapter develops and investigates the bundle pricing problem for the LTL carriers in Physical Internet considering the future possible request and based on the analysis of historical data. First, we develop a mixed integer nonlinear programming model considering two scenarios, no split request and split request, to help carriers to compute optimal requests bundle and determine the optimal bidding price for the bundle. Second, we propose a general data analysis method to obtain the function of unit transport price from historical data. Third, based on actual data from a transport company, we determine the unit transport price function in general. At last, a numerical study is proposed to evaluate the feasibility of the bundle pricing model.

The main contribution of the work in this chapter is the bundle pricing model, integrating bundle generation and pricing for the bundle together, for the LTL carriers in PI. The developed model considers the possible profit from the future requests in the next hubs on the route. When there are higher possible profit in the future, the carrier might save more capacity to the future request, which means the requests to be bundled will be reduced. The bundle pricing model provides carriers with guidelines and decision-making tools to optimize the request bundle and the expected profit.

This work has some limitations that could be improved. The first one is the algorithm to solve the MINLP optimization model. As we discussed in section 6.3, the bundle pricing problem for LTL carrier is a NP-hard problem. Thus, in order to find good solutions in reasonable amount of time, an algorithm should be developed to solve it. Second, due to the lack of data, we just assume several important parameters that could influence the optimization result significantly, for example the winning probability of the bundle price and the unit transport price. In the future, we should find a more reliable way to assess the performance of the model.

# Chapter 7. Conclusions and perspectives

This chapter gives a synthesis of the main contributions of this dissertation, followed by a discussion of the possible applications of the work carried out in this research. The main limits in this research and the perspectives to extend this work in the future are also discussed.

## 7.1 Summary of this thesis

As presented in the introduction, this thesis investigates the potential of applying Revenue Management (RM) to Physical Internet (PI) that represents a highly dynamic network of logistics services with concentrated demands in hubs, to improve the revenue of LTL carriers in the freight transport market. To this end, we study four sub problems of RM (pricing, capacity control, forecasting, bundle pricing) and propose corresponding optimization models for each sub problems respectively. Thus, the contributions of this thesis could be concluded as follows.

**(1) Study systematically the Revenue Management in a highly dynamic environment.** Originating from the airline industry, Revenue Management has been applied in many different industries. For example, in hotels and rental business. Moreover, more and more actors in freight transport industries adopt RM to improve their revenue. There is also an arising number of researches focused on the application of RM in freight transport. RM is mainly used to respond to the fluctuation in the market and better utilize resources' capacity but the current logistics networks are not as dynamic as PI, which is a highly interconnected network of different logistics networks. PI is an innovative logistic concept that aims to integrate current logistics networks in an open global logistic system thus concentrating demands in hubs. Under this context, in PI, there will be abundant and frequent requests flows, which is much more dynamic than the transport demand in the traditional logistics networks. Besides, as discussed in Chapter 2, there are few researches on the application of RM in road freight transport. Therefore, the work in this thesis does not only contribute to the research on RM in highly dynamic network but also on the RM in road freight segment.

This thesis investigates the application of RM in PI in breadth on four sub research problems in RM, pricing, capacity control, forecasting, and bundle pricing. Besides, the bundle pricing problem is integrated with the other three problems. The work in this research gives a general and systematical sight to how to apply the RM in a dynamic road freight transport network as the first step.

**(2) Investigate the less-than-truckload dynamic pricing problem in Physical Internet.** First, this research introduces and defines the less-than-truckload dynamic pricing problem considering one-leg in Physical Internet, which is quite different to and more complex than the traditional pricing problem in the freight transport industry. Because the pricing problem in PI is very dynamic and sequential for the carriers who face stochastic arriving requests. Besides, through reviewing the existing research on the pricing problem in LTL industry, we found that the literature is very limited. Our work also contributes to the research relating to pricing policies for LTL carriers. Moreover, this work is the first research on the pricing problem in the Physical Internet, which provides the basis to study the similar problem in more depth in the next step.

According to the experimental study result, we found that the request number, remaining capacity, and the transport cost could significantly influence the bidding price and the expected profit for the carrier. This finding could help carriers decide their bidding price based on their current status of the requests, capacity and cost. Besides, we also found the variable pricing strategy could bring more profit than the unique pricing strategy, but on the other hand increase the operation complexity. The carriers could select the pricing strategy based on their preferences, more profit or simple process.

**(3) Discuss the request pricing and selection problem in Physical Internet.** This work studies the pricing problem when facing with various requests and meanwhile the request selection problem. This research contributes to the revenue optimization problem in the situation in which there are different kinds of requests with various destinations. The request selection problem in a stochastic environment is barely studied up to now. Our work also fills this gap in the literatures and models.

A revenue optimization model based on a dynamic pricing model and IP optimization models to help the carrier select the best LTL requests was proposed. The numerical study result presents the influence of the request quantity and the transport distance to the request selection decision. But what need to mention is the influence of the distance might be different for different carriers, because the transport cost based on the distance could be different. Besides, two decision-making model were developed to make the request selection decision for two kinds of carriers, full-capacity carrier and partially loaded carrier.

**(4) Evaluate the influence of forecasting to the decision making.** This research investigates the forecasting problem for LTL carriers in the dynamic pricing and request selection decisions making process in PI. The objective of this work is to evaluate the influence of considering the future requests to the pricing and request selection decisions. When carriers participate several auction periods, it is essential to consider the arriving requests in the next periods. The numerical study result shows that the optimal bidding price is different and the expected profit is higher when the carrier considers the future requests in next auction periods. The influence of forecasting uncertainty to the expected profit that could influence the request selection decision is also studied. The numerical study results show that forecasting uncertainty could significantly influence the expected profit when the request quantity or transport distance exceed a threshold.

This work contributes to the research of forecasting of Revenue Management in Physical Internet, which extends the dynamic pricing problem to multi-periods and considers the future requests as a stochastic distribution.

**(5) Investigate the bundle pricing problem for LTL carriers in Physical Internet.** The bundle pricing problem is widely studied in the frame of Combinatorial Auctions, but most of the research are focus on full-truckload carriers. Little research is focus on the LTL transport. First, our work fills this gap in the literatures. Moreover, the bundle pricing model, which integrates bundle generation and pricing for the bundle together, for the LTL carriers in PI is also a main contribution. One of the most novelties of this model is that it considers the possible profit from the future requests in the next hubs on the route.

The experimental study based on the bundle pricing model gives a sight that what factors could influence the bundle pricing decision. The future possible requests in the network could influence the decision by influencing the possible future profit. The lane distance could affect the transport cost and then results in different decisions. Besides, whether the requests on one lane could be split is also important to the bundle pricing. Because it will be easier to improve the fill rate of the vehicle with more flexible bundle options if the requests could be split.

Overall, the proposed research problems all have their specific characteristics and contribute to the literatures in the corresponding area. In addition, the developed optimization models could also provide significant contribution to the decision making of carriers: (1) Provide guidelines for carrier to decide the request price dynamically based on his capacity, request quantity and the time. (2) Provide a decision-making tool for carriers to select the most profitable request to optimize the revenue. (3) Give carriers a sight of whether the forecasting could influence his decision and whether to consider the future request when making the decision. (4) Provide guidelines and decision-making tools for carrier to optimize the request bundle and the expected profit.

## 7.2 The application of the work for carriers

In this research, four research questions were discussed. How to use the results for various carriers and how to apply the method in practice is presented below.

### 7.2.1 Application for various carriers

Various carriers who have different situations and objectives could adopt the results of each research question selectively (see Table 7. 1).

Table 7. 1 Research question models used by carriers

| Network | Carrier | | Models |
|---|---|---|---|
| Abundant requests | care more about simple process | Fixed route | RQ1 |
| | | Various routes | RQ2 |
| | Seek more profit | Fixed route | RQ1+RQ3 |
| | | Various routes | RQ2+RQ3 |
| A small number of requests | Seek more profit | Various routes | RQ4 |

In a network with abundant requests, there are carrier who prefer a simple operation process and just have several fixed routes. Then they could just adopt the dynamic pricing model for one-leg (RQ1). While for the major carriers with their own network consisting with various routes, they should consider the request selection model (RQ2). In addition, if the carriers prefer to get more profit, they should take the future requests into consideration, which means forecasting model should be adopted (RQ1+RQ3 for small actors and RQ2+RQ3 for major actors). However, if there are not many requests in the market or during some specific periods, carriers could consider request bundle to increase their expected profit. The model of bundle pricing (RQ4) could be adopted.

### 7.2.2 Application in practice

This thesis firstly aims to develop the methods and models for carriers to improve their revenue in PI, which is a highly dynamic future logistics system that relies on real-time optimization. Currently, there has not been a high-interconnected open logistics network like PI. However, the model proposed can still be used in today's freight market, as it has been becoming more and more dynamic and agile. Examples include city pickup and delivery transportation services, logistics nodes or ports. The current pricing strategy used to optimize carrier revenue, which is normally based on a predefined price catalog (static pricing), is increasingly inadequate in such a highly dynamic environment. It is foreseeable that carriers will tend to employ a dynamic pricing strategy to maximize their revenue and better use their capacity. Therefore, the proposed models may help carriers change their pricing strategy from static to dynamic. In addition, due to the increasing competition in freight transport, it is essential to find solutions to improve the loading rate and the transport efficiency. Request bundle is one possible method and the pricing method for the bundle is also important to improve carriers' revenue.

## 7.3 Principal limits

The main limits of this research are coming from: the formulation, the experimental study, and the solving method.

### 7.3.1 Limits of the formulation

The proposed models, including pricing model, request selection model, request pricing/selection models with forecasting, and bundle pricing model, are based on numbers of assumptions due to lack of appropriate and complete actual data. One of the important assumptions is the winning probability of the bidding price. We assume the winning price follows a Weibull distribution and assume the parameters. However, in practice, this distribution and the parameters should be obtained through analyzing the historical data from the market. Thus, the winning probability might be altered in different markets and even at different time. This could bring different optimization results.

Besides, to start the research, we consider several constraints. One constraint that has significant influence to the models is the request size. To simplify the models, we just consider the same size request on each lane and assume the size is one unit. However, in reality, there are various requests with different sizes on each lane. When considering a mixed request situation, a new problem will arise. For example, how to price and select the various requests with different sizes.

### 7.3.2 Limits of the experimental study

The feasibility of the proposed models in this thesis are evaluated respectively based on assumed data. The influence of some factors on the optimal decisions are also investigated based on the assumed data. However, these experimental studies are staying at the theoretical level. Due to the lack of actual data, it is difficult to estimate the performance of the proposed models in the market. Besides, the comparison between the current strategies (e.g. pricing, request selection, request bundle) and the new strategies proposed in our work is also hard to make in a rigorous manner. In addition, still because of lacking enough actual data, we could not design a systematical case study to demonstrate the benefit of the proposed models.

### 7.3.3 Limits of the solving methods

To solve the optimization problems, metaheuristics methods are usually adopted to generate rapid and good solutions in a reasonable amount of time. Nevertheless, in this thesis, we focus on the problem definition and modelling. The experimental study is used to check the feasibility of the proposed models and the consistency of the proposed models. The efficiency to solve the large instances of the optimization problems is not the objective of this research. However, if we want to investigate the potential application of the models in practice, the solving method and the quality of the solution will be a significant issue to consider. Thus, corresponding algorithms for different optimization problems should be developed, especially for the bundle pricing problem, which is NP-hard.

# 7.4 Perspectives

Our study defines the Revenue Management problem in Physical Internet. Several models for different problems were proposed and verified to be feasible. Nevertheless, this is just the first step to study the application of RM in PI. We propose following directions for future research on this topic.

## 7.4.1 In-depth study

The works in this thesis conduct a broad study to the application of RM in PI, following four research questions. In the next, an in-depth study could be conducted to each research questions. Here are some examples. For the pricing problem, the mixed sizes requests could be considered. Thus, improved pricing models should be developed to respond to this situation. Besides, different pricing model could be developed. And the comparison of these models could be made to select the best one according to the context. For the forecasting problem, the method to do the forecasting could be investigated. For the bundle pricing, other methods to decide the price could also be developed. Besides, the synergy among the requests in the bundle is also an interesting problem to study.

## 7.4.2 Application

As we presented previously, the experiment studies in this thesis are still theoretical. The performance of the proposed models in real market has not been investigated. Besides, the current research is based on the Physical Internet, which is not accomplished yet. It is meaningful to study how to apply our works into current market to improve the carrier's revenue. To achieve this objective, effective case study should be designed based on the reliable data from the market in the major logistics hubs. Thus, it is also a research topic to collect actual data and generate the effective input data using effective methods, e.g. forecasting, statistics, or data mining.

## 7.4.3 Study the revenue problem for other actors in the market

This thesis focuses on the carrier in freight transport and study how to improve their revenue. Nevertheless, in the market, there are also other actors, which are mainly shippers and intermediaries. The possible extensions of the current work could be: (1) study the Revenue

Management for shippers. One of the objectives could be minimizing the cost on their shipments delivery. (2) Investigate the strategy to improve the revenue of intermediaries, for example the freight forwarders, or hub operators in PI. They should consider the carriers and shippers at the same time to manage their revenue.

## 7.5 Publications

### Journal:

I. Qiao, B., S. Pan and E. Ballot (2016). Dynamic pricing model for less-than-truckload carriers in the Physical Internet. Journal of Intelligent Manufacturing: 1-13. 10.1007/s10845-016-1289-8

II. Pan, S., V. Giannikas, Y. Han, E. Grover-Silva and B. Qiao (2017). Using Customer-related Data to Enhance E-grocery Home Delivery. Industrial Management & Data Systems 117(9): 1917-1933.

III. Qiao, B., S. Pan and E. Ballot (2018). Revenue Optimization for Less-than-truckload Carriers in the Physical Internet: dynamic pricing and request selection. Computers & Industrial Engineering: 10.1016/j.cie.2018.12.010

### Conference:

I. Qiao, B., S. Pan and E. Ballot (2016). Less-than-truckload Dynamic Pricing Model in Physical Internet. The 5th Institute of Industrial Engineers Asian Conference.

II. Qiao, B., S. Pan and E. Ballot (2017). OPTIMIZATION OF LESS-THAN-TRUCKLOAD REQUEST PRICING AND SELECTION FOR CARRIER IN PHYSICAL INTERNET. The 47th International Conference on Computers & Industrial Engineering (CIE47).

III. Pan, S., H. Yufei, B. Qiao, E. Grover-Silva and V. Giannikas (2016). Mining Customer-related Data to Enhance Home Delivery in E-commerce: an experimental study. 6th International Conference on Information Systems, Logistics and Supply Chain (ILS2016).

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# Appendix

## Appendix 1: Set of optimal prices tested in Scenario 2 in Chapter 3 (Line- the remaining capacity; Column- the number of remaining requests.)

| R\D | 20 | 19 | 18 | 17 | 16 | 15 | 14 | 13 | 12 | 11 | 10 | 9 | 8 | 7 | 6 | 5 | 4 | 3 | 2 | 1 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 50 | 0.98 | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 49 | 0.98 | 0.99 | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 48 | 0.97 | 0.98 | 0.99 | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 47 | 0.97 | 0.98 | 0.99 | 1 | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 46 | 0.97 | 0.98 | 0.99 | 1 | 1.01 | / | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 45 | 0.96 | 0.97 | 0.98 | 0.99 | 1 | 1.02 | / | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 44 | 0.96 | 0.97 | 0.98 | 0.99 | 1 | 1.01 | 1.02 | / | / | / | / | / | / | / | / | / | / | / | / | / |
| 43 | 0.95 | 0.96 | 0.97 | 0.98 | 1 | 1.01 | 1.02 | 1.03 | / | / | / | / | / | / | / | / | / | / | / | / |
| 42 | 0.95 | 0.96 | 0.97 | 0.98 | 0.99 | 1 | 1.02 | 1.03 | 1.04 | / | / | / | / | / | / | / | / | / | / | / |
| 41 | 0.94 | 0.95 | 0.96 | 0.97 | 0.99 | 1 | 1.01 | 1.02 | 1.04 | 1.05 | / | / | / | / | / | / | / | / | / | / |
| 40 | 0.94 | 0.95 | 0.96 | 0.97 | 0.98 | 0.99 | 1.01 | 1.02 | 1.03 | 1.05 | 1.06 | / | / | / | / | / | / | / | / | / |
| 39 | 0.93 | 0.94 | 0.95 | 0.96 | 0.98 | 0.99 | 1 | 1.02 | 1.03 | 1.04 | 1.06 | 1.07 | / | / | / | / | / | / | / | / |
| 38 | 0.92 | 0.94 | 0.95 | 0.96 | 0.97 | 0.98 | 1 | 1.01 | 1.02 | 1.04 | 1.05 | 1.07 | 1.09 | / | / | / | / | / | / | / |
| 37 | 0.92 | 0.93 | 0.94 | 0.95 | 0.97 | 0.98 | 0.99 | 1.01 | 1.02 | 1.03 | 1.05 | 1.07 | 1.08 | 1.1 | / | / | / | / | / | / |
| 36 | 0.91 | 0.92 | 0.94 | 0.95 | 0.96 | 0.97 | 0.99 | 1 | 1.02 | 1.03 | 1.05 | 1.06 | 1.08 | 1.1 | 1.12 | / | / | / | / | / |
| 35 | 0.91 | 0.92 | 0.93 | 0.94 | 0.96 | 0.97 | 0.98 | 1 | 1.01 | 1.03 | 1.04 | 1.06 | 1.07 | 1.09 | 1.11 | 1.13 | / | / | / | / |
| 34 | 0.9 | 0.91 | 0.92 | 0.94 | 0.94 | 0.96 | 0.98 | 0.99 | 1.01 | 1.02 | 1.04 | 1.05 | 1.07 | 1.09 | 1.11 | 1.13 | 1.15 | / | / | / |
| 33 | 0.9 | 0.91 | 0.92 | 0.93 | 0.94 | 0.96 | 0.97 | 0.99 | 1 | 1.02 | 1.03 | 1.05 | 1.07 | 1.08 | 1.1 | 1.13 | 1.15 | 1.18 | / | / |
| 32 | 0.89 | 0.9 | 0.91 | 0.92 | 0.93 | 0.95 | 0.96 | 0.98 | 1 | 1.01 | 1.03 | 1.04 | 1.06 | 1.08 | 1.1 | 1.12 | 1.15 | 1.18 | 1.21 | / |
| 31 | 0.88 | 0.89 | 0.91 | 0.92 | 0.92 | 0.94 | 0.96 | 0.97 | 0.99 | 1 | 1.02 | 1.04 | 1.06 | 1.08 | 1.1 | 1.12 | 1.14 | 1.17 | 1.21 | 1.26 |
| 30 | 0.88 | 0.89 | 0.9 | 0.91 | 0.92 | 0.94 | 0.95 | 0.97 | 0.99 | 0.99 | 1.02 | 1.03 | 1.05 | 1.07 | 1.09 | 1.11 | 1.14 | 1.17 | 1.21 | 1.26 |
| 29 | 0.88 | 0.88 | 0.89 | 0.9 | 0.91 | 0.93 | 0.94 | 0.96 | 0.98 | 0.99 | 1.01 | 1.03 | 1.05 | 1.07 | 1.09 | 1.11 | 1.14 | 1.17 | 1.2 | 1.26 |
| 28 | 0.87 | 0.88 | 0.89 | 0.9 | 0.9 | 0.92 | 0.94 | 0.95 | 0.97 | 0.98 | 1 | 1.02 | 1.04 | 1.06 | 1.08 | 1.11 | 1.13 | 1.16 | 1.2 | 1.26 |
| 27 | 0.87 | 0.87 | 0.88 | 0.89 | 0.9 | 0.92 | 0.93 | 0.95 | 0.96 | 0.98 | 1 | 1.02 | 1.03 | 1.06 | 1.08 | 1.1 | 1.13 | 1.16 | 1.2 | 1.25 |
| 26 | 0.87 | 0.87 | 0.88 | 0.88 | 0.89 | 0.91 | 0.92 | 0.94 | 0.95 | 0.97 | 0.99 | 1.01 | 1.03 | 1.05 | 1.07 | 1.1 | 1.12 | 1.15 | 1.19 | 1.25 |
| 25 | 0.86 | 0.87 | 0.87 | 0.88 | 0.88 | 0.9 | 0.91 | 0.93 | 0.95 | 0.96 | 0.98 | 1 | 1.02 | 1.04 | 1.07 | 1.09 | 1.12 | 1.15 | 1.19 | 1.25 |
| 24 | 0.86 | 0.86 | 0.87 | 0.87 | 0.88 | 0.89 | 0.91 | 0.92 | 0.94 | 0.95 | 0.98 | 0.99 | 1.02 | 1.04 | 1.06 | 1.09 | 1.11 | 1.15 | 1.19 | 1.24 |
| 23 | 0.86 | 0.86 | 0.87 | 0.87 | 0.87 | 0.88 | 0.9 | 0.91 | 0.93 | 0.95 | 0.97 | 0.99 | 1.01 | 1.03 | 1.05 | 1.08 | 1.11 | 1.14 | 1.18 | 1.24 |
| 22 | 0.86 | 0.86 | 0.86 | 0.87 | 0.87 | 0.87 | 0.89 | 0.91 | 0.92 | 0.94 | 0.96 | 0.98 | 1 | 1.02 | 1.05 | 1.07 | 1.1 | 1.14 | 1.18 | 1.24 |
| 21 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.9 | 0.91 | 0.93 | 0.95 | 0.97 | 0.99 | 1.02 | 1.04 | 1.07 | 1.1 | 1.13 | 1.17 | 1.23 |
| 20 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.89 | 0.9 | 0.92 | 0.94 | 0.96 | 0.98 | 1.01 | 1.03 | 1.06 | 1.09 | 1.12 | 1.17 | 1.23 |
| 19 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.89 | 0.91 | 0.93 | 0.95 | 0.97 | 1 | 1.02 | 1.05 | 1.08 | 1.12 | 1.16 | 1.22 |
| 18 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.87 | 0.89 | 0.9 | 0.92 | 0.94 | 0.96 | 0.99 | 1.01 | 1.04 | 1.08 | 1.11 | 1.16 | 1.22 |
| 17 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.89 | 0.91 | 0.93 | 0.95 | 0.98 | 1.01 | 1.03 | 1.07 | 1.1 | 1.15 | 1.21 |
| 16 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.87 | 0.89 | 0.9 | 0.92 | 0.94 | 0.97 | 1 | 1.03 | 1.06 | 1.1 | 1.14 | 1.21 |
| 15 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.89 | 0.91 | 0.93 | 0.96 | 0.98 | 1.01 | 1.05 | 1.09 | 1.14 | 1.2 |
| 14 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.9 | 0.92 | 0.94 | 0.97 | 1 | 1.04 | 1.08 | 1.13 | 1.19 |
| 13 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.87 | 0.88 | 0.9 | 0.93 | 0.96 | 0.99 | 1.03 | 1.07 | 1.12 | 1.19 |
| 12 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.87 | 0.89 | 0.91 | 0.94 | 0.98 | 1.01 | 1.06 | 1.11 | 1.18 |
| 11 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.9 | 0.93 | 0.96 | 1 | 1.04 | 1.1 | 1.17 |
| 10 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.89 | 0.91 | 0.95 | 0.99 | 1.03 | 1.09 | 1.16 |
| 9 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.9 | 0.93 | 0.97 | 1.01 | 1.07 | 1.15 |
| 8 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.88 | 0.91 | 0.95 | 1 | 1.06 | 1.14 |
| 7 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.89 | 0.93 | 0.98 | 1.04 | 1.12 |
| 6 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.87 | 0.9 | 0.95 | 1.02 | 1.1 |
| 5 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.88 | 0.92 | 0.99 | 1.08 |
| 4 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.89 | 0.95 | 1.05 |
| 3 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.91 | 1.02 |
| 2 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.96 |
| 1 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 | 0.86 |

# Appendix 2: Complete optimal bidding price for each status in Section 5.5.1

| Capacity | Optimal bidding price | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Considering several auction periods | | | | | | | | | | | | | | | | | | Not considering several auction periods | | |
| | Scenario 1 | | | Scenario 2 | | | Scenario 3 | | | Scenario 4 | | | Scenario 5 | | | Scenario 6 | | | | | |
| | 50 | 100 | 150 | 50 | 150 | 100 | 100 | 150 | 50 | 100 | 50 | 150 | 150 | 100 | 50 | 150 | 50 | 100 | 50 | 100 | 150 |
| 1 | \ | 1.37 | 1.3 | \ | 1.37 | 1.27 | \ | 1.35 | 1.22 | \ | 1.36 | 1.3 | \ | 1.34 | 1.22 | \ | 1.34 | 1.27 | 1.22 | 1.27 | 1.3 |
| 2 | \ | 1.34 | 1.28 | \ | 1.34 | 1.25 | \ | 1.33 | 1.19 | \ | 1.33 | 1.28 | \ | 1.31 | 1.19 | \ | 1.31 | 1.25 | 1.19 | 1.25 | 1.28 |
| 3 | \ | 1.33 | 1.26 | \ | 1.32 | 1.23 | \ | 1.31 | 1.17 | \ | 1.31 | 1.26 | \ | 1.29 | 1.17 | \ | 1.29 | 1.23 | 1.17 | 1.23 | 1.26 |
| 4 | \ | 1.31 | 1.25 | \ | 1.31 | 1.21 | \ | 1.29 | 1.15 | \ | 1.29 | 1.25 | \ | 1.27 | 1.15 | \ | 1.27 | 1.21 | 1.15 | 1.21 | 1.25 |
| 5 | \ | 1.3 | 1.23 | \ | 1.3 | 1.2 | \ | 1.28 | 1.14 | \ | 1.28 | 1.23 | \ | 1.26 | 1.14 | \ | 1.26 | 1.2 | 1.14 | 1.2 | 1.23 |
| 6 | \ | 1.29 | 1.22 | \ | 1.29 | 1.19 | \ | 1.27 | 1.12 | \ | 1.27 | 1.22 | \ | 1.25 | 1.12 | \ | 1.25 | 1.19 | 1.12 | 1.19 | 1.22 |
| 7 | \ | 1.28 | 1.21 | \ | 1.28 | 1.18 | \ | 1.26 | 1.11 | \ | 1.26 | 1.21 | \ | 1.24 | 1.11 | \ | 1.24 | 1.18 | 1.11 | 1.18 | 1.21 |
| 8 | \ | 1.27 | 1.2 | \ | 1.27 | 1.17 | \ | 1.25 | 1.09 | \ | 1.25 | 1.2 | \ | 1.23 | 1.09 | \ | 1.23 | 1.17 | 1.09 | 1.17 | 1.2 |
| 9 | \ | 1.26 | 1.2 | \ | 1.26 | 1.16 | \ | 1.24 | 1.08 | \ | 1.24 | 1.2 | \ | 1.22 | 1.08 | \ | 1.22 | 1.16 | 1.08 | 1.16 | 1.2 |
| 10 | \ | 1.25 | 1.19 | \ | 1.25 | 1.15 | \ | 1.23 | 1.07 | \ | 1.23 | 1.19 | \ | 1.21 | 1.07 | \ | 1.21 | 1.15 | 1.07 | 1.15 | 1.19 |
| 11 | \ | 1.24 | 1.18 | \ | 1.25 | 1.14 | \ | 1.23 | 1.06 | \ | 1.22 | 1.18 | \ | 1.2 | 1.06 | \ | 1.2 | 1.14 | 1.06 | 1.14 | 1.18 |
| 12 | \ | 1.24 | 1.17 | \ | 1.24 | 1.13 | \ | 1.22 | 1.05 | \ | 1.22 | 1.17 | \ | 1.19 | 1.05 | \ | 1.19 | 1.13 | 1.05 | 1.13 | 1.17 |
| 13 | \ | 1.23 | 1.17 | \ | 1.23 | 1.13 | \ | 1.21 | 1.04 | \ | 1.21 | 1.17 | \ | 1.19 | 1.04 | \ | 1.18 | 1.13 | 1.04 | 1.13 | 1.17 |
| 14 | \ | 1.23 | 1.16 | \ | 1.23 | 1.12 | \ | 1.21 | 1.03 | \ | 1.2 | 1.16 | \ | 1.18 | 1.03 | \ | 1.18 | 1.12 | 1.03 | 1.12 | 1.16 |
| 15 | \ | 1.22 | 1.16 | \ | 1.22 | 1.11 | \ | 1.2 | 1.02 | \ | 1.2 | 1.16 | \ | 1.17 | 1.02 | \ | 1.17 | 1.11 | 1.02 | 1.11 | 1.16 |
| 16 | \ | 1.21 | 1.15 | \ | 1.22 | 1.1 | \ | 1.2 | 1.01 | \ | 1.19 | 1.15 | \ | 1.17 | 1.01 | \ | 1.16 | 1.1 | 1.01 | 1.1 | 1.15 |
| 17 | \ | 1.21 | 1.14 | \ | 1.21 | 1.1 | \ | 1.19 | 1 | \ | 1.19 | 1.14 | \ | 1.16 | 1 | \ | 1.16 | 1.1 | 1 | 1.1 | 1.14 |
| 18 | \ | 1.2 | 1.14 | \ | 1.21 | 1.09 | \ | 1.19 | 0.99 | \ | 1.18 | 1.14 | \ | 1.16 | 0.99 | \ | 1.15 | 1.09 | 0.99 | 1.09 | 1.14 |
| 19 | \ | 1.2 | 1.13 | \ | 1.2 | 1.09 | \ | 1.18 | 0.98 | \ | 1.18 | 1.13 | \ | 1.15 | 0.98 | \ | 1.15 | 1.09 | 0.98 | 1.09 | 1.13 |
| 20 | 1.21 | 1.19 | 1.13 | 1.21 | 1.2 | 1.08 | 1.21 | 1.18 | 0.98 | 1.21 | 1.17 | 1.13 | 1.22 | 1.14 | 0.98 | 1.21 | 1.14 | 1.08 | 0.98 | 1.08 | 1.13 |

# Résumé

Bien que le transport de marchandises joue un rôle essentiel dans le secteur économique et que la demande de transport de marchandises augmente, les transporteurs sur le marché du fret ont encore du mal à maintenir et à améliorer leurs revenus. Pour répondre aux défis, Revenue Management (RM) et l'Internet Physique (PI) sont adoptés comme solution dans cette thèse. RM est une méthode, issue de l'industrie du transport aérien, qui permet de maximiser les revenus. PI est un système logistique entièrement interconnecté, ouvert et dynamique visant à développer des réseaux logistiques mondiaux interconnectés ouverts afin d'accroître l'efficacité et la durabilité de la logistique. Cette thèse examine l'application de RM dans PI pour améliorer les revenus des transporteurs de chargement partiel.

L'application de RM dans PI est étudiée à partir de quatre questions de recherche sur RM : la tarification, le contrôle de capacité, les prévisions et la tarification groupée. De plus, pour chaque question de recherche, une étude expérimentale est menée pour évaluer la faisabilité et les performances des modèles d'optimisation proposés correspondant à chaque question. Les résultats fournissent aux transporteurs des implications en termes de gestion et des conseils constructifs leur permettant d'optimiser leurs revenus à plusieurs niveaux, en tenant compte de situations et de scénarios différents.

Dans l'ensemble, cette recherche examine Revenue Management du point des transporteurs de chargement partiel opérant dans un environnement très dynamique tel que l'Internet Physique. Les travaux de cette recherche donnent un aperçu général et systématique de l'application de Revenue Management dans un réseau dynamique de transport de marchandises par route. Les réalisations de cette thèse fournissent une base pour la future étude approfondie sur le problème des revenus dans un environnement dynamique.



# Mots Clés

Revenue Management, Internet Physique, transport de fret, Tarification dynamique, enchères



# Abstract

Although the freight transport plays vital role in the economic sector and the freight transport demand is increasing, there are still challenges for the carriers in the freight market to keep and improve their revenue. To respond to the challenges, Revenue Management (RM) and Physical Internet (PI) are adopted as the solution in this thesis. RM is a method, which is originated from airline industry, to maximize the revenue. PI is a fully interconnected, open, dynamic logistics system aiming to develop an open global interconnected logistics networks to increase the logistics efficiency and sustainability. This thesis investigates the application of RM in PI to improve the revenue of less-than-truckload (LTL) carriers.

The application of RM in PI is studied based on four research questions in RM, i.e. pricing, capacity control, forecasting, and bundle pricing. In addition, for each research question, an experimental study is conducted to evaluate the feasibility and performance of the proposed optimization models corresponded to each question. The results provide the carriers managerial implications and constructive guidance to make decisions to optimize their revenue at several levels, considering different situations and scenarios.

Overall, this research investigates the Revenue Management from the point of view of LTL carriers operating in a highly dynamic environment like Physical Internet. The work in this research gives a general and systematical sight to the application of RM in a dynamic network of road freight transport. The achievements of this thesis give a basis for the future in-depth study on the revenue problem in a dynamic environment.



# Keywords

Revenue Management, Physical Internet, Freight transport, Dynamic Pricing, Auction