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Modélisation des Performances de Fiabilité pour les Systèmes de Fabrication Reconfigurables

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ÉCOLE DOCTORALE SCIENCES DES MÉTIERS DE L'INGÉNIEUR

Laboratoire de Conception, Fabrication et Commande (LCFC) – Campus de Metz

THÈSE

présentée par : **Tian ZHANG**

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Spécialité : **Génie industriel**

Reliability Performance Modeling For Reconfigurable Manufacturing System

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Résumé étendu en Français

Introduction

La quatrième révolution industrielle, Industrie 4.0 (I4.0), née en 2011 d'un projet de la stratégie high-tech du gouvernement allemand, influencera inévitablement la manière dont les systèmes industriels se développeront à l'avenir. En bref, pour rendre la fabrication plus rapide, plus efficace et plus centrée sur le client, I4.0 rassemble les développements tels que l'intelligence artificielle (IA), le Big Data, la fabrication additive, l'Internet des objets (IoT), l'informatique en nuage et l'analytique dans les installations de production et dans l'ensemble de leurs opérations. Il est nécessaire d'utiliser l'idée de l'I4.0 comme base pour développer les systèmes de fabrication à l'heure actuelle.

Dans le plan I4.0, un indice particulier auquel on accorde une grande importance est *qualité*. Pour évaluer la qualité, de nombreuses études ont été réalisées et de nombreux outils ont été utilisés. Tout aussi important que la qualité, l'indice *fiabilité* - en tant que *qualité évoluant dans le temps* - a joué un rôle important dans la conception et l'évaluation des systèmes de fabrication. Cependant, l'analyse de l'attribut important *fiabilité* peut donner lieu à une grande variété de systèmes et d'architectures I4.0. Dans différents contextes, la qualité ou la fiabilité peut être définie par la durabilité, la disponibilité, la probabilité ou la dégradation. Outre les aspects susmentionnés, la qualité et la fiabilité peuvent également être mesurées à l'aide d'indices de performance spécifiquement développés. Par exemple, l'efficacité globale des équipements (OEE), qui est définie par trois facteurs : la disponibilité, la performance et la qualité.

Au cours des deux dernières décennies, les systèmes de fabrication ont évolué en permanence pour répondre à la concurrence industrielle dans le contexte de l'I4.0. Un paradigme de système de fabrication reconfigurable (RMS) a réussi à répondre aux caractéristiques de la mondialisation : réponse rapide à faible coût et haute qualité.

L'analyse de la fiabilité des RMS est un problème difficile qui se pose dans le cadre d'un tel développement. Ce problème est difficile à traiter pour trois raisons principales :

1. La définition de la fiabilité varie considérablement en fonction du contexte, en particulier pour les paradigmes de systèmes de fabrication nouvellement établis. De nouvelles méthodologies d'analyse de la fiabilité seront nécessaires pour répondre aux systèmes I4.0 nouvellement introduits.
2. Le nombre d'interactions/interfaces (mécaniques ou non) au sein des RMS est énorme et pourtant extrêmement influent. Cela entraîne une augmentation significative de la complexité du modèle.

3. Au fur et à mesure que le RMS passe de la théorie à l'application, des problèmes plus réalistes se poseront, nécessitant une analyse de fiabilité plus axée sur l'application et la reconfigurabilité.

En résumé, il est nécessaire de mener des recherches sur la fiabilité des RMS en utilisant des concepts de fiabilité nouvellement définis, de prendre en compte la particularité de ce paradigme de système et d'accorder plus d'attention à la reconfigurabilité et à d'autres caractéristiques cruciales dans l'application.

Comment les choix effectués pour les systèmes de fabrication reconfigurables influencent-ils les différentes formes de fiabilité pendant toute la procédure de traitement malgré la complexité croissante des systèmes ?

La réponse à la question ci-dessus permettra d'économiser l'énergie et le temps consacrés à l'analyse de fiabilité pour une entreprise de fabrication, d'améliorer la qualité des produits fabriqués dans les systèmes de fabrication reconfigurables, d'aider à interpréter les résultats du diagnostic pendant la fabrication et d'accroître l'efficacité du système de production.

Pour relever ce défi, le cadre de la méthodologie de recherche est créé. La méthodologie est divisée en deux parties principales : 1) l'établissement de la base et 2) le développement, la validation et la vérification des modèles. En haut du cadre méthodologique figurent les outils, les approches ou les méthodes appliqués, les cases du milieu indiquent les principales étapes de cette recherche et, en bas, les résultats et les principales contributions.

Cette thèse est structurée en trois Chapitres distincts, chacun d'entre eux abordant un aspect unique du sujet de recherche. Le Chapitre 1 présente les concepts généraux de l'analyse de fiabilité et des systèmes de fabrication reconfigurables. Des analyses documentaires ont été menées sur quatre aspects : les méthodes d'analyse de la fiabilité, les paradigmes des systèmes de fabrication, les outils de fabrication reconfigurables et l'analyse de la fiabilité dans les systèmes de fabrication reconfigurables. Pour le quatrième aspect en particulier, qui est aussi le principal intérêt de cette recherche, une analyse du réseau de citations (CNA) a été effectuée, sur la base de laquelle des cartes conceptuelles ont été construites, afin de clarifier les branches existantes et le champ de la recherche. Sur la base de l'étude précédente, la particularité de l'analyse de fiabilité des RMS par rapport aux systèmes de fabrication généraux a été discutée, révélant le défi détaillé de cette thèse présenté sous forme d'une série de questions et d'un organigramme.

Le Chapitre 2 présente la description du RMS. Le concept d'outils de fabrication reconfigurables (RMT) a été utilisé pour réaliser la reconfigurabilité. Le RMT répond à quatre des caractéristiques de la reconfigurabilité : modularité, intégrabilité, convertibilité et diagnostic. Des modèles de fiabilité des RMS ont ensuite été présentés. Tout d'abord, les modèles basés sur deux distributions de probabilité ont été développés : la distribution exponentielle et la distribution de Weibull. Les impacts des ordres de reconfiguration sur les performances de fiabilité ont été analysés respectivement. Ensuite, un modèle basé sur des politiques d'évaluation a été construit, qui peut être plus applicable lorsque l'incertitude épistémique existe. Les cas optimiste et pessimiste servent de deux cas extrêmes, restreignant tous les niveaux possibles de performances de fiabilité. Outre les modèles de fiabilité, trois autres parties comprennent l'explication de la complexité pour l'identification des paramètres, la configuration présentée dans la chaîne de Markov et l'analyse de la causalité entre les configurations. Ces trois parties étaient spéciales et nécessaires pour l'analyse de la fiabilité des RMS par rapport aux systèmes de fabrication généraux.

Le Chapitre 3 se concentre sur la validation et la vérification des modèles créés au Chapitre 2. Tout d'abord, un organigramme et des algorithmes de simulation ont été créés pour effectuer des simulations de Monte Carlo sur les performances de fiabilité avec différentes options de configuration. Ensuite, les performances ont été évaluées, en accordant une attention particulière à la moyenne quadratique avec différents ordres de configuration. Les résultats des simulations ont été comparés aux conclusions tirées des formulations mathématiques. En outre, une analyse de sensibilité et des exemples numériques illustrant l'utilisation ont été donnés. Le Chapitre 4 évalue les modèles du Chapitre 3 par une analyse de sensibilité et des évaluations de performance. Des exemples d'application montrent l'approche d'application des modèles.

Enfin, la thèse présente des conclusions et des suggestions pour les recherches futures.

Chapitre 1 : Analyse bibliographique de l'analyse de fiabilité dans les systèmes de fabrication reconfigurables

1.1 Analyse de fiabilité des systèmes de fabrication

Nous avons donc formalisé une analyse systématique de la littérature sur l'analyse de la fiabilité des systèmes de fabrication, les paradigmes des systèmes de fabrication, les systèmes de fabrication reconfigurables (RMS), les outils de fabrication reconfigurables (RMT) et l'analyse de la fiabilité dans les systèmes de fabrication reconfigurables. Pour *l'analyse de fiabilité dans les systèmes de fabrication reconfigurables* en particulier, une analyse du réseau de citations (CNA) a été menée pour analyser les associations entre les littératures, localisant ainsi les aspects importants de la recherche et les articles influents correspondants. Les diverses définitions et méthodes tirées de la littérature ont été résumées dans des cartes conceptuelles. Ensuite, sur la base de la recherche ci-dessus, la spécialité de l'analyse de la fiabilité du SGI a été discutée, et les défis de l'étude ont été présentés dans un organigramme et une série de questions auxquelles il faudra répondre dans les chapitres suivants.

L'ingénierie de la fiabilité est une discipline formelle basée en particulier sur la théorie des probabilités et les statistiques, qui vise à permettre aux systèmes et aux composants de fonctionner sans défaillance. Les essais de fiabilité et la modélisation de la fiabilité sont les deux principales branches de l'ingénierie de la fiabilité. Les études traditionnelles se concentrent sur l'essai de durée de vie [1] ou l'essai de dégradation [2], grâce auxquels la fiabilité peut être calculée ou estimée par des distributions statistiques [3]. Avec l'amélioration des technologies et des systèmes, la complexité des études de fiabilité augmente également.

Pour étudier les principaux courants évoqués ci-dessus, il est essentiel d'adopter des approches appropriées. Les chercheurs ayant des compétences académiques variées utilisent diverses approches pour évaluer la fiabilité d'un système ou d'un équipement. Les techniques et modèles courants peuvent être classés en cinq catégories, dont certaines peuvent apparaître plusieurs fois.

- **Modèle d'État** Chaîne de Markov (MC) [4–6], Petri-nets [7, 8].
- **Modèle probabiliste** Distributions Exponential, Weibull, Normal, Log-normal, Extreme Value, Erlang, Chi-Square, Gamma et Distributions auxiliaires, Estimation bayésienne de la fiabilité [8].
- **Modèles de systèmes composites** L'analyse de l'arbre de défaillances (FTA), L'analyse des modes

de défaillance, de leurs effets et de leur criticité (AMDEC) [9], k -out-of- n [10], Méthode de décomposition [11], Mean Time To Failure (MTTF), Mean Time Between Failure (MTBF) [12].

- **Technique graphique** Probability plotting for parameters, Chaîne de Markov [4, 6], Petri-nets [13, 14], Non-Parametric Plotting [15].
- **Algorithmes et techniques de calcul** Algorithme Génétique (GA) [16], fuzzy Lambda-Tau technique [14], Supplementary Variable Technique (SVT) [17].

Lorsqu'elle est analysée à l'aide de ces techniques et modèles, la fiabilité peut être étroitement liée à la disponibilité, à la maintenabilité, à la fiabilité et à la dégradation, etc.

Dans cette section, un examen des méthodes d'identification des paramètres est présenté, et dans la Section 2.3, une discussion plus approfondie sera menée pour prouver que les méthodes d'identification des paramètres ne sont pas adaptées à la recherche dans cette thèse, et donc pour demander que cette recherche examine d'autres solutions au problème. L'identification des paramètres est couramment utilisée dans le développement de modèles et de contrôleurs. Les méthodes courantes d'identification des paramètres sont les suivantes :

- **Probability Plotting (PP)**, une méthode d'identification des valeurs des paramètres en traçant les données sur un papier spécial et en calculant les paramètres à partir du tracé visuel. Par exemple, Weibull Probability Plot (WPP) est une méthode de tracé des probabilités spécialement conçue pour la distribution de Weibull. [18].
- **Least Squares Method (LSM)**, une méthode qui identifie les valeurs des paramètres qui minimisent la somme des carrés résiduels [19].
- **Maximum Likelihood Estimation (MLE)**, qui recherche les valeurs des paramètres qui optimisent la fonction de vraisemblance compte tenu d'un ensemble d'observations [20].
- **Bayesian Estimation Methods**, un ensemble de méthodes d'identification des paramètres qui tentent de minimiser l'espérance a posteriori de la fonction d'utilité. Cela signifie que les connaissances existantes sur une situation sont formées, que des preuves sont obtenues et que les informations a posteriori sont utilisées pour mettre à jour les idées. [21].

1.2 Paradigmes des systèmes de fabrication

Les systèmes de fabrication continuent d'évoluer au fil des décennies grâce à l'amélioration et au progrès de la technologie. L'émergence constante de nouveaux matériaux, de nouveaux produits et de nouvelles applications nécessite de nouvelles stratégies de fabrication qui permettent une grande fiabilité et un faible coût. Cette section vise à effectuer un bref examen des paradigmes des systèmes de fabrication existants, ainsi qu'une introduction détaillée de notre objet de recherche - les systèmes de fabrication reconfigurables.

Pour organiser les paradigmes de systèmes en fonction de la chronologie, certains des premiers paradigmes comprennent la production artisanale et les ateliers, qui nécessitent une forte implication humaine et fournissent des produits de faible volume. Ensuite, l'apparition des systèmes de fabrication dédiés (DMS) a permis de produire en masse des types de produits limités. À l'ère moderne, certains paradigmes de systèmes de fabrication bien connus comprennent les systèmes de fabrication flexibles (FMS), les systèmes de fabrication reconfigurables (RMS) et les systèmes de fabrication modifiables (CMS). Le nombre de publications sur ces paradigmes est resté relativement élevé depuis 2010 [22]. Parmi les paradigmes de systèmes de fabrication récemment étudiés figurent les systèmes de fabrication intelligents (SMS) et les systèmes de production cyberphysiques (CPPS), qui ont la capacité de recueillir intelligemment des informations sur leur environnement et d'agir de manière indépendante.

1.3 Système de fabrication reconfigurable (RMS)

*Pour être compétitifs au niveau mondial, les systèmes de fabrication du XXI^e siècle doivent avoir trois objectifs : produire à **faible coût**, améliorer **la qualité du produit** et répondre **rapidement et de manière rentable** aux changements du marché. [23].*

Le RMS a été introduit par Yoram Koren [24, 25] en 1999 pour relever le défi des changements soudains dans les exigences du marché ou de la réglementation. Afin de réagir et de répondre rapidement et efficacement aux exigences changeantes, ce paradigme de système peut permettre d'ajouter, de retirer, de modifier ou d'échanger des composants de machine, des logiciels de machine ou des unités de maintenance. Le mot-clé "Reconfigurable Manufacturing" présente 211 000 citations dans Google Scholar. Par ailleurs, d'après un article de synthèse rédigé par Bortolini [26], jusqu'à 60% de la base de données d'articles ont été publiés après 2010, et le nombre d'articles est resté élevé après avoir atteint

son apogée en 2012. Les informations ci-dessus suffisent à prouver l'intérêt des universitaires pour ce domaine.

1.4 Outils de fabrication reconfigurables (RMT)

La RMT est l'un des éléments les plus importants parmi les machines reconfigurables, les autres étant la machine d'inspection reconfigurable (RIM), les montages reconfigurables et la machine d'assemblage reconfigurable (RAM) [27]. Une RMT est composée de modules qui peuvent être assemblés et désassemblés sur des interfaces optionnelles, au cours du processus de fabrication. Contrairement aux machines à commande numérique par ordinateur (CNC), le RMT peut répondre aux besoins de personnalisation, de convertibilité, d'intégrabilité et de modularité de manière rapide et rentable, grâce à ses différentes configurations. Les interfaces sont d'une importance capitale pour atteindre ces caractéristiques. Les interfaces comprennent les interfaces mécaniques et les interfaces pour les données, l'énergie et les matériaux auxiliaires. Les interfaces mécaniques peuvent déterminer non seulement le degré de convertibilité et d'intégrabilité des RMT, mais aussi leur vitesse et leur coût. Les deux paramètres d'interface courants qui ont un impact sur la fiabilité sont le positionnement géométrique et les vibrations des outils.

1.5 Analyse de fiabilité dans RMS

L'émergence de nouveaux paradigmes de systèmes de fabrication a soulevé la question de savoir comment les méthodes et les outils de fiabilité pourraient jouer un rôle dans cette nouvelle ère. Les systèmes de fabrication reconfigurables font partie des systèmes complexes qui compliquent l'analyse de la fiabilité pour les deux raisons suivantes :

1. Avec l'aide des nouvelles technologies et des nouveaux matériaux, les paradigmes dérivés de la fabrication reconfigurable évoluent rapidement. Par exemple, certains paradigmes dérivés comprennent le système de fabrication reconfigurable durable (SRMS), le système de fabrication auto-reconfigurable intelligent (SSrMS), le système de fabrication reconfigurable cellulaire (CRMS), etc. Tous ces paradigmes de systèmes nouvellement conçus nécessiteront des méthodes d'analyse de fiabilité adaptées qui se concentrent sur leurs caractéristiques et s'y conforment.
2. Le nombre d'interfaces dans un système de fabrication reconfigurable est considérable, que ce soit avant ou pendant le traitement. Chaque choix effectué et chaque étape franchie dans un

système de fabrication reconfigurable peuvent avoir un impact considérable sur les performances en matière de fiabilité.

Pour faire systématiquement un examen approfondi des recherches concernant ce sujet, l'outil logiciel a été appliqué pour construire et visualiser les réseaux bibliométriques – VOSviewer [28]. Il s'agit d'un outil d'analyse des réseaux bibliométriques largement utilisé par de nombreux chercheurs. Il montre clairement les liens et présente les connexions. L'examen de la littérature a été effectué par VOSviewer sous trois aspects :

1. **Méthodes d'analyse de la fiabilité dans le domaine de la fabrication**
2. **Fabrication reconfigurable**
3. **L'analyse de fiabilité appliquée à la RMS**

1.6 Défis de la recherche

Après avoir examiné les principales différences entre les paradigmes du RMS et du système général, cette section présente les défis que cette lacune de la recherche a soulevés. Pour relever ces défis, des modèles mathématiques sont donc élaborés dans les dernières sections (voir la Section 2.4, 2.5 et 2.6).

Étant donné que les caractéristiques du RMS sont largement différentes de celles des systèmes de fabrication conventionnels lors de l'analyse de la fiabilité, les défis suivants se posent en matière de recherche :

- *Comment vérifier si les interactions/interfaces ont une incidence sur la fiabilité d'un SGI ?*
- *Dans quels cas les impacts sont-ils négligeables ou non négligeables ?*
- *Si les impacts existent, comment décrire les causalités entre les configurations ?*
- *Lors de la description des causalités entre les configurations, comment estimer et fixer des limites ?*
- *Si les interactions/interfaces ont une incidence sur la fiabilité d'un SGI, quelle est l'importance de cette incidence et comment la mesurer ?*

En conclusion, les orientations entourant notre sujet d'étude - l'analyse de fiabilité utilisée dans les systèmes de fabrication reconfigurables - ont été systématiquement passées en revue dans cette section.

Une fois l'analyse de la fiabilité de la fabrication, divers paradigmes de systèmes de fabrication et des outils de fabrication reconfigurables ont été présentés. Une analyse a été réalisée à l'aide d'un programme de construction et de visualisation de réseaux bibliométriques et s'est concentrée sur trois aspects : les méthodes d'analyse de la fiabilité dans le domaine de la fabrication, la fabrication reconfigurable et l'analyse de la fiabilité appliquée aux systèmes de fabrication reconfigurables.

Ensuite, en utilisant les informations obtenues à partir de l'étude ci-dessus, une carte conceptuelle est créée. Enfin, la particularité de l'analyse de fiabilité des RMS a été examinée et les défis de la recherche sont énumérés en conséquence. Ainsi, une discussion visant à différencier l'évaluation de la fiabilité dans un système de fabrication ordinaire et dans un système de fabrication reconfigurable est présentée. Dans le chapitre suivant, les modèles construits pour l'analyse des performances de fiabilité des systèmes de fabrication reconfigurables seront présentés.

Chapitre 2 : Modèles de fiabilité des systèmes de fabrication reconfigurables

Dans ce chapitre, deux types de modèles mathématiques pour les performances de fiabilité des systèmes de fabrication reconfigurables ont été élaborés : 1) deux modèles probabilistes comprenant un modèle basé sur la distribution exponentielle et un modèle basé sur la distribution de Weibull et 2) un modèle basé sur l'évaluation optimiste ou pessimiste.

Dans la première section, le système est défini avec ses caractéristiques générales, ses hypothèses et ses caractéristiques RMS. Ensuite, la reconfigurabilité basée sur les ordres de configuration est expliquée et présentée sous forme de chaîne de Markov. Les modèles présentant les causalités sont également présentés dans cette section.

Dans la deuxième section, les trois modèles sont présentés avec leurs hypothèses spécifiques et leurs formulations mathématiques. Enfin, les caractéristiques des modèles et leurs limites sont discutées.

2.1 Description du système

Afin de développer des modèles, il est nécessaire de définir les caractéristiques, les paramètres et les hypothèses du système. Cette section vise à expliquer l'objet d'étude de cette recherche - le RMS composé de RMT, ainsi que le fonctionnement des différentes configurations et le processus de reconfiguration. La reconfigurabilité du système est ensuite examinée. Ensuite, un cas réel de RMS

composé de RMT est présenté, avec la conception de l'agencement du système, des machines et des outils.

Le plan de traitement avec différents ordres de configuration est ensuite représenté dans les états de transfert de Markov. Enfin, la spécification du RMS par rapport au système de fabrication général lors de l'évaluation de la fiabilité est discutée.

2.2 Ordres de configuration modélisés par une chaîne de Markov (MC)

Dans cette section, les ordres de configuration des RMT sont présentés dans un MC par le biais d'une illustration conceptuelle et d'un cas spécifique.

Un MC est un modèle mathématique qui peut être utilisé pour décrire le comportement d'un système qui change au fil du temps, où l'état futur du système est déterminé uniquement par son état actuel et non par son histoire antérieure [29]. En d'autres termes, un MC est un processus qui traverse une gamme d'états possibles, la probabilité de passer d'un état à l'autre étant déterminée uniquement par l'état actuel et non par les états précédents. Par conséquent, il s'agit d'un processus sans mémoire puisqu'il ne conserve aucune connaissance de son historique.

Une fois les ordres de configuration modélisés, l'étape suivante consiste à identifier les paramètres. Dans la section suivante, la complexité de l'identification des paramètres sera examinée, en expliquant pourquoi il est nécessaire d'analyser les causalités entre les configurations dans différents ordres.

2.3 Complexité de l'identification des paramètres

Comme indiqué dans la section 1.1.3, l'identification des paramètres est un domaine de la statistique qui implique l'estimation des paramètres d'une distribution. Il s'agit généralement d'une étape courante pour les modèles probabilistes. Cependant, dans cette recherche, les approches d'identification des paramètres ne correspondent plus, ce qui nécessite la recherche d'autres solutions.

Le degré de complexité de l'identification des paramètres dans cette étude est la cause de cette inadéquation. Sur la base du système défini à la section 2.1.1, considérons une chaîne de traitement composée de RMT avec trois configurations optionnelles : *config.1*, *config.2*, *config.3*. La procédure d'identification des paramètres serait nécessaire, à chaque moment de la configuration du système, pour toutes les possibilités suivantes, comme le montre la Fig.2.8.

2.4 Causalités entre les configurations

En tant que solutions alternatives au problème de l'identification des paramètres, cette section contribue à la modélisation des causalités entre les configurations afin de démontrer comment le traitement des premières configurations affecte les dernières.

Au cours du traitement, les outils peuvent être installés sur les modules de bras fonctionnels par l'intermédiaire de plusieurs interfaces. Par exemple (voir Fig.2.4), lorsque l'opération nécessite de passer de l'installation A à l'installation B, les outils passent de *Milling 1* à *Tapping*. Il est indéniable que les processus de fraisage et de taraudage entraînent une usure plus ou moins importante. C'est pourquoi il est essentiel de construire des modèles de causalité pour les différents ordres de configuration.

2.5 Modèles probabilistes

La manière la plus classique d'analyser la fiabilité des systèmes de fabrication est le modèle probabiliste. Ce modèle a de nombreuses applications, que ce soit pour l'estimation de la durée de vie, l'évaluation des défaillances ou la conception de la politique de maintenance. Les distributions les plus courantes pour l'analyse de la fiabilité sont les distributions exponentielle, de Weibull, normale, log-normale, de valeur extrême, d'Erlang, de Khi-deux, Gamma et les distributions auxiliaires, l'estimation bayésienne de la fiabilité. Dans cette section, les deux distributions appliquées dans les modèles sont la distribution exponentielle et la distribution de Weibull. Le choix de la distribution a été fait sur la base du fait que 1) la distribution exponentielle a la caractéristique unique de ne pas avoir de mémoire, ce qui suscite l'intérêt de la recherche, et 2) la distribution de Weibull est une distribution générique qui peut décrire le taux de défaillance sous différentes formes [30]. Leurs caractéristiques générales et leurs formulations ont été présentées dans la Section 1.1.2.

2.6 Modèle de politique d'évaluation

Cette section présente une solution différente des modèles probabilistes, un modèle de politique d'évaluation, qui offre plus de souplesse dans l'obtention des résultats. Les décisions relatives à la politique peuvent être très optimistes, très pessimistes ou se situer entre les deux.

2.7 Conclusions

Le système défini dans ce chapitre répond à la majorité des propriétés générales du RMS, y compris la modularité, l'intégrabilité, la convertibilité et la flexibilité personnalisée. Il convient de mentionner que la diagnostiquabilité est au centre de cette thèse.

Après l'étude des causalités potentielles entre les configurations, deux types de modèles mathématiques des performances de fiabilité des systèmes de fabrication reconfigurables ont été construits : deux modèles probabilistes basés sur la distribution exponentielle et la distribution de Weibull, et un autre modèle basé sur une évaluation optimiste ou pessimiste.

Sur la base du modèle fondé sur la distribution exponentielle, il a été prouvé que les ordres de reconfiguration n'ont finalement pas d'incidence sur la fiabilité d'une chaîne de traitement. Cela est dû à l'absence de mémoire du mode de défaillance à distribution exponentielle. Grâce à cette conclusion, lorsque le mode de défaillance est identifié comme étant distribué de manière exponentielle, une organisation manufacturière économisera à la fois du temps et de l'argent sur la conception de la reconfiguration. Sur la base du modèle de distribution de Weibull, il a été prouvé que les ordres de reconfiguration ont un impact sur la fiabilité d'une chaîne de traitement. Les modèles O/P peuvent évaluer les performances de fiabilité dans des scénarios optimistes ou pessimistes. Dans un scénario optimiste, la fiabilité d'une configuration ultérieure est moins ou pas du tout influencée par les configurations antérieures et l'historique d'utilisation du système. Dans les scénarios pessimistes, l'impact est considéré comme plus important. Pour les modèles ci-dessus, il est nécessaire d'effectuer des simulations pour montrer le niveau d'importance de l'impact.

Dans le chapitre suivant, des simulations et des exemples de cas seront utilisés pour vérifier les conclusions proposées à partir des modèles.

Chapitre 3 : Implémentation et évaluation des modèles de performance de fiabilité des systèmes de fabrication reconfigurables

La validation et la vérification constituent la phase finale du cadre proposé pour l'analyse de la fiabilité dans les SGI.

Pour valider les modèles, l'accent est mis sur la simulation et les évaluations de performance, qui sont basées sur les modèles développés au chapitre 2. Les organigrammes de la simulation de Monte

Carlo sont présentés en premier lieu.

Les entrées du cadre sont les paramètres de défaillance, les ordres de configuration et les politiques d'évaluation.

Les résultats sont ensuite les performances de fiabilité pour différentes configurations. Une analyse de sensibilité et des exemples d'application sont fournis pour vérification à la fin de ce chapitre. L'exemple d'utilisation aidera les chercheurs ultérieurs qui pourraient être intéressés par le travail et démontrera la signification pratique de la recherche.

3.1 Simulation de Monte Carlo (MCS)

La simulation de Monte Carlo (MCS) estime des fonctions mathématiques et simule les activités de systèmes complexes à l'aide d'un échantillonnage aléatoire et d'une modélisation statistique. Étant donné sa capacité à se rapprocher de la réalité, elle constitue un solide outil de modélisation pour l'étude des systèmes complexes.

Par rapport aux tests de fiabilité réels, la MCS peut réduire de manière significative les coûts et la durée des tests tout en simulant suffisamment les défaillances du système. Un test de fiabilité classique utilisé pour prédire les taux de défaillance, les temps moyens de défaillance ou d'autres caractéristiques indiquant le comportement de défaillance de composants spécifiques, peut être réalisé physiquement dans un laboratoire à des coûts et dans des délais d'essai raisonnables, alors que pour un système complexe avec différentes configurations, il n'est pas pratique compte tenu des coûts et du temps.

3.2 Évaluations des performances

Avec les algorithmes construits, il a été possible d'évaluer la performance de fiabilité du RMS en se référant à différents modèles : les modèles probabilistes et les modèles d'évaluation.

Les expériences montrent que le temps d'itération (taille de l'échantillon lors du comptage des processus non défaillants à chaque étape) et le temps de simulation (taille de l'échantillon d'ajustement normal du comptage des processus non défaillants) supérieurs à 100 donnent des résultats d'une bonne cohérence.

3.3 Analyse de sensibilité (AS)

Dans cette section, une analyse de sensibilité (AS) est menée sur la SCM proposée dans la Section [?], en ce qui concerne le paramètre : taille de l'échantillon d'itération.

Lors de l'utilisation de simulations de Monte Carlo, il est souvent nécessaire d'effectuer une AS à la fin pour déterminer quelles variables ont la plus grande influence sur les résultats du modèle. Il existe différentes techniques de SA en fonction des caractéristiques du modèle : One-At-a-Time (OAT), méthodes locales basées sur la dérivée, analyse de régression, méthodes basées sur la variance, etc.

En général, lors de l'analyse statistique, on suppose que les variables d'entrée sont indépendantes les unes des autres. Cependant, cette condition peut ne pas être remplie dans certains cas, et il est alors nécessaire de procéder à une Analyse de Sensitivité Globale (ASG). En outre, l'effet d'interaction peut être mesuré par l'indice de sensibilité d'ordre total. Dans cette thèse, on suppose que les variables de l'AS sont indépendantes les unes des autres.

Par conséquent, en suivant la procédure la plus générale, sans tenir compte des interactions entre les variables, cette section évalue la précision de la simulation de Monte Carlo, en vérifiant l'impact des variables d'entrée sur les résultats.

3.4 Exemples d'application

Pour illustrer l'exemple numérique, des ensembles de données provenant d'une étude de Nourelfath et al. [31] sont cités. Ce cas n'est plausible que sur la base de notre conclusion selon laquelle les ordres de reconfiguration n'ont aucun effet sur la fiabilité lorsque le mode de défaillance est de Poisson. Un ajustement logique est effectué sur les données basées sur les hypothèses des auteurs pour s'adapter à notre scénario. Dans leur travail, les auteurs mentionnent qu'en cas de défaillance d'un équipement non essentiel, le système peut continuer à fonctionner. Ainsi, seuls les équipements essentiels sont inclus dans notre ensemble de données. D'après la définition de l'auteur, un RMS est constitué de plusieurs composants qui sont configurés par l'équipement. Chaque fois que le composant est utilisé, une technologie est appliquée, qui décidera de la configuration de l'équipement et du mode de défaillance en même temps. Il existe 3 types de composants, offrant 3 ensembles de données pour notre modèle (Table 3.3).

3.5 Conclusions

Ce chapitre comprend les organigrammes et les algorithmes du MCS, les performances de fiabilité obtenues à partir de la simulation, l'analyse de sensibilité et des exemples d'application.

Les simulations ont été réalisées sur la base des mêmes ensembles de données de fabrication à des fins d'illustration. Les résultats des simulations ont confirmé les conclusions de l'analyse de chaque modèle. L'algorithme de simulation basé sur la méthode de Monte Carlo a été développé par étapes :

- Prendre les paramètres de distribution des défaillances comme entrées.
- Calcul de la fiabilité et de la probabilité conditionnelle.
- Comparaison des valeurs théoriques avec la variable aléatoire.
- Itérer les étapes précédentes.
- Génération de la probabilité qu'aucune défaillance ne se produise à chaque étape.

L'algorithme a réussi à prouver son efficacité. Mais l'essence de la méthode MCS a rendu l'algorithme très fiable sur la base d'hypothèses. Or, dans la plupart des cas, ces hypothèses doivent être justifiées. Par exemple, l'algorithme ne conviendra pas aux scénarios comportant une politique de maintenance.

L'une des principales contributions de ce chapitre est la preuve supplémentaire par simulation que lorsque le mode de défaillance suit une distribution exponentielle, l'ordre de reconfiguration n'a pas d'impact sur les performances de fiabilité. En procédant à des étapes de traitement, les performances en matière de fiabilité finissent par converger.

Cette nouvelle découverte démontre deux choses. Premièrement, lorsqu'une entreprise manufacturière confirme que sa défaillance RMS suit la distribution exponentielle, il n'est pas nécessaire d'investir dans des simulations avec différents ordres de configuration puisque les performances de fiabilité sont cohérentes dans tous les cas. Deuxièmement, lorsque le mode de défaillance suit la distribution de Weibull, les ordres de configuration ont un impact significatif sur les performances de fiabilité. Par conséquent, une approche visant à améliorer les performances de fiabilité d'une entreprise pourrait consister à travailler sur les ordres de configuration.

Conclusion et travaux futurs

Conclusion

L'objectif de cette recherche est de proposer un cadre pour l'analyse de fiabilité appliquée dans les SGI. Pour rappel et comme indiqué dans l'introduction, un objectif global a été fixé au début de la recherche :

*Comment **les choix** faits pour les systèmes de fabrication reconfigurables **impactent** les différentes formes de **performance de fiabilité** pendant toute la procédure de traitement malgré la complexité croissante des systèmes ?*

Examen de l'analyse de fiabilité dans les systèmes de fabrication reconfigurables

Pour répondre à la question soulevée dans l'objectif général, une recherche de fond a été nécessaire et des tâches dispersées ont été énumérées, comme le montre le Chapitre 1 ci-dessous.

Le Chapitre 1 a jeté les bases de la recherche en triant les connaissances de base, en procédant à des analyses documentaires et en analysant les tendances actuelles de la recherche. Des efforts particuliers ont été consacrés à l'examen de *l'analyse de fiabilité appliquée aux SGI*, avec l'application de VOSviewer et de cartes conceptuelles, sur la base des techniques de l'analyse du réseau de citations.

Les étapes ci-dessus ont permis de conclure que l'analyse de fiabilité des RMS diffère grandement de celle d'un système de production conventionnel. Par conséquent, deux contributions principales ont été apportées : les distinctions fondamentales entre les RMS et les systèmes de fabrication généraux lors de l'analyse de fiabilité et les défis de l'étude dans cette thèse, comme indiqué dans la liste suivante :

- *Comment vérifier si les interactions/interfaces ont un impact sur les performances de fiabilité d'un RMS ?*
- *Dans quels cas, les impacts sont négligeables ou non négligeables ?*
- *Si les impacts existent, comment décrire les causalités entre les configurations ?*
- *Lors de la description des causalités entre les configurations, comment estimer et fixer les limites ?*
- *Si les interactions/interfaces ont un impact sur la fiabilité d'un RMS, quelle est l'importance de cet impact et comment le mesurer ?*

Modèles de fiabilité des systèmes de fabrication reconfigurables

Les tâches ayant été décomposées au Chapitre 1, le Chapitre 2 a été consacré à la construction de modèles prenant en compte ces critères uniques.

Tout d'abord, le système objectif a été décrit avec ses caractéristiques générales, ses hypothèses et ses caractéristiques RMS. La reconfigurabilité basée sur les ordres de configuration est ensuite discutée et illustrée par une chaîne de Markov. Cette étape de la recherche comprend également les modèles qui décrivent les causalités. Ensuite, deux types de modèles mathématiques des performances de fiabilité des systèmes de fabrication reconfigurables ont été développés : deux modèles probabilistes, l'un basé sur la distribution exponentielle et l'autre sur la distribution de Weibull, et un modèle basé sur une évaluation optimiste ou pessimiste. Enfin, les trois modèles sont décrits en détail, y compris leurs hypothèses et leurs formulations mathématiques. Une explication des propriétés du modèle et de l'étape suivante de la vérification est fournie. Jusqu'à présent, il a été possible de répondre à certaines questions :

Comment vérifier si les interactions/interfaces ont un impact sur la fiabilité d'un RMS ?

L'impact peut être vérifié par le biais de trois approches facultatives : le calcul d'une formule mathématique, le résultat d'une simulation et l'application d'un cas réel. Une définition du système était absolument nécessaire, car différents RMS pouvaient avoir des interactions/interfaces différentes. Dans cette recherche, le calcul de la formule mathématique et la simulation ont été adoptés sur la base des conditions disponibles.

Dans quels cas les impacts sont-ils négligeables ou non négligeables ?

Les formulations mathématiques des deux modèles probabilistes ont prouvé que, lorsque le mode de défaillance suit une distribution exponentielle, la réponse est *Non*, ce qui signifie qu'il n'y a pas d'impact des itérations/interfaces du RMS. Lorsque le mode de défaillance suit la distribution de Weibull, la réponse est *Oui*, ce qui signifie qu'un tel impact existe. La raison en est la caractéristique de non-mémorisation de la distribution exponentielle, qui permet à un composant d'être utilisé indépendamment de son historique d'utilisation. Dans d'autres cas, l'historique d'utilisation d'un composant ne peut être ignoré, et l'impact est donc censé exister.

Si les impacts existent, comment décrire les causalités entre les configurations ?

Comme il a été répondu à la Question 2, l'impact n'existe pas lorsque le mode de défaillance suit

une distribution exponentielle. On suppose donc que toutes les autres distributions nécessitent la prise en compte de l'impact. Pour les modes de défaillance suivant d'autres distributions, les causalités ont été analysées par le biais d'un classement, qui prend en compte autant de possibilités que possible pour être exhaustif : pas d'impact, impact limité, impact total, impact basé sur la continuité et causalité hybride.

When describing the causalities between configurations, how to estimate and set limit

The third model, O/P assessment policy model, was built to describe the causalities between configurations and set limits to the reliability performances. Due to the comprehensive knowledge being hard to be acquired in real cases, the epistemic uncertainty of the system can not be ignored. In this case, the two extreme cases, the most optimistic and the most pessimistic situation, could set the limits for the model. Further more, a parameter showing the level of optimism and pessimism would help with the estimation.

Simulation et évaluation des modèles de performance de fiabilité des systèmes de fabrication reconfigurables

La dernière étape du cadre proposé pour l'analyse de fiabilité dans les SGI est la vérification et la validation.

Afin de valider les modèles, le Chapitre 3 se concentre sur la simulation et les évaluations de performance, qui sont basées sur les modèles développés au Chapitre 2. Ce chapitre contribue à l'élaboration des organigrammes et de l'algorithme de simulation de Monte Carlo. Les paramètres de défaillance, les ordres de configuration et les politiques d'évaluation sont les entrées du cadre. Les résultats sont alors les performances de fiabilité pour différentes configurations.

Enfin, des exemples d'application sont fournis pour aider les futurs chercheurs qui pourraient être intéressés par ce travail et pour démontrer l'importance pratique de la recherche.

Le Chapitre 3 répond à la dernière question :

Si les interactions/interfaces ont un impact sur la fiabilité d'un RMS, quelle est l'importance de cet impact et comment le mesurer ? L'importance de l'impact nécessitait une présentation plus intuitive au moyen de données, obtenues soit par simulation, soit par expérimentation. Dans cette recherche, la simulation de Monte Carlo a été adoptée pour répondre à cette question. Au cours de la mesure, il a fallu accorder une attention particulière à la précision de la simulation et au réglage des paramètres. En

fin de compte, la simulation de Monte Carlo permet de mieux vérifier les conclusions des formulations mathématiques, comme indiqué dans la réponse à la Question 2.

Perspectives futures

Comme nous l'avons vu dans cette thèse, il y a certaines limites à la modélisation des problèmes. Cette thèse a principalement étudié deux distributions, et a testé brièvement deux autres distributions. Les études ultérieures d'autres modèles et leur sélection méritent d'être étudiées. Le paramètre défini pour le modèle O/P, le niveau d'optimisme et de pessimisme, était un indice simplifié, décrivant les situations de manière idéale, bien que dans les scénarios réels, il puisse être plus compliqué. Le mécanisme de défaillance du RMT se réfère aux prototypes existants, alors que les différents types peuvent nécessiter des méthodes spécifiques d'analyse des performances en matière de fiabilité. Les explications détaillées des perspectives d'avenir sont présentées ci-dessous, conformément aux limitations susmentionnées.

Mode de défaillance suivant d'autres distributions

Les modes de défaillance qui suivent la distribution exponentielle et la distribution de Weibull ont été étudiés et modélisés dans cette thèse. Le modèle O/P était également basé sur la distribution de Weibull. D'autres distributions probabilistes, adaptées aux données de défaillance de l'objet de recherche, ont été testées sur les modèles. Parmi les autres distributions courantes pouvant faire l'objet de tests supplémentaires, citons : Valeur extrême, Erlang, Chi-carré, distributions Gamma et distributions auxiliaires, estimation bayésienne de la fiabilité. Bien que le cadre proposé puisse s'adapter à toutes ces distributions, l'analyse des résultats de ces autres distributions peut être intéressante, car elles possèdent toutes des caractéristiques uniques. La méthodologie permettant de choisir les distributions avec précision peut également être étudiée.

Paramètre du niveau d'optimisme et de pessimisme

Comme indiqué au Chapitre 2, un paramètre indiquant le niveau d'optimisme et de pessimisme mérite d'être étudié. Cette thèse ne s'est pas efforcée de définir ce paramètre spécifique pour répondre aux scénarios réels, alors que dans l'étape suivante du modèle O/P, il peut s'agir d'un élément crucial. Ce paramètre, le niveau d'O/P, peut être défini en fonction de nombreux facteurs : les caractéristiques des produits, l'historique d'utilisation du système, l'importance de la commande, la préférence de

l'entreprise en matière de décision, etc. Tous ces facteurs peuvent avoir une influence sur le degré d'optimisme ou de pessimisme du modèle. Lorsque ces facteurs tendent à être conservateurs, il convient d'adopter une politique d'évaluation plus pessimiste.

Mécanisme de défaillance d'un outil de fabrication reconfigurable

Lorsqu'une recherche interdisciplinaire est possible, certains chercheurs estiment qu'il peut être intéressant d'approfondir le mécanisme de la défaillance. La question qui se pose est la suivante : comment les différentes configurations influencent-elles les performances en matière de fiabilité ? Quel est l'impact des différentes configurations sur la fiabilité des performances de l'outil de fabrication reconfigurable en ce qui concerne ses mécanismes de défaillance ? Dans ce cas, les RMT ont besoin de modèles 3D concrets, avec l'aide de logiciels de modélisation mécanique et d'analyse des forces. Cette perspective convient mieux à un cas réel de RMS composé de RMT, dans des entreprises de fabrication réelles. En outre, les modèles présentés dans cette thèse se sont concentrés sur la probabilité qu'aucune défaillance ne se produise à chaque étape. Une autre perspective peut être l'étude du nombre de défaillances survenant au cours du processus de fabrication, pour laquelle une hypothèse de *réparabilité* est ajoutée. Dans ce scénario, un modèle *k-out-of-m* serait applicable puisque les composants peuvent être réparés par réarrangement et maintenance [32].

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Acronym and notations

Acronym	
I4.0	Industrial 4.0
AI	Artificial Intelligence
IoT	Internet of Things
OEE	Overall Equipment Effectiveness
CNA	Citation Network Analysis
RMS	Reconfigurable Manufacturing System
RMTs	Reconfigurable Manufacturing Tools
ML/AI	Machine Learning and Artificial Intelligence
AR	Augmented Reality
VR	Virtual Reality
MC	Markov Chain
FTA	Fault Tree Analysis
FMEA	Failure Mode and Effect Analysis
MTTF	Mean Time To Failure
MTBF	Mean Time Between Failure

LISTE DES TABLEAUX

GA	Genetic Algorithm
SVT	Supplementary Variable Technique
CDF	Cumulative Distribution Function
PDF	Probability Distribution Function
PP	Probability Plotting
WPP	Weibull Probability Plot
LSM	Least Squares Method
MLE	Maximum Likelihood Estimation
DMS	Dedicated Manufacturing System
FMS	Flexible Manufacturing System
CMS	Changeable Manufacturing System
SMS	Smart Manufacturing System
CPPS	Cyber-Physical Production System
RTSs	Reconfigurable Transportation Systems
RIM	Reconfigurable Inspection Machine
RAM	Reconfigurable Assembly Machine
CNC	Computer Numerical Control
RPKM	Reconfigurable Parallel Kinematic Machine
SRMS	Sustainable Reconfigurable Manufacturing System
SSrMS	Smart Self-Reconfigurable Manufacturing System
CRMS	Cellular Reconfigurable Manufacturing System

WoS	Web of Science
FMCs	Flexible Manufacturing Cells
PT	Place/Transition
O/P	Optimistic and Pessimistic
MCS	Monte Carlo Simulation
SA	Sensitivity Analysis
OAT	One-At-a-Time
GSA	Global Sensitivity Analysis
CV	Coefficient of Variation
 Notation	
t	System time
k	Number of working component
n	Number of component consisting a system or number of equipment consisting a component
$F(t)$	Unreliability function at time t in general sense
$R(t)$	Reliability function at time t in general sense
λ	Failure rate in general sense
η	Scale parameter of the Exponential distribution and the Weibull distribution
β	Shape parameter of the Weibull distribution
$f(t)$	PDF function at time t in general sense

LISTE DES TABLEAUX

i	The i th processing step during manufacturing
$config.m$	The m th configuration
M_p	Total number of processing steps
M	Total number of configurations
$\lambda_{i,m}(t)$	Failure rate of m th configuration on the i th processing step at time t
S_i	System time when i th processing step finishes
N	The minimum number of RMTs in a processing line
T_Q	Total processing time required to meet the demands
T_w	Working time for each RMT
R_{tr}	Reliability threshold for each machine, with given time unit
I	Total number of functions for one RMT
J	Total number of tool parameters for one RMT
N_c	The optional configurations for one RMT
m_k	Number of interfaces
$n_{k,l}$	number of tools for function k with parameter l
U_i, D_i	Up and down state for i th processing step
$F_{i,m}(t)$	Component unreliability function at time t with $config.m$ on processing step i
$R_{i,m}(t)$	Component reliability function at time t with $config.m$ on processing step i
$\mu_{i,m}(t)$	Repairing rate of m th configuration on the i th processing step
$\kappa_{i,m}$	Non-repairing rate on the i th processing step
f_i	PDF function of processing step i

LISTE DES TABLEAUX

P_i	Probability that the i th processing step finishes without failure
T_i	Time duration before failure occurs for processing step i
$t_{i,m}$	Processing time of configuration for m on i th processing step
β_m, η_m	Shape and scale parameters of <i>config.m</i> of the Weibull distribution
T	Time duration before failure occurs in a general sense
ξ	Number of parameters of a distribution
$N_{para}(m)$	Number of parameters for a processing line with m configurations
θ_m, α_m	Weibull parameters presented in another form
r, s	Random time duration in a general sense
τ_m	Starting time of Weibull distribution of <i>config.m</i>
c	Constant value
ρ	Level of optimism and pessimism during for assessment policy
U	Generated data from random distribution over (0,1]
CO_γ	The γ th configuration order
Γ	Gamma function

Introduction

The fourth industrial revolution, Industry 4.0 (I4.0), originated in 2011 from a project in the high-tech strategy of the German government, will unavoidably influence how industrial systems develop in the future. In a nutshell, to make manufacturing faster, more efficient and more customer-centric, I4.0 brings together the developments like Artificial Intelligence (AI), Big Data, Additive Manufacturing, Internet of Things (IoT), cloud computing and analytic in production facilities and across their operations (see Fig.1). It is necessary to use the I4.0 idea as a foundation for developing manufacturing systems in the current time.

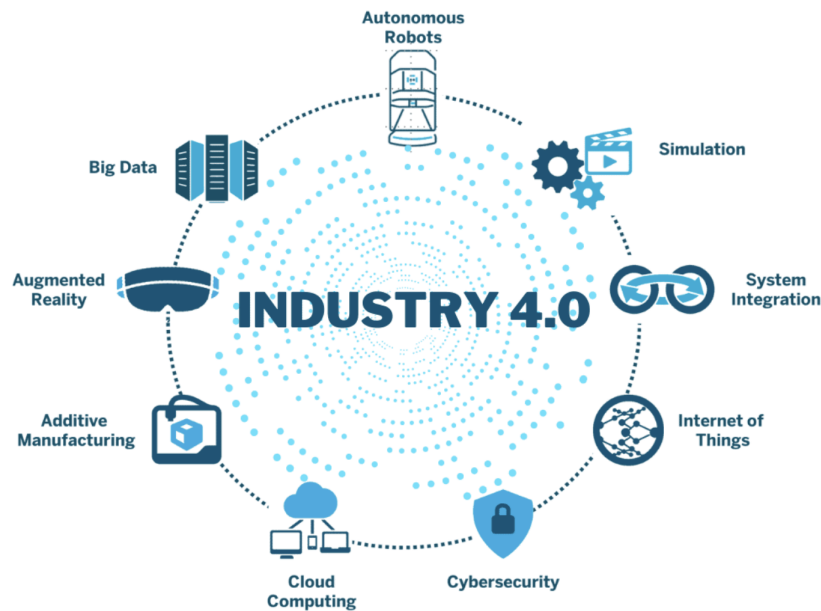


FIGURE 1 – Main concepts in Industry 4.0 [33]

In the I4.0 plan, a particular index that is given significant weight is *quality*. To evaluate quality, a lot of studies have been done and numerous tools have been applied. Equally important as quality, the index *reliability* – as *quality changing over time* – has played an important role in the design and evaluation of manufacturing systems. However, when analyzing important attribute *reliability*, there can be a huge variety of I4.0 systems and architectures. Under different contexts, quality or reliability can be defined by : durability, availability, probability or degradation. Beside the above aspects, quality and reliability can also be measured by specifically developed performance indexes. For example the Overall Equipment Effectiveness (OEE), which is defined by three factors : availability, performance, and quality.

For last two decades, manufacturing system has been continuously evolving to meet the industrial competition under the I4.0 context. A paradigm of Reconfigurable Manufacturing System (RMS) managed to meet the characterizations of globalization : rapid response with low cost and high quality.

A challenging problem which arises with such development is the reliability analysis of RMS. The problem is difficult to handle for three main reasons :

1. The definition of reliability varies greatly depending on the context, especially for newly established manufacturing system paradigms. New reliability analysis methodologies will be required in response to the newly introduced I4.0 systems.
2. The number of interactions/interfaces (mechanical or non-mechanical) within RMS is enormous, yet extremely influential. This leads to a significant increase in model complexity.
3. As RMS advances from theory to application, more realistic problems will arise, necessitating reliability analysis that is more concerned with the application and reconfigurability.

In summary, as shown in Fig.2 , it is necessary to conduct research on the reliability of RMS using newly defined concepts of reliability, take into account the particularity of this system paradigm, and pay more attention to the reconfigurability and other crucial characteristics in application.

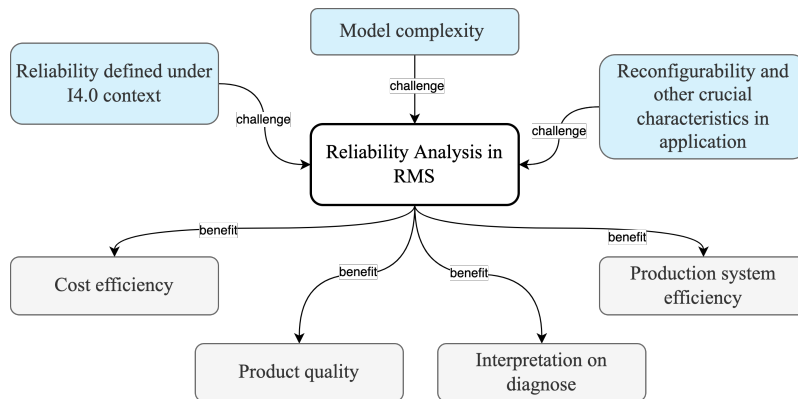


FIGURE 2 – Research challenges and benefits

This thesis located the research in response to the question :

How do the choices made for reconfigurable manufacturing systems impact various forms of reliability performance during the whole processing procedure despite the increasing complexity of the systems ?

Answering the question above will benefit in saving the energy and time of reliability analysis for a

manufacturing company, improving the quality of products produced in RMS, helping interpreting the results from diagnose during manufacturing and increasing production system efficiencies (see Fig.2).

To tackle the challenge, the framework of the research methodology shown in Fig.3 is created. The methodology is divided into two main bodies : 1) establishment of the foundation and 2) models development, validation and verification. On the top of the methodology framework, are the tools, approaches or methods applied, the boxes in the middle shows the main steps in this research and on the bottoms are the outputs and main contributions.

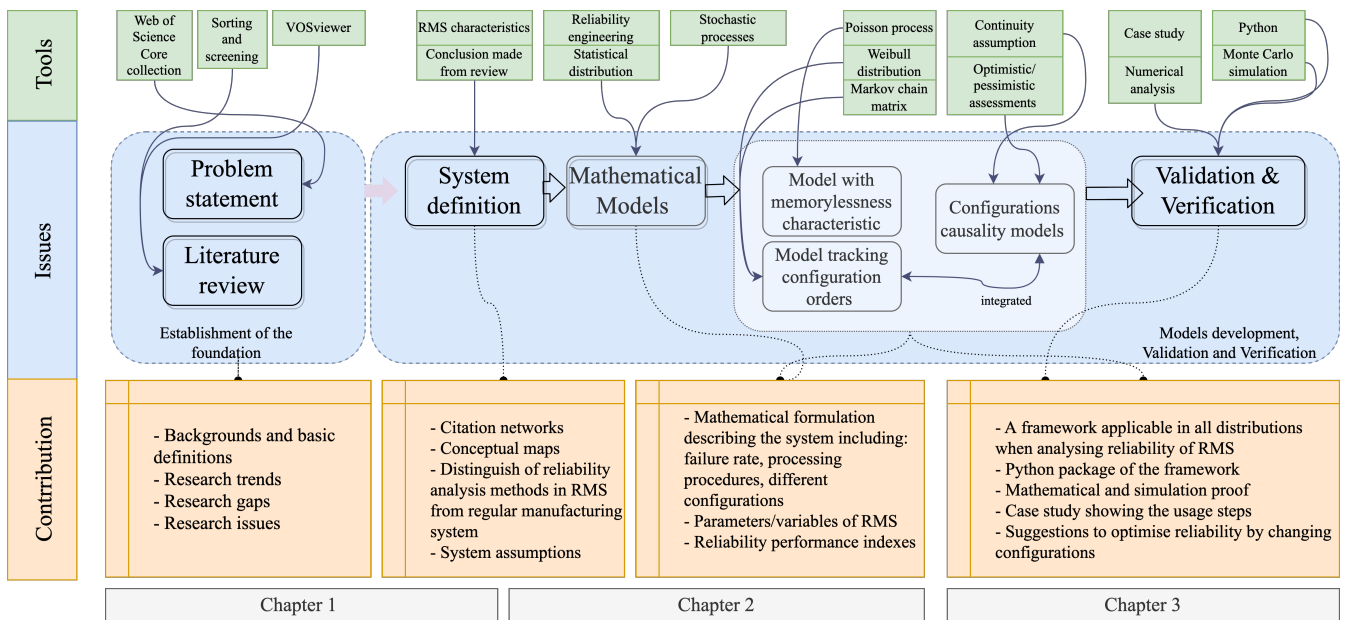


FIGURE 3 – Research methodology

This thesis is structured into three distinct chapters, each of which delves into a unique aspect of the research topic. Chapter 1 introduces the general concepts of reliability analysis and reconfigurable manufacturing systems. Literature reviews were carried out by four aspects : reliability analysis methods, manufacturing system paradigms, reconfigurable manufacturing tools and reliability analysis in RMS. Specifically for the fourth aspect, which is also the main interest of this research, Citation Network Analysis (CNA) was conducted, and based on which conceptual maps were built, to clarify both existent branches and the scope of research. Based on the preceding study, the particularity of RMS reliability analysis in comparison to general manufacturing systems was discussed, revealing the detailed challenge of this thesis presented in a series of questions and a flowchart.

Chapter 2 presents the description of the RMS. The Reconfigurable Manufacturing Tools (RMTs) concept was utilized to realize reconfigurability. The RMT meets four of the reconfigurability characteristics – modularity, integrability, convertibility and diagnosability. Then models of reliability performance of RMS were presented. Firstly, the models based on two probability distributions were developed – Exponential distribution and Weibull distribution. The impacts of reconfiguration orders on reliability performance were analyzed respectively. Then a model based on assessment policies was built, which can be more applicable when the epistemic uncertainty exists. The optimistic and pessimistic occasions serve as two extreme cases, restraining all the possible level of reliability performances into it. Besides the reliability models, three other parts include explanation of the complexity for parameter identification, configuration presented in Markov chain, and causality analysis between configurations. These three parts were special and necessary for RMS reliability analysis in comparison to general manufacturing systems.

Chapter 3 focuses on validating and verifying the models created in Chapter 2. First, a flow-chart and simulation algorithms were created to perform Monte Carlo simulations on the reliability performance with various configuration options. Second, the performances were evaluated, with specific attention to the RMS with different configuration orders. The evaluation results from simulation were compared with the conclusions drawn from mathematical formulations. Additionally, sensitivity analysis and numerical examples illustrating usage were given.

In the end, the thesis gives conclusions and suggestions for future research.

Chapitre 1

A Review of Reliability Analysis in Reconfigurable Manufacturing Systems

To begin the research, investigations of the existing studies are necessary, so we formalized a systematic literature analysis of reliability analysis of manufacturing systems, manufacturing system paradigms, Reconfigurable Manufacturing Systems (RMS), Reconfigurable Manufacturing Tools (RMTs) and reliability analysis in RMS. Especially for *reliability analysis in RMS*, Citation Network Analysis (CNA) was conducted to analyze associations between literatures, thus locating important research aspects and corresponding influential articles. The various definitions and methods gleaned from the literatures were summarized in conceptual maps. Then, based on the research above, the specialty of RMS reliability analysis was discussed, and challenges of study were given in a flowchart and series of questions to be answered in the following chapters.

1.1 Reliability analysis of manufacturing systems

Reliability engineering is a formal discipline based particularly on probability theory and statistics which aims at enabling systems and components to function without failure. Reliability testing and reliability modeling are the two main branches of reliability engineering. Traditional studies focus on life test [1] or degradation test [2], through which reliability can be calculated or estimated through statistic distributions [3]. With technology and systems improving, the complexity of reliability studies also increases.

1.1.1 Quality and reliability in various scenarios

Some common quality and reliability assessment tools under the I4.0 context include :

- Machine Learning and Artificial Intelligence (ML/AI) [38,39]
- Mobile technology, Augmented Reality (AR), and Virtual Reality (VR) [40]
- Cloud technologies [41]
- Connected Devices and Edge Devices [42]
- Big Data and Data Lakes [43]
- Block-chain [44]

Despite their close relationship, quality and reliability are distinct ideas. *Reliability* can be commonly interpreted as *quality changing over time*. More specifically, the distinction between quality and reliability is that quality demonstrates how well an object fulfills its intended job, whereas reliability

shows how well this thing retains its initial level of quality through time and under diverse situations. The reliability in this research is defined as system performance at various processing times.

Through the last few decades, extensive research has been conducted on reliability analysis as it applies to manufacturing systems [30, 45–47]. The main aim of reliability analysis of systems is to quantify the probability of failure of a system, via a collection of formal approaches for studying the uncertain boundaries between system functioning and failure. Some questions to be addressed include :

- How system fail caused by failure mechanisms.
- How to design a reliable system.
- How to diagnose a system, such as the measure and the test of reliability.
- How to main the reliability of a system, such as maintenance and repair.

And to answer the questions above, the following issues are listed :

- Describe the system with definitions, assumptions and models.
- Quantify the system models.
- Represent, propagate and quantify the uncertainties in the system behavior.

These problems above still exist today, even though system reliability analysis is an established field. And the increasing complexity of the systems may have made them more difficult [37]. In summary, the main research streams are : machine/system performance analysis, reliability analysis of complex systems, product reliability analysis, fatigue reliability, reliability testing and human reliability analysis, etc.

In accordance with research topics in this thesis, some important research streams have been refined, with special attention to flexible designs [30] : quality-reliability model [48–50], multi-state system reliability [10, 51–57] and dynamic maintenance strategy [58–60].

The quality-reliability model focuses on how the system reliability and product quality are interdependent. When assessing co-effect between quality and reliability, the model takes into account the deterioration of any component that could lead to a decline in the quality of the final product [48, 49]. And at the same time, the system reliability performance can be impacted by deterioration of the incoming product quality [50]. This model accounts for the intricate propagation relationship between product quality and component reliability, but it also necessitates a high degree of system diagnosability. However, obtaining a high level of diagnosability is not always simple in real life.

The multi-state system reliability analysis assumes that reliability could be featured as the degradation state of components/systems. Usually, reliability problem either assume that components are working or failed or assume that components could work under a range of degraded states [51]. Reliability has been defined as the probability that a required demand can be fulfilled from source to sink through the multi-state links [52, 53], or for a multi-state manufacturing network with joint buffer [54–56], or reliability function based on survival signature [57]. The k -out-of- n model assumes that a system with n components could still function with only k working components (see Fig.1.1). And hence, it is a type of multi-state system. A system’s reliability can sometimes be increased by altering the value of k . Examples include altering k during each stage of a phased mission, in response to a component failure, altering k in cyclic systems or in response to the ambiguity of operating conditions [10]. However, when employed by a manufacturing company, the term *multi-state system* is more theoretical than a particular manufacturing system paradigm.

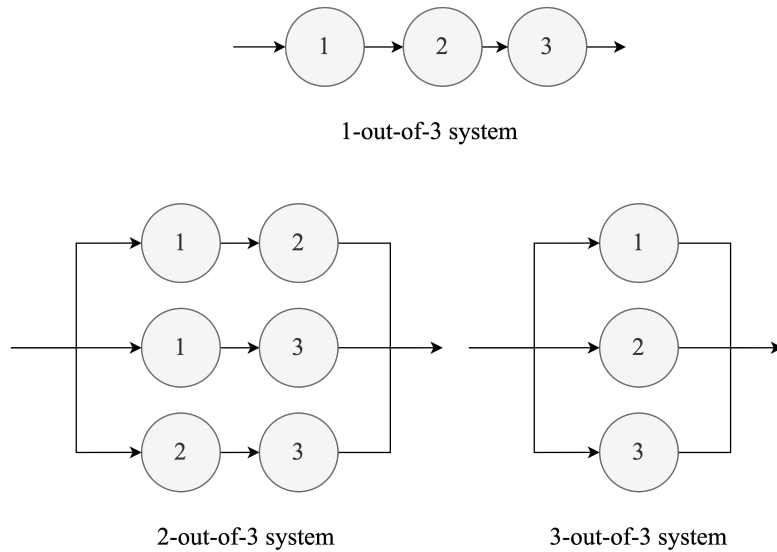


FIGURE 1.1 – k -out-of- n models

The maintenance strategy conducts preventive maintenance to improve the reliability of manufacturing systems [58, 59]. Lu et Zhou [60] mentioned a future research perspective of extending the existent maintenance strategy to the reconfigurable manufacturing systems, which requires a dynamic maintenance strategy capable of adapting to the system.

In summary, the focus of the above reliability analysis differs according to different scenarios. When applied in non-repairable systems, the binary-state reliability problem either assume that components

are working or failed, in which research object is the measurement of the probability of functioning state $\{Up\}$. In systems with repairability or multi-state characteristics, reliability is analyzed with integration of maintainability and repairability. Multi-state systems assume the ability of system and components to function under a range of degraded states. In such systems, the fault dependence and competitions between components triggered research interest of many scholars [61–64].

1.1.2 Reliability analysis techniques and models

To study on the main streams discussed above, suitable approaches are essential. Researchers with various academic expertise use diverse approaches to evaluate the reliability performance of a system or an equipment. Common techniques and models can be categorized into five categories, in which some of them may appear more than once.

- **State model** Markov Chain (MC) [4–6], Petri-nets [7, 8].
- **Probabilistic model** Exponential, Weibull, Normal, Log-normal, Extreme Value, Erlang, Chi-Square, Gamma Distributions and Auxiliary distributions, Bayesian reliability estimation [8].
- **Composite system models** Fault Tree Analysis (FTA), Failure Mode and Effect Analysis (FMEA) [9], k -out-of- n [10], Decomposition Method [11], Mean Time To Failure (MTTF), Mean Time Between Failure (MTBF) [12].
- **Graphical technique** Probability plotting for parameters, Markov Chain (MC) [4, 6], Petri-nets [13, 14], Non-Parametric Plotting [15].
- **Computational algorithms and techniques** Genetic Algorithm (GA) [16], fuzzy Lambda-Tau technique [14], Supplementary Variable Technique (SVT) [17].

When analyzed by these techniques and models, reliability may be closely related to : availability, maintainability, dependability and degradation etc.

Generally, the Cumulative Distribution Function (CDF) of T , denoted by $F(t)$, is the probability that lifetime does not exceed time t , as shown in Equation 1.1 :

$$F(t) = \Pr\{T \leq t\}, \quad 0 < t < \infty \quad (1.1)$$

When CDF is a continuous function of t , the lifetime variable T is continuous. The Probability

Density Function (PDF) of T is its derivative, and is denoted by $f(t)$, as shown in Equation 1.2

$$F(t) = \int_0^t f(x)dx, \quad 0 \leq t < \infty \quad (1.2)$$

Then the reliability function is shown in Equation 1.3 :

$$R(t) = 1 - \int_0^t f(x)dx, \quad 0 \leq t < \infty \quad (1.3)$$

Several common probabilistic models have the following characteristics and reliability functions.

(i) **Exponential distribution** with constant failure rate implies that the components have no memory of the past, or, in other words, do not age. A component following Exponential distribution also has the characteristic of MTTF equals to η . Its failure rate function is defined as shown in Equation 1.4 :

$$\lambda(t) = \begin{cases} 0, & t < 0 \\ \frac{1}{\eta}, & t \geq 0 \end{cases} \quad (1.4)$$

Its reliability function is shown in Equation 1.5 [65] :

$$R(t) = \exp\left\{-\frac{1}{\eta} \int_0^t dx\right\} = \exp\{-t/\eta\} \quad (1.5)$$

Then, the unreliability, CDF is shown in Equation 1.6 :

$$F(t) = 1 - \exp\{-t/\eta\} \quad (1.6)$$

With the reliability and unreliability functions, the PDF is shown in Equation 1.7 :

$$f(t) = \begin{cases} 0, & t < 0 \\ \frac{1}{\eta} \exp(-t/\eta), & t \geq 0 \end{cases} \quad (1.7)$$

Where η is called scale parameter, later parts will illustrate its connection with the Weibull distribution.

(ii) **Weibull distribution** is frequently used to describe component failure data. Weibull distribution is commonly defined by shape parameter β and scale parameter η .

The failure rate of Weibull distribution is defined as shown in Equation 1.8 :

$$\lambda(t) = \begin{cases} 0, & t < 0 \\ \lambda(t) = \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1}, & t \geq 0 \end{cases} \quad (1.8)$$

One of the most essential characteristic of this distribution is the effect of value β on the entire Weibull distribution. When $\beta < 1$, the component has a decreasing failure rate, or as called *infantile* or *early life failure*. When $\beta = 1$, it becomes Exponential distribution, the component has random failures with constant failure rate. When $\beta > 1$, the component has a increasing failure rate, or as called *late life failure*.

The reliability function is shown in Equation 1.9 [65] :

$$R(t) = \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right) \quad (1.9)$$

Then, the unreliability, CDF is shown in Equation 1.10 :

$$F(t) = 1 - \exp\left(-\left(\frac{t}{\eta}\right)^\beta\right) \quad (1.10)$$

With the reliability and unreliability functions, the PDF is shown in Equation 1.11.

$$f(t) = \begin{cases} 0, & t < 0 \\ \frac{\beta}{\eta} \left(\frac{t}{\eta}\right)^{\beta-1} e^{-\left(\frac{t}{\eta}\right)^\beta} & t \geq 0 \end{cases} \quad (1.11)$$

A component following Weibull distribution has the MTTF as shown in Equation 1.12

$$MTTF = \eta \times \Gamma\left(1 + \frac{1}{\beta}\right) \quad (1.12)$$

Besides the common reliability analysis techniques and models discussed in this section, the parameter identification is an important aspect to be discussed in this thesis.

1.1.3 Parameter Identification Methods

In this section, a review of the parameter identification methods is given, and in Section 2.3, further discussion will be given to prove why parameter identification methods do not fit the research in this thesis, and thus requesting that this research look into alternative solutions to the problem. Parameter identification is commonly utilized in the development of models and controllers. The common parameter identification methods include :

- **Probability Plotting (PP)**, a method of identifying parameter values by plotting data on special plotting paper and calculating parameters from the visual plot. For example, the Weibull Probability Plot (WPP) is the probability plotting method especially for Weibull distribution [18].

- **Least Squares Method (LSM)**, a method which identifies parameter values that minimizes the sum of residual squares [19].
- **Maximum Likelihood Estimation (MLE)**, which seeks parameter values that optimize the likelihood function given a collection of observations [20].
- **Bayesian Estimation Methods**, a batch of parameter identification methods that attempt to minimize the posterior expectation of the utility function. This indicates that existing knowledge about a situation is formed, evidence is obtained, and then posterior information is used to update the ideas [21].

All of above strategies provide parameter estimators with a variety of useful characteristics.

In conclusion, the majority of prior researches has investigated reliability as an output, generated by system architecture and production process, while reliability could play role of input. A more dynamic point of view would pay attention to the interaction between quality and reliability, during evaluation performance of a system [66, 67]. Indeed, for general manufacturing systems, reliability analysis has formed mature frameworks and methods. Yet a further question is, *with emerging of the new manufacturing system paradigms, whether these reliability analysis methods and tools adapt to the new complexity?* This question will be further discussed in section 1.5.

1.2 Manufacturing system paradigms

Manufacturing systems continue to evolve over many decades driven by the improvement and advancement of technology. Constant emerging of new materials, new products and new applications require new manufacturing strategies which enable high reliability and low cost. This section aims to carry out a brief review of the existing manufacturing system paradigms, as well as a detailed introduction of our research object – reconfigurable manufacturing systems.

1.2.1 Sorting by appearance orders

To organize the system paradigms according to timeline, some of the earliest paradigms include craft production and job shops, which require high human involvements and provide low-volume products. Then the occurrence of Dedicated Manufacturing System (DMS) made it possible to mass produce limited kinds of products. In modern ages, some well-known manufacturing system paradigms

1.2. MANUFACTURING SYSTEM PARADIGMS

include Flexible Manufacturing System (FMS), Reconfigurable manufacturing System (RMS) and Changeable Manufacturing System (CMS). The number of publications of these system paradigms have remained relatively high since 2010 [22]. Some of the newly studied manufacturing system paradigms include Smart Manufacturing System (SMS) and Cyber-Physical Production System (CPPS) which possess the ability to intelligently gather information from their environment and act independently.

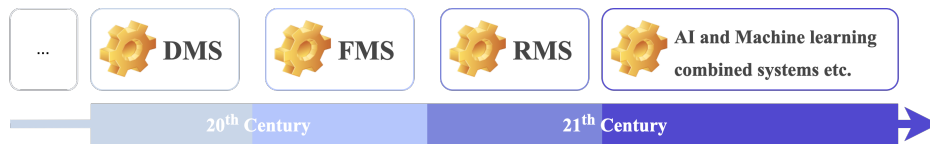


FIGURE 1.2 – Appearance timeline of system paradigms

Fig. 1.2 shows a timeline of the occurrence of the main paradigms : DMS, FMS, RMS and others. DMS first existed before the mid-twenties and was widely used in industries throughout the second half of the twentieth century. FMS first arose in the latter half of the twentieth century. RMS was proposed at the end of the twentieth century. And the systems with the help from AI or machine learning techniques such as SMS emerges in the start of the twenty-first century and will keep evolving. This thesis concentrates on the RMS paradigm since it has now reached the stage of transition from theory to implementation.

1.2.2 Comparison among the system paradigms

RMS, FMS and DMS are frequently being compared in research [68–70]. DMS is created for mass production for just one or a small number of product types, using the *Economy of Scale* concept to maximize productivity and cut costs. Although the main benefit of DMS is cost effectiveness when manufacturing volume is very high, this conclusion may be erroneous when inventory costs and defective costs are taken into account. FMS and RMS, in contrast to DMS, are *variety-oriented* production systems that enable a wide variety of products. But RMS emphasizes on product family, which FMS emphasized on machines. FMS has the features of adaptability, responsiveness, agility, waste reduction and lean manufacturing. RMS has the features of modularity, integrability, customization, convertibility, diagnosability and scalability. Relatively, FMS provides general flexibility, by adjustable system structure and fixed machine structure. While RMS provides customized flexibility, by adjustable system structure and adjustable machine structure, based on intermediate expenses. Beyond flexibility

and reconfigurability, the changeability enables dynamic adaption of the production on the levels till systems, factories and production networks. For manufacturing systems, the design of RMS/FMS integrated within CMS is feasible. Briefly, FMS has the most diversity and the lowest volume, whereas

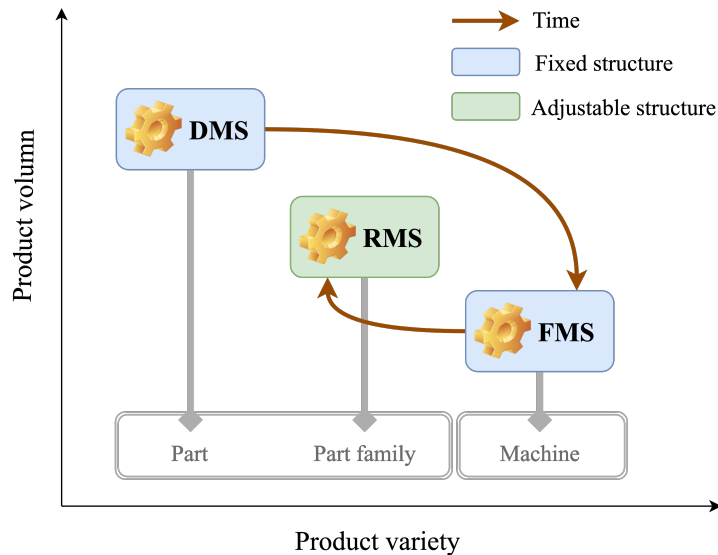


FIGURE 1.3 – Comparison between system paradigms

DMS has the least variety and the highest volume. RMS is ideally situated between them as shown in Fig.1.3, where the three paradigms in terms of product diversity and volume were compared, as well as system structure and emphasis. In this thesis, RMS is the main research object.

1.3 Reconfigurable Manufacturing System (RMS)

*To compete globally, the twenty-first century manufacturing systems should have three goals : produce at **low cost**, enhance **product quality** and respond **rapidly and cost-effectively** to market changes [23].*

RMS was introduced by Yoram Koren [24,25] in 1999 to face the challenge of sudden changes in market or regulatory requirements. In order to react and respond quickly and efficiently to changing requirements, this system paradigm may enables adding, removing, modifying, or exchanging machine components, machine software, or material handling units. The keyword 'Reconfigurable Manufacturing' presents 211,000 citations in Google Scholar. Meanwhile, based on a review article made by Bortolini [26], up to the 60% of the paper database is published after 2010, and the paper numbers

have remained high after reaching its peak in 2012. The information above is sufficient to prove the academic interest in this field.

1.3.1 RMS characteristics

The six RMS features as mentioned in section 1.2 enable the reduction of reconfiguration time and cost, thereby enhancing responsiveness to markets :

- **Modularity** : The machines or the components could both be constructed using a modular design to accommodate for changeability.
- **Integrability** : All the modules could be integrated. For example, the spindle and axes of tools' motions could be integrated to form different machine, the machines could be integrated to form new systems, and the machine controllers could be integrated into the factory control system.
- **Customization** : Flexibility of a system or machine around a part family, obtaining customized flexibility within the part family.
- **Convertibility** : System is able to quickly convert functions to produce all members of a part family.
- **Diagnosability** : Despite the frequent reconfiguration, measurement systems are capable of accurately diagnosing the production process.
- **Scalability** : The system is able to change quickly its maximum production volume by adding or removing components.

The features could be expanded and classified into three categories [23] :

- **The objectives of RMS** – scalability, convertibility and adaptability.
- **The functioning of RMS** – diagnosability and reconfiguration strategy.
- **The design of RMS** – modularity, integrability and mobility.

1.3.2 Reconfigurable manufacturing research trends

The current popular research trends of reconfigurable manufacturing include [26], (also see Fig.1.4) :

- Reconfigurability level assessment
- Analysis of RMS features

1.3. RECONFIGURABLE MANUFACTURING SYSTEM (RMS)

- Analysis of RMS performances
- Applied research and field applications
- Reconfigurability toward Industry 4.0 goals

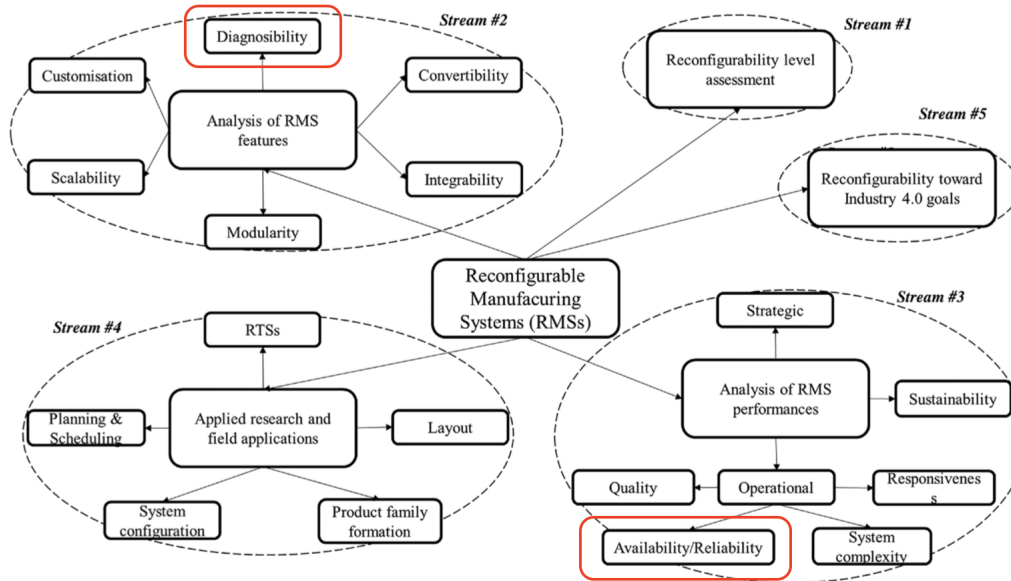


FIGURE 1.4 – Schematic of RMS research perspectives [26]

For **Reconfigurability level assessment**, frameworks and models are typically developed for mapping the capabilities and characteristics of the system, providing a set of composite reconfigurability metrics defining indices for the main RMS attributes, and assessing RMS through global reconfigurability indices.

Analysis of RMS features includes analyzing modularity, integrability, diagnosability, convertibility, customisation or scalability.

Analysis of RMS performances includes the analysis defining their own performances of RMS, which can be on the operational, strategic or sustainability levels.

Applied research and field applications focuses on Reconfigurable Transportation Systems (RTSs), the layout challenge, the product-family formation problem, the creation of reconfigurable cellular manufacturing systems, RMS configuration selection, and RMS scheduling.

Reconfigurability toward Industry 4.0 goals focuses on designing and developing reconfigurability

in the context of I4.0, by applying the technologies and tools from updated advanced science.

Concerning the research scope of this thesis, the reliability analysis belongs to **the functioning of RMS – diagnosability and reconfiguration strategy**, in which the focus is on the *RMS reliability performance analysis*. As shown in Fig.1.4, the two main issues of this thesis have been highlighted : **Diagnosability** and **Availability/Reliability**. It doesn't mean that the RMS in this research only possess the feature diagnosability, the system also possess other features but they are not focal points.

In this thesis, the concentration is on the reconfigurability achieved through Reconfigurable Manufacturing Tools (RMTs), which will be further introduced in the following section.

1.4 Reconfigurable Manufacturing Tools (RMTs)

RMT is one of the most important integrant among the reconfigurable machines, some others include Reconfigurable Inspection Machine (RIM), reconfigurable fixtures and Reconfigurable Assembly Machine (RAM) [27]. A RMT is composed of modules that could be assembled and disassembled on optional interfaces, during the manufacturing process. Different from Computer Numerical Control (CNC) machines, RMT could meet the need of customization, convertibility, integrability and modularity rapidly and cost-effectively, through its variation of configurations. The interfaces are of utmost importance in achieving these features. The interfaces include mechanical interfaces and interfaces for data, energy, and auxiliary materials. The mechanical interfaces could determine not only the degree of RMT's convertibility and integrability, but also their speed and cost. The two common interface parameters which impact the reliability performance are the geometrical positioning and the vibration of the tools. In a sense, RMT could play the role of a *group of machines*, whereas different from a group of machines, its change of reliability performance during reconfiguration is non-neglectable. Gadalla and Xue [34] categorized RMT into a) RMT with modular architecture and b) RMT with integral architecture. The illustration of the two types are shown in Fig.1.5.

• Modular architecture

In modular architecture, components with similar functions are grouped together as modules. To produce one kind of product, multiple modules could be applied to form various configurations. Commonly, the modules include a base module and functional tool modules, and accessory modules

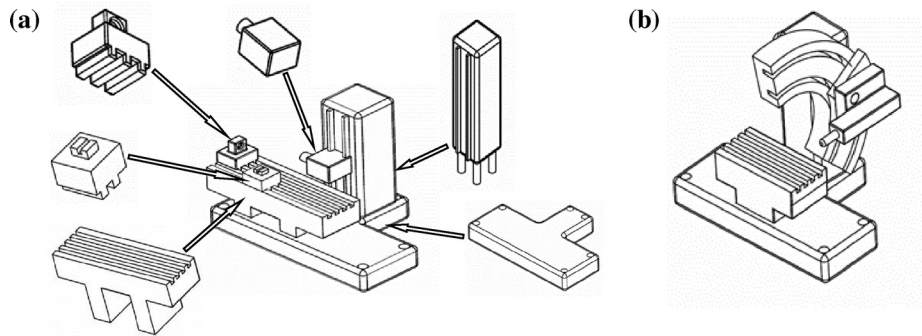


FIGURE 1.5 – Two types of RMTs [34]

could be included when necessary. The interfaces between the modules could function for mechanical/power/control usage. Besides, the structure could be designed as open or semi-open, which means whether the modules have the capability to be implemented on a variety of platforms, or merely on base of one company. In order to give an intuitive example, a RMT prototype designed by Huang et al. [35] for multi-part families is shown in Fig.1.6. The functional arms are installed on the base module, and could be converted to different shapes. With various types of tools installed on the functional arms, the RMT could function as both milling or turning machine.

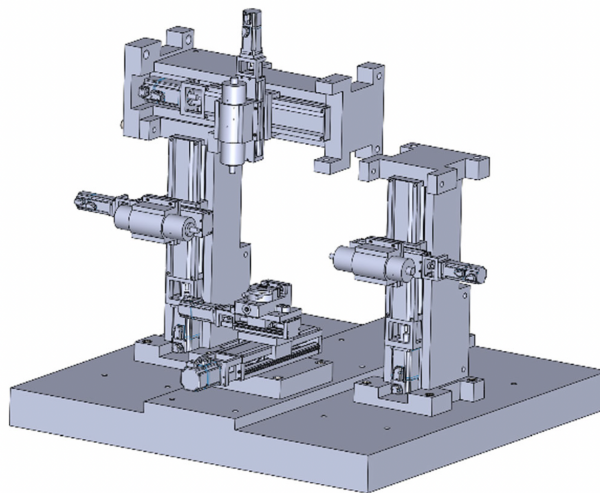


FIGURE 1.6 – Typical RMT prototype [35]

- **Integral architecture**

Integral architecture was designed to module changes during processing. The arch-type RMT is an example of integral architecture, usually applied in manufacturing part family with inclined surfaces,

with machine tools having degrees of freedom on three axis. Another example is Reconfigurable Parallel Kinematic Machine (RPKM), with modules such as links, joints, actuators and tool holders connected through parallel kinematics [71].

The existent RMT research has two main areas of interest RMT design and RMT configuration selection. RMT design typically focuses on kinematic feasibility and geometric shapes of the tools [72]. RMT selection is typically based on the module library, which solves an optimal problem by balancing the number of modules, cost, and process accuracy [73,74]. However, neither of these two main strands of research includes reconfigurability achieved by modifying the configuration orders of the RMT. Hence this thesis investigated RMT operation in various configuration orders to see how reliability varies as a result. More information will be provided in Section 2.

1.5 Reliability analysis in RMS

As discussed in 1.1, the emergence of new manufacturing system paradigms have raised a question of how the reliability methods and tools could play a role in the new era. Reconfigurable manufacturing system is one of the complex systems which harden the reliability analysis due to the following two reasons :

1. With assistance of new technology and materials, the paradigms which are derivative of reconfigurable manufacturing is evolving rapidly. For example some derivative paradigms include Sustainable Reconfigurable Manufacturing System (SRMS), Smart Self-Reconfigurable Manufacturing System (SSrMS), Cellular Reconfigurable Manufacturing System (CRMS) etc. All these newly designed system paradigm will need an according reliability analysis methods which focus on and conform to their characteristics.
2. The number of interfaces in a reconfigurable manufacturing system is considerable, no matter before or during processing. Each choice made and each step taken in a RMS could impact hugely on the reliability performance.

To systematically make a in-depth review on the researches regarding this topic, the software tool was applied for constructing and visualizing bibliometric networks – VOSviewer [28]. It is a broadly applied CNA tool that has already applied by many researchers. And it vividly shows the links and presents the connections. The review of literature were conducted by VOSviewer regarding three

aspects :

1. **Reliability analysis methods in the field of manufacturing**
2. **Reconfigurable manufacturing**
3. **Reliability analysis applied in RMS**

The relationships between these three aspects are depicted in Fig.1.7, where the first two aspects investigated are the foundation for the third aspect – reliability analysis applied in RMS.

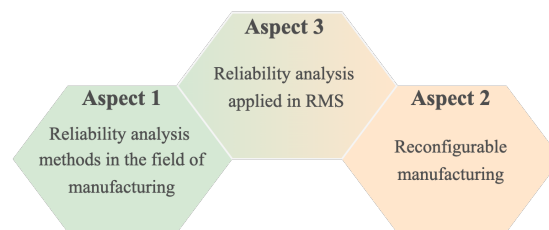


FIGURE 1.7 – The three aspects for literature review

The review includes two steps : screening the papers from Web of Science (WoS) core collections, the term co-occurrence maps and citation networks were obtained and then we were able to construct conceptual map indicating the links between concepts related to the three aspects by analyzing influential papers and critical terms.

1.5.1 Citation Network Analysis

To begin, the papers were screened using indexes such as minimum occurrence/citations, as well as manual methods to eliminate unrelated fields and topics. Articles with no citation links with the others in the database are excluded from the figures. The detailed searching parameters on WoS for each aspect are shown in Appendix A. The criteria for setting parameters include not only the quality, relevance, and publication year of the results, but also a manageable number of outcomes. During the citation network analysis, the co-occurrence analysis map provides the most information, proving that it is appropriate for analyzing our database papers. It evaluates the relatedness of items based on the number of documents in which they appear together. Fig.1.8, Fig.1.9 and Fig.1.10 shows the co-occurrence analysis map of the three aspects. Colors indicate concentrated years of the terms. And the size of the circle illustrates the occurrence times of the term.

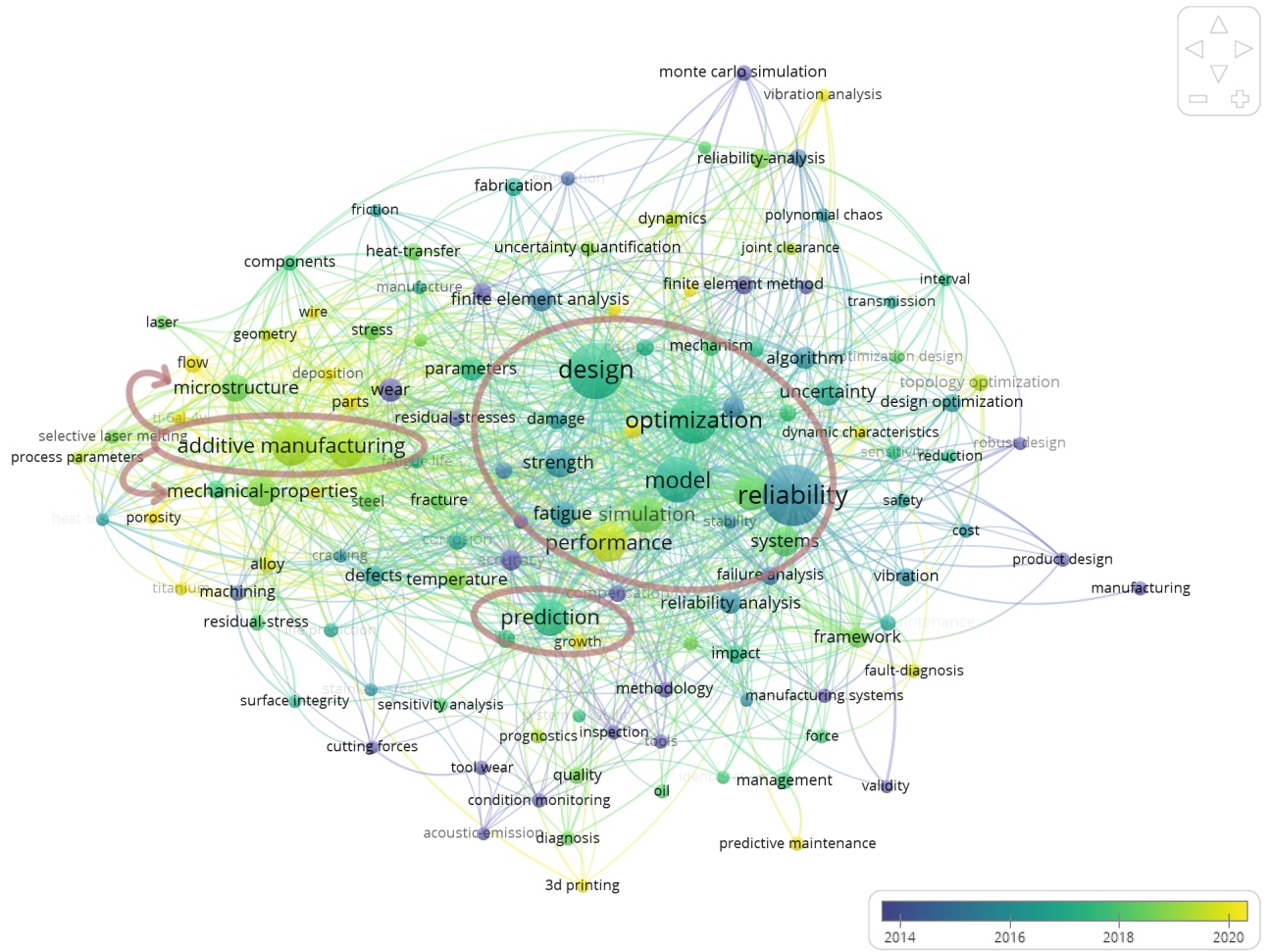


FIGURE 1.8 – Co-occurrence map of aspect 1 - Reliability analysis methods in the field of manufacturing

1.5. RELIABILITY ANALYSIS IN RMS

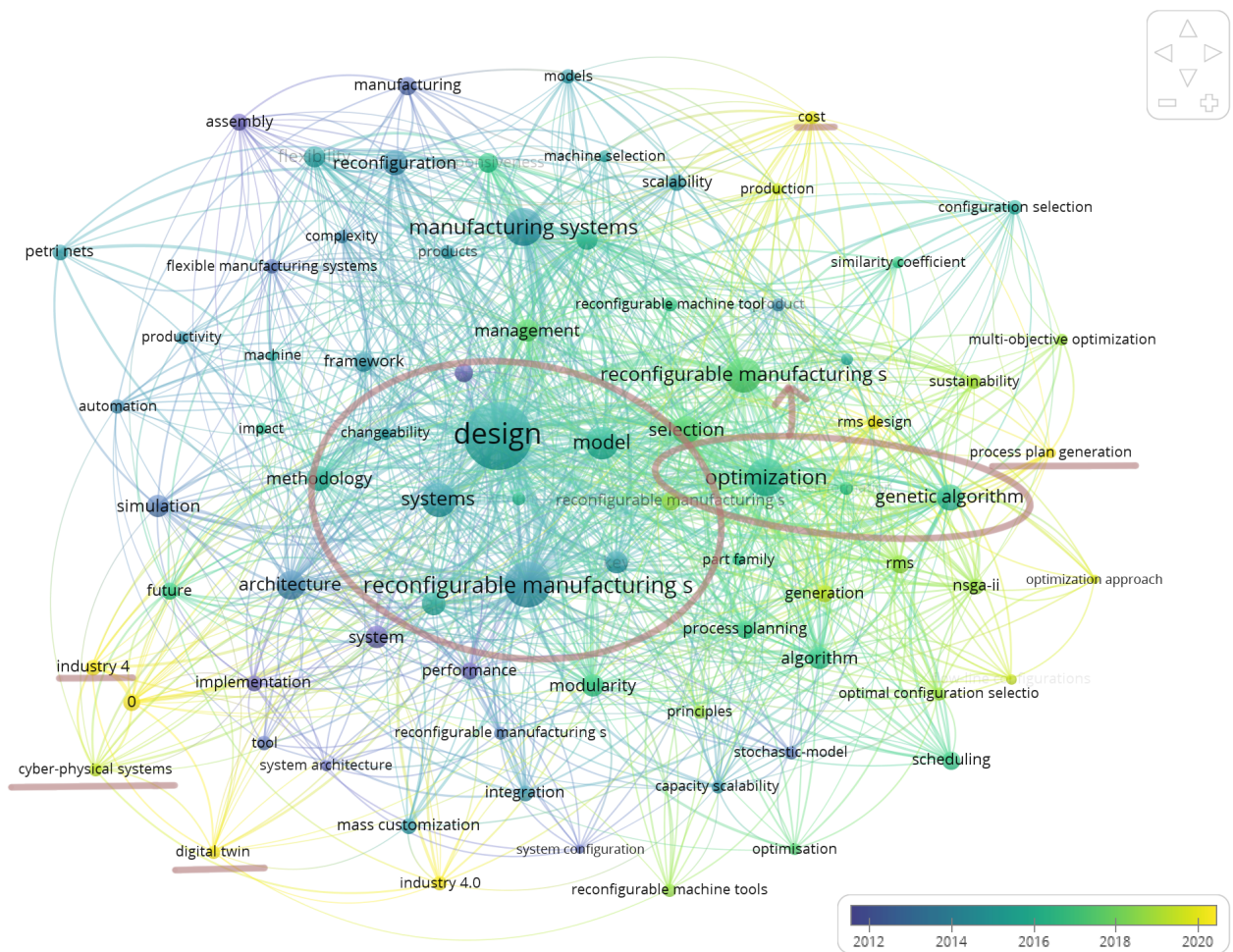


FIGURE 1.9 – Co-occurrence map of aspect 2 - Reconfigurable manufacturing

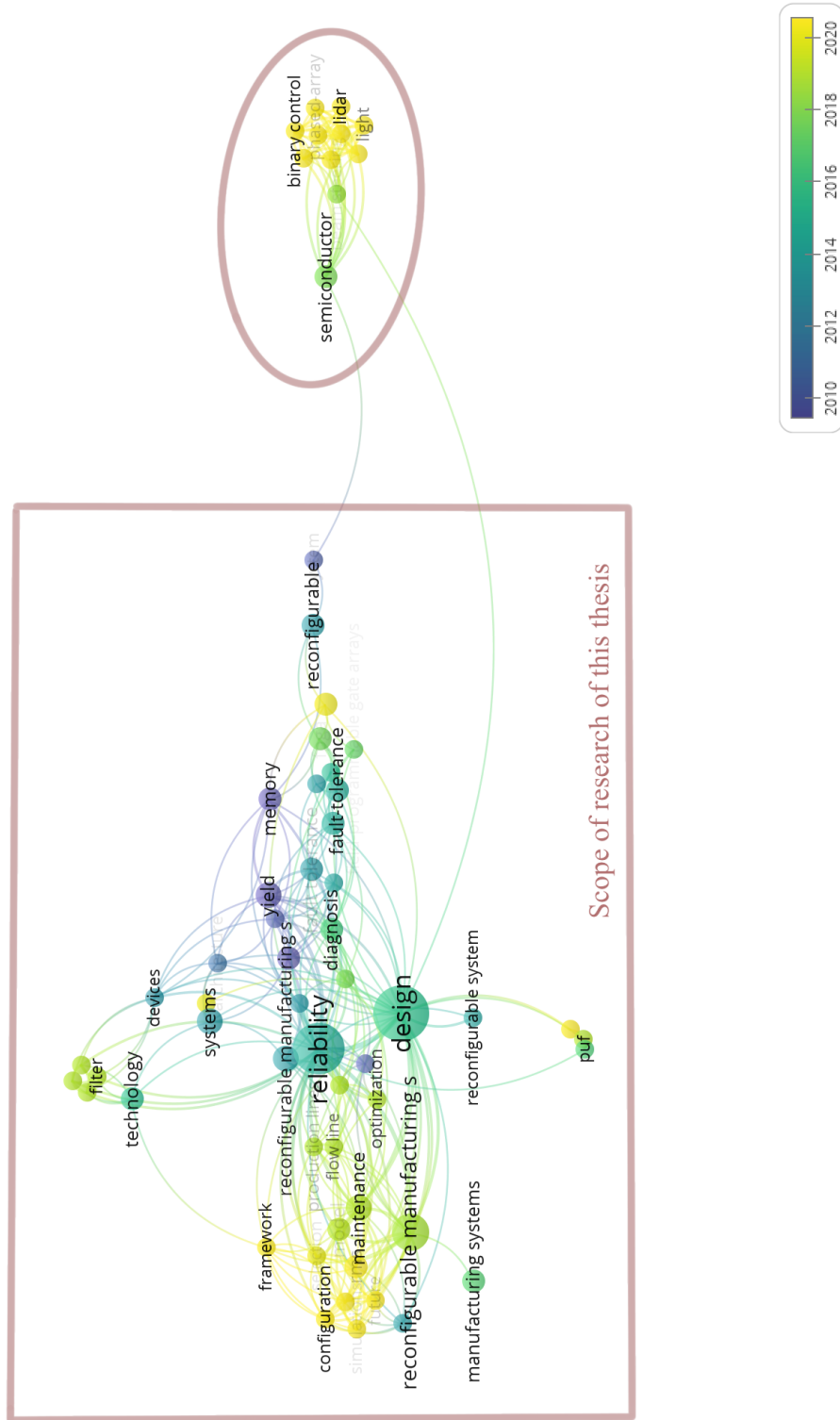


FIGURE 1.10 – Co-occurrence map of aspect 3 - Reliability analysis applied in RMS

1.5. RELIABILITY ANALYSIS IN RMS

As shown in Fig.1.8, the general research focus shifted from conventional wear analysis to the solution to optimisation problems, and finally to some novel paradigms like additive manufacturing. Other recent developments include reliability growth analysis, predictive maintenance, and 3D printing etc. It is important to note that *reliability performance* research is both influential and up to date.

Through the map generated for the **Aspect 1**, it can be concluded that :

1. The biggest interest when it comes to reliability analysis in manufacturing stays in the designing of the system to obtain optimized reliability performance, as circled in Fig.1.8.
2. Another obvious research interest is the reliability analysis on Additive Manufacturing, in which mechanical-properties and micro-structure are two important concerns (see arrows in Fig.1.8). This trend also has a lighter color, which corresponds to the development of I4.0, in which additive manufacturing is one of the important system paradigms.
3. The reliability prediction is also an important topic, with main research interests gathering around year 2018, as circled in Fig.1.8.

In Fig.1.9, numerous distinct groupings are displayed. The RMS core characteristics – modularity, capacity scalability and integrability – are the two mainly studied objects. Also some supplementary characteristics such as sustainability and productivity have also attracted attentions. Common tools or models applied in design or analysis of RMS include genetic algorithm, simulations, similarity coefficient for part families, multi-objective optimization etc. And, as mentioned in Section 1.2.2, FMS is frequently being mentioned whenever RMS occurs, for the purpose of comparison.

Through the map generated for the **Aspect 2**, it can be concluded that :

1. The biggest interest when it comes to reconfigurable manufacturing stays in the design of the system, as circled in Fig.1.9.
2. The second important research stream is the optimization of the reconfigurable manufacturing through Genetic Algorithm. (As shown by the circle and arrow in Fig.1.9)
3. Some of the new subjects worth noticing include Cyber-Physical Systems, Digital Twin, the context I4.0 and Process Plan Generation. Besides, cost is usually a non-neglectable index for research of reconfigurable manufacturing.

In Fig.1.10 representing the **Aspect 3**, the cluster on the right (the circled part), which appears to be an outlier given the clear clustering pattern, focuses mostly on actual products used in en-

engineering applications. Our research scope stays in the cluster on the left (the squared part). The design of RMS is a significant topic with the greatest frequency on the map, as is shown in Fig.1.10. Besides, some of the newest significant subjects around year 2020 include framework for maintenance/configuration/reliability design or assessment.

1.5.2 Conceptual map

Fig.1.11 shows the conceptual map built based on the study above.

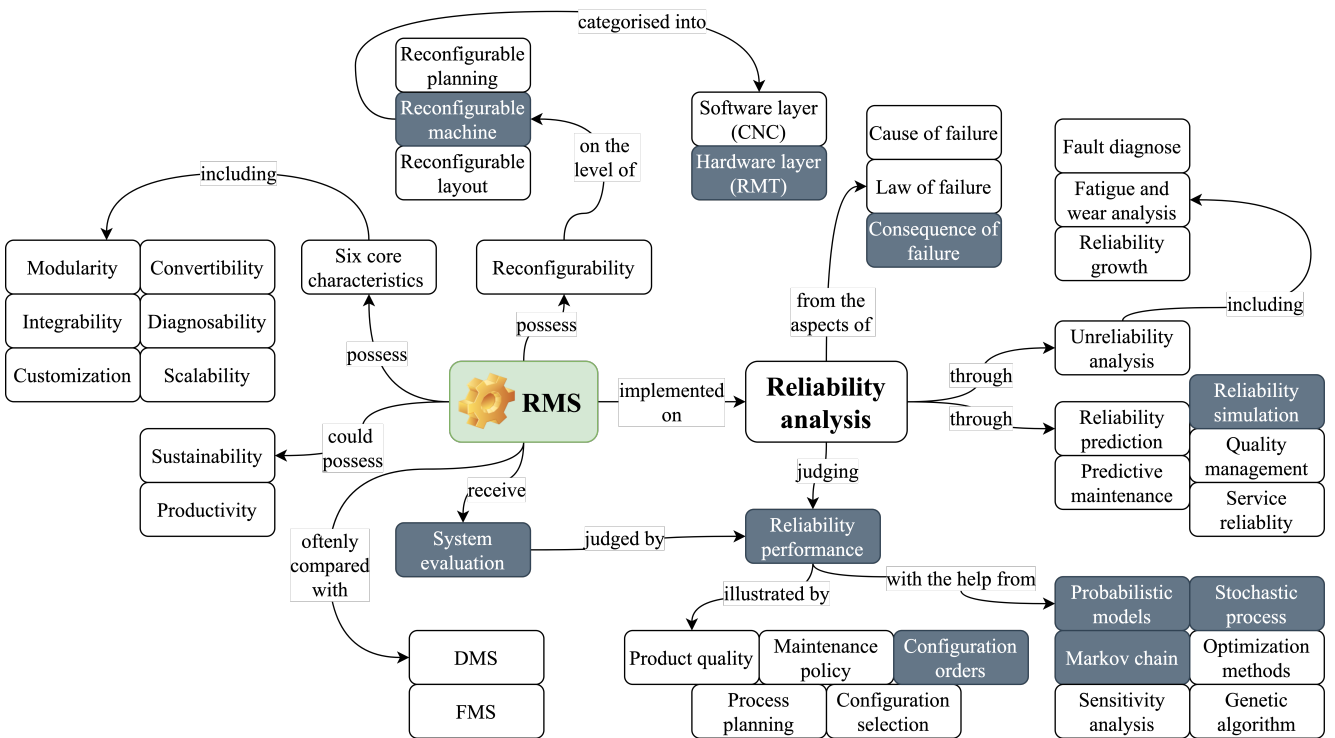


FIGURE 1.11 – Conceptual map of reliability analysis applied in reconfigurable manufacturing systems [36]

As shown in the map, *reliability analysis* and *RMS* are the two main concepts in our research. Dark color is used to emphasize concepts that our research topic concerns. This thesis, which primarily focuses on RMT, aims to investigate the reliability performance fluctuations brought on by configuration orders.

The conceptual map contributes in two part : concepts are placed properly inside their respective fields, which will assist make the study words more understandable, and the connections between the

ideas could inspire research questions.

It will not only supports us in defining our scope of research, but will also be helpful to other academics who intend to conduct similar research.

1.5.3 In comparison to general manufacturing systems

The reliability analysis of a RMS differs significantly from that of a general manufacturing system. This part discusses the main differences between them. As briefly discussed in the individual literature reviews of reliability analysis on general manufacturing systems and that on RMS (see Section 1.1 and 1.5), reliability on RMS is distinguished mainly in the following two parts :

- **Number of interactions/interfaces :** In compare to a general manufacturing system, a RMS has a large number of interactions/interfaces (mechanical or non-mechanical). The impact of them conducted on reliability performance can not be neglected. Moreover, their enormous numbers can increase intensely the complexity of the mathematical models.
- **Dimension of diagnosability :** RMS can perform in different configurations, consequently, it requires diagnosability for each configurations to track precisely the faults during processing. Such kind of diagnosability requires more cost in reliability analysis than conventional manufacturing systems, but can be reduced if regular patterns of reliability performance of certain RMS can be found.

1.6 Challenges of the study

With the main differences between RMS and general system paradigms discussed, this section presents the challenges that this research gap raised. To meet the challenges, mathematical models are thus built in the latter sections (see Section 2.4,2.5 and 2.6).

Since RMS features are largely different from those of conventional manufacturing systems during reliability analysis, the following research challenges emerge :

- *How to verify whether the interactions/interfaces impact the reliability performance of an RMS ?*
- *In what cases, the impacts are neglectable or non-neglectable ?*
- *If the impacts exist, how to describe the causalities between the configurations ?*

- *When describing the causalities between configurations, how to estimate and set limit ?*
- *If interactions/interfaces impact the reliability performance of an RMS, how significant is the impact and how to measure it ?*

The challenges are interlocked consecutively (see Fig.1.12), and it is intended to address them one by one in the following sections of this thesis.

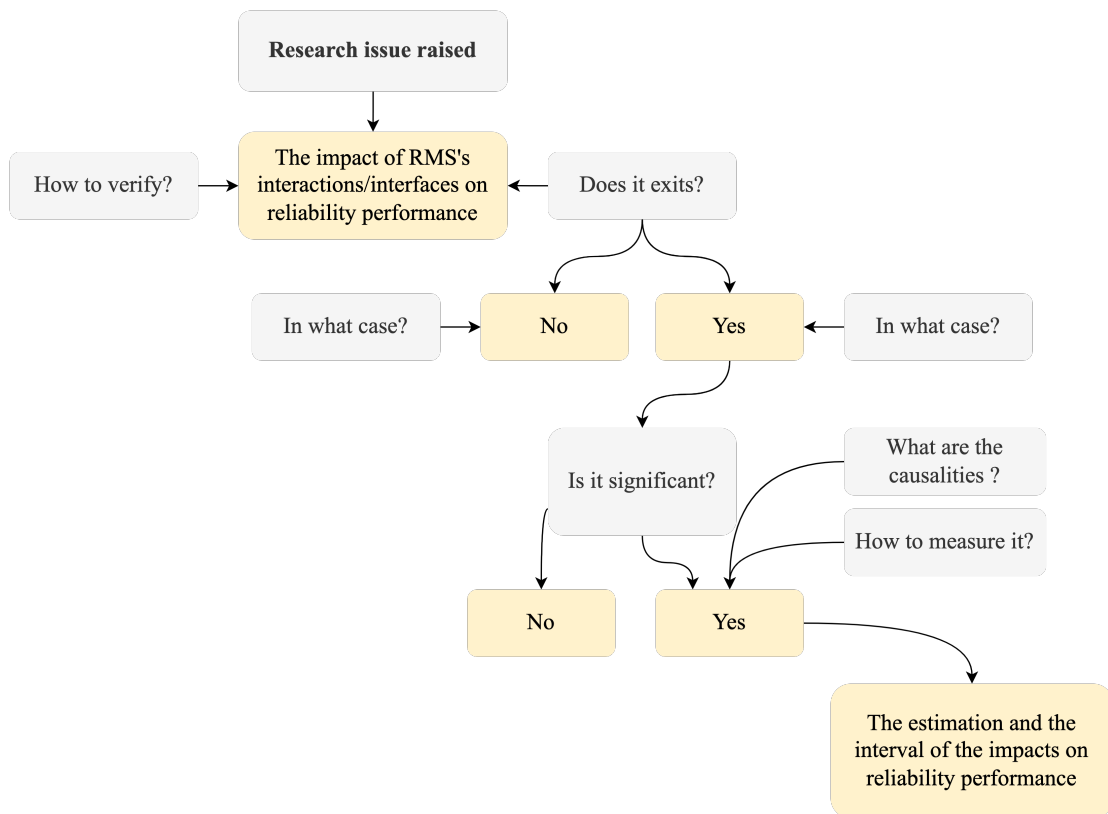


FIGURE 1.12 – Flowchart of challenges of study

1.7 Conclusion

The directions surrounding our study topic—reliability analysis used in reconfigurable manufacturing systems—have been systematically reviewed in this section. Once manufacturing reliability analysis, various manufacturing system paradigms, and reconfigurable manufacturing tools have been introduced. A review were conducted using a program for building and visualizing bibliometric networks and focused at three aspects : reliability analysis methods in the field of manufacturing, reconfigurable manufacturing and reliability analysis applied in RMS. Then, by using the information

1.7. CONCLUSION

gained from the study above, a conceptual map is created. At the end, the particularity of RMS reliability analysis was discussed, and research challenges are listed accordingly. Thus, a discussion in order to differentiate the reliability assessment in a regular manufacturing system and a reconfigurable manufacturing system is given. In the following chapter, the models built for reliability performance analysis of RMS will be presented.

Chapitre 2

Models of Reliability Performance of Reconfigurable Manufacturing Systems

In this chapter, two kinds of mathematical models for reliability performance of reconfigurable manufacturing systems were built– 1) two probabilistic models including a model based on Exponential distribution and a model based on Weibull distribution and 2) one model based on optimistic or pessimistic assessment.

In the first section, the system is defined with its general characteristics, assumptions and RMS characteristics. And then the reconfigurability based on configuration orders is explained and presented in Markov chain. The models presenting the causalities are also given in this section.

In the second section, the three models are presented with their specific assumptions and mathematical formulations. At the end, discussions of the models' characteristics and their limitations are given.

2.1 System description

In order to develop models, it is necessary to define the characteristics, settings and assumptions of the system. This section aims to explain study object in this research – the RMS composed of RMTs, as well as how the various configurations function and the reconfiguration process works. The system's reconfigurability is then discussed. Then, a real case of RMS composed of RMTs is presented, complete with the design of the system layout, machines, and tools.

The processing plan with various configuration orders is then depicted in Markov transfer states. Lastly, RMS specification in comparison to the general manufacturing system during reliability assessment is discussed.

2.1.1 General definition

The RMS in this study has the core facility of RMT, which can enable the system customisable flexibility via reconfiguration process.

2.1. SYSTEM DESCRIPTION

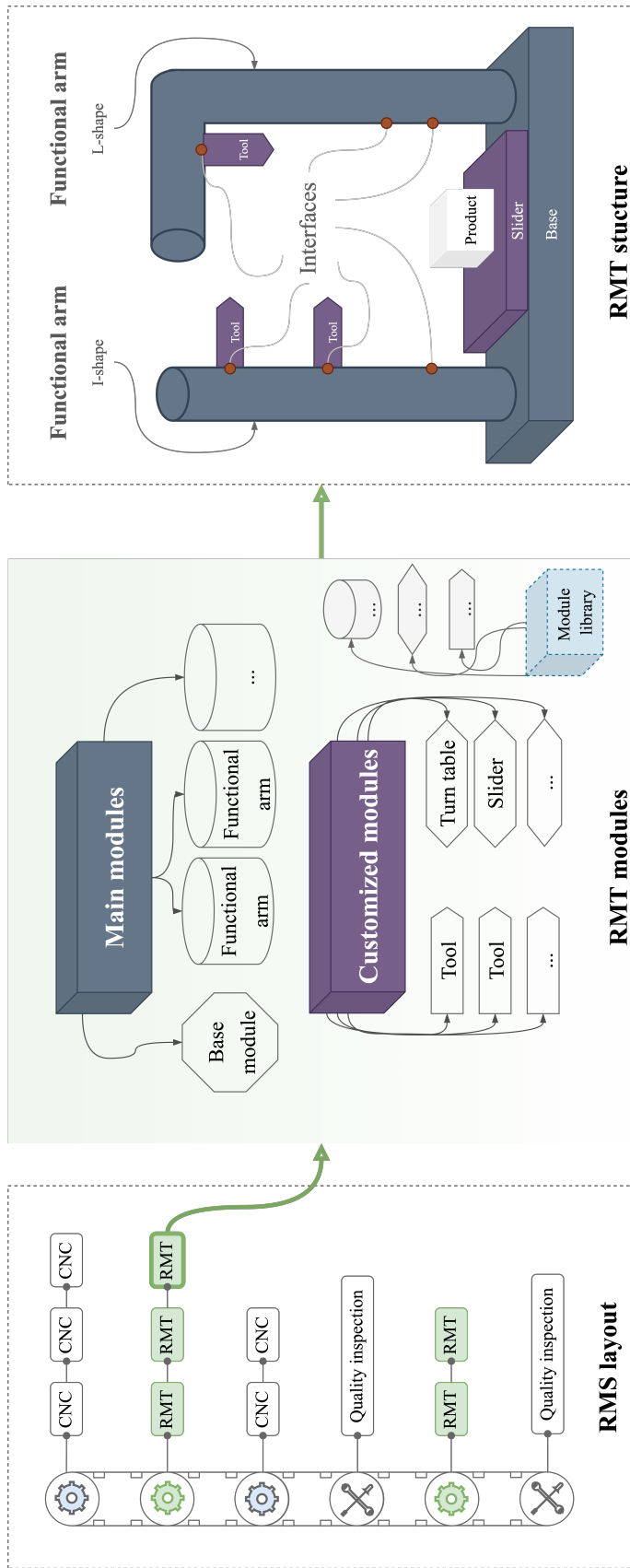


FIGURE 2.1 – Illustration graph of RMS comprised of RMT

Fig.2.1 depicts a step-by-step expanded example of a RMS processing line comprised of RMT. The RMS layout on the left side is a serial processing line with typical reconfigurable manufacturing machines, including CNCs, RMTs and quality inspection stations. When the product arrives at the processing line, it is assigned to interchangeable CNCs and RMTs in accordance with the processing plan. The inspection stations serve the aim of quality control both during and after the procedure.

The zoom-in of RMT in the middle of Fig.2.1 is comprised of two categories of modules : main modules including base module and functional arms and customized modules including tools, turn slider etc. The modules can be pulled from the module library or be replaced. The optimal module selection might be explored, as described in Section 1.4, however in this thesis, module selection and installation are pre-defined. It is worth noting that this research focus on exploring reliability assessment in various configurations.

A RMT prototype is illustrated on the left side of Fig.2.1. It is composed of one base module and two functional arms. The functional arms are either *I-shaped* or *L-shaped* [35], allowing them to operate from different directions on x-axes and z-axes. A slider on the base module holds the product and enables y-axis flexibility during operation. Interfaces on the functional arms enables installation of customized tools. In this case, there are six interfaces for installation.

In this thesis, the scope of research is limited to the level of machines (right side of Fig.2.1), particularly on the RMTs. The research focuses on the RMT operating in different configuration orders. However, the research excludes reconfigurability at the system level (left side of Fig.2.1) such as layout problem, processing planning problems etc.

2.1.2 Assumptions and reconfigurability

Several assumptions are made to define the RMS as research object, as shown in Fig.2.2.

- **Reconfigurability** : at the machine level, the manufacturing system can be reconfigured. Manufacturing machines are made up of RMTs. Different configurations are created by constructing and placing machining tools on the interfaces of RMTs. The RMTs refer to model components.
- **Failure mode** : degradation exists in both platforms and tools in the failure mode. As a result, the configuration order affects how the reliability varies during processing. The components have the same physical composition and structural logic, resulting in diverse configurations that follow

2.1. SYSTEM DESCRIPTION

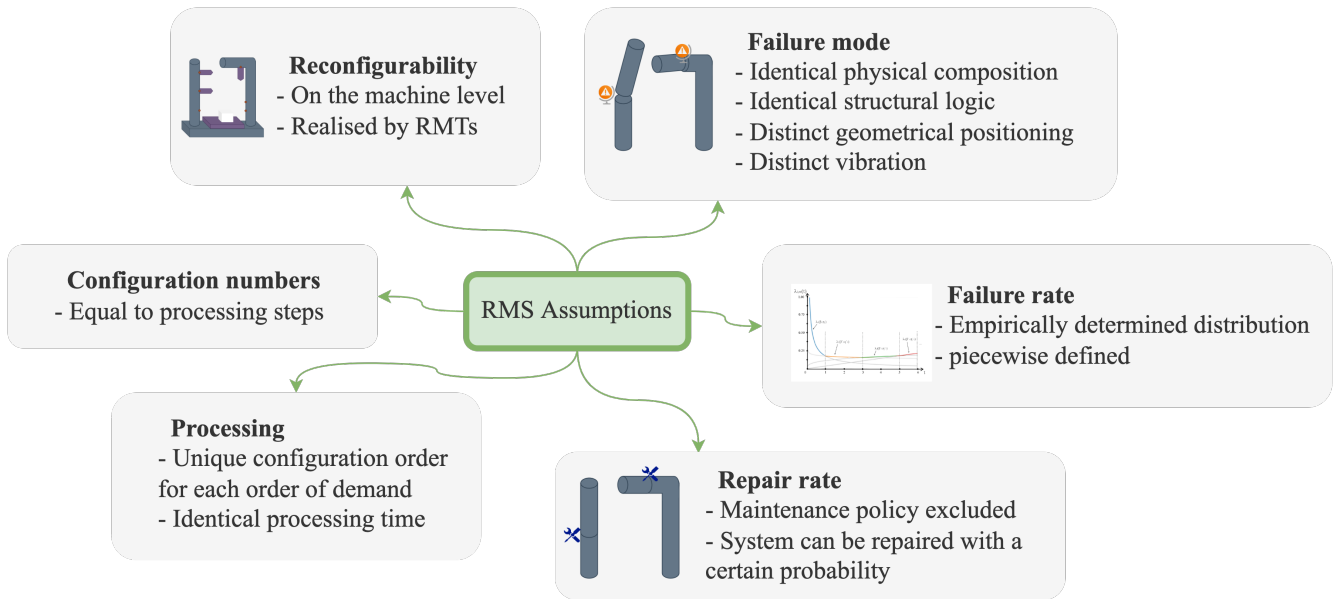


FIGURE 2.2 – Assumptions made for the RMS

the same failure mode as defined. Despite the fact that discrepancies in geometrical positioning and vibrations during tool processing can result in various sets of distribution parameters for the components. When a component fails, the manufacturing process is halted until the component is repaired or replaced.

- **Failure rate** : the components are utilized for a variety of functions and in a variety of environments. They have various failure rate parameters. The failure rate follows an empirically determined distribution, such as Exponential distribution or Weibull distribution. Due to the nature of the reconfiguration process, the failure rate model is piecewise defined, as each configuration of a component has a unique set of distribution parameters.
- **Repair rate** : normally, the system can be fixed using a set of repair rates for each process. Maintenance is not included, and repairs will be performed only if a failure occurs. When the repair is complete, the system switches from the Down to the Up state. Otherwise, the system operator must decide whether to fix or replace the components. To reduce the level of complexity, the repair rate for the probabilistic models was not studied during the mathematical modeling in this study. However, in order to illustrate a comprehensive reconfiguration process, this thesis

conceptually incorporated the repair rate in the figures.

- **Processing** : the production lines are reconfigured to produce different part families. There would be a defined configuration order for each order of demand. Each configuration operates on the product for a specific amount of time determined by pre-set parameters. The processing time does not vary when configuration orders are changed.
- **Configuration numbers** : a configuration can be utilized repeatedly during processing in practice. Simultaneously, a configuration may not be used at all for particular part families. To avoid mathematical complexity, this research begins by assuming configuration numbers equal to processing steps. Consequently, each configuration will occur only once during the manufacturing process.

The research on an RMS's reliability performance is primarily concerned with the *diagnosability* amongst the six RMS characteristics. Moreover, the study object in this research meets *modularity*, *integrability*, *convertibility*, and *customized flexibility*. The RMTs are made up of main modules and customized modules that can be integrated in a wide range of ways. The machine function can be changed by changing the tool types and installations on *I-shaped* and *L-shaped* functional arms. The interfaces on the I-shaped and L-shaped functional arms have been designed to allow for the installation of customized tools in the future.

2.2 Configuration orders modeled by Markov Chain (MC)

In this section, the configuration orders of RMTs are presented in MC via a conceptual illustration and a specific case.

A MC is a mathematical model that can be utilized to describe the behavior of a system that changes over time, where the system's future state is determined only by its current state and not by its prior history [29]. In other words, a MC is a process that travels through a range of possible states, with the probability of going from one state to the next being determined only by the present state and not by any previous states. As a result, it is a memory-less process since it does not retain any knowledge about its history.

In most cases, the MC based approach can effectively model and analyze a stochastic system. Hamasha et al. [75] applied Markov chain based approaches to describe the stochastic process of

2.2. CONFIGURATION ORDERS MODELED BY MARKOV CHAIN (MC)

Flexible Manufacturing Cells (FMCs), and concluded that the tool can be applied for building more advanced systems. Ye et al. [4] proposed a model that represents the stochastic process of system failures and repairs as a continuous-time MC. Wu et al. [76] evaluated the solar power system reliability based on the MC method, and the method was simulated and verified in the end. But there are other tools that could achieve the similar results, for example the Petri-net, or Place/Transition (PT) net, is another mathematical modeling languages used to describe similar systems. It is worth noticing that in this research, there is no comparison between the these tools. Markov methods may have restraints such as single monotonic, non-temporal failure degradation pattern [77], etc. But Markov models can describe the states of a machine and transit amount the states, which suits the need in this research.

As shown in Fig.2.3, there are three RMTs on the station zoomed in. For each RMT, the tools in the illustration include milling tool type 1, milling tool type 2, drilling tool and tapping tool. Furthermore, a reconfigurable manufacturing tool typically leaves one or more interfaces available for later tool installation, leading to customized flexibility, scalability, and convertibility. The RMTs in this thesis are designed with six interfaces (see Fig.2.1), thus leaving two empty interfaces for later tool installation.

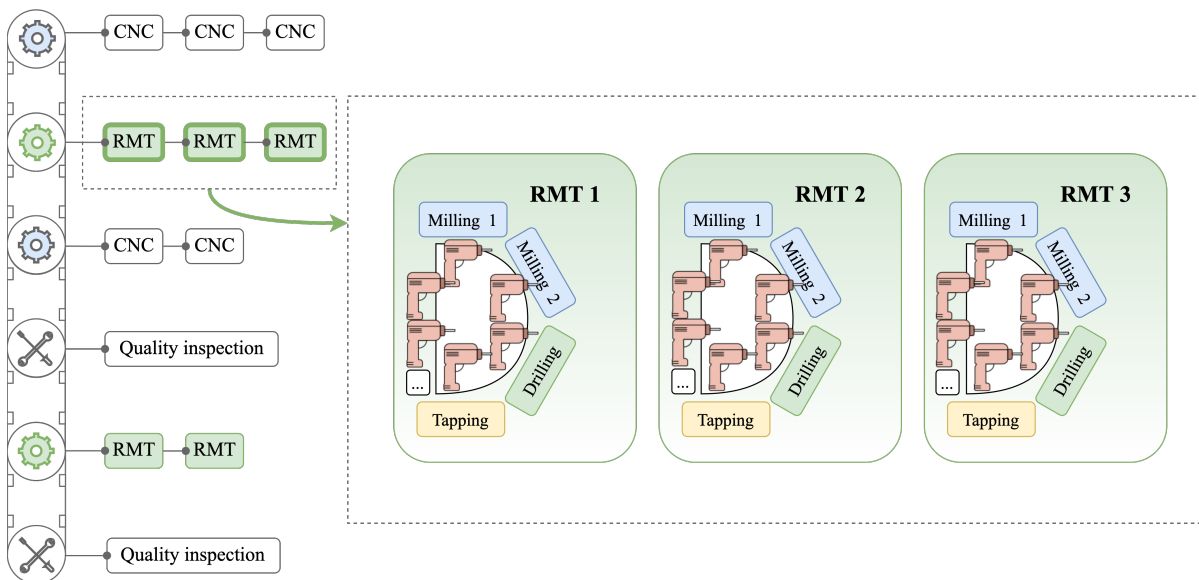


FIGURE 2.3 – The RMTs with various functions

Fig.2.4 depicts four types of installation procedures when there are four interfaces on the platform. The arrow lines represent the processing paths that follow the predefined configuration orders. Three

2.2. CONFIGURATION ORDERS MODELED BY MARKOV CHAIN (MC)

configuration orders are depicted for each installation.

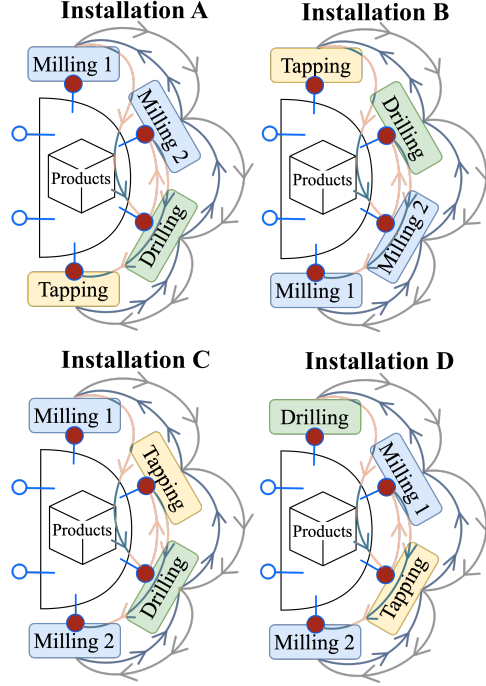


FIGURE 2.4 – Configuration orders through different installation of reconfigurable manufacturing tools

The failure rate can be presented by Eq. 2.1 :

$$\lambda_{i,m}(t) = \begin{cases} \lambda_{1,m}(t) & 0 \leq t \leq S_1 \\ \lambda_{2,m}(t) & S_1 < t \leq S_2 \\ \dots & \\ \lambda_{i,m}(t) & S_{i-1} < t \leq S_i \\ \dots & \\ \lambda_{M_p,m}(t) & S_{M_p-1} < t \leq S_{M_p} \end{cases} \quad (2.1)$$

With all the pre-definition completed, several pieces of information regarding the processing line and RMT configurations including 1) minimum number of RMTs, 2) optional configurations for one RMT and 3) possible configuration orders can be calculated. The minimum number of RMTs in a processing line is N as shown in Eq. 2.2 :

$$N = T_Q / (T_w \cdot R_{tr}) \quad (2.2)$$

In which T_Q is total processing time required to meet the demands, T_w is working time for each RMT and R_{tr} is reliability threshold for each machine, with given time unit.

2.2. CONFIGURATION ORDERS MODELED BY MARKOV CHAIN (MC)

The optional configurations for one RMT, N_c , is shown in Eq. 2.3 :

$$N_c = \sum_{k=1}^I (m_k \cdot \sum_{j=1}^J (n_{k,l})) \quad (2.3)$$

Then the possible configuration orders has the size of $N_c!$. The results obtained from the above calculations can assist in determining the basic settings of the processing line.

With the system defined, the next issue to be addressed is the intuitive presentation of configuration orders. Because this research focuses on how configuration orders affect reliability performance. Gao et al. [78] proposed a multi-state Markov transfer equation of the manufacturing unit to evaluate structural vulnerability of RMS. Each manufacturing unit had corresponding performance values presented by the states.

In this thesis, the configurations are presented as a multi-state MC during manufacturing process. A conceptual illustration of the configuration orders is shown in Fig.2.5.

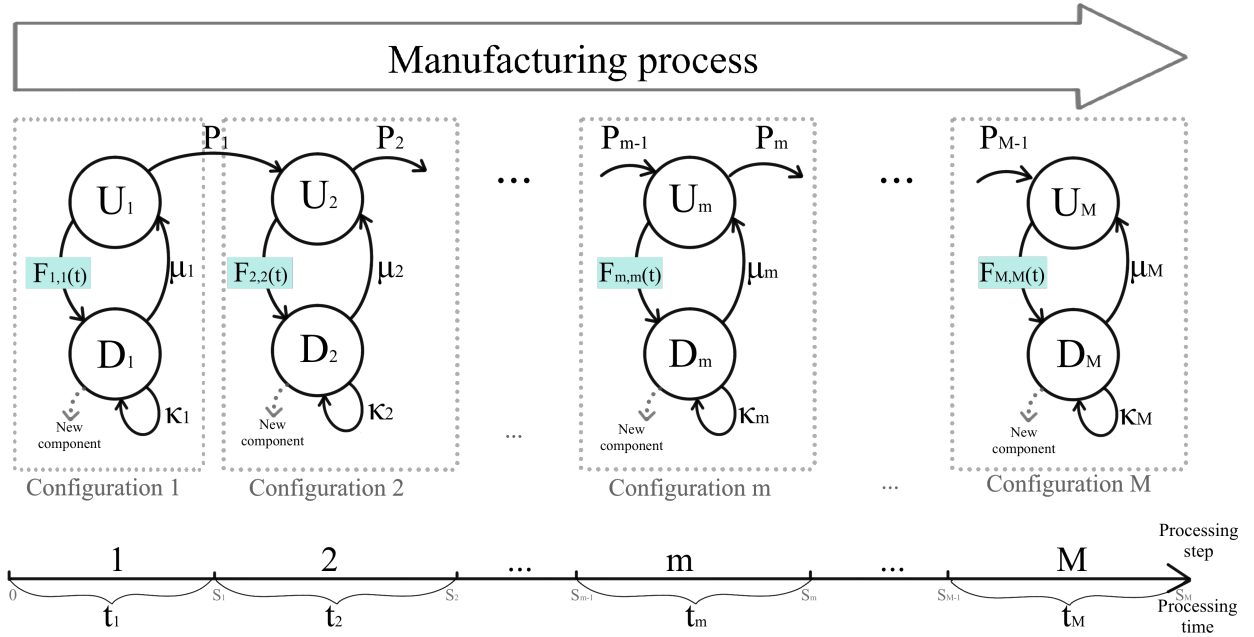


FIGURE 2.5 – Sequential configuration orders presented by Markov transfer states

Fig.2.5 shows an ideal case in which configurations follow a sequential order during processing. But in reality, the configuration order can be completely non-sequential. M processing steps were considered in this thesis and the processing time duration for each step was taken as t_i . For each processing step : the states could be : $\{Up, Down\}$, the transition probability from U_m to D_m is

2.2. CONFIGURATION ORDERS MODELED BY MARKOV CHAIN (MC)

unreliability $F_{i,m}$, and transition probability from D_i to U_i is repairing rate $\mu_{i,m}$. There is probability $\kappa_{i,m}$ that the repair failed or a replacement is necessary. When replacement takes place, the procedure would go to a new series of MC. The study in this thesis does not include the scope of replacement.

Based on the conceptual illustration, a more specific example is provided in Fig.2.6, by the design illustrated in Fig.2.4.

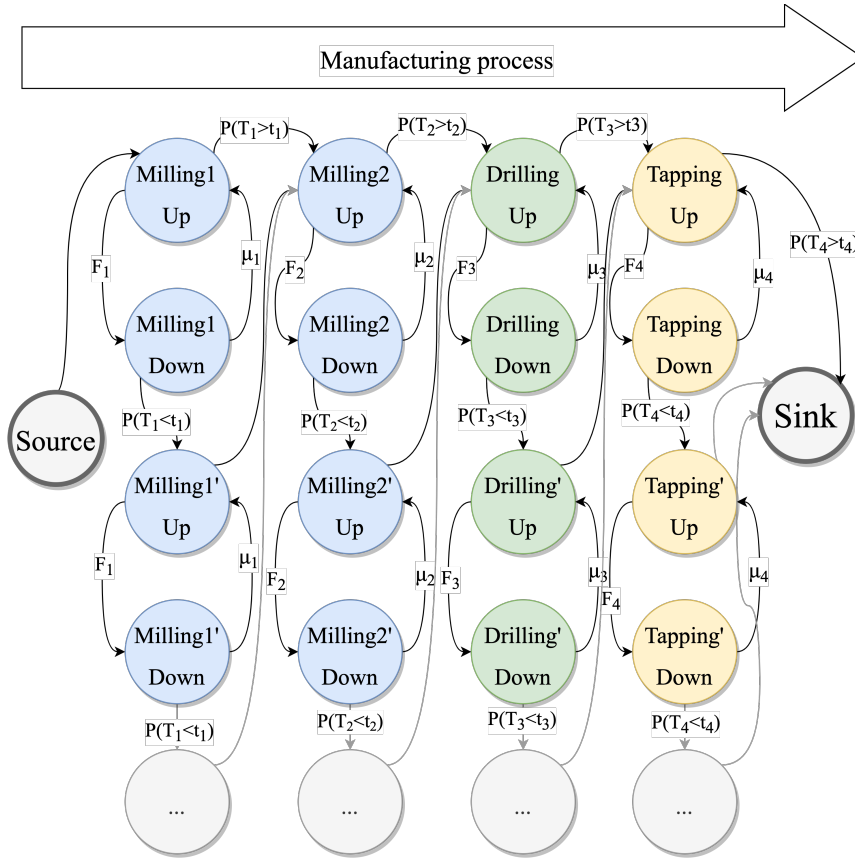


FIGURE 2.6 – A case of configuration orders presented by Markov transfer states

As shown in Fig.2.6, the probability that the machines will fail calculated based on Eq. 2.4. Each process would have a corresponding repair rate μ_i . The probability that the time to first failure T_i is larger than the processing time of process i .

$$P(T_i > t_i). \quad (2.4)$$

If the failure occurs before the end of i th processing time, then the tool will be fixed or replaced. In this case the transfer probability is $P(T_i < t_i)$. After the required processing time ends, the line

2.2. CONFIGURATION ORDERS MODELED BY MARKOV CHAIN (MC)

will go to the next process, otherwise the states will keep transferring to replacements. After all the processes finish, the products are finished and sent to sink.

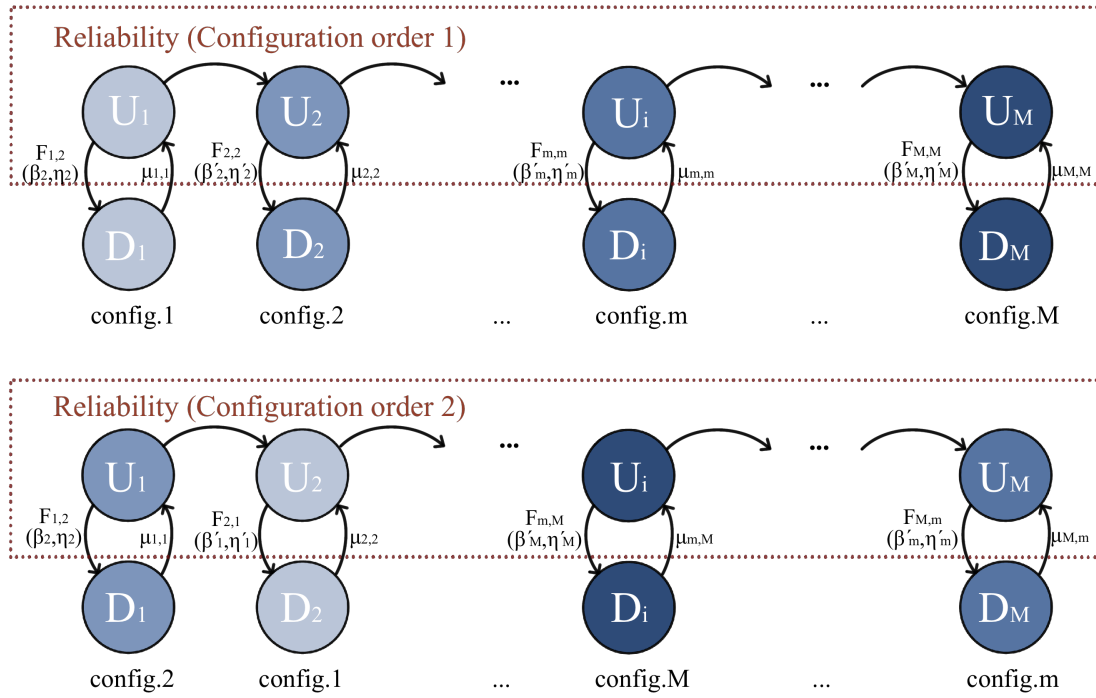


FIGURE 2.7 – Different configuration orders

When the configuration orders change, as demonstrated in Fig.2.7, the orders of the Markov transfer states will update accordingly. Configuration order 1 depicts sequentially ordered processing, while configuration order 2 depicts randomly ordered processing.

It is worth noticing that the case presented in Fig.2.6 is merely one kind of maintenance policy, different maintenance policies would present different kinds of Markov chains.

With the configuration orders modeled, the next step is to identify the parameters. In the following section, the complexity of parameter identification will be discussed, explaining why it is necessary to analyze causalities between the configurations in different orders.

2.3 Complexity of Parameter Identification

As mentioned in Section 1.1.3, parameter identification is a field of statistics that involves estimating the parameters of a distribution. It is usually a common step for probabilistic models. However, in this research, parameter identification approaches no longer match, necessitating the investigation of an alternate solutions.

The complexity degree of parameter identification in this study is the cause of the mismatch. Based on the system defined in Section 2.1.1, consider a processing line consisted of RMT with three optional configurations : *config.1*, *config.2*, *config.3*. The procedure of parameter identification would be required, on each system time of configuration, for all the following possibilities, as shown in Fig.2.8 :

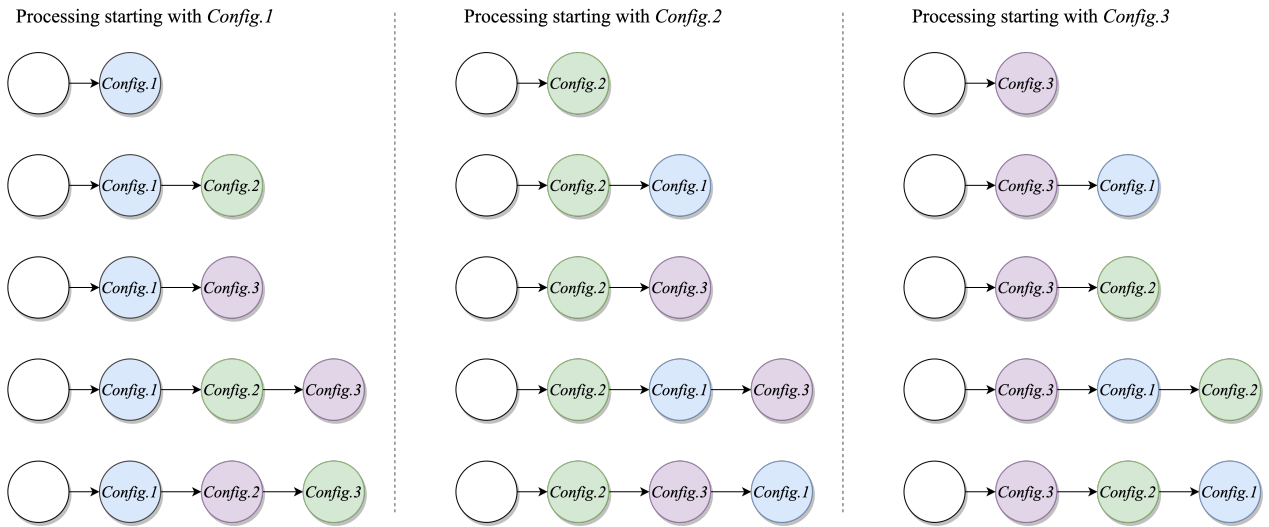


FIGURE 2.8 – A processing line with three optional configurations

For each possibility, each system time of configuration shown in Fig.2.8 requires would require parameter identification :

Processing line starting with *config.1* :

$$T(\text{config.1})$$

$$T(\text{config.2}|\text{config.1})$$

$$T(\text{config.3}|\text{config.1})$$

2.3. COMPLEXITY OF PARAMETER IDENTIFICATION

$T(\text{config.3}|\text{config.2}, \text{config.1})$

$T(\text{config.2}|\text{config.3}, \text{config.1})$

Processing line starting with *config.2* :

$T(\text{config.2})$

$T(\text{config.1}|\text{config.2})$

$T(\text{config.3}|\text{config.2})$

$T(\text{config.3}|\text{config.1}, \text{config.2})$

$T(\text{config.1}|\text{config.3}, \text{config.2})$

Processing line starting with *config.3* :

$T(\text{config.3})$

$T(\text{config.1}|\text{config.3})$

$T(\text{config.2}|\text{config.3})$

$T(\text{config.2}|\text{config.1}, \text{config.3})$

$T(\text{config.1}|\text{config.2}, \text{config.3})$

The form $T(\text{config.A}|\text{config.B}, \text{config.C})$ represents the time duration before failure occurs for *config.A* under the condition that *config.B* and *config.C* had operated successfully. The formulations are in accordance with the processes shown in Fig.2.8. It can be counted that a processing line consisted of RMT with three optional configurations would require parameter identification for 15 scenarios.

Taking two parameter Weibull distribution as an example, there would be overall 66 parameters, which is an extremely big number.

More generally, for a processing line with m configurations, and the failure mode distribution with ξ parameters, the number of parameters are shown in Eq.2.5 :

$$\begin{aligned}
 N_{para}(m = 1) &= \xi \\
 N_{para}(m = 2) &= (1 + 2) \cdot 2 \cdot \xi = 6 \cdot \xi \\
 N_{para}(m = 3) &= (1 + 2 \cdot 2 + 3 \cdot 2) \cdot 3 \cdot \xi = 33 \cdot \xi \\
 &\dots
 \end{aligned}
 \tag{2.5}$$

This is a simple example of how large the possibilities become as the number of configurations grows, necessitating the need to analyze them in another manner. Thus, this thesis seeks another way of obtaining parameters, as further discussed in the next section.

2.4 Causalities between configurations

As the alternate solutions for parameter identification problem, this section contributes in modeling of causalities among configurations in order to demonstrate how processing of the former configurations affects the latter configurations.

During processing, the tools might be installed on the functional arms modules via several interfaces. For example (see Fig.2.4), when the operation necessitates switching from installation A to installation B, the tools switch from *Milling 1* to *Tapping*. It is undeniable that the milling and tapping processes will result in varying degrees of wear. This is why it is essential to construct models of causalities caused by different configuration orders.

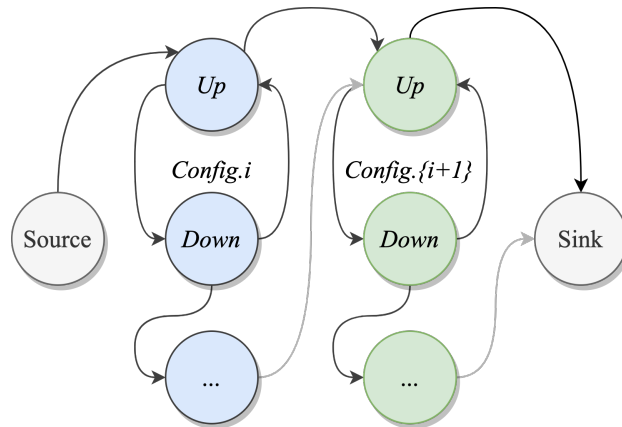


FIGURE 2.9 – Two configurations during processing

As shown in Fig.2.9 and Fig.2.10, there can be impact caused by the former configurations on the latter configurations. The highlighted part in the fig, *causalities*, is what this thesis is interested in. By reviewing literature and carefully examining the fundamentals, the following is a list of the causality mode's possibilities :

1. **No impact** : the former configurations do not impact the latter configuration. The tool performs like new every time a different configuration is installed on the functioning arms. This type of

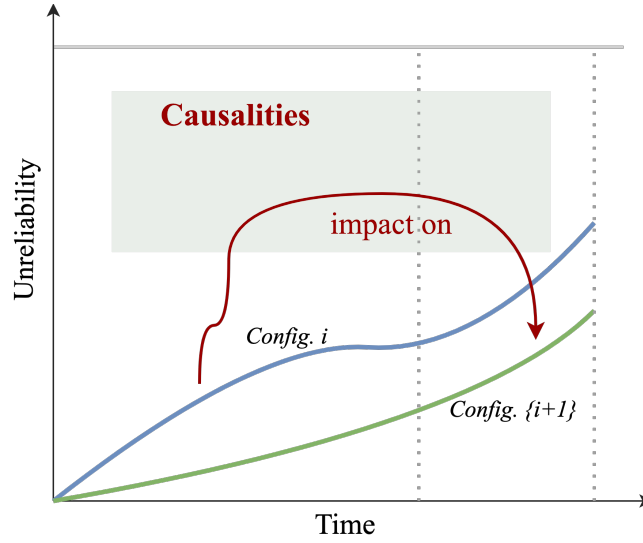


FIGURE 2.10 – Causalities between two configurations

causality is also seen as the most optimistic.

2. **Limited impact** : the former configurations have no effect on the latter configuration, but the processing time of the former configurations would have impact on the latter due to wear of the platform/arm module. In this case, no matter how the configuration order changes, the unreliability value at the end of the processing is unaffected.
3. **Full impact** : the former configurations fully impact the latter configuration in the most pessimistic way. That is, when the former configuration has lesser reliability than the latter, the latter's reliability collapses to the former one's reliability completely.
4. **Continuity-based impact** : the continuity assumption is imposed on the reliability/unreliability function or failure rate function. In this case, the continuity impact could be realized through changing the various parameters of the latter configuration.
5. **Hybrid causality** : the causation is comprised of all of the above options, with varying degrees of impact depending on the situation, such as age, surroundings, and evaluation policy.

Some of the above causalities are relatively more optimistic, which means the reliability is less likely to be deducted due to the usage history. Meanwhile, some of the above causalities are relatively more pessimistic, which means the reliability is more likely to be deducted due to the usage history. The tendency is shown in Fig.2.11. Full impact and no impact are the two extreme cases, with continuity impact and limited impact in between. Besides, hybrid causality does not have a specific location on

2.4. CAUSALITIES BETWEEN CONFIGURATIONS

the axes because it must be evaluated in relation to its context.

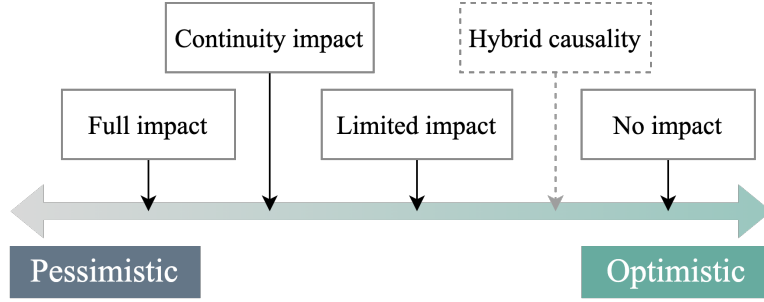


FIGURE 2.11 – Causalities in terms of their optimism and pessimism

To vividly present the concept of this section, the continuity impact of a processing line with components that follow the Weibull distribution is demonstrated.

Based on the example in Fig.2.4, the unreliability function of each cell F_m could be described by Weibull distribution with $\beta > 1$ as shown in Eq.2.6 :

$$F_m(t) = \begin{cases} 1 - e^{-\theta_{1,p}(t)^{\beta_{1,p}}} & 0 < t \leq s_1 \\ 1 - e^{-\theta_{2,p}(t-\tau_1)^{\beta_{2,p}}} & s_1 < t \leq s_2 \\ 1 - e^{-\theta_{3,p}(t-\tau_2)^{\beta_{3,p}}} & s_2 < t \leq s_3 \\ 1 - e^{-\theta_{4,p}(t-\tau_3)^{\beta_{4,p}}} & s_3 < t \leq s_4 \end{cases} \quad (2.6)$$

in which $\theta = \alpha^{-\beta}$.

And the manufacturing line has the system unreliability shown in Eq.2.7 :

$$F(t) = \prod_{m=1}^4 F_m(t). \quad (2.7)$$

2.4. CAUSALITIES BETWEEN CONFIGURATIONS

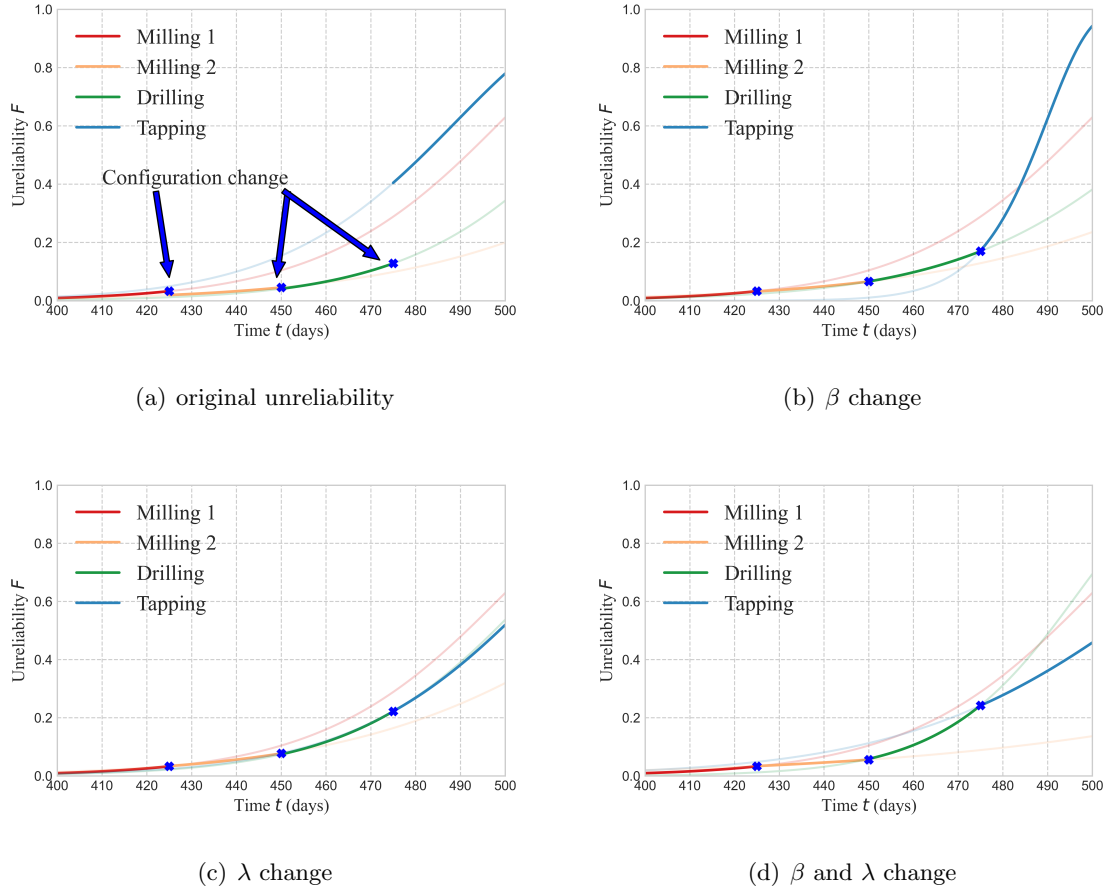


FIGURE 2.12 – Assumptions on the configuration change

As shown in Fig.2.12 , the arrows point out the time when process line goes from one configuration to another configuration. In Fig.2.12(a), the unreliability functions are under no assumption, Fig.2.12(b), Fig.2.12(c) and Fig.2.12(d) are under the assumption of continuity, realized by changing β , λ and β, λ correspondingly. Jiang et al. [79] made the assumption of continuity on reliability function and calculate the sectional time points. In this case, the processing time is settled. Hence either β or λ could change to obtain continuity. And in assumption shown in Fig.2.12(d), it is necessary to add constraints or rules of how β, λ changes. In Fig.2.12(d), it is assumed that the the absolute value of the difference between two configurations' reliability values at reconfiguration time will influence on the parameter of the latter configuration. The Weibull parameter data applied in Fig.2.12 originates from data sets of composites with degradation due to fracture strength. The data sets are applicable because the RMTs could share the same kind of failure mechanism. The next step is to build models

of failure rate distributions for the system.

2.5 Probabilistic models

The most classical way to analyze reliability of manufacturing systems is through probabilistic model. It has broad application, either in life time estimation, failure assessment or maintenance policy designing. The common distributions for reliability analysis include Exponential, Weibull, Normal, Log-normal, Extreme Value, Erlang, Chi-Square, Gamma Distributions and Auxiliary distributions, Bayesian reliability estimation. In this section, two distributions being applied in the models are Exponential distribution and Weibull distributions. The choice of distribution was made based on the fact that 1) Exponential distribution has the unique characteristic memorylessness which brings research interest, and 2) Weibull distribution is a generic distribution which could describe failure rate in various shapes [30]. Their general characteristics and formulations have been introduced in Section 1.1.2.

2.5.1 Exponential distribution failure mode based model

2.5.1.1 Model description

Exponential distribution is the probability distribution of the time between events in a Poisson point process. Poisson process is one of the basic mathematical models that have been used to describe occurrence of random events. Therefore, when the CDF of components failure rate is verified as exponential function distribution, and the failures are independent to each other, the failure occurrence during manufacturing process can be considered as a Poisson process [80].

In manufacturing applications, Exponential distribution has been applied in order to describe failure occurrence (e.g., automobile, wind turbines and integrated circuits etc. [81]).

Following assumptions are considered to build the model in this case :

- The component failure mode can be described by an Exponential distribution.
- Each configuration has constant failure rate.
- Failure rate and reliability function of different configurations are independent to each other during processing.
- For each configuration, the scale parameter of the Exponential distribution are unknown values.

2.5.1.2 Mathematical formulations

Based on the above assumptions, a probabilistic model is defined as follows.

Each configuration *config.m* possess a corresponding failure speed as shown in Eq.2.8 :

$$\lambda_{i,m} : T_i \sim Exp(\lambda_{i,m}) \quad (2.8)$$

In a manufacturing system, MTBF is the expected value of T_i , equals to $1/\lambda_{i,m}$.

In a Poisson process, failure rate for time period t can transform to $\lambda_{i,m}t$.

The probability that no failure occurs during a manufacturing process consisted of m configurations as shown in Eq.2.9 :

$$\begin{aligned} P_{M_p}(Failure = 0) &= P(T_1 > t_{1,m}) \cdot P(T_2 > t_{1,m} + t_{2,m} | T_1 > t_{1,m}) \cdot \\ &\dots \cdot P(T_i > \sum_{j=1}^m t_j | T_1 > t_{1,m} \& T_2 > t_{1,m} + t_{2,m} \& \dots \& T_{i-1} > \sum_{j=1}^{i-1} t_j) \cdot \\ &\dots \cdot P(T_{M_p} > \sum_{j=1}^{M_p} t_j | T_1 > t_{1,m} \& T_2 > t_{1,m} + t_{2,m} \& \dots \& T_{M_p-1} > \sum_{i=1}^{M_p-1} t_j) \end{aligned} \quad (2.9)$$

For a manufacturing process with Poisson process failure mode, the time duration between failures follows an exponential distribution function. And it is worth noticing that exponential distribution has the property of memorylessness :

$$P(T > r + s | T > r) = P(T > s) = e^{-\lambda s} \quad (2.10)$$

Due to this property, Eq.2.11 is formalized as follows :

$$\begin{aligned} P_{M_p}(Failure = 0) &= P(T_1 > t_{1,m}) \cdot P(T_2 > t_{2,m}) \cdot \dots \cdot P(T_i > t_{i,m}) \cdot \\ &\dots \cdot P(T_{M_p} > t_{M_p,m}) = \prod_{i=1}^{M_p} P(T_i > t_{i,m}) \end{aligned} \quad (2.11)$$

Then,

$$P_{M_p}(Failure = 0) = \prod_{i=1}^{M_p} P(f_i = 0) = e^{-\sum_{i=1}^{M_p} \lambda_i} \quad (2.12)$$

Thus the reliability performance of processing step i at time t are obtained as shown in Eq.2.13 :

$$F(t) = 1 - R(t) = 1 - e^{-\sum_{i=1}^{M_p} \lambda_i t} \quad (2.13)$$

Based on the mathematical properties of Eq.2.13, it can be concluded that when a processing line follows Poisson process as failure mode, its MTBF follows exponential distribution function which is memory-less. Thus, the configuration order during processing does not have an impact on the reliability of the system. For example, and as shown in Fig.2.7, the configuration can come in the order as $\{config.1, config.2, \dots config.m, \dots config.M\}$ or $\{config.2, config.1, \dots config.M, \dots config.m\}$ and the reliability performance would be the same.

2.5.2 Weibull distribution failure mode based model

2.5.2.1 Model description

When a RMS processing procedure can not be viewed as a Poisson process, the system loses its memoryless character which enables the configuration order changing without impacting reliability performance. To take the memory into account, a processing procedure with failure rate following Weibull distribution is considered. Memory of a processing line refers to the usage history of components.

Weibull distribution is a more generalized distribution of exponential distribution when modeling reliability [82]. Compared with exponential distribution failure rate, Weibull distribution gives a better insight of system failure in the process of decision making on machine reliability [83]. An application showing the flexibility of Weibull distribution is the Bathtub Curve [84], which provides a decreasing failure rate in the early stage, a constant failure rate in usage life, and an increasing failure rate in late stage.

The following assumptions are made to build the model :

- The component failure mode can be described by a Weibull process.
- Failure rate and reliability function possess the characteristic of continuity during processing.
- For each configuration, the shape and scale parameters of the Weibull distribution are unknown values.

2.5.2.2 Mathematical formulations

The reliability performance of *config.m* when failure rate follows Weibull distribution is given by Eq.2.14 and Eq.2.15.

$$F_{i,m}(t) = 1 - R_{i,m}(t) = 1 - e^{-\left(\frac{t-\tau_m}{\eta_m}\right)^{\beta_m}} \quad (2.14)$$

$$\lambda_{i,m}(t) = \frac{\beta_m}{\eta_m} \left(\frac{t-\tau_m}{\eta_m}\right)^{\beta_m-1} \quad (2.15)$$

For system with piecewise-defined failure rate as presented in Section 2.2, and due to the continuity assumption, the following formulations can be proposed :

$$\lambda_{i,m}(S_i) = \lambda_{i+1,m}(S_i) \quad (2.16)$$

$$R_{i,m}(S_i) = R_{i+1,m}(S_i) \quad (2.17)$$

Let β_i and η_i denote the shape and the scale parameters on processing step i , then the following formulations stand :

$$\frac{\beta_i}{\eta_i} \cdot \left(\frac{S_i}{\eta_i}\right)^{\beta_i-1} = \frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \quad (2.18)$$

$$\frac{\beta_i}{\eta_i} \cdot \left(\frac{S_i}{\eta_i}\right)^{\beta_i-1} \cdot e^{-\left(\frac{S_i}{\eta_i}\right)^{\beta_i}} = \frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \cdot e^{-\left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}}} \quad (2.19)$$

By combining Eq.2.18 and Eq.2.19, following Eq.2.20 is obtained (the detailed derivation steps are given in Appendix B) :

$$S_i = \frac{\eta_{i+1}^{\beta_{i+1}}}{\eta_i^{\beta_i}} \quad (2.20)$$

When configuration order changes, S_i would change at the same time. Taking the configuration orders in Fig.2.7 as an example, the first order has : $S_1 = t_1, S_2 = t_1 + t_2$ and the second order has : $S_1 = t_2, S_2 = t_1 + t_2$.

From Eq.2.20, it is shown that when the former step's configuration is decided, S_i would have an impact on the current step's Weibull scale and shape parameters : $\eta_{i+1}^{\beta_{i+1}} = cS_i$. This characteristic extends from starting time to the end of processing.

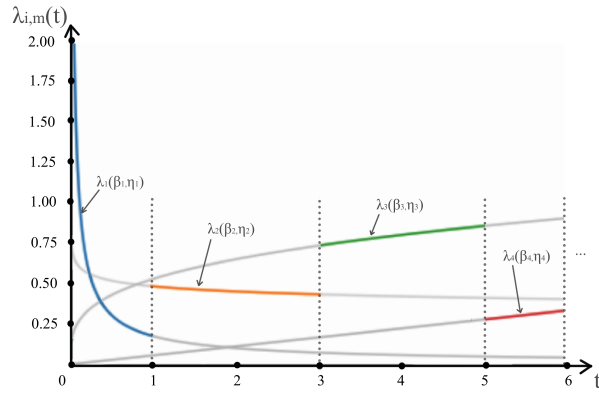


FIGURE 2.13 – Weibull distribution based failure rate of configurations without constraints

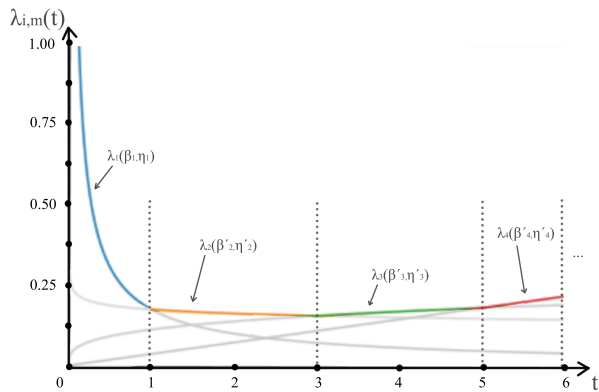


FIGURE 2.14 – Weibull distribution based failure rate of configurations with constraints

Fig.2.13 shows the piecewise-defined failure rate of configurations when they are independent to each other. The y-axis shows the failure rate, $\lambda_{i,m}(t)$. Fig.2.14 shows the piecewise-defined failure rate of processing when step i influences the step $i + 1$ on its Weibull parameters. This is an illustration of how failure rate changes when the continuity is forced on the model. It can be observed from the comparison of Fig.2.13 and Fig.2.14 that when the continuity assumption is added to the system, the former configuration will have significant impact on the latter configuration.

To illustrate the engineering significance of Fig.2.14, a RMT with modular architecture is given as an example (see Fig.2.15). It is composed of a base module and functional tool modules, which enable drilling and milling, having different types of installations .

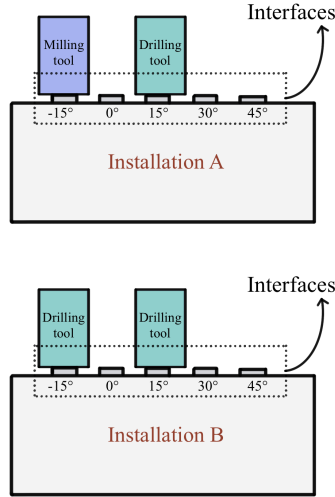


FIGURE 2.15 – RMT with different installations

When the process requires the RMT to convert from Installation *A* to Installation *B*, the tools installed on the -15 degree would change from Milling to Drilling. It is for sure that milling and drilling process would cause different levels of degradation caused by wear. In this thesis, such causalities caused by different configuration orders have been modeled based on continuity assumption, which is merely one kind of the solutions.

The reliability of system with Weibull distribution failure mode is shown in Fig.2.7, with an idealized scenario with 100% reparability for simplicity of illustration. Based on computation with hypothetically convergent MC, reliability can be calculated by the probability that the system is in U_p state in a MC :

$$R(t) = \sum_{i=1}^{M_p} P(State = U_i|t) \quad (2.21)$$

As shown in Fig.2.7, except the configuration in the first processing step, the remaining configurations would all have derivative Weibull parameters based on the former steps. Thus, the reliability performance is decided by the scale and the shape parameter of Weibull distribution. Logically, it can be concluded that the configuration order would have an impact on the reliability performance when the system is Weibull distribution based failure rate. However, different from the model that is based on Exponential distribution failure mode, the memory-less character does not stand anymore in this

model. The configurations add usage history to the component and thus enable *memory* for a RMS when configuration order changes.

Probabilistic models suit the case when knowledge of the system is comprehensive, yet sometimes a manufacturing system is not certain with its occasion, thus require human to take different policies, as presented in the following section.

2.6 Assessment policy model

This section presents a different solution from probabilistic models, an assessment policy model, which gives more flexibility when obtaining the results. The decisions on the policy can be either very optimistic, very pessimistic or in between.

2.6.1 Epistemic uncertainty of models

Section 2.4 studies on the possible causalities between configurations. For the models in Section 2.5, the causalities are either limited impact or continuity-based impact. The former is supported by the mathematical features of Exponential distribution, whereas the latter is supported by the imposed definition. However, when a manufacturing organization lacks information about the failure functions, except the above two instances, the optimum model to examine the reliability performance of RMS would be one that responds its incapacity of responding. A model who provides such answer is preferable to one who confidently provides an incorrect answer with limited information. This is why the epistemic uncertainty of models is addressed in this section.

Epistemic uncertainty is usually being compared with aleatoric uncertainty. Epistemic uncertainty, also known as systematic uncertainty, refers to uncertainty produced by a lack of information. Aleatoric, also known as statistical uncertainty, relates to the concept of randomness, that is, the variability in the outcome of an experiment caused by essentially random events.

To assess RMS reliability performance while accounting for model epistemic uncertainty, 1) research can enhance the amount of information or knowledge about the model, or 2) research can create result boundaries for the model taking into account its most optimistic and pessimistic scenarios. The level of optimism or pessimism becomes a parameter to be set later in the latter scenario. The model's epistemic uncertainty could be reduced by inputting more data on the level of optimism or pessimism.

2.6.2 Optimistic and Pessimistic (O/P) assessment models

2.6.2.1 Model description

The Optimistic and Pessimistic (O/P) assessment models consider the most optimistic and pessimistic scenarios of the reliability performance evaluation. The flowchart of the assessment steps is presented in Fig.2.16, using a process with three configurations as an illustrative example. The model first decides whether the assessment policy is optimistic or pessimistic, and then decides whether the latter configuration's reliability value is larger than the former configuration's reliability value, if the policy is pessimistic. The details will be listed in the assumptions.

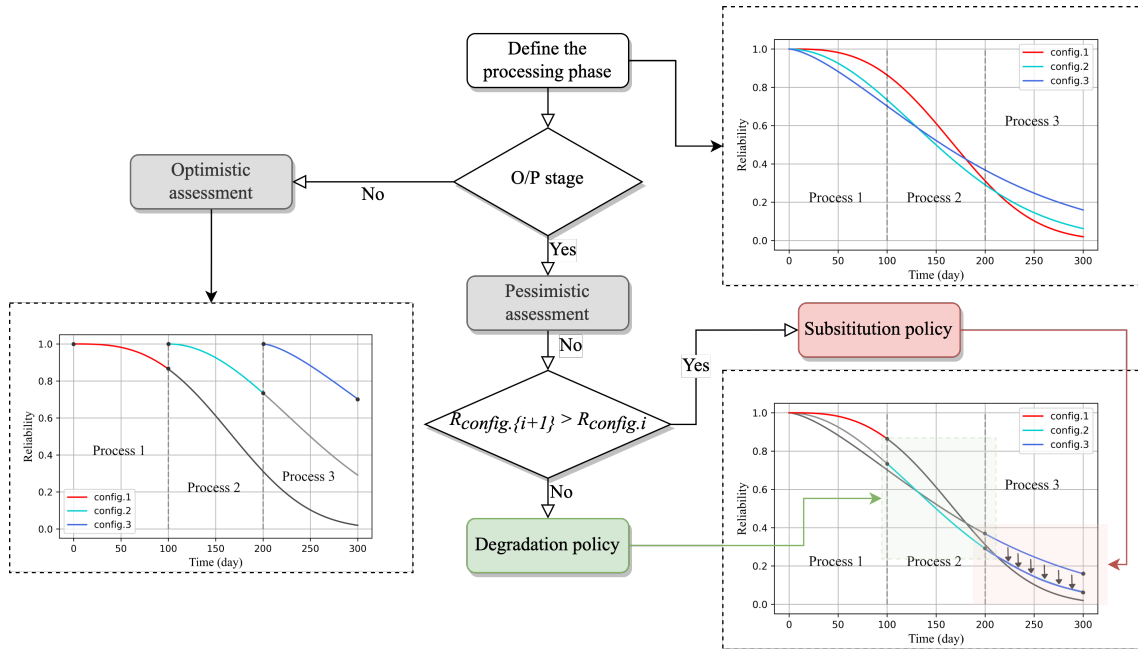


FIGURE 2.16 – Flowchart of optimistic and pessimistic assessment steps

The following assumptions are made to build the model :

- The component failure mode can be described by any statistical distributions that suit in the failure mode of RMTs.
- The component failure mode can be described by a Weibull distributed process.
- During processing, the reliability function and failure rate function may not be continuous.
- In the most optimistic scenarios, the components are brand new when installed for processing, with no effect from previous processing (as shown in Fig.2.16).

- The components degrade when installed for processing in the most pessimistic scenario, according to the processing time prior to installation. This results in two options : A) if the latter component has greater reliability, it collapses to the former reliability value (as shown in Fig.2.16 with arrows, titled with *Substitution policy*); and B) if the latter component has lower reliability, it remains at its original value (as shown in Fig.2.16 titled with *Degradation policy*).

2.6.2.2 Mathematical formulations

To present the concept analytically, it is assumed that the failure mode distribution is Weibull distributed once again. Other distributions can also fit the model by simply replacing the distribution functions (as presented in assumption 1).

The reliability functions of the failure rate following Weibull distribution can be referred to Eq.2.14 and Eq.2.15 in Section 2.5.2.

$$F_{i,m}(t) = 1 - R_{i,m}(t) = 1 - e^{-\left(\frac{t}{\eta_m}\right)^{\beta_m}} \quad (2.22)$$

$$\lambda_{i,m}(t) = \frac{\beta_m}{\eta_m} \left(\frac{t}{\eta_m}\right)^{\beta_m-1} \quad (2.23)$$

It is worth noticing that they are used to present a special scenario when the configurations are operating by themselves through the whole processing, without re-configurations. It is a scenario that does not exist in our presumed processing line, but it visually displays the original distributions.

The reference indicator of the level of optimism and pessimism decides which stage suits the current situation, follows Uniform distribution, as shown in Eq.2.24.

$$\rho \sim U(-1, 1) \quad (2.24)$$

The following is the illustration of the usage of this indicator.

When $\rho = 1$, the model employs the most optimistic assessment policy. When the configurations are setup for processing, they are as good as new. That is, the impact of the system's age can be neglected under this policy.

The piecewise-defined failure rate of the processing procedure can be obtained as shown in Eq.2.25.

$$\lambda_{i,m}(t) = \begin{cases} \frac{\beta_1}{\eta_1} \left(\frac{t}{\eta_1}\right)^{\beta_1-1} & 0 \leq t \leq S_1 \\ \frac{\beta_2}{\eta_2} \left(\frac{t}{\eta_2}\right)^{\beta_2-1} & S_1 < t \leq S_2 \\ \dots & \\ \frac{\beta_m}{\eta_m} \left(\frac{t}{\eta_m}\right)^{\beta_m-1} & S_{i-1} < t \leq S_i \\ \dots & \\ \frac{\beta_{M_p}}{\eta_{M_p}} \left(\frac{t}{\eta_{M_p}}\right)^{\beta_{M_p}-1} & S_{M_p-1} < t \leq S_{M_p} \end{cases} \quad (2.25)$$

And the unreliability function can be obtained as shown in Eq.2.26.

$$F_{i,m}(t) = \begin{cases} 1 - e^{-\left(\frac{t}{\eta_1}\right)^{\beta_1}} & 0 \leq t \leq S_1 \\ 1 - e^{-\left(\frac{t}{\eta_2}\right)^{\beta_2}} & S_1 < t \leq S_2 \\ \dots & \\ 1 - e^{-\left(\frac{t}{\eta_m}\right)^{\beta_m}} & S_{i-1} < t \leq S_i \\ \dots & \\ 1 - e^{-\left(\frac{t}{\eta_{M_p}}\right)^{\beta_{M_p}}} & S_{M_p-1} < t \leq S_{M_p} \end{cases} \quad (2.26)$$

When $\rho = -1$, the model employs the most pessimistic assessment policy. The reliability performance of the processing procedure is chain-like defined. Unreliability and failure rate of each configuration is decided based on its comparison with former configuration. The first configuration's unreliability is shown in Eq.2.27 :

$$F_{1,m}(t) = 1 - e^{-\left(\frac{t}{\eta_1}\right)^{\beta_1}} \quad (2.27)$$

Based on the Eq.2.27, the unreliability function of the latter configurations are shown in Eq.2.28 :

$$F_{i+1,m}(t) = \begin{cases} 1 - e^{-\left(\frac{t-\tau_m}{\eta_{i+1}}\right)^{\beta_{i+1}}} & F_{i,m} < 1 - e^{-\left(\frac{t-\tau_m}{\eta_{i+1}}\right)^{\beta_{i+1}}} \\ 1 - e^{-\left(\frac{t-\tau_m}{\eta_i}\right)^{\beta_i}} & F_{i,m} > 1 - e^{-\left(\frac{t-\tau_m}{\eta_{i+1}}\right)^{\beta_{i+1}}} \end{cases} \quad (2.28)$$

It is clear from the Eq.2.27 that there is no system's age related impact on the first processing.

When $-1 < \rho < 1$, it becomes as a parameter rather than a conditional indicator. In this case, ρ can be integrated into the models, by either achieving more information or more knowledge of the models. This research perspective was not explored further in this thesis.

2.7 Conclusions

The system defined in this chapter meets the majority of the general RMS properties, including modularity, integrability, convertibility, and customized flexibility. It is worth mentioning that diagnosability is the focus in this thesis.

Following the investigation of putative causalities among the configurations, two types of mathematical models of the reliability performance of reconfigurable manufacturing systems were constructed : two probabilistic models based on the Exponential distribution and the Weibull distribution, and another model one based on an optimistic or pessimistic assessment.

Based on the Exponential distribution based model, it has been proved that reconfiguration orders do not impact the reliability performance of a processing line in the end. It is caused by the memorylessness of the exponential distributed failure mode. Benefit from this conclusion, when the failure mode is identified as exponentially distributed, a manufacturing organization will save both time and money on reconfiguration design. Based on the Weibull distribution based model, it has been proved that reconfiguration orders do impact the reliability performance of a processing line. The O/P models can assess the reliability performance under optimistic or pessimistic scenarios. In optimistic scenario, the reliability of a latter configuration is less or not impact by the former configurations and usage history of the system. While in pessimistic scenarios, the impact is considered to be larger. For the models above, it is necessary to conduct simulations to shown the significance level of the impact.

In the following chapter, simulation and example cases will be used to further verify the proposed conclusion reached from the models. Then the questions raised in Section 1.6 will be answered accordingly :

- *How to verify whether the interactions/interfaces impact the reliability performance of an RMS ?*
- *In what cases, the impacts are neglectable or non-neglectable ?*
- *If the impacts exist, how to describe the causalities between the configurations ?*
- *When describing the causalities between configurations, how to estimate and set limits ?*
- *If interactions/interfaces impact the reliability performance of an RMS, how significant is the impact and how to measure it ?*

Chapitre 3

Implementation And Evaluation of the Reliability Performance Models of Reconfigurable Manufacturing Systems

Contenu

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Validation and verification are the final phase of the proposed framework for reliability analysis in RMS. To validate the models, the focus is on simulation and performance evaluations, which are based on the models developed in Chapter 2. The flowcharts of Monte Carlo simulation are presented firstly. The inputs for the framework are the failure parameters, configuration orders and assessment policies. Then, the outputs are the reliability performances for different configurations. Sensitivity analysis and examples of application are provided for verification at the end of this chapter. The usage example will assist later scholars who may be interested in the work and to demonstrate the practical meaning of the research.

3.1 Monte Carlo Simulation (MCS)

Monte Carlo Simulation (MCS) estimates mathematical functions and simulates the activities of complicated systems using random sampling and statistical modeling. Given its capacity to achieve a closer adherence to reality, it is a strong modeling tool for the investigation of complex systems.

When compared to actual reliability tests, MCS may significantly reduce both costs and testing duration while sufficiently simulating system breakdown. A classical reliability test used to predict failure rates, mean times to failure, or other characteristics indicating the failure behavior of specific components, can be carried out physically in a lab at reasonable costs and in reasonable testing times, while for a complex system with different configurations, it is impractical considering the cost and time.

The steps in a typical MCS are as follows [85] :

- Describe a system as a (series of) PDFs.
- Repeatedly sample from the PDFs.
- Tally/compute the statistics of interest.

For the models in this research, the PDFs are based on Exponential distribution and Weibull distribution. And then the same processes were consistently repeated, resulting in a series of events, showing how the reliability performance varies through processing procedures. In the end, attributes can be observed from the simulation results. The following (Fig.3.1) is an example of simulating the random walk on the system configurations through MCS : if the system reaches T_M without reaching the fault configuration, it functions through ; if the system reaches the fault configuration subsets Γ

3.1. MONTE CARLO SIMULATION (MCS)

(for example, the circled configuration 3), it fails before mission time T_M .

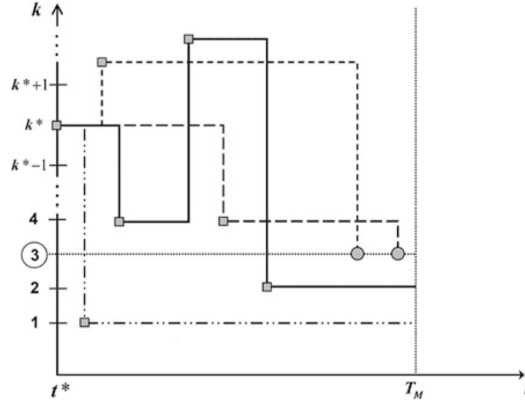


FIGURE 3.1 – System random walks in the system configuration versus time plane [37]

With reference to a given time t , the estimation of the probability that the system does not fail before this time $1 - \hat{F}_T(t)$ can be simulated.

Different from the failure mechanisms of the case given in Fig.3.1, in this research, the failure does not occur due to the appearance of a certain configuration, but it can occur at any configurations. Similar to the case given in Fig.3.1, the final results to be obtained is the estimation of the probability that the system does not fail before this time.

3.1.1 Flowcharts of the MCS

The simulation procedures as flowcharts are given so that readers may concentrate on the main logic without getting distracted by programming language syntax. The following (see Fig.3.2) is the flowchart of MCS of model in Section 2.5.

The procedure presented in Fig.3.2 applies to both of Exponential distributed model and Weibull distributed model (as highlighted in the figure). The two probabilistic models differ in the values of shape parameter $\{\beta_m\}$. When the model is exponential distributed, it has the characteristic of memorylessness, which means the system has no impact from usage history, so the procedure goes to the next step directly. On the contrary, when the model is Weibull distributed, it loses the characteristic and requires certain assumptions on the causality. Thus the failure rate continuity assumption is imposed and generate new sets of shape and scale parameters.

The following Fig.3.3 depicts the flowchart of MCS of O/P models.

In Fig.3.3, the assessment policy model is highlighted in green color. At the beginning of the procedures, the decision of whether it is optimistic or pessimistic will be made. If the optimistic policy is adopted, it is considered that a configuration has no usage age effect, that is to say, it is brand new when installed on the RMT. If the pessimistic policy is adopted, a judgement on the reliability values of the former and latter configurations is conducted, referring to the same system time. Based on the comparison results, the latter configuration's reliability will vary accordingly. The rest part of the flowchart is the same as in Fig.3.2.

3.1.2 Simulation algorithms

The MCS procedure is shown in Algorithm 1. With the inputs including configuration order γ , processing time sequence, shape parameter, and scale parameter sequence for γ th configuration order, the outputs are the mean and standard error of the probability that there is no failure until the end of processing for configuration order γ . Steps 1 to 4 are initial setting, including discretization of time and generate the system's time list accordingly. Steps 5 to 8 are conduction of MCS. Steps 9 and 10 are normal fitting and calculation based on Equation 1. The associated algorithm for Weibull distribution based model in Section 2.5.2.1 is presented in Algorithm 2. As discussed in the assumptions made for the model, continuity on failure rate (step 3) for simulation is added, thus generating new sets of Weibull parameters (step 4).

The associated algorithm for O/P models in Section 2.6 is presented in Algorithm 3. As discussed, it will lead to different reliability values of a newly-installed configuration based on a series of control.

1. *Which of the policy is adopted, optimistic or pessimistic ? (step 2)*
2. *Whose reliability value is larger, the latter configuration or the former configuration ? (step 3)*

All of the algorithms described above are implemented in Python, and the simulation results are shown in the following Section 3.2 . The Python codes are available online if any scholars intend to conduct additional research based on this thesis : https://github.com/mellotina/RE-SS_model.git

3.2 Performance evaluations

With the algorithms built, it was possible to assess the reliability performance of the RMS referring to different models : probabilistic models and assessment models.

3.2.1 Probabilistic models

3.2.1.1 Exponential distribution failure mode based model

To validate the conclusion made from equation 2.11, the algorithm is applied on one manufacturing data set derived from Jeon and Sohn [86] (by altering the Weibull shape parameter to $\beta = 1$). The sets of exponential distribution parameters obtained are shown in Table 3.1. The six configuration orders are listed in Appendix C.1.1.

TABLE 3.1 – Exponential parameters of manufacturing failure data under different configurations

Configuration	1	2	3	4	5
β	1.00	1.00	1.00	1.00	1.00
η	2.53	2.78	2.14	1.94	1.88
Configuration	6	7	8	9	10
β	1.00	1.00	1.00	1.00	1.00
η	2.37	1.95	0.42	3.14	2.46

Through experiments, the iteration time (sample size when counting the non-failure processes in each step) and simulation time (normal fitting sample size of counting of non-failure processes) being larger than 100 provides results with good consistency.

Fig.3.4 shows the failure functions including reliability functions and conditional probability functions for all six orders. The memorylessness of Poisson process explains the conditional probability being constants in each processing step. As shown in the figure, the conditional probability have constant values for during each processing steps, due to the memorylessness characteristic of Exponential distribution based model.

Fig.3.5 shows the function $P(\text{failure} = 0)$ at each processing step under different configuration orders (see numerical data in C.2.1). Four parameter settings were put into simulation, with uniformed and random processing time with 1000 and 10000 steps (decided by value of *timeUnit*), as presented in the sub-figures. Considering C.2.1, the probability that no failure occurs until certain time can be estimated. For example, when processing time is uniformed and $\gamma = 1$, the probability that there is

3.2. PERFORMANCE EVALUATIONS

no failure until the whole processing finishes (365 days), is 2.5%. If the threshold value is set at 80%, then preventive maintenance is required between processing steps 2 and 3 (at day 73).

When each configuration has identical processing time (0.1 year, equals to 36.5 days), the whole processing time lasts for 1 year. As shown in Fig.3.5(a) and (b), the probability function coincides more when being compared with random processing time. It is worth noticing that **the x axis in Fig.3.5 presents processing steps not the time**. This can also explain why in Fig.3.5(a) and (b), the lines are more collected considering the degradation of some configurations while bigger processing time are compressed in the same time span on the x axis.

In the case of Fig.3.5(c) and (d), the processing time sequence is a set of randomly generated values within the reasonable period of Weibull distribution reliability function. The whole processing time lasts for 2.15 year (i.e., 785 days). When $\gamma = 2$, the line shows particularity because in this configuration order, $\eta = 0.42$ which is the only set of Weibull parameter in which $\eta < 1$. Due to the nature of Weibull distribution, when $\eta < 1$, the failure tends to occur in a very early stage when comparing with other cases. Thus, the fact that this configuration being ahead amongst others, causes this phenomenon in Fig.3.5(c) and (d).

It is obvious that $P(Failure = 0)$ has trend of convergence with processing step pushing on in all the parameter settings, which further confirms the conclusion made from Eq. 2.11. And $P(Failure = 0)$ with different steps have basically the same graph, this is due to the nature of exponential distribution.

When one configuration is switched to another, the starting reliability for the new configuration is set based on its time distance from the last switch. This calculation could be avoided by setting fixed steps for each processing step. But in the simulation in this thesis, fixed time unit not fixed steps was set considering the two solutions would have largely consistent results.

3.2.1.2 Weibull distribution failure mode based model

The simulation is conducted using the same manufacturing data as in the case study in Section 3.2.1.1 (Appendix C.1.1).

With processing time set as identical and simulation step set as 1000, the reliability function and conditional probability are shown in Fig.3.6. There exists certain level of deviation when $\gamma = 1$, which is caused by the configuration order's characteristic. Then the probabilities of non-failure at each

3.2. PERFORMANCE EVALUATIONS

processing time are simulated. By observing the MCS results (Fig.3.7), it is obvious that the lines are divergent and do not have the convergent characteristic as in Section 3.2.1.1.

The results show that when the configuration order changes, the reliability performance would change at the same time in this case. Considering that the characteristic is obvious enough, no further sets of MCS parameters are applied.

3.2.1.3 Applications on other distributions

Besides the Exponential distribution and Weibull distribution, other probabilistic models have been tested to apply to the same model and same simulation. As long as the distribution suits the scenario for reliability analysis, the model is applicable.

3.2. PERFORMANCE EVALUATIONS

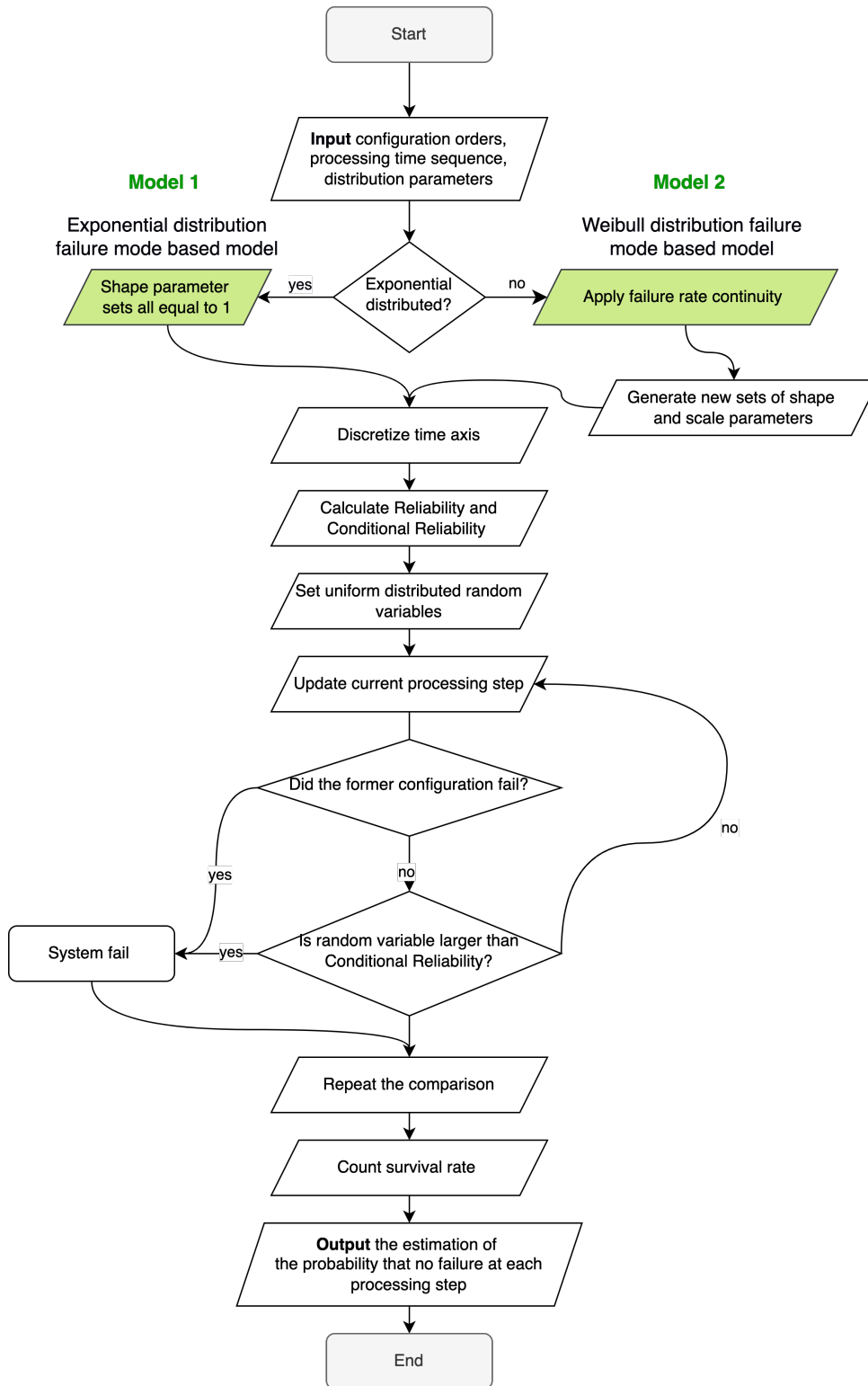


FIGURE 3.2 – Flowchart of Monte Carlo simulation on probabilistic models

3.2. PERFORMANCE EVALUATIONS

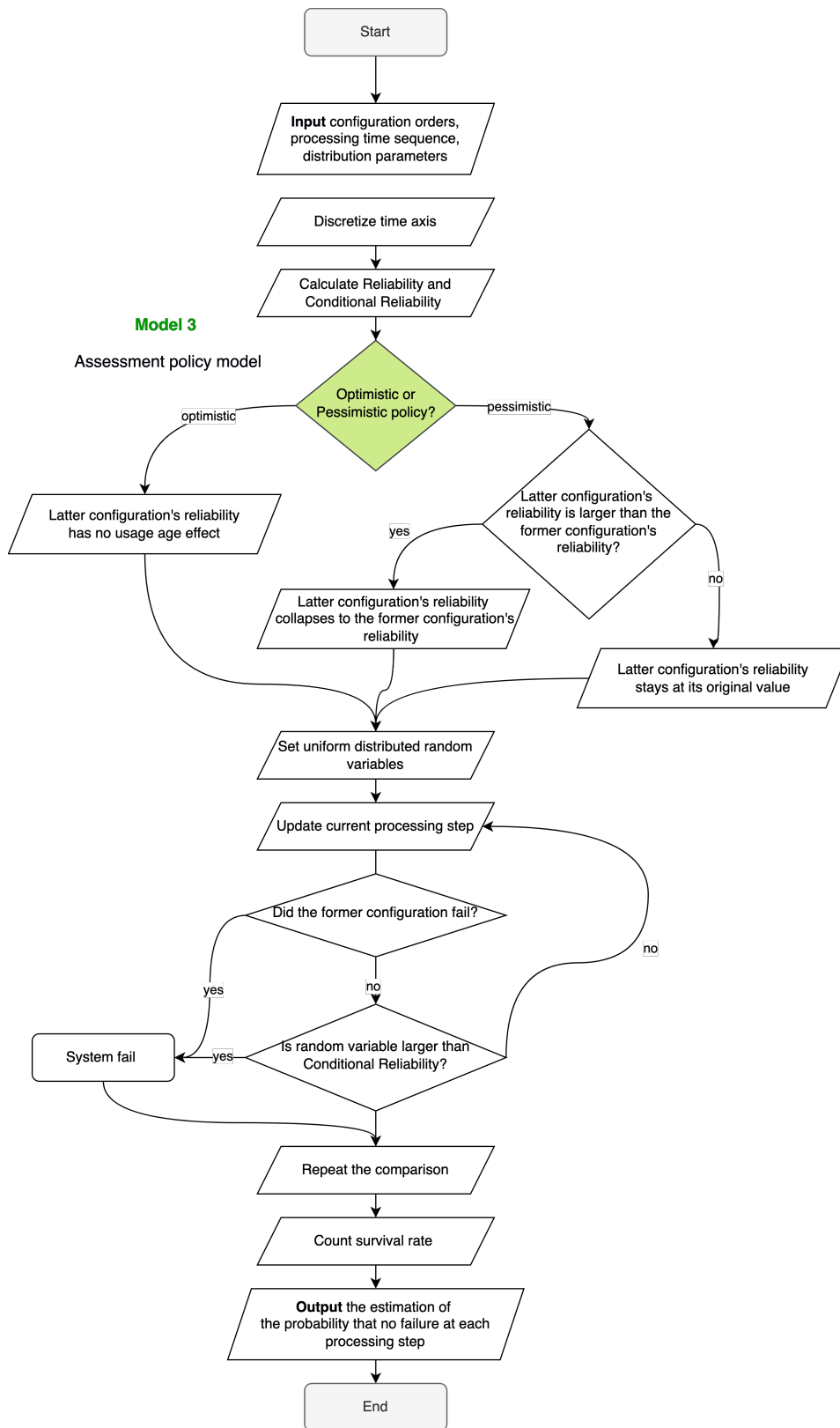


FIGURE 3.3 – Flowchart of Monte Carlo simulation on assessment policy model

Algorithm 1

MCS – Comparing failure rate under different configuration orders

Input: γ , $\{t_{i,m}\}$, $\{\beta_m\}$, $\{\eta_m\}$, M_p

1. **Require** configuration order γ .
2. According to γ , **require** processing time sequence $\{t_{i,m}\}$, shape and scale parameter sequence $\{\beta_m, \eta_m\}$.
($\{\beta_m\}=1$ when the model has failure mode of exponential distribution.)
3. **Discretize** time axis :
Set *steps* to define *timeUnit* as discretization of time during MCS.
System time list $[t]$ is generated with the size of $:steps = \sum t_{i,m}/timeUnit$.
4. **Calculate** reliability $R(t) = e^{(-t/\eta_m)^{\beta_m}}$ with size *steps*.
5. **Calculate** *ConditionalProbability* $= R[t]/R[t - 1]$.
6. **Generate** Random Variable $rv \sim U(0,1)$ with size *steps*.
7. **Compare** rv with R at each system time.
For *process* = $[1, M_p]$:
if *NoFailure*(*process* - 1) = *True* :
if $rv[t] > ConditionalP[t]$:
NoFailure(*process*) = *False*
Return the boolean value *Nofailure*.
8. **Repeat** the process by *iterationTimes* and calculate survival rate :
survivalrate = $count(NoFailure = 1)/iterationTimes$
9. **Set** simulation times and conduct normal fitting to obtain mean and stand error of conditional probability in each step : $P(T_m > \sum_{i=1}^m t_i | T_1 > t_1 \& T_2 > t_1 + t_2 \& \dots \& T_{m-1} > \sum_{i=1}^{m-1} t_i)$, std_{P_m}
10. **Generate** list of $\{\mu\}$ and $\{std.\}$ at each system time :
(a) $\mu_1 = P(T_1 > t_{1,m})$
(b) $\mu_2 = \mu_1 \cdot P(T_2 > t_{1,m} + t_{2,m} | T_1 > t_{1,m})$
(c) ...
(d) $\mu_i = \mu_{i-1} \cdot P(T_i > \sum_{j=1}^i t_j | T_1 > t_{1,m} \& T_2 > t_{1,m} + t_{2,m} \& \dots \& T_{i-1} > \sum_{j=1}^{i-1} t_j)$
(a) $std_1 = std_{P_1}$
(b) $std_2 = \mu_1 \cdot std_{P_2} + P(T_2 > t_{1,m} + t_{2,m} | T_1 > t_{1,m}) \cdot std_{P_1}$
(c) ...
(d) $std_i = P_i \cdot std_{i-1} + \mu_{i-1} \cdot std_{P_i}$
11. **Calculate** $P(Failure = 0)$ until the last configuration as presented in Equation 2.9.

Output: $\{\mu\}$ and $\{std.\}$ of $P(Failure = 0)$ under configuration order γ

Algorithm 2

MCS – Weibull parameters with constraint : failure rate continuity

Input: γ , $\{t_{i,m}\}$, $\{\beta_m\}$, $\{\eta_m\}$, M_p

1. **Run** same steps 1 to3 in algorithm 1.
2. **Calculate** failure rate $\lambda(S_i)$ each time reconfiguration is conducted.
3. **Set** η_{i+1} as unknown variable and solve the function as shown in Equation2.18.
4. **Generate** new sets of shape and scale parameters.
5. **Run** same steps 4 to 11 in algorithm 1.

Output: $\{\mu\}$ and $\{std.\}$ of $P(Failure = 0)$ under configuration order γ

Algorithm 3

MCS – Failure rate assessment of model with optimistic and pessimistic perspective

Input: processing time $\{t_i\}$, processing step n , Weibull distribution parameters $\{\beta_m, \eta_m\}$

1. **Generate** system time (size= s) and reconfiguration time S_i (size= n) based on processing time and time unit.
2. **Choose** optimistic/pessimistic policy
3. **Generate** $R(t)$ data sets by $\{\beta_m, \eta_m\}$ with size s according to :
 $R(S_{i+1}) = R(S_i|config.(i + 1))$ (if optimistic)
 $R(S_{i+1}) = \begin{cases} R(S_i + 1|config.(i + 1)) & \text{if } (R(S_{i+1}|config.i) > R(S_2|config.(i + 1))) \\ R(S_{i+1}|config.i) & \text{if } (R(S_{i+1}|config.i) < R(S_{i+1}|config.(i + 1))) \end{cases}$ (if pessimistic)
4. **Generate** random variables $rv \sim Uniform(0, 1)$ (size= s)
5. **Set** boolean variable $noFailure = 1$ (size= n)
 For each processing step i :
 if $noFailure[i - 1] = 1$:
 if $rv[t] > R[t]$:
 $noFailure[i] = 0$
6. **Repeat** last step and calculate *mean* and *std.* of $P(Failure = 0)$ at each S_i

Output: $P(failure = 0)$ at each S_i

3.2. PERFORMANCE EVALUATIONS

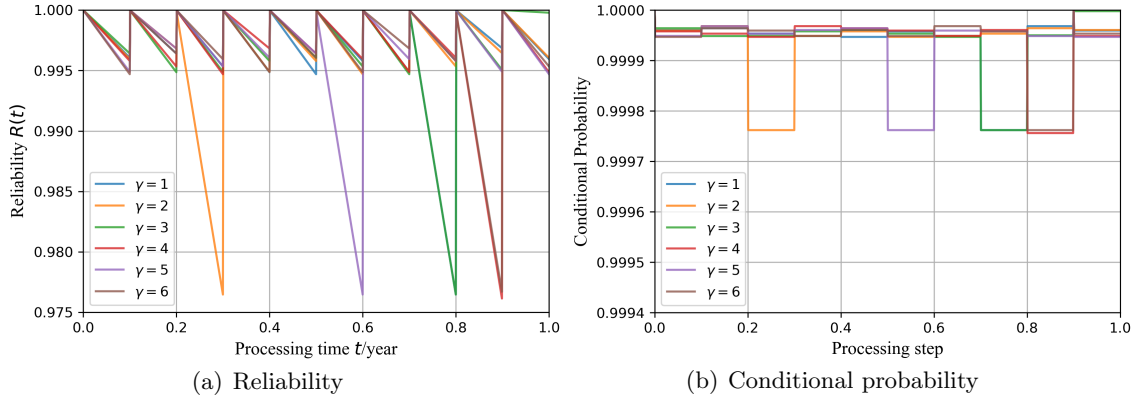


FIGURE 3.4 – Exponential distribution based failure functions

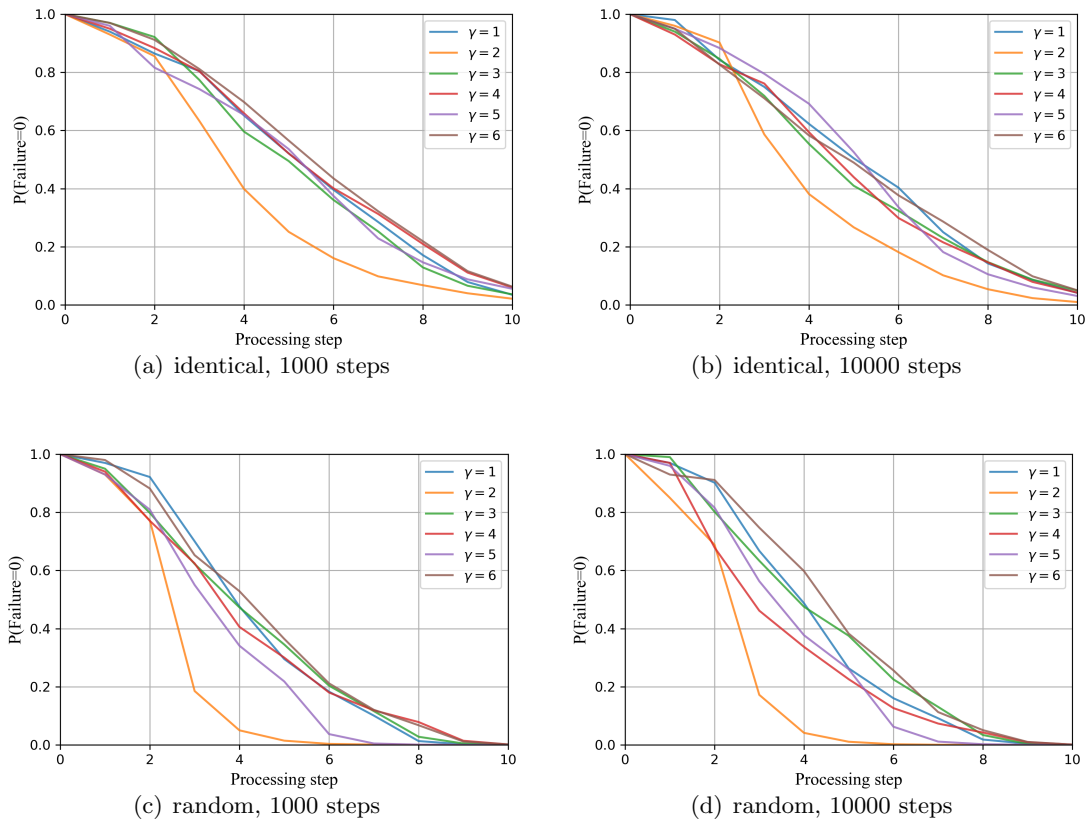


FIGURE 3.5 – Probability of no failure at each processing step for Exponential distribution based model

3.2. PERFORMANCE EVALUATIONS

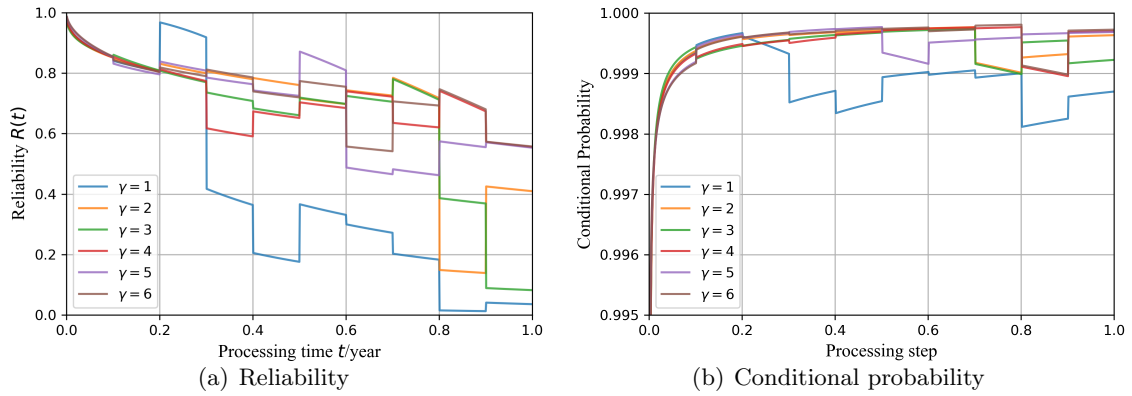


FIGURE 3.6 – Weibull distribution based failure functions

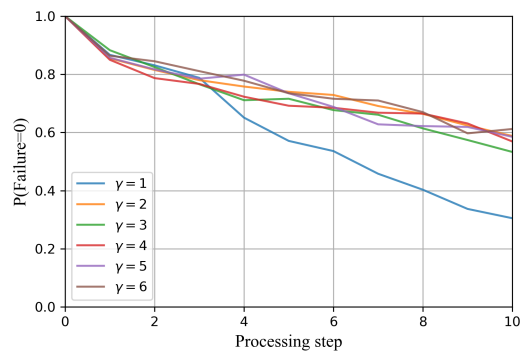


FIGURE 3.7 – Probability of no failure at each processing step for Weibull distribution based model

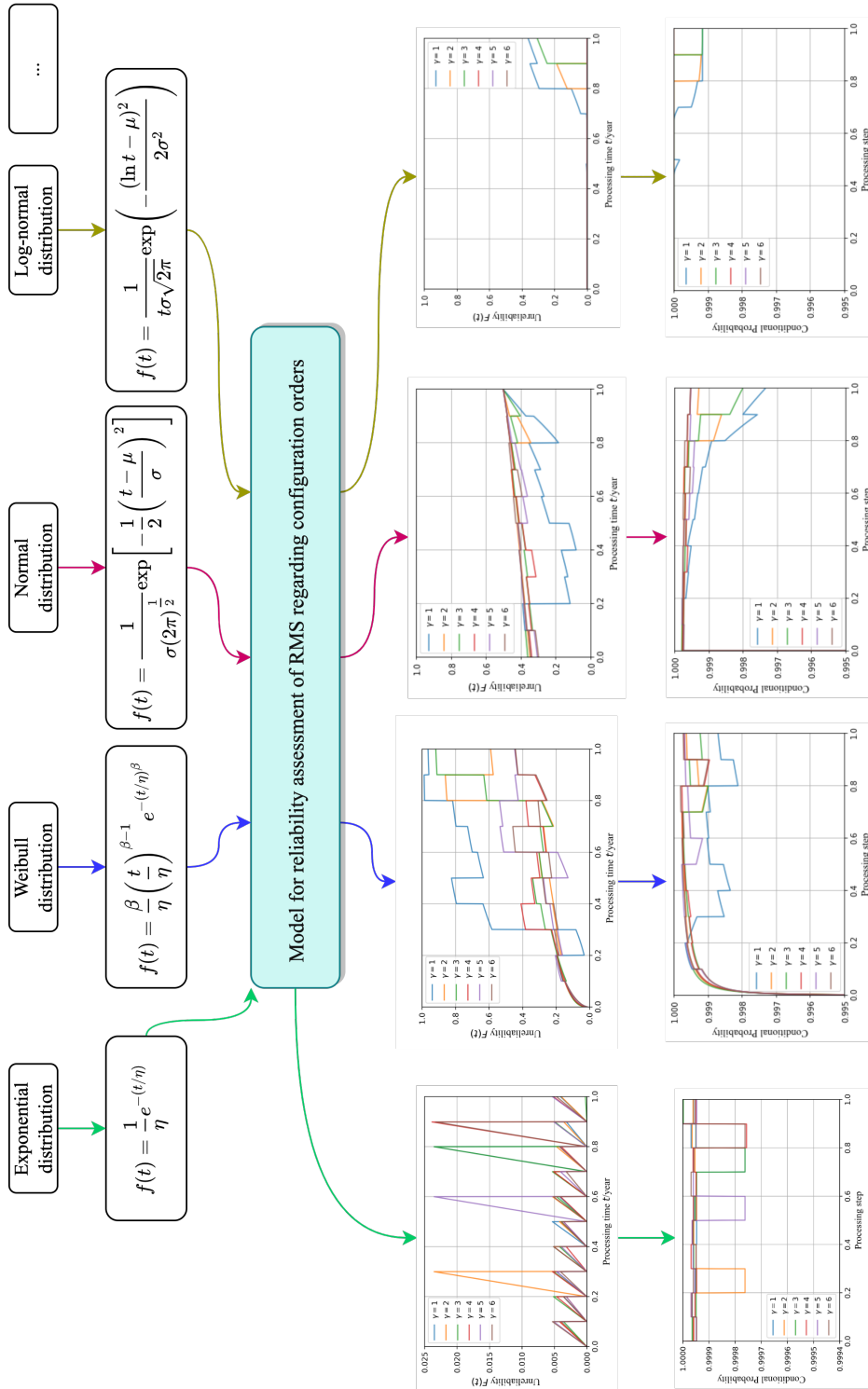


FIGURE 3.8 – Framework applied for different distributions

3.2. PERFORMANCE EVALUATIONS

Fig.3.8 illustrates the framework proposed in this thesis applied to different probabilistic models, with the input probability density functions and the output conditional probability under six different configuration orders. (The graphical illustration of the common distributions in reliability analysis include : normal distribution ($f(t) = \frac{1}{\sigma(2\pi)^{\frac{1}{2}}} \exp \left[-\frac{1}{2} \left(\frac{t-\mu}{\sigma} \right)^2 \right]$) and log-normal distribution ($f(t) = \frac{1}{t\sigma\sqrt{2\pi}} \exp \left(-\frac{(\ln t-\mu)^2}{2\sigma^2} \right)$), with mean and standard deviation parameters μ, σ .)

The data for generating the results in Fig.3.8 are only for illustration of application, therefore applied as the same batch of data from simulation in Section 3.2.1.1 and 3.2.1.2, although further verification of the data will be needed if applied in a real scenario.

3.2.2 Assessment policy model

Same as before, the assessment policy model was simulated by a number of six configuration orders, following the steps presented in Algorithm 3. The component original reliability functions, under the optimistic policy and under the pessimistic policy, are shown in Fig.3.9 and Fig.3.10 accordingly. Here we only present those of the first configuration order to avoid abundance, considering they have a great similarity despite different configuration orders. (The reliability functions under optimistic and pessimistic policies for all six configuration orders can be seen in Appendix C.2).

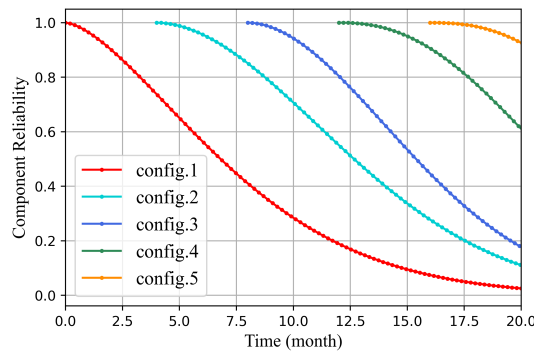


FIGURE 3.9 – Component reliability functions - Optimistic

The Fig.3.9 clearly shows the main characteristic under optimistic assessment policy : the component are like brand new when they are installed into the system. And Fig.3.10, which is applied with the pessimistic assessment policy, presents the straight decrease at reconfiguration system time, given the latter configuration reliability is larger than the former configuration reliability.

3.2. PERFORMANCE EVALUATIONS

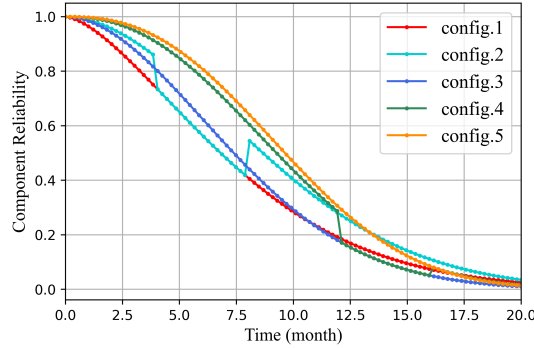


FIGURE 3.10 – Component reliability functions - Pessimistic

Afterwards, the Fig.3.11 and Fig.3.12 shows the reliability and conditional reliability obtained. By comparing the conditional reliability of the two policies, it is obvious that optimistic policy produces higher conditional reliability values, which is also logical under the given model assumptions.

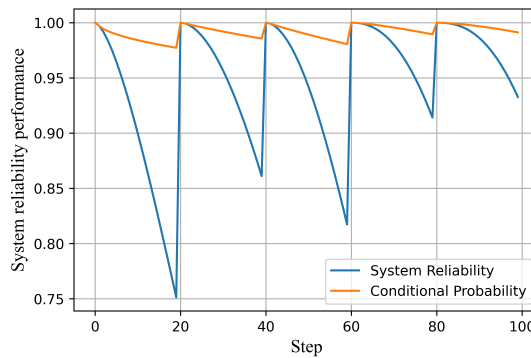


FIGURE 3.11 – Optimistic policy based failure functions

At the end is the survival rate of the system under O/P assessment models for all six configuration orders (see Fig.3.13). Several conclusion can be summed up from the performance results by comparing the figures.

- It can be seen that, for all six configurations, they have the same survival rate at the beginning. It suits the theoretical part of the model since on the first processing step, no reconfiguration has been done yet.
- The pessimistic policy always obtain lower system survival rate than optimistic policy. And with the given manufacturing data in this simulation, the survival rate functions share similar trends.

3.3. SENSITIVITY ANALYSIS (SA)

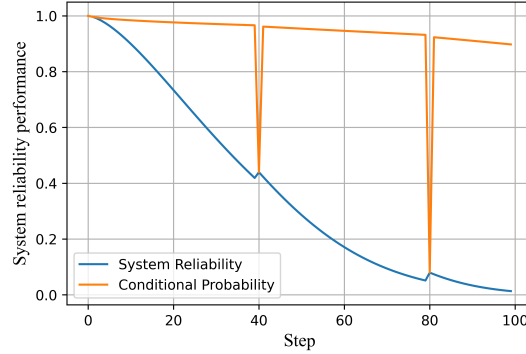


FIGURE 3.12 – Pessimistic policy based failure function

The detailed component reliability and system reliability figures of all six configuration orders are in Appendix C.2.

With the results above obtained, the next section presents the sensitivity analysis which will further verify the models.

3.3 Sensitivity Analysis (SA)

In this section, a Sensitivity Analysis (SA) is conducted on the MCS proposed in Section [?], with concern to the parameter : iteration sample size.

When operating Monte Carlo simulations, it is most often necessary to perform a SA at the end to determine which variables have the greatest influence on the model results. There are various techniques for SA depending on the model's characteristics : One-At-a-Time (OAT), Derivative-based local methods, Regression analysis, Variance-based methods, etc.

Generally, when performing SA, it is often assumed that the input variables are independent of each other. However, this condition may not be satisfied in some cases, then, Global Sensitivity Analysis (GSA) is required. Also, the interaction effect can be measured by total-order sensitivity index. In this thesis, it is assumed that the variables for SA are independent of each other.

Therefore, by following the most general procedure, without concerning the interactions between variables, this section assesses Monte Carlo simulation accuracy, by checking how the results are impacted by input variables. The procedure have the following steps :

3.3. SENSITIVITY ANALYSIS (SA)

1. Determine the degree of uncertainty in each input such as the ranges or probability distributions.
2. Determine the model output that will be examined.
3. Run the model repeatedly using the design of experiments, taking into account the input uncertainty.
4. Calculate the relevant sensitivity metrics based on the model results that were obtained.

Input Variables for SA

In this thesis, the input variable that is identified as uncertain during MCS is the iteration sample size. The other inputs including reconfiguration orders, Weibull parameters and processing time sequence are considered fixed variables.

Output

The output of the simulation is the probability of no failure at each processing step.

Sensitivity Metrics

The most important focus of this output regarding this thesis's research is *how much do configuration orders impact the reliability performance until the end of processing?* In another word, *how much do configuration order cause the level of dispersion in the end of processing?* So, the three metrics considered relevant to dispersion are analyzed : 1) Variance, 2) Range and 3) Coefficient of Variation (CV).

The following (Table 3.2) contains the sensitivity settings and analysis results :

TABLE 3.2 – Sensitivity analysis settings and results

Test	Variable	Sensitivity Metrics		
	Iteration Sample Size	Variance	Range	CV
1	100	0.021	0.47	0.264
2	500	0.011	0.314	0.2
3	1000	0.01	0.294	0.19
4	1500	0.01	0.299	0.186
5	2000	0.01	0.307	0.197
6	2500	0.01	0.295	0.19

As shown in Table 3.2, the iteration sample size was firstly set at 100, and afterwards arithmetically increase, each time by 500 times. There are some very noticeable data changes in the table. First, from test 1 to test 2, when the iteration sample size increases by 400%, variance decreases dramatically by

95%, range decreases by 33%, CV decreases by 24%. While afterwards, the variances decrease sequentially by 9%, and then reach stable. Among the three metrics, CV has relatively smaller fluctuation in absolute value because the data mean's impact on the variance is eliminated through division.

The comparison between the metrics are shown in Fig.3.14, which clearly shows a dramatic decrease of variance, range, and CV after 500 iteration sample size. Especially for the variance, it has reached stable after 500 iteration sample size. The data after 500 iteration sample size are relatively leveling off. This indicates the fact that with the iteration sample size larger than 500 times, the variable uncertainty impacting the reliability performance results is already negligible, and therefore, only configuration selections are impacting the reliability performance results. So, with iteration sample size larger than 500 times, the Monte Carlo simulatino result can be considered accurate.

3.4 Application examples

To conduct the numerical example for illustration, data sets from a study by Nourelfath et al. [31] are cited. Only on the basis of our finding that, reconfiguration orders have no effect on reliability when failure mode is Poisson, is this case plausible. Logical adjustment is conducted on the data based on authors' assumptions to fit our scenario. In their work, the authors mentioned that at the failure of a non-essential equipment, the system is allowed to continue operating. So only essential equipment is included in our data set. Based on the author's definition, a RMS is consisted of several components which are configured by equipment. Each time the component is put into use, a technology is applied, which will decide the configuration of equipment and the failure mode at the same time. There are 3 types of component, offering 3 data sets for our model (Table 3.3).

Reconfiguration process happens when the component's operation switch from one technology to another. Theoretically, component with M configurations would have $M!$ possible configuration orders. The equipment has the failure rate following exponential distribution.

Degradation mode of equipment would influence the failure rate of the components in processing. Two kinds of degradation modes of equipment are considered for comparison :

- Multiplicative failure mode.
- Competing failure mode (same as assumptions from the original author).

For a component with multiplicative failing equipment, reliability performance outcomes are ob-

3.4. APPLICATION EXAMPLES

TABLE 3.3 – Failure rate of configurations for three types of component

Component type	Failure rate			
type-I	<i>Config.1</i>	Equipment 1 10^{-4}	Equipment 2 $1.2 * 10^{-4}$	
	<i>Config.2</i>	Equipment 1 10^{-4}	Equipment 3 $1.3 * 10^{-4}$	
	<i>Config.3</i>	Equipment 1 $0.8 * 10^{-4}$	Equipment 2 $1.4 * 10^{-4}$	Equipment 3 $1.2 * 10^{-4}$
type-II	<i>Config.1</i>	Equipment 1 $1.5 * 10^{-4}$	Equipment 2 $1.3 * 10^{-4}$	
	<i>Config.2</i>	Equipment 1 $1.5 * 10^{-4}$	Equipment 2 $1.3 * 10^{-4}$	
	<i>Config.3</i>	Equipment 1 $0.85 * 10^{-4}$	Equipment 2 10^{-4}	Equipment 3 $1.7 * 10^{-4}$
	<i>Config.4</i>	Equipment 1 $0.85 * 10^{-4}$	Equipment 2 10^{-4}	Equipment 4 $1.7 * 10^{-4}$
type-III	<i>Config.1</i>	Equipment 1 $1.8 * 10^{-4}$	Equipment 2 $1.4 * 10^{-4}$	
	<i>Config.2</i>	Equipment 1 $1.8 * 10^{-4}$	Equipment 2 $1.4 * 10^{-4}$	

tained in Table 3.4. Each *config.i* has a corresponding failure speed by multiplying failure speed of configured equipment. The performance indexes include reliability and unreliability functions. According to observation of the performance results, when the failure speed of one equipment is much lower on order of magnitude compared with others, its influence on reliability is almost negligible. Taking component type-I as an example, *config.1* and *config.2* deliver significantly bigger influences due to their order of magnitude. Secondly, among the three components following the configuration processes, the first reconfiguration process provides the highest reliability performance, and the third reconfiguration process provides the lowest reliability performance. This is clearly shown in Fig.3.15(a) which combines the three reliability curves into one graph. In this numerical example, the first reconfiguration process has advantage in reliability performance. But it is worth mentioning that under real-time situations, constraints such as cost is required for optimal solution choice.

For a component with competing failing equipment, same steps are conducted. The reliability performance are obtained as shown in Table 3.5 and Fig.3.15(b).

By comparing the results from Fig.3.15(a) and Fig.3.15(b), it is evident that the reconfiguration process with optimal reliability performance has changed, from the 1st configuration to the 3rd configu-

3.4. APPLICATION EXAMPLES

TABLE 3.4 – Reliability performance of RMS with Exponential distribution failure mode (multiplicative failing equipment)

Component type	M	λ	$R(t)$	$F(t)$
I	3	$1.20 * 10^{-8}$	$e^{-2.50*10^{-8}t}$	$1 - e^{-2.50*10^{-8}t}$
		$1.30 * 10^{-8}$		
		$1.34 * 10^{-12}$		
II	4	$1.95 * 10^{-8}$	$e^{-3.90*10^{-8}t}$	$1 - e^{-3.90*10^{-8}t}$
		$1.95 * 10^{-8}$		
		$1.45 * 10^{-12}$		
		$1.45 * 10^{-12}$		
III	2	$2.52 * 10^{-8}$	$e^{-5.04*10^{-8}t}$	$1 - e^{-5.04*10^{-8}t}$
		$2.52 * 10^{-8}$		

TABLE 3.5 – Reliability performance of RMS with Exponential distribution failure mode (competing failing equipment)

Component	M	λ	$R(t)$	$F(t)$
type-I	3	$2.20 * 10^{-4}$	$e^{-7.90*10^{-4}t}$	$1 - e^{-7.90*10^{-4}t}$
		$2.30 * 10^{-4}$		
		$3.40 * 10^{-4}$		
type-II	4	$2.80 * 10^{-4}$	$e^{-12.70*10^{-4}t}$	$1 - e^{-12.70*10^{-4}t}$
		$2.80 * 10^{-4}$		
		$3.55 * 10^{-4}$		
		$3.55 * 10^{-4}$		
type-III	2	$3.20 * 10^{-4}$	$e^{-6.40*10^{-4}t}$	$1 - e^{-6.40*10^{-4}t}$
		$3.20 * 10^{-4}$		

ration. This is because when the failure mode is competing rather than multiplicative, huge difference in order of magnitude doesn't occur anymore. Generally, under the competing failure mode, reliability tends to drop more abruptly compared with multiplicative failure mode. This outcome also fits the nature of the failure mode since for competing failure mode, one equipment's failure would lead to the ceasing of the manufacturing system.

Therefore, in this simulation case, all the configuration orders lead to the similar reliability performances. It is due to the component failure occurring as Exponential distribution, in which the configuration order will not impact on reliability function as discussed in Section 3.2.1.1.

3.5 Conclusions

This chapter include the flowcharts and algorithms for the MCS, the reliability performance obtained from the simulation, sensitivity analysis and application examples. The simulations were performed based on the same sets of manufacturing data for illustration. The results from simulations accorded the conclusion in analysis of each model. The algorithm for the simulation based on Monte Carlo method was developed by the steps :

- Taking failure distribution parameters as inputs.
- Calculating the reliability and conditional probability.
- Comparing the theoretical values with random variable.
- Iterating the former steps.
- Generating probability of no failure occurring at each step as output.

The algorithm managed to prove its effectiveness. But the essence being MCS method made the algorithm highly reliable on assumptions. Yet the assumptions needed to be justified in most cases. For example, the algorithm won't suit scenarios with maintenance policy.

One of the main contribution in this chapter is the further proof by simulation that when failure mode follows Exponential distribution , reconfiguration order does not impact the reliability performance. With proceeding processing steps, the reliability performance will converge in the end.

This novel finding demonstrates two things. First, when a manufacturing company confirms that their RMS failure follows the Exponential distribution, there is no need to invest cost to simulate with different configuration orders since the reliability performance is consistent in any case. Second, when the failure mode follows Weibull distribution, configuration orders would have significant impact on the reliability performance. As a result, an approach to improve reliability performance for a company could be working on the configuration orders.

3.5. CONCLUSIONS

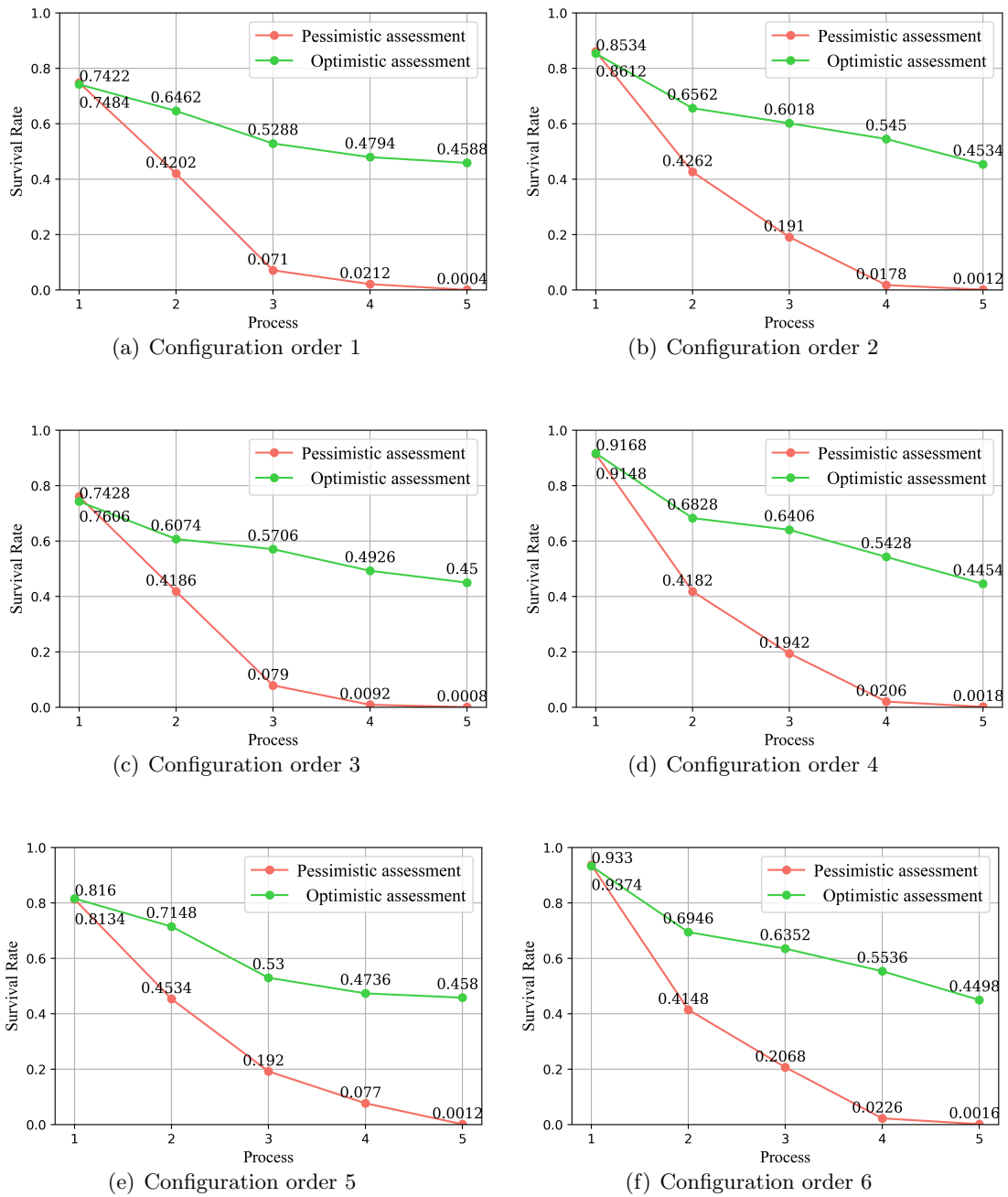


FIGURE 3.13 – O/P assessment based model survival rate

3.5. CONCLUSIONS

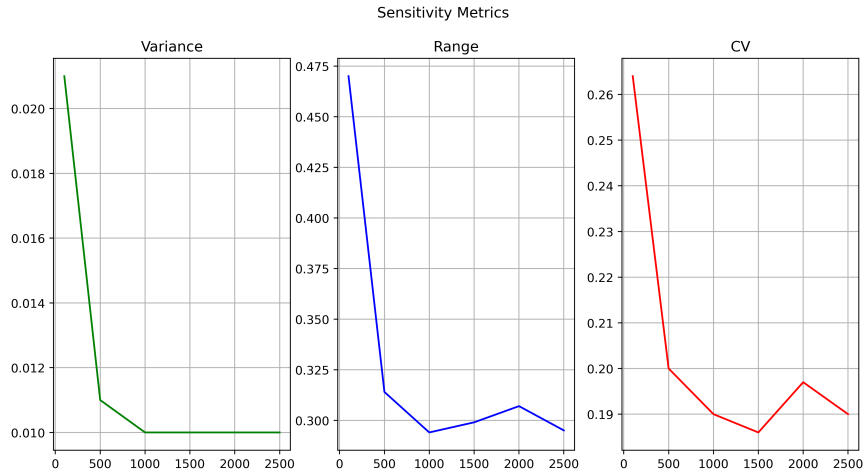


FIGURE 3.14 – Sensitivity analysis results

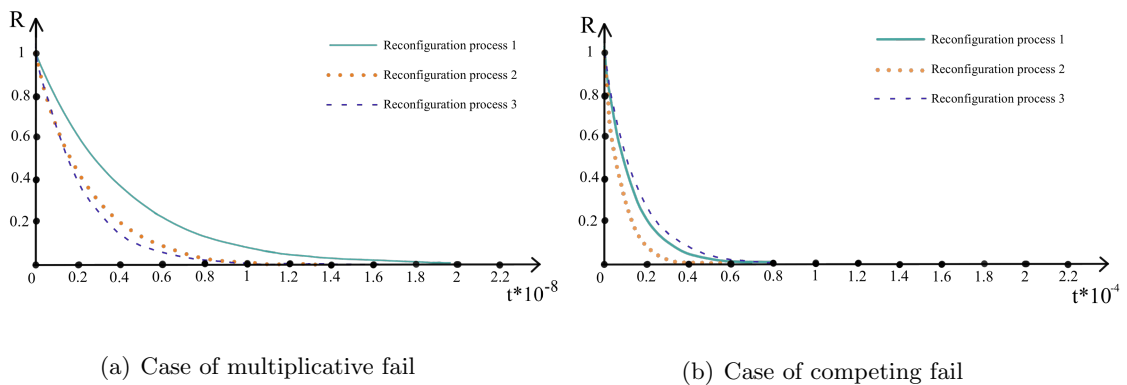


FIGURE 3.15 – Reliability function of Exponential distribution failure mode

Conclusion and Future Works

Conclusion

This research was separated into three chapters :

- **Chapter 1** A Review of Reliability Analysis in Reconfigurable Manufacturing Systems
- **Chapter 2** Models of Reliability Performance of Reconfigurable Manufacturing Systems
- **Chapter 3** Simulation And Evaluation of the Reliability Performance Models of Reconfigurable Manufacturing Systems

The aim of this research is to propose a framework for the reliability analysis applied in RMS. As a reminder and as indicated in introduction, an overall objective was raised at the beginning of the research :

*How do **the choices** made for reconfigurable manufacturing systems **impact** various forms of **reliability performance** during the whole processing procedure despite the increasing complexity of the systems ?*

A Review of Reliability Analysis in Reconfigurable Manufacturing Systems

To respond to the question raised in overall objective, background research was needed and disassembled tasks would be listed, as shown in the following Chapter 1.

Chapter 1 set basis of the research by sorting out the background knowledge, conducting literature reviews and analyzing the current research trends. Specific efforts were put into the review of *reliability analysis applied in RMS*, with application of VOSviewer and Conceptual Maps, based on the techniques of Citation Network Analysis.

Sum up from the above steps, it is concluded that RMS reliability analysis differs greatly from that of a conventional production system. Therefore, two main contributions were given : the fundamental distinctions between RMS and general manufacturing systems during reliability analysis and challenges of the study in this thesis, as shown in the following list :

- *How to verify whether the interactions/interfaces impact the reliability performance of an RMS ?*
- *In what cases, the impacts are neglectable or non-neglectable ?*
- *If the impacts exist, how to describe the causalities between the configurations ?*
- *When describing the causalities between configurations, how to estimate and set limit ?*

- *If interactions/interfaces impact the reliability performance of an RMS, how significant is the impact and how to measure it?*

Models of Reliability Performance of Reconfigurable Manufacturing Systems

As the tasks had been disassembled in Chapter 1, Chapter 2 was targeted at constructing models that take these unique criteria into consideration.

Firstly, the objective system was outlined with its general features, assumptions, and RMS characteristics. The reconfigurability based on configuration orders is then discussed and shown in a Markov chain. This stage of research also includes the models that depict the causalities. Then, two types of mathematical models of the dependability performance of reconfigurable manufacturing systems were developed : two probabilistic models, one based on the Exponential distribution and the other based on the Weibull distribution, and one based on optimistic or pessimistic evaluation. Last, the three models are described in detail, including their assumptions and mathematical formulations. An explanation of the model's properties and the next stage in verification is provided. So far, some of the questions can be answered :

How to verify whether the interactions/interfaces impact the reliability performance of an RMS ?

The impact could be verified through three optional approaches : calculation of mathematical formula, resulting from simulation and application of real case. A system definition was definitely required, because different RMS could have different interactions/interfaces. In this research, the calculation of mathematical formula and simulation were adopted based on available conditions.

In what cases, the impacts are neglectable or non-neglectable ?

The mathematical formulations for the two probabilistic models proved that, when the failure mode follows Exponential distribution, the answer is *No*, which mean there is no impact from iterations/interfaces of the RMS. When the failure mode follows Weibull distribution, the answer is *Yes*, which means such impact exists. The reason behind is the memorylessness characteristic of Exponential distribution that enables a component to be used regardless of its usage history. In other cases, the usage history of a component can not be ignored, and thus, the impact is expected to exist.

If the impacts exist, how to describe the causalities between the configurations ?

As answered in Question 2, the impact does not exist when the failure mode follows Exponential

3.5. CONCLUSIONS

distribution. Thus, it is assumed that all the other distributions would require a consideration of the impact. For failure mode following other distributions, the causalities were analyzed through grading, which takes as much as possibilities into account for comprehensiveness : no impact, limited impact, full impact, continuity-based impact and hybrid causality

When describing the causalities between configurations, how to estimate and set limit

The third model, O/P assessment policy model, was built to describe the causalities between configurations and set limits to the reliability performances. Due to the comprehensive knowledge being hard to be acquired in real cases, the epistemic uncertainty of the system can not be ignored. In this case, the two extreme cases, the most optimistic and the most pessimistic situation, could set the limits for the model. Further more, a parameter showing the level of optimism and pessimism would help with the estimation.

Simulation And Evaluation of the Reliability Performance Models of Reconfigurable Manufacturing Systems

The final stage of the proposed framework for reliability analysis in RMS is verification and validation.

In order to validate the models, Chapter 3 focuses on simulation and performance evaluations, which are based on the models developed in Chapter 2. This chapter contributes in building the flowcharts and simulation algorithm for Monte Carlo simulation. The failure parameters, configuration orders, and assessment policies are the framework's inputs. The outputs are then the reliability performances for various configurations.

In the end, examples of application are provided to assist future scholars who may be interested in the work and to demonstrate the practical significance of the research.

Chapter 3 answers to the last question :

If interactions/interfaces impact the reliability performance of an RMS, how significant is the impact and how to measure it ? The significance of the impact required more intuitive presentation through data, either acquired through simulation or experiments. In this research, Monte Carlo simulation was adopted to answer to this question. During the measurement, special attention to simulation precision and parameter setting was required. And in the end, the Monte Carlo simulation further

3.5. CONCLUSIONS

verifies the conclusion from mathematical formulations, as presented in the answer to Question 2.

Future perspectives

As discussed in this thesis, there are certain limitations during modeling for the problems. This thesis mainly studied two distributions, and test briefly for two other distributions. While the further studies of other models and their selection can worth studying. And the parameter defined for the O/P model, level of optimism and pessimism, was an simplified index, describing the situations in an ideal way although in actual scenarios it can be more complicated. The Failure mechanism of the RMT was referred to existing prototypes, while different types can require specific reliability performance analysis methods. The following are the detailed explanations of the future perspectives in accordance to these limitations above.

Failure mode following other distributions

Failure modes that follow the Exponential distribution and the Weibull distribution were studied and modeled in this thesis. The O/P model was based on the Weibull distribution as well. And other probabilistic distributions, which suit the failure data of the research object, have been tested on the models. While some of the other common distributions that can be further tested include : Extreme Value, Erlang, Chi-Square, Gamma Distributions and Auxiliary distributions, Bayesian reliability estimation. Although the proposed framework can fit all these distributions, the analysis of the results from these other distributions can be interesting, since they all possess unique characteristics. And the methodology for choosing the distributions accurately can be studied.

Parameter of optimism and pessimism level

As discussed in the Chapter 2, a parameter indicating the level of optimism and pessimism is worthy of studying. This thesis did not put effort in defining this specific parameter to meet the real scenarios, while it the next stage for the O/P model, it can be a crucial part. This parameter, level of O/P, can be defined with concern to many factors : the products' characteristics, the usage history of the system, the importance of the order, the decision preference of the company, etc. All these factors could have influences on how optimistic or pessimistic should the model be. When these factors tend

to be conservative, a more pessimistic assessment policy should be adopted.

Failure mechanism of Reconfigurable Manufacturing Tool

When an interdisciplinary research is feasible, for some researchers, a further dig into the mechanism of the failure can be worth studying. The question would be : How the different configurations impact the reliability performance of RMS with concern to its failure mechanisms. In this case, the RMTs would need concrete 3D models, with the help from mechanical modeling and force analysis software. This perspective suits better for a real case of RMS consisted of RMTs, in actual manufacturing companies. Besides, the models in this thesis have focused on the probability that no failure occurs at each step. Another perspective can be the study of how many failures occur during the manufacturing process, for which an assumption of *repairability* is added. In this scenario, a *k-out-of-m* model would be applicable since components can be repaired by rearrangement and maintenance [32].

CONCLUSION

Consigne bibliographie

Rappel : qu'est-ce qu'une bibliographie ?

- une liste ordonnée de références de documents concernant un auteur ou un sujet.
- permet l'identification claire des sources citées, présentées de manière ordonnée et conforme à des normes prescrites.

Le style de présentation de la bibliographie (ponctuation, majuscules,...) peut varier selon les disciplines et les documents. Il est à choisir avec la·le directeur·rice de thèse.

En Sciences humaines et sociales, privilégier un style de type ■ AUTEUR (date). TITRE ■ : comme les normes APA, Chicago ou Vancouver. Dans le domaine de l'informatique et des sciences de l'ingénieur, privilégier le style IEEE : style numérique, par ordre d'apparition des références dans la thèse.

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Annexe A

Literature searching criteria



FIGURE A.1 – Aspect 1



FIGURE A.2 – Aspect 2



FIGURE A.3 – Aspect 3

Annexe B

Formula derivation

B.1 Weibull distribution failure mode based model under continuity assumption

With the assumptions, the following Equations are acquired :

$$\frac{\beta_i}{\eta_i} \cdot \left(\frac{S_i}{\eta_i}\right)^{\beta_i-1} = \frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \quad (\text{B.1})$$

$$\frac{\beta_i}{\eta_i} \cdot \left(\frac{S_i}{\eta_i}\right)^{\beta_i-1} \cdot e^{-\left(\frac{S_i}{\eta_i}\right)^{\beta_i}} = \frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \cdot e^{-\left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}}} \quad (\text{B.2})$$

Then the following derivations are acquired :

$$\frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \cdot e^{-\left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}}} = \frac{\beta_{i+1}}{\eta_{i+1}} \cdot \left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}-1} \cdot e^{-\left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}}} \quad (\text{B.3})$$

$$e^{-\left(\frac{S_i}{\eta_i}\right)^{\beta_i}} = e^{-\left(\frac{S_i}{\eta_{i+1}}\right)^{\beta_{i+1}}} \quad (\text{B.4})$$

$$S_i^{\beta_i} \cdot \eta_i^{-\beta_i} = S_i^{\beta_{i+1}} \cdot \eta_i^{-\beta_{i+1}} \quad (\text{B.5})$$

$$S_i = \eta_{i+1}^{\beta_{i+1}} \cdot \eta_i^{-\beta_i} \quad (\text{B.6})$$

Annexe C

Manufacturing data and reliability performance evaluation results for Monte Carlo simulation

C.1 Inputs

C.1.1 Manufacturing failure data and configuration orders

Configuration	1	2	3	4	5
Rules	Rule 2-1 RR	Rule 2-2 HH	Rule 2-3 XX	Rule 2-4 XR	Rule 2-5 HR
β	0.39	0.36	0.47	0.51	0.53
η	2.53	2.78	2.14	1.94	1.88
Configuration	6	7	8	9	10
Rules	Rule 2-6 XH	Rule 2-7 KR	Rule 2-8 RH	Rule 2-9 DD	Rule 2-10 KK
β	0.42	0.51	2.38	0.31	0.41
η	2.37	1.95	0.42	3.14	2.46

TABLE C.1 – Weibull parameters of different configurations from manufacturing failure data

Processing order	1	2	3	4	5	6	7	8	9	10
$\gamma=1$ (Sequential)	1	2	3	4	5	6	7	8	9	10
$\gamma=2$ (Backwards)	10	9	8	7	6	5	4	3	2	1
$\gamma=3$	2	4	7	6	1	3	5	8	10	9
$\gamma=4$	6	3	5	9	2	10	7	1	8	4
$\gamma=5$	7	9	3	1	2	8	10	6	4	5
$\gamma=6$	5	2	10	7	1	4	9	6	8	3

TABLE C.2 – Configuration orders

C.2. RESULTS

<i>Config.m</i>	1	2	3	4	5	6	7	8	9	10
Identical processing time (year)	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10	0.10
Accumulated identical processing time (year)	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00
Random processing time (year)	0.10	0.10	0.40	0.30	0.10	0.05	0.10	0.50	0.20	0.30
Accumulated random processing time (year)	0.10	0.20	0.60	0.90	1.00	1.05	1.15	1.65	1.85	2.15

TABLE C.3 – Configuration and accumulated processing time

C.2 Results

C.2.1 Probability of $P(\text{Failure} = 0)$ at each processing step with mean and standard error value

Processing step	1		2		3		4		5		6	
	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.
1	0,970	0,064	0,980	0,040	0,960	0,066	0,960	0,066	0,970	0,046	0,970	0,046
2	0,892	0,154	0,843	0,152	0,883	0,155	0,864	0,120	0,902	0,105	0,825	0,156
3	0,776	0,224	0,598	0,241	0,733	0,208	0,752	0,192	0,767	0,190	0,734	0,232
4	0,613	0,278	0,425	0,249	0,608	0,277	0,661	0,225	0,659	0,234	0,638	0,316
5	0,460	0,271	0,297	0,231	0,517	0,303	0,575	0,255	0,501	0,267	0,492	0,319
6	0,350	0,268	0,217	0,209	0,398	0,285	0,483	0,260	0,301	0,263	0,393	0,313
7	0,255	0,227	0,141	0,165	0,283	0,257	0,329	0,233	0,189	0,199	0,287	0,295
8	0,151	0,171	0,092	0,126	0,164	0,185	0,227	0,231	0,089	0,125	0,218	0,263
9	0,066	0,096	0,054	0,090	0,098	0,127	0,141	0,173	0,053	0,092	0,127	0,186
10	0,031	0,052	0,026	0,050	0,057	0,091	0,070	0,109	0,027	0,055	0,068	0,118

TABLE C.4 – Data of Fig.3.5-(a)

Processing step	1		2		3		4		5		6	
	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.
1	0,960	0,049	0,950	0,067	0,930	0,100	0,940	0,080	0,970	0,046	0,910	0,104
2	0,864	0,118	0,845	0,139	0,846	0,179	0,837	0,160	0,834	0,164	0,801	0,128
3	0,717	0,193	0,566	0,200	0,702	0,242	0,686	0,248	0,759	0,228	0,713	0,181
4	0,595	0,246	0,340	0,196	0,583	0,264	0,549	0,267	0,516	0,276	0,563	0,217
5	0,458	0,260	0,238	0,174	0,461	0,289	0,390	0,257	0,434	0,279	0,462	0,227
6	0,325	0,217	0,152	0,142	0,345	0,279	0,300	0,247	0,273	0,243	0,346	0,218
7	0,208	0,197	0,079	0,093	0,266	0,269	0,228	0,221	0,172	0,188	0,235	0,196
8	0,100	0,124	0,049	0,068	0,157	0,208	0,153	0,185	0,096	0,129	0,158	0,162
9	0,056	0,082	0,030	0,046	0,085	0,131	0,072	0,109	0,048	0,082	0,080	0,100
10	0,025	0,048	0,012	0,022	0,043	0,079	0,033	0,061	0,021	0,044	0,039	0,056

TABLE C.5 – Data of Fig.3.5-(b)

C.2. RESULTS

Processing step	1		2		3		4		5		6	
	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.
1	0,990	0,030	0,870	0,127	0,970	0,046	0,940	0,066	0,890	0,083	0,970	0,064
2	0,941	0,095	0,705	0,175	0,844	0,155	0,780	0,115	0,828	0,134	0,922	0,126
3	0,828	0,166	0,162	0,095	0,624	0,262	0,577	0,250	0,629	0,246	0,765	0,214
4	0,538	0,247	0,036	0,044	0,518	0,274	0,439	0,264	0,472	0,279	0,642	0,289
5	0,312	0,219	0,009	0,014	0,389	0,272	0,320	0,255	0,330	0,277	0,443	0,305
6	0,190	0,183	0,002	0,004	0,225	0,203	0,208	0,225	0,056	0,086	0,239	0,231
7	0,120	0,141	0,000	0,001	0,135	0,158	0,133	0,174	0,011	0,023	0,146	0,174
8	0,018	0,033	0,000	0,000	0,014	0,028	0,076	0,126	0,002	0,005	0,083	0,121
9	0,002	0,006	0,000	0,000	0,003	0,007	0,011	0,027	0,000	0,001	0,013	0,027
10	0,001	0,002	0,000	0,000	0,000	0,001	0,001	0,004	0,000	0,000	0,002	0,005

TABLE C.6 – Data of Fig.3.5-(c)

Processing step	1		2		3		4		5		6	
	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.	mean	std.
1	0,990	0,030	0,850	0,092	0,990	0,030	0,970	0,046	0,940	0,080	0,970	0,046
2	0,861	0,144	0,671	0,143	0,851	0,105	0,795	0,122	0,827	0,141	0,892	0,127
3	0,715	0,206	0,215	0,161	0,639	0,157	0,636	0,177	0,587	0,207	0,732	0,241
4	0,436	0,229	0,045	0,056	0,473	0,212	0,439	0,219	0,399	0,223	0,593	0,290
5	0,279	0,191	0,007	0,014	0,392	0,249	0,294	0,206	0,280	0,238	0,474	0,307
6	0,159	0,137	0,002	0,005	0,247	0,200	0,168	0,165	0,039	0,062	0,313	0,260
7	0,075	0,079	0,000	0,001	0,143	0,152	0,096	0,111	0,005	0,014	0,194	0,207
8	0,015	0,023	0,000	0,000	0,019	0,041	0,046	0,067	0,001	0,003	0,099	0,142
9	0,003	0,006	0,000	0,000	0,004	0,011	0,009	0,017	0,000	0,001	0,018	0,036
10	0,001	0,001	0,000	0,000	0,001	0,002	0,001	0,002	0,000	0,000	0,002	0,007

TABLE C.7 – Data of Fig.3.5-(d)

C.2.2 Weibull parameters without and with constraints

Failure rate	(β, η)	(β', η')
λ_1	(2.00, 0.20)	(2.00, 0.20)
λ_2	(2.00, 0.90)	(6.20, 0.90)
λ_3	(2.00, 1.30)	(6.58, 1.30)
λ_4	(6.00, 2.00)	(7.41, 2.00)

TABLE C.8 – Randomly generalized data for illustration

C.2.3 Component reliability functions under optimistic assessment policy

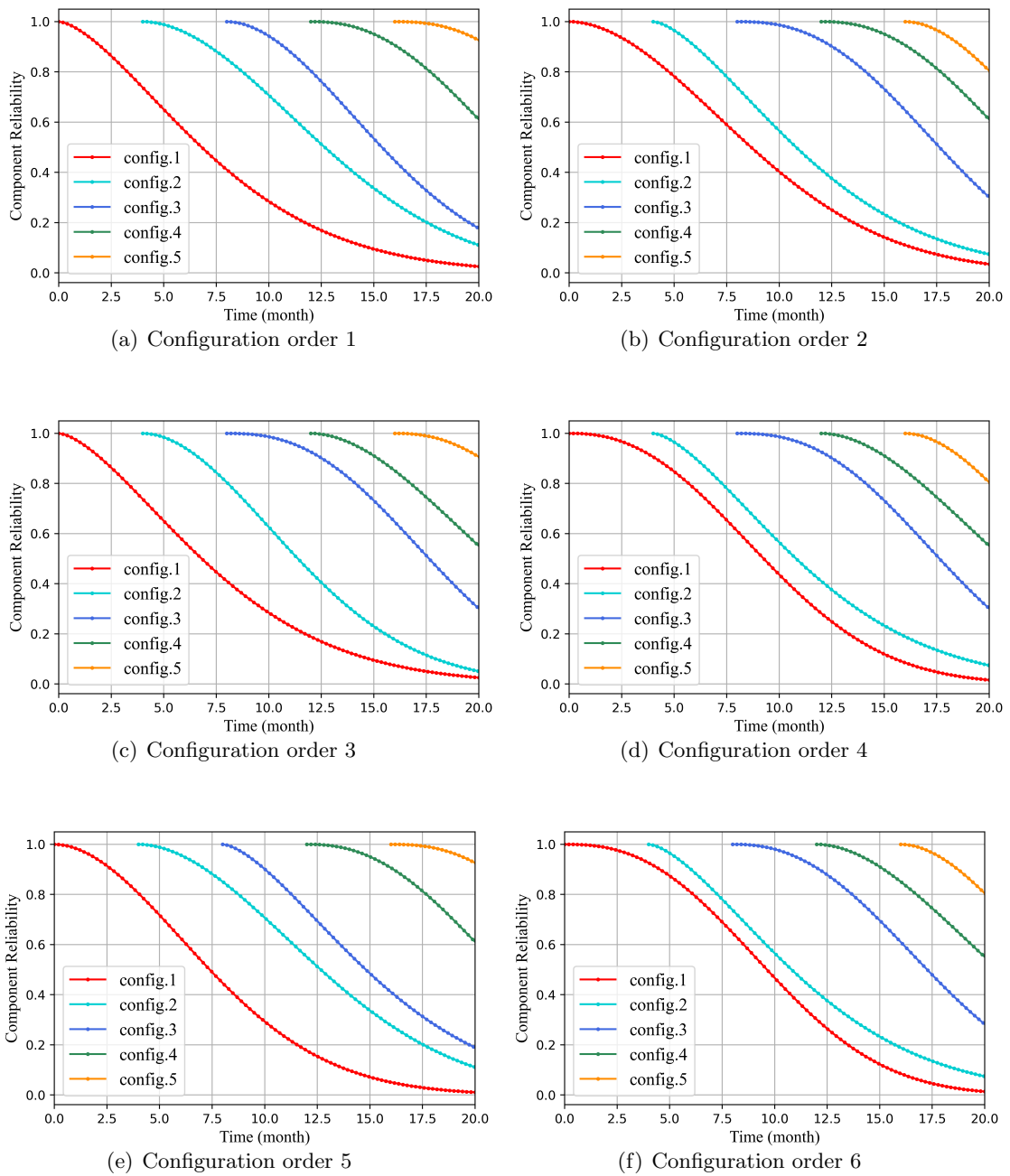


FIGURE C.1 – Component Reliability - Optimistic Policy

C.2.4 Component reliability functions under pessimistic assessment policy

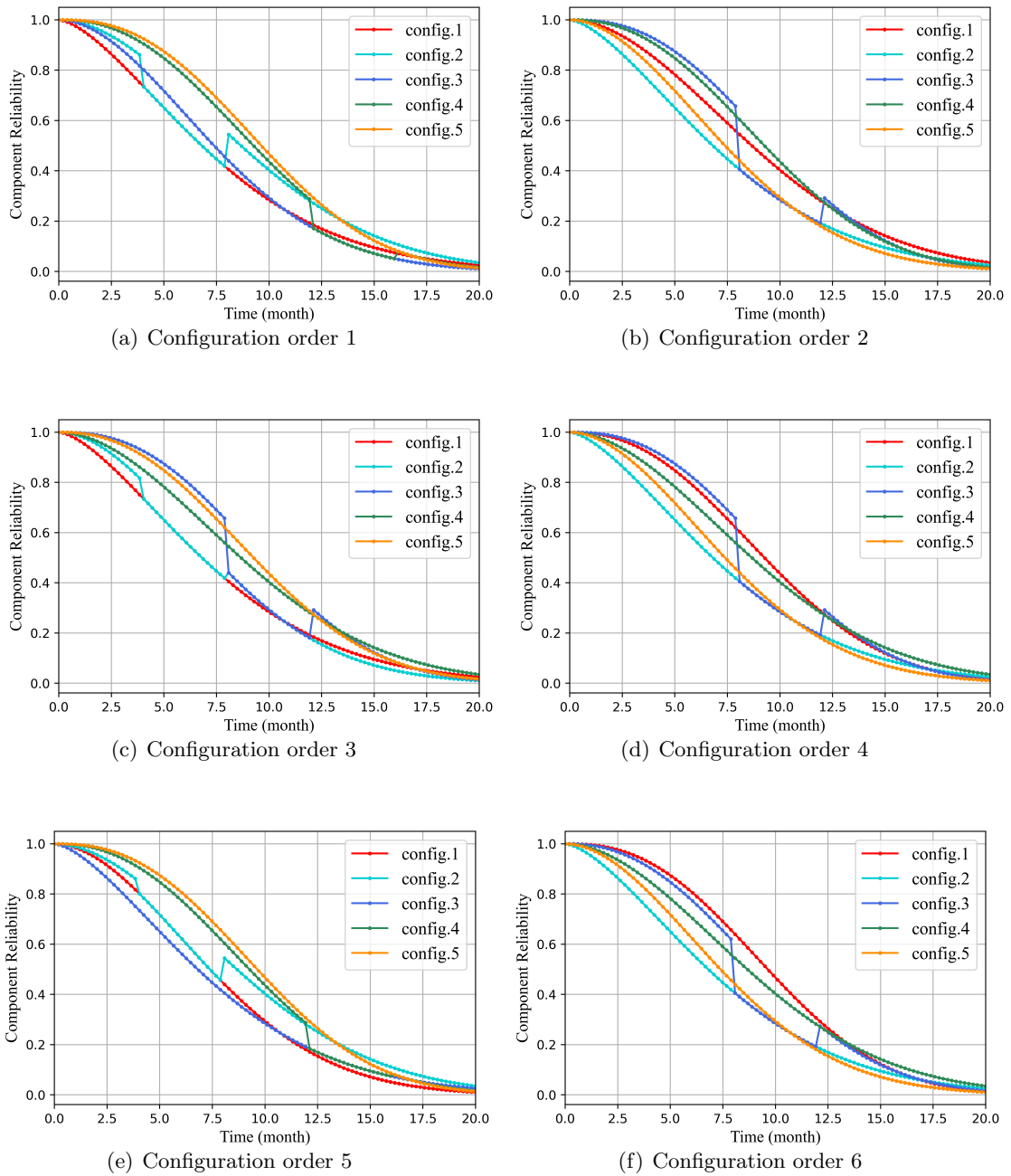


FIGURE C.2 – Component Reliability - Pessimistic Policy

C.2.5 System reliability performance under optimistic assessment policy

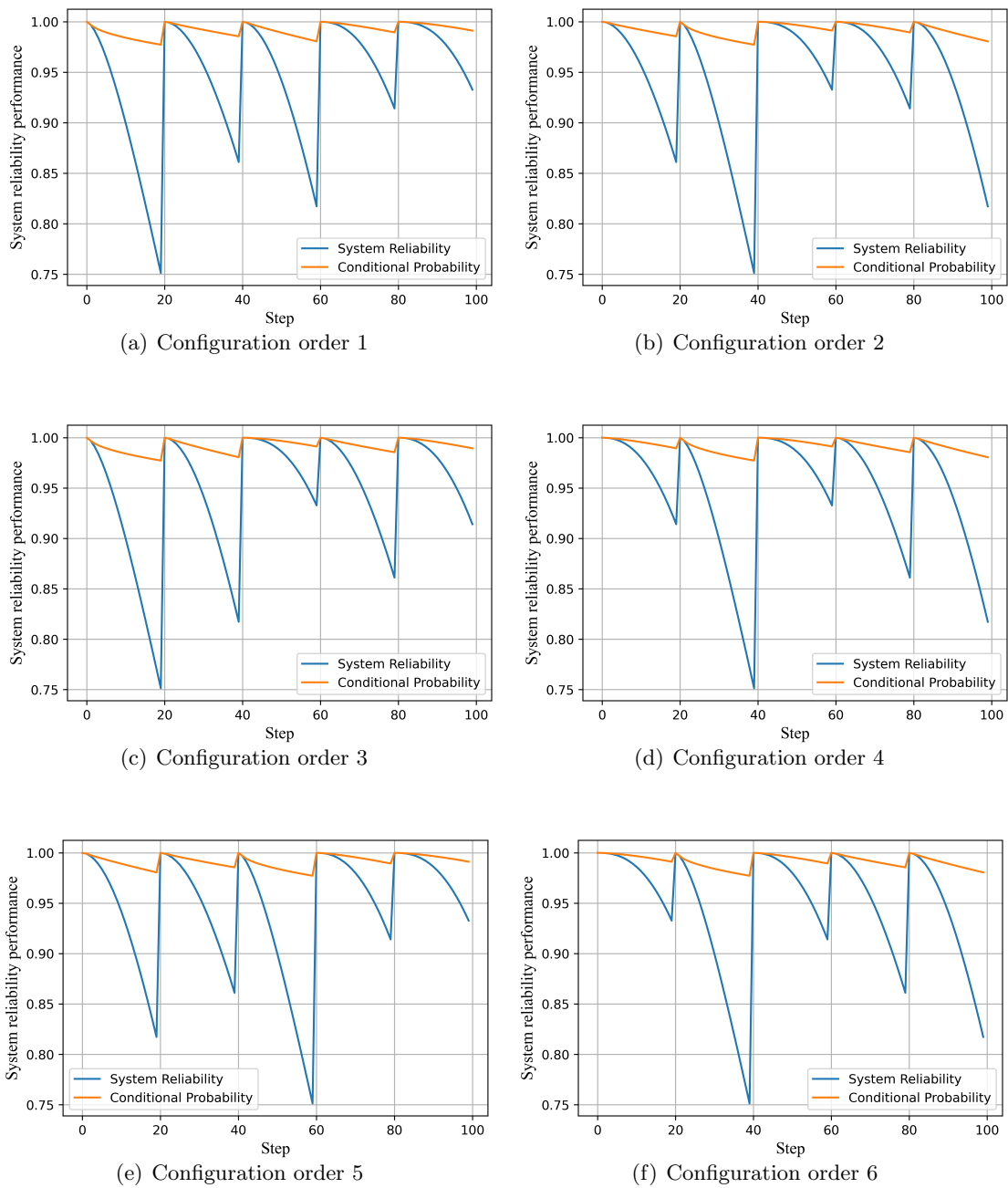


FIGURE C.3 – System Reliability - Optimistic Policy

C.2.6 System reliability performance under pessimistic assessment policy

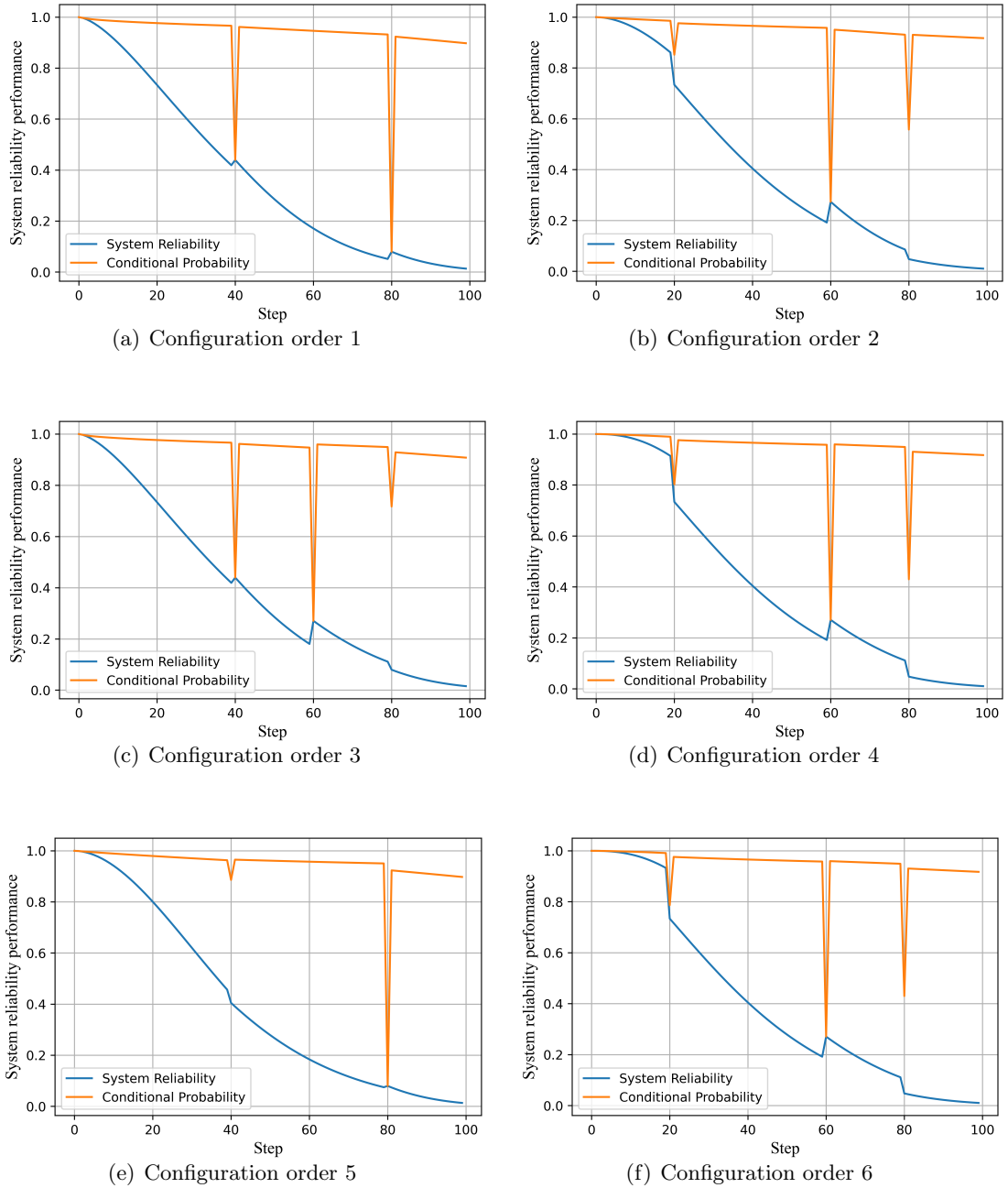


FIGURE C.4 – System Reliability - Pessimistic Policy



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Reliability Performance Modeling For Reconfigurable
Manufacturing System

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Résumé : Les systèmes de production reconfigurables (RMS) deviennent de plus en plus complexes, pour répondre à une production variée de produits et l'analyse de leur performances et fiabilité demeure un enjeu crucial. Lors des reconfigurations, les différents changements et interactions entre les composants du système deviennent importantes et les ainsi les ordres de configurations peuvent avoir un impact non négligeable sur le comportement et la fiabilité des RMS. Ainsi, ces travaux de thèse portent sur l'analyse comment les reconfigurations et les différentes décisions faites sur ce type de système peuvent impacter ses performances de fiabilité en considérant leurs ordres d'importance. Un cadre méthodologique est proposé pour la modélisation et l'évaluation de la fiabilité des RMS. Dans ce cadre, les modèles basés sur la chaîne de Markov ont permis de représenter les ordres de configuration et les causalités entre les configurations. Dans un premier temps, deux modèles probabilistes, un basé sur la distribution exponentielle et l'autre sur la distribution de Weibull, sont proposés et implémentés pour estimer et évaluer la fiabilité des RMS. Les résultats d'analyse basés sur le modèle dépendant de la distribution exponentielle, ont mis en évidence que les ordres de configuration n'ont pas d'impact sur la fiabilité. En revanche, pour le modèle basé sur la distribution de Weibull, l'impact s'avère significatif. Ensuite, un modèle basé sur une évaluation optimiste ou pessimiste est développé afin de mesurer l'importance de l'impact en fonction de diverses situations. Des applications sur des exemples de systèmes à travers de la simulation Monte Carlo et l'analyse de sensibilité, sont réalisées enfin afin de valider les modèles proposés.

Mots clés : Le Systèmes de Fabrication Reconfigurable, Analyse des Performances de Fiabilité, La Distribution Exponentielle, La Distribution de Weibull, Modèles Probabilistes, Simulation de Monte Carlo.

Abstract : The assessment of reconfigurable manufacturing system reliability is critical due to the complexity of the system and the potential consequences of failures in critical applications. During re-configurations, the quantity of interactions and interfaces can be substantial, the configuration orders and the causalities between configurations can have non-negligible effects on the reliability of the system. Therefore, the main research in this thesis is how the decisions made for reconfigurable manufacturing system impact the different aspects of reliability performance throughout the entire processing procedure, despite the increasing complexity of these systems. A proposed framework for reliability performance analysis for reconfigurable manufacturing system helps to verify whether the interactions and interfaces have impact on the reliability performance of an RMS, through analyzing the system, evaluating potential impacts, and assessing their significance. In the framework, models based on Markov chain managed to present the configuration orders and causalities between configurations. Two probabilistic models to describe the reliability performance include one based on the Exponential distribution and the other based on the Weibull distribution. For the Exponential distribution based model, results have proved that configuration orders have no impact on reliability. While for the Weibull distribution based model, the impact is significant. Besides, a model based on optimistic or pessimistic evaluation can set limits and measure the significance of the impact based on various situations. In the end, Monte Carlo simulation, sensitivity analysis and usage examples validate and verify the framework proposed.

Keywords : Reconfigurable Manufacturing System, Reliability Performance Analysis, Exponential Distribution, Weibull Distribution, Probabilistic Models, Monte Carlo Simulation.

