



HAL
open science

Supply chain management under availability & uncertainty constraints

Yahong Zheng

► **To cite this version:**

Yahong Zheng. Supply chain management under availability & uncertainty constraints. Other. Ecole Centrale de Lille, 2012. English. NNT : 2012ECLI0019 . tel-00757822

HAL Id: tel-00757822

<https://theses.hal.science/tel-00757822>

Submitted on 27 Nov 2012

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

ÉCOLE CENTRALE DE LILLE

THÈSE

présentée en vue d'obtenir le grade de

DOCTEUR

en

Spécialité : Automatique, Génie Informatique, Traitement du Signal et Image

par

Yahong ZHENG

DOCTORAT DELIVRE PAR L'ÉCOLE CENTRALE DE LILLE

Titre de la thèse :

**Supply Chain Management under availability & uncertainty
constraints**

Soutenue le 10 octobre 2012 devant le jury d'examen :

Président	Slim HAMMADI, Professeur, Ecole Centrale de Lille
Rapporteur	Alain QUILLIOT, Professeur, Université Blaise Pascal, Clermont-Ferrand,
Rapporteur	Aziz MOUKRIM, Professeur, Université de Technologie de Compiègne
Membre	Bernard DESCOTES-GENON, Professeur, Université Joseph Fourier, Grenoble
Membre	Abdelhakim ARTIBA, Professeur, Université de Valenciennes et du Hainaut -Cambrésis
Directeur de thèse	Khaled MESGHOUNI, Maître de Conférence, HDR, École Centrale de Lille

Thèse préparée dans le Laboratoire d'Automatique, Génie Informatique et Signal

École Doctorale SPI 072 (Lille I, Lille III, Artois, ULCO, UVHC, EC Lille)

PRES Université Lille Nord-de-France

*À mes parents,
à ma sœur,
à toute ma famille,
à mes professeurs,
et à mes chère(s) ami(e)s.*

Acknowledgements

The research work presented in this PHD thesis is realized in the Laboratoire d'Automatique, Génie Informatique et Signal (LAGIS) in École Centrale de Lille, with the research team "Optimisation des Systèmes Logistiques (OSL)". My PhD study was supported by the cooperation between the China Scholarship Council (CSC) and the Écoles-Centrales Intergroup. I am very honored to come to France for my PHD study under their financial support.

Firstly, I would like to express my great gratitude to my supervisor, Mr. Khaled MESGHOUNI. Thanks to his insights and advices, I am able to complete this work under his supervision. His patience and understanding always make it pleasant to discuss with him.

My sincere thanks to the jury members of my PHD committee. Thanks Prof. Alain QUILLIOT and Prof. Aziz MOUKRIM, who have reviewed carefully my thesis. And my heartfelt thanks go to Prof. Slim HAMMADI, Prof. Bernard DESCOTES-GENON and Prof. Abdelhakim ARTIBA, for their helpful discussions and sharing of researching experience.

It is a great pleasure to be a member in the research team OSL. I have learned much in the team meeting. Thanks gratefully all other colleagues in the team.

I am also grateful to the colleagues in my office, Jin, Ismahelle, Andreea, Minzhi, Yue, Tian, Daji, and the staff in our laboratory, Chistine, Brigitte, Patrick, Bernard, for their kindly help during the past three years. I would like also thank Vanessa Fleury and Virginie Leclercq who helped me with the administrative matters.

I wish to offer special thanks to my French teacher, Prof. Hélène Catsiapis, who contributes much in my understanding of French language and culture. During the wonderful trips she organized, I have spent several joyful weekends with

ACKNOWLEDGEMENTS

students from different countries and visited lots of extremely scenic parts in France.

My appreciation to my friends, Huarong, Jian, Dapeng, Jinlin, Bo, Guoguang, Wenhua, Lian, Yifan, \dots , for their friendship and immense help, which bring much convenience to my life and give me peaceful mind to do research.

At last, I would like to say thanks to my parents and all my families. It is their consistent emotional support that makes me able to pass difficult moments in the research life. Their encouragement and support is the greatest consolation of my soul.

Villeneuve d'Ascq, France
18, September, 2012

Yahong ZHENG

Résumé en français

Dans cette thèse je présente les résultats de mes recherches à l'École Centrale de Lille au cours des trois dernières années, de 2009 à 2012.

Le management de la chaîne logistique (supply chain management: SCM) est un thème très intéressant avec une portée internationale à la fois dans le domaine industriel et académique. La disponibilité des ressources dans la chaîne logistique n'est pas à la hauteur de nos attentes. L'essence de SCM est l'intégration des ressources pour améliorer les performances des activités de la chaîne logistique. L'SCM traditionnel est basée sur un environnement statique. Cette hypothèse idéale n'est pas adaptée à la situation réelle où existent des contraintes de disponibilité et d'incertitude. Beaucoup de chercheurs ont abordés l'aspect incertain dans les chaînes logistiques, mais pas d'une façon systématique et n'ont pas proposé de méthode générale pour traiter l'incertitude dans les SCM. Les contraintes de disponibilité et d'incertitude rendent le management de la chaîne logistique très compliqué. Nos travaux de recherche se focalisent justement sur la prise en compte de ces difficultés et de présenter à la communauté des méthodologies et algorithmes pour la résolution des problèmes d'incertitude dans le management de la chaîne logistique.

Contexte

Depuis l'émergence de la chaîne logistique, cette dernière a été beaucoup étudiée par les chercheurs et les industriels. Le premier domaine d'utilisation été l'armée pour son approvisionnement. Dans les années 90, le SCM a connu une ascension importante en attirant les attentions des gestionnaires des grandes entreprises. Les recherches menées ont permis la mise au point de l'intégration de la gestion

de logistique interne et les relations coopératives entre les différentes sociétés impliquées dans la chaîne de gestion. Ce concept de SCM a permis à de nombreux gestionnaires de prendre des décisions non pas seulement au point de vue de leurs entreprise, mais plutôt au niveau de toute la chaîne logistique. La maîtrise de la chaîne logistique est devenue une arme très importante pour la survie de l'entreprise. En générale, de nombreuses stratégies et activités dans SCM, telles que la planification de la chaîne logistique, la coopération des membres de la chaîne, le processus de fabrication, le transport, opèrent tous dans un environnement statique (certain). Toutefois, dans les faits, nous trouvons beaucoup de situations d'incertitude dans le SCM, qui se produisent dans le système de fabrication, la procédure de distribution, dans les marchés de l'offre et de la demande. Ces incertitudes que nous ne pouvons pas prévoir vont influencer considérablement les opérations de la chaîne logistique. Par exemple, l'approvisionnement en retard peut affecter le temps de production, puis influencer le délai de livraison et peut-être le prix de vente. Une modification de la quantité demandée peut induire à des gaspillages de la production. Une baisse de la productivité aura un impact sur la quantité de l'approvisionnement, sur le niveau des stocks, et également sur le prix de vente. Le problème de véhicules dans le processus de distribution perturbe directement le temps de distribution. Par conséquent, l'incertitude est un facteur très important dans l'étude de SCM.

Une chaîne logistique est généralement un réseau de services et d'entreprises qui remplissent les fonctions d'approvisionnement de produits et de matières, de transformation de matières, et la fabrication et la distribution des produits finis aux clients. Plus généralement, une chaîne logistique commence à partir de la matière première et se termine par la livraison au client, elle commence donc par l'achat des matières premières, puis la fabrication, puis le stock, et ensuite la transformation et se termine par la distribution.

Bien que la structure et le degré de complexité de la chaîne logistique peuvent varier considérablement en fonction des secteurs d'activités et des entreprises, néanmoins, le fonctionnement normal et la structure sont similaires. Nous pouvons diviser une chaîne logistique en cinq phases : l'approvisionnement, la fabrication, le stockage, la distribution, et la demande. Dans chaque phase de la chaîne logistique, il existe différents types d'incertitudes. Ainsi, nous pouvons nous concentrer sur l'incertitude dans chaque phase pour analyser ses conséquences

et tenter de réduire son influence. Nos travaux de recherche se distinguent de l'existant par le fait que nous analysons la chaîne logistique globale même si nous résolvons le problème partiel (stock, transport, fabrication . . .).

Aperçu de la thèse

Dans chaque chapitre, nous traitons l'incertitude dans un stade de la chaîne logistique. Nous nous concentrons sur les problèmes classiques dans SCM. Pour chaque type d'incertitude, tout d'abord, nous donnons un aperçu de ce qui existe dans la littérature, puis nous introduisons l'algorithme pour résoudre le problème, et nous finissons par présenter des exemples numériques tirés des benchmarks (s'ils existent) pour démontrer l'efficacité des algorithmes que nous proposons.

Le chapitre 1 est une introduction des recherches existantes sur l'incertitude dans la chaîne logistique. Tout d'abord, nous introduisons l'importance de considération de l'incertitude dans l'SCM, et nos motivations pour cette partie. Puis, nous passons en revue l'état de l'art de la recherche connexe selon notre classification de l'incertitude (notre façon de considérer cette incertitude) dans la chaîne logistique. Et nous concluons cette chapitre par présenter les enjeux et les limites de cette recherche dans la littérature.

Le chapitre 2 traite l'incertitude dans la demande. A la différence des méthodes traditionnelles, telles que le contrôle des stocks dynamiques, l'estimation de la demande, nous proposons d'appliquer la stratégie d'ajournement pour traiter la demande incertaine dans SCM. Tout d'abord, nous simplifions le réseau normal de la chaîne logistique en plusieurs sous-systèmes avec une relation entre l'offre et la demande. Nous suivons la sens de la circulation de l'information, du consommateur à l'approvisionnement, pour calculer les sous-systèmes, un par un. Afin de satisfaire la demande inattendue pour chaque sous-système, nous le ferons en deux étapes, la première consiste à exécuter une réaffectation de la demande aux fournisseurs en utilisant pleinement le stock existant de ces derniers. La deuxième étape concerne le cas où la quantité demandée dépasse la possibilité de l'offre. Dans ce cas, nous appliquons la stratégie d'ajournement de l'approvisionnement ce qui conduit à autoriser un retard de livraison. La distance de transport pour la période de l'approvisionnement est utilisée comme fonction objectif pour la réaffectation des demandes.

Dans le chapitre 3 nous nous focalisons sur l'aspect incertain dans le système de production. Nous avons choisi le cas des problèmes de type job-shop pour leur pouvoir d'adaptabilité aux variations des demandes des marchés. L'indisponibilité des machines est la principale incertitude dans ce type de problème (job-shop), afin de réduire l'effet de cette dernière, nous suggérons d'utiliser la maintenance conditionnelle (CBM) qui est une sorte de maintenance préventive permettant de surveiller le fonctionnement des machines et fournit des données pour la planification de la machine avant l'apparition de la panne. L'application du CBM rend le problème de l'ordonnancement de job shop flexible dynamique. Nous proposons d'insérer les tâches préventive de maintenance (PM) dans un pré ordonnancement obtenu par la résolution du problème standard d'ordonnancement du job-shop flexible (FJSP). Pour la résolution de ce dernier (FJSP), nous proposons trois approches: l'algorithme génétique hiérarchique (HGA), l'algorithme génétique intégré (IGA) et enfin, un algorithme de colonies de fourmis intégré (IACO).

Dans le chapitre 4 nous nous intéressons à l'incertitude dans la distribution, et plus particulièrement au niveau du transport. Nous nous concentrons sur le problème de tournées de véhicules (VRP) qui a reçu beaucoup d'attentions ces dernières années. Le problème de tournées de véhicules avec ramassage et livraison (VRPPD) est une extension de VRP avec deux types de demandes de clients. Pour traiter cette incertitude dans la distribution pour les clients, nous modélisons le problème de transport en tant que VRPPD non apparié, dans lequel les relations de ramassage et de livraison ne sont pas déterminées à l'avance. Un algorithme de groupement génétique modifié (GGA) est développé pour résoudre ce VRPPD non apparié. À notre connaissance, c'est la première fois que le VRPPD non apparié est traité en utilisant des métaheuristiques.

Pour le chapitre 5, nous traitons le problème bi-niveau du vendeur de journaux, ce dernier représente à lui seul une chaîne logistique miniature. Deux classes différentes d'incertitude sont considérées; l'incertitude sur la demande et celle sur le rendement (ou l'incertitude de l'offre). Dans ce problème bi-niveau, le vendeur et le fournisseur sont considérés ensemble et doivent avoir une bonne coopération car ils représentent les deux côtés de la même chaîne. Le rendement incertain est causé principalement par la quantité incertaine des produits. Nous

utilisons deux algorithmes populaires pour la résolution de ce type de problème; l'approche Bayésienne et un algorithme hybride flou intelligent.

Nos contributions

Suite à la revue de la littérature existante, nous pouvons dire qu'il existe beaucoup de travaux concernant l'incertitude dans la chaîne logistique, mais nos travaux se distinguent par leur aspect systématique qui traite l'ensemble des problèmes d'incertitude dans les SCM.

Nous avons en premier lieu, classé l'incertitude en perspective du management de la chaîne logistique. En se basant sur des situations pratiques et réelles, la classification de l'incertitude est complète et couvrira tous les stades de la chaîne logistique. Nous donnons également les trois principales classifications de l'incertitude trouvées dans la littérature; à savoir celle de la demande, celle de la production et celle de la distribution.

En deuxième lieu, pour l'incertitude principale de la chaîne logistique, nous traitons le problème classique, cependant les méthodes que nous proposons pour résoudre les trois principales incertitudes ne sont pas des véritables méthodes parallèles. L'approche que nous proposons pour faire face à l'incertitude de la demande se situe au niveau de la stratégie appliquée aux SCM permettant de déterminer la manière de gérer les opérations de la chaîne logistique. La réalisation de cette stratégie a besoin de l'aide de la part des autres étapes comme la fabrication, l'approvisionnement et la distribution. Naturellement, nos recherches se sont dirigées vers ces étapes du niveau opérationnel dans la chaîne logistique en étudiant de manière concrète de l'incertitude de fabrication à la distribution.

Troisièmement, pour le traitement de l'incertitude dans la distribution aux clients, nous nous sommes concentrés sur le problème de tournées de véhicules non apparié avec ramassage et livraison (VRPPD). À notre connaissance, c'est la première fois qu'une métaheuristique est appliquée pour résoudre VRPPD non apparié.

Quatrièmement, avec l'algorithme génétique intégré, testé sur des instances de benchmark nous obtenons de meilleurs résultats pour FJSP que ceux présentés dans la littérature.

Cinquièmement, nous proposons d'appliquer la maintenance conditionnelle comme méthode d'entretien préventive pour réduire l'indisponibilité des machines dans le système de fabrication. L'algorithme de l'insertion que nous avons proposé pour résoudre le problème d'ordonnancement de job shop flexible avec la maintenance conditionnelle (FJSPPM) est comparable à un autre algorithme dans la littérature.

Sixièmement, nous avons démontré l'efficacité de l'algorithme génétique (GA) que nous avons utilisés dans nos trois exemples de FJSPPM. En outre, dans notre démarche de résolution de FJSPPM, nous constatons que les résultats trouvés par GA devancent ceux trouvés par l'algorithme de colonies de fourmis (ACO).

Septièmement, nous proposons deux approches différentes, l'approche bayésienne et l'approche à base de variables floues, pour représenter l'incertitude de la demande et celle du rendement dans le problème du vendeur de journaux. Nous avons obtenu une valeur de seuil en fonction des paramètres du problème comme le prix et le coût en utilisant la méthode bayésienne.

Limitation de nos recherches

Toutefois, il existe des limites à nos recherches, tels que le manque de comparaison avec d'autres approches pour résoudre le VRPPD non apparié ainsi que dans le problème bi-niveau du vendeur de journaux. Ce manque de comparaison est dû principalement au manque considérable de recherche dans cette partie et donc l'inexistence de benchmark, ce qui prouve par la même occasion l'originalité de notre démarche. Concernant les résultats obtenus pour le FJSPPM, nous pensons qu'il est encore possible de les améliorer en utilisant de meilleurs heuristiques et/ou des combinaisons de métaheuristiques. Malheureusement, nous n'avons pas pu appliquer notre démarche aux problèmes concrets rencontrés dans le monde industriel afin de pouvoir montrer l'efficacité de nos démarches de résolution. Néanmoins nous espérons pouvoir le faire dans un avenir très proche.

Contents

Acknowledgements	2
Résumé en français	5
Table of Contents	11
List of Figures	16
List of Tables	19
Abbreviations	20
Introduction	23
1 Uncertainty in supply chain	29
1.1 Supply chain management	29
1.2 Significance of considering uncertainty in SCM	30
1.3 Research review about uncertainty in supply chain	31
1.3.1 Uncertainty in supply	32
1.3.2 Uncertainty in demand	34
1.3.2.1 Factors causing uncertainty in demand	34
1.3.2.2 Impact of uncertainty in demand on supply chain	34
1.3.2.3 Conventional methods to cope with uncertainty in demand	35
1.3.3 Uncertainty in manufacturing	38
1.3.3.1 Complexity of keeping stability and flexibility in modern manufacturing system	38
1.3.3.2 Advanced manufacturing system	39

CONTENTS

1.3.3.3	Research on strategic level to consider uncertainty in manufacturing system	40
1.3.3.4	Research on operational level to consider uncertainty in manufacturing system	42
1.3.4	Uncertainty in distribution	43
1.3.4.1	Research priorities of uncertainty in distribution	43
1.3.4.2	Research of uncertainty in transportation system	44
1.3.5	Other kinds of uncertainty	45
1.4	Conclusions	48
2	Coping with uncertain demand in supply chain	49
2.1	Introduction of postponement strategy	49
2.2	Postponement applied to address uncertain demand in supply chain	51
2.2.1	Decomposition of supply chain	52
2.2.2	Description of approach of application of postponement	53
2.2.2.1	Optimal fraction of total postponed demand	56
2.2.2.2	Optimal fraction of supply quantity to each supplier	57
2.3	Instance of application of the approach of postponement	60
2.3.1	Description of model from the original SC network	60
2.3.2	Results of calculation for the case with estimated demand	63
2.3.2.1	Calculation results of subsystem 1	63
2.3.2.2	Calculation results of subsystem 2	64
2.3.3	Results of calculation for the case with unexpected demand	65
2.3.3.1	Calculation results of subsystem 1	65
2.3.3.2	Calculation results of subsystem 2	66
2.3.4	Discussions	68
2.4	Conclusions	69
3	Flexible job shop scheduling problem under uncertainty environment	71
3.1	Reducing unavailability of machines in FJSP	71
3.1.1	Introduction and literature on FJSPPM	72
3.1.1.1	Flexible Job-shop Scheduling Problem (FJSP)	73
3.1.1.2	Preventive Maintenance	74

3.1.1.3	Flexible Job-shop Scheduling Problem with Pre-ventive Maintenance	75
3.1.1.4	Condition Based Maintenance	76
3.1.2	Mathematical modeling for FJSPPM	78
3.1.3	Solution approach for FJSPPM	80
3.1.3.1	Hierarchical Genetic Algorithm for FJSP	81
3.1.3.2	Integrated Genetic Algorithm for FJSP	86
3.1.3.3	Integrated Ant Colony Optimization for FJSP	89
3.1.3.4	Comparing effectiveness of the three approaches for FJSP	93
3.1.3.5	Complete approach for FJSPPM	99
3.1.4	Numerical experiments of FJSPPM	103
3.1.4.1	Results analysis	107
3.1.4.2	Discussions	107
3.2	FJSP with dynamic arrival jobs	108
3.2.1	Inserting algorithm of new arrival job	109
3.2.2	Rescheduling resting operations with new arrival jobs	110
3.3	Impact of uncertain processing time of jobs to FJSP	111
3.4	Conclusions	116
4	Distribution problem under uncertain environment	119
4.1	Uncertainty of clients in distribution	119
4.2	Vehicle routing problem	121
4.2.1	Practical application of VRP	122
4.2.2	Classic model of VRP	123
4.2.2.1	Definition of classic VRP	123
4.2.2.2	Solution approach for classic VRP	124
4.2.3	Classification and extension of VRP	124
4.2.3.1	Capacitated VRP (CVRP)	125
4.2.3.2	VRP with Time Windows (VRPTW)	125
4.2.3.3	VRP with Pick-Up and Delivery (VRPPD)	126
4.2.3.4	VRP with Stochastic Demand (VRPSD)	126
4.2.3.5	Other types of VRP	127
4.3	Unpaired Vehicle Routing Problem with Pickup and Delivery	128
4.3.1	Motivation of studying unpaired VRPPD	129

4.3.1.1	Model of unpaired VRPPD for distribution stage in supply chain	129
4.3.1.2	Coping with uncertainty of clients	129
4.3.2	Description of mathematic model	131
4.3.2.1	Model of distribution problem	131
4.3.2.2	Formulation for unpaired VRPPD	133
4.3.3	Solution algorithm	135
4.3.4	Experiment of numerical example	138
4.4	Conclusions	139
5	Uncertainty of demand and yield in bi-level newsboy problem	141
5.1	Introduction of uncertainty in newsboy problem	142
5.2	Mathematical model for bi-level newsboy problem with uncertain demand and supply	145
5.3	Bayesian approach for representing double uncertainty of stochas- tic variables	148
5.3.1	Description of Bayesian approach	148
5.3.2	Modeling of stochastic demand and yield	148
5.3.2.1	Product qualification ratio	149
5.3.2.2	Uncertain demand	149
5.3.3	Bayesian approach to represent double uncertainty of vari- ables	150
5.3.3.1	Direct information updating	150
5.3.3.2	Indirect information updating	151
5.3.4	Model of describing the problem with stochastic variables .	153
5.3.4.1	Discussion of relationship among different param- eters of price	155
5.3.4.2	Computation based on our hypothesis	157
5.3.4.3	Discussion	158
5.4	Uncertainty represented with fuzzy variable	158
5.4.1	Credibility theory	159
5.4.1.1	Credibility measure and credibility space	159
5.4.1.2	Fuzzy simulation	160
5.4.2	Solutions with fuzzy variables	161
5.4.3	Operations of genetic algorithm	162

5.5	Numerical examples	163
5.6	Conclusions	169
	Conclusions and Perspectives	171
	References	174

List of Figures

2.1	Normal supply chain structure	52
2.2	Simplified supply chain structure	52
2.3	Procedure of the scheduling with the postponement strategy . . .	54
2.4	Supply chain network consisting of factories, warehouses and distributors	61
2.5	Simplified subsystems	61
3.1	P-F curve	77
3.2	Hierarchical Genetic Algorithm (HGA) for FJSP	83
3.3	Integrated Genetic Algorithm (IGA) for FJSP	87
3.4	Decoding procedure	88
3.5	Digraph of sequence scheduling in ACO	91
3.6	Gantt chart of best solution of J8M8	98
3.7	Gantt chart of best solution of J10M10	98
3.8	Gantt chart of best solution of J15M10	98
3.9	Two algorithms of solving FJSPPM	99
3.10	Compact PM to left when PM is initialized to latest moment . . .	100
3.11	Compact PM to right when PM is initialized to earliest moment .	100
3.12	Change machine to treat collision of PM and job	101
3.13	Gantt chart of best solution of J8M8PM	104
3.14	Gantt chart of best solution of J10M10PM	106
3.15	Gantt chart of best solution of J15M10PM	106
3.16	Disruption of maintenance arrives at an existing preschedule of FJSP	108
3.17	Ongoing scheduling scheme before new job arrival	109
3.18	Scheduling independently for new arrival job	109
3.19	Inserting algorithm of new arrival job	110

LIST OF FIGURES

3.20	Rescheduling resting operations with new arrival job	110
3.21	Impact of more processing time on job shop scheduling	112
3.22	Impact of less processing time on job shop scheduling	112
3.23	Impact of increasing processing time with 1 time unit to J8M8 . . .	114
3.24	Impact of increasing processing time with 2 time units to J8M8 . .	114
3.25	Optional solution 1 for J8M8	115
3.26	Optional solution 2 for J8M8	115
3.27	Optional solution 3 for J8M8	116
4.1	Distribution procedure	121
4.2	Normal VRP scheduling scheme	130
4.3	Unpaired VRPPD model	131
4.4	Original allocation of delivering merchandizes	132
4.5	Unpaired VRPPD model for distribution problem	133
4.6	Encoding form for chromosome	135
4.7	Crossover procedure	137
4.8	Solution for an example with 30 clients	139
5.1	Results of computation with GA	164
5.2	Results of executing 100 times	165
5.3	Change with different wholesale price	165
5.4	Change with different retail price	166
5.5	Comparison with different fuzzy demand	167
5.6	Comparison with different qualification ratio	168

List of Tables

2.1	Transport costs from factories to warehouses (cent/case)	62
2.2	Transport cost from warehouses to distributors (cent/case)	62
2.3	Capacities of factories and warehouses	62
2.4	Estimated demand of distributors (case)	63
2.5	Random demand of distributors (case)	63
2.6	Allocation of the demand of distributors to each warehouse in the case with estimated demand	64
2.7	Allocation of demand of warehouses to each factory in the case with estimated demand	64
2.8	Allocation of demand of warehouses to each factory in the case with estimated demand	64
2.9	Allocation of demand of distributors to each warehouse for subsystem 1 in the case with unexpected demands in regular period	65
2.10	Allocation of the demand of distributors to each warehouse for subsystem 1 in the case with unexpected demands in postponement period	65
2.11	Optimal allocation of demand of warehouses to each factory in case 1	66
2.12	Optimal allocation of demand of warehouses to each factory in regular period	67
2.13	Optimal allocation of demand of warehouses to each factory in postponement period	67
2.14	Optimal allocation of the demands of warehouses to each factory in case 2	67
2.15	Optimal allocation of demand of warehouses to each factory in regular period in case 3	68

LIST OF TABLES

2.16	Optimal allocation of demand of warehouses to each factory in postponement period in case 3	68
3.1	Machine assignment to operations	83
3.2	Result of comparing tournament and roulette wheel in GA-1	85
3.3	Parameters of GA	85
3.4	Sequence scheduling	86
3.5	Result of comparing scheduling sequence methods in integrated GA on example J8M8	89
3.6	Result of comparing scheduling sequence methods in integrated GA on example J15M10	89
3.7	Parameters of ACO	93
3.8	Problem J8M8 with 27 operations (partial flexibility)	94
3.9	Problem J10M10 with 30 operations (total flexibility)	95
3.10	Problem J15M10 with 56 operations	96
3.11	Result of three approaches applied to three examples of FJSP	97
3.12	Comparison of different methods of SSA	102
3.13	PM tasks in J8M8PM	104
3.14	PM tasks in J10M10PM	104
3.15	PM tasks in J15M10PM	104
3.16	Result of seven approaches applied on examples of FJSPPM	105
5.1	Calculation of posterior distribution with direct information updating	151
5.2	Price relationship for different industries *	157
5.3	Results of optimal ordering quantity and potential loss with different wholesale price	166
5.4	Results of optimal ordering quantity and potential loss with different retail price	167
5.5	Results of optimal ordering quantity and potential loss with different fuzzy demand	168
5.6	Results of optimal ordering quantity and potential loss with different qualification ratio	169

Abbreviations

ABC - Artificial bee colony
ACO - Ant colony optimization
AMT - Advanced manufacturing technologies
CAD - Computer aided design
CAM - Computer aided manufacturing
CBM - Condition based maintenance
CDF - Cumulative distribution function
CIMS - Computer integrated manufacturing system
CNC - Computer numerical control
CVRP- Capacitated vehicle routing problem
CVRPTW - Capacitated VRP with time windows
DARP - Dial-a-ride problem
ERP - Enterprize resource planning
FIFO - First In First Out
FJSP - Flexible job shop scheduling problem
FJSPPM - Flexible job shop scheduling problem with preventive maintenance
FMS - Flexible manufacturing system
GA - Genetic algorithm
GGA - Grouping genetic algorithm
HGA - Hybrid generic algorithm
IA - Inserting algorithm
IACO - Integrated ant colony optimization
IGA - Integrated genetic algorithm
JSSP - Job shop scheduling problem
LP - lean production
LPT - Longest processing time

ABBREVIATIONS

MDVRP - Multi depot vehicle routing problem
MDVRPTW - Multi depot vehicle routing problem with time windows
MRP - Material requirement planning
MRPII - Manufacturing resource planning
MWR - Most work remaining
NLP - Non linear programming
PDF - Probability density function
PDP - Pickup and delivery problem
PM - Preventive maintenance
PVRP - Probabilistic vehicle routing problem
SA - Simulated annealing
SC - Supply chain
SCM - Supply chain management
SDVRP - Split delivery vehicle routing problem
SPT - Shortest processing time
SSA - Simultaneous scheduling algorithm
SSA1 - Simultaneous scheduling algorithm 1
SSA2 - Simultaneous scheduling algorithm 2
SSA3 - Simultaneous scheduling algorithm 3
SST - Shortest starting time of operation
SVRP - Stochastic vehicle routing problem
TLJ - Length of unscheduled tasks in job
TS - Tabu search
TSP - Traveling salesman problem
TSPPD - TSP with pickup and delivery
VRP - Vehicle routing problem
VRPDT - Vehicle routing problem with due times
VRPM - Vehicle routing problem with multi use of vehicles
VRPPD - Vehicle routing problem with pickup and delivery
VRPSD - Vehicle routing problem with stochastic demand
VRPTW - Vehicle routing problem with time windows
VRSP - Vehicle routing and scheduling problem

Introduction

This thesis presents results of my research in École Centrale de Lille in France during the past three years, from 2009 to 2012.

Supply chain management (SCM) is an attractive theme both in business and academy in international scope. Availability of resource in supply chain is always not so optimistic as we expected. The essence of SCM is integrating resource to improve performance of supply chain activities. Traditional SCM is based on a static environment. This ideal hypothesis is not suitable for practical situation where exist constraints of availability and uncertainty. Despite of immense research on uncertainty in SCM, there is no systematic research, neither no general method for treating uncertainty in supply chain. Constraints of availability and uncertainty make SCM complicated. Our research is surrounding SCM taking into account these constraints. We aim to offer some reference to researchers and decision makers in this research area.

Background

Supply chain has been focused by lots of scholars and practitioners as early as the concept of logistic emerged. Logistic first emerged in army. With supply chain the army can get enough support to prepare for the war or defence. Since 1990s, SCM has become a hot topic in business. It has attracted attentions of high level managers. Research of SCM has developed from integration of internal logistic management and relationship among cooperated companies to value addition of the whole value chain. This concept of SCM makes many managers of enterprizes make decision not at the standpoint of only his company as before, but at the height of the whole supply chain. In the war of business, supply chain has become a strong weapon. Generally, many strategies and activities in

SCM, such as scheduling of supply chain, cooperation of members of supply chain, process of logistics, transport, manufactures, etc., are all operated in a static environment imagined. However, factually in procedure of the total SCM, there are many uncertain cases occurring in manufacturing system, distribution procedure, demand markets, and supply. Uncertainties which we cannot know predictably will influence supply chain operations. For example, delayed supply may affect production time then influence delivery time and maybe selling price. Changed demand quantity may induce waste of production. Decline in productivity will impact quantity of supply, inventory level, and also selling price. Problems of vehicles in distribution process will disturb directly distribution time. Therefore, dealing with uncertainty is a very important task in SCM.

A supply chain is generally a network of facilities and companies that perform the functions of procurement of materials, transformation of materials into intermediate and finished products, manufacturing, and distribution of finished products to customers. More generally, a supply chain begins from the raw materials and ends at the customer, consisting purchasing of raw materials, manufacturing, stock, transformation and distribution. Although the structure and degree of complexity of supply chain may vary greatly in different industries and in different firms, the normal function and structure are similar. We can divide a supply chain into five phases: supply, manufacturing, stock, distribution, and demand. In each phase of supply chain, there exists uncertainty. Thereby we can concentrate on uncertainty in each phase to analyze its consequence and attempt to reduce its influence. The difference of our work to existing research of distinct type of uncertainty in supply chain is that even when we concentrate on concrete problem in supply chain, we analyze the problem from the standpoint of SCM.

Outline of the thesis

In each chapter, we treat uncertainty in a certain stage of supply chain. We concentrate on classic problems in SCM. For each kind of uncertainty, firstly we give a literature survey, and then we introduce algorithm to solve the problem, at last numerical examples in benchmark in literature are used to demonstrate effectiveness of our proposed algorithms.

Chapter 1 is introduction of existing research about uncertainty in supply chain. Firstly, we introduce the significance of research of SCM with uncertainty in consideration, which is our motivation of the research. Then, we survey the state of the art of related research according to our classification of uncertainty in supply chain. This classification is also the way we consider uncertainty in SCM. Limitations and challenges of research in literature is concluded.

Chapter 2 concentrates on treating uncertainty in demand. Different from the traditional methods, such as dynamic inventory control, estimation of demand, we propose to apply postponement strategy to treat uncertain demand in SCM. Firstly, we simplify normal supply chain network with different stages into several sub systems with relationship of demand-supply. We follow the direction of flow of information, from consumer market to material supply, to calculate the sub systems one by one. For each sub system, to satisfy unexpected demand, we satisfy them during two stages. In the first stage, we execute reallocation of demand to suppliers to make full use of existing stock of suppliers. For demand quantity exceeding supply quantity, we postpone supply to it to a delayed delivery time allowed, which is the second stage. Transport distance during supply period is considered as objective function to reallocate demand to suppliers.

Chapter 3 focuses on the problem in manufacturing system with uncertainty in consideration. Job shop, as an adaptive manufacturing mode for variation of products in consuming market, is chosen for our research in manufacturing system. Unavailability of machines is the most important type of uncertainty in job shop. To reduce this uncertainty, we suggest using condition based maintenance (CBM), a sort of preventive maintenance to monitor machines' situation and provide data to plan maintenance before machines' breakdown. Application of CBM makes flexible job shop scheduling problem (FJSP) dynamic. We propose an inserting algorithm to add PM into preschedule obtained in normal FJSP. To solve traditional FJSP, we propose three approaches, a Hierarchical Genetic Algorithm (HGA), an Integrated Genetic Algorithm (IGA), and an Integrated Ant Colony Optimization (IACO).

Chapter 4 highlights uncertainty in distribution, especially in transportation stage. We focus on vehicle routing problem (VRP) which is paid unabated attentions in last several decades. Vehicle routing problem with pickups and deliveries (VRPPD) is an extension of VRP, allowing two different sorts of demand of

clients. To treat uncertainty of clients during distribution, we model the transportation problem as unpaired VRPPD, in which relationship of pick up and delivery are not determined in advance. A modified grouping genetic algorithm (GGA) is developed for solving unpaired VRPPD. To our knowledge, this is the first time using metaheuristic for solving unpaired VRPPD.

Chapter 5 is an application of considering uncertainty in a supply chain. We focus on bi-level newsboy problem, which is a miniature of supply chain. Two different classes of uncertainty are considered, demand uncertainty and yield uncertainty which can also be called supply uncertainty. In bi-level newsboy problem, newsboy is considered together with his supplier. Both sides are with a good cooperation relationship. Research of bi-level newsboy problem is critical and basic to the research of SCM. In newsboy problem we conclude that to the decision maker, the newsboy, uncertain yield of the manufacturer is caused mainly by uncertain qualification ratio of products. We adopt two popular algorithms to solve this kind of newsboy problem, the Bayesian approach and fuzzy hybrid intelligent algorithm.

Contributions of our research

From literature review, we can see that there has been immense research on uncertainty in supply chain, but our work is the first to give a systematic research.

Firstly, we classify uncertainty from the perspective of supply chain management. Based on analysis of supply chain in practical situation, classification of uncertainty is complete and can cover all stages of supply chain. In addition to classification method, we give literature review for the three main classes of uncertainty, uncertainty in demand, distribution and manufacturing.

Secondly, for uncertainty in the main stage of supply chain, we focus on classic problems to treat them. However, our proposed methods for treating the three main kinds of uncertainty are factually not parallel. The approach of coping with uncertainty in demand is at the strategic level of SCM, as it determines the management manner of supply chain operations. Realization of the strategy needs assistance of other stages in supply chain, distribution, manufacturing, supply, etc. Direction of our research is naturally directed to these stages of operational

level in supply chain. Rather than vague discussion, we consider uncertainty in concrete executing manner of distribution and manufacturing.

Thirdly, for treating uncertainty of clients in distribution, we focus on unpaired vehicle routing problem with pickups and deliveries (VRPPD). To our knowledge, this is the first time of applying metaheuristic to solve unpaired VRPPD.

Fourthly, with integrated genetic algorithm, we get a better result of an instance in a benchmark for FJSP than that in literature.

Fifthly, we propose to apply condition based maintenance as preventive maintenance to reduce unavailability of machines in manufacturing system. The inserting algorithm we proposed to solve flexible job shop scheduling problem with preventive maintenance (FJSPPM) is comparable with another algorithm in literature.

Sixthly, we have demonstrated the effectiveness of genetic algorithm (GA) which we have used in three instances of FJSPPM. Furthermore, in procedure of solving FJSPPM, we find that GA outperforms ant colony optimization (ACO).

Seventhly, we propose two different approaches, Bayesian approach and fuzzy variable, to represent uncertainties of demand and yield in newsboy problem. We have obtained a threshold value of relationship between price parameters when using Bayesian method to solve the problem.

Limitation in our research

There exist limitations in our research, such as lack of comparison with other approaches in solving unpaired VRPPD and bi-level newsboy problem. This is actually because there is no benchmark for the research, which just shows originality of our research. Improvement of results in FJSPPM is needed. Better heuristic and combination of metaheuristic can be endeavored. We are look forwarding to do some research in these aspects. Furthermore, we do not have any applicatory case of supply chain to demonstrate capability of our strategy and approaches in solving practical problems. We hope there will be some case studies in this domain.

Chapter 1

Uncertainty in supply chain

Traditional supply chain management (SCM) is generally based on a static and determined environment, including deciding production plan, inventory level, distribution strategy, etc. However, in practical cases, there are always some uncertain factors impacting execution of plan of decision makers. We give some examples in literature about the important sense of considering uncertainty in SCM. The significance of the research topic is just motivation of our research. In this chapter, we analyze the potential occurring of uncertainty in supply chain and propose a classification for it. According to this classification, we give a survey of research on uncertainty in supply chain in literature, the problem focused and approaches deployed to treat them.

1.1 Supply chain management

Supply chain has been focused by lots of scholars and practitioners as early as the concept of logistic emerged. Logistic first emerged in armies. With supply chain the army can get enough support to prepare for the war or defence. Since 1990s, supply chain management (SCM) has attracted attentions of the high level managers. Research of SCM has developed from integration of the internal logistic management and relationship among cooperated companies to the efficiency and the value addition of the whole value chain. SCM involves wide range of areas and multidisciplinary application. It can conclude various activities and decision making in each stage of a supply chain.

1. UNCERTAINTY IN SUPPLY CHAIN

The concept of SCM in business makes managers of enterprises make decisions not at the standpoint of only his company as before, but at the height of the whole supply chain. In the war of business, supply chain has become a strong weapon. Generally, many strategies and activities in SCM, such as scheduling of supply chain, cooperation of members of supply chain, process of logistics, transport, manufactures, etc., are all operated in a static environment. However, in the real process of the total SCM, there are many uncertain cases occurring in manufacturing, distribution, demand markets, supply, and other stages in supply chain. Uncertainties which we cannot know predictably can easily influence supply chain operations. For example, delayed supply may affect production time and consequently influence delivery time and probably selling price. Changed demand quantity may induce production waste. Decline in productivity may impact easily supply quantity, inventory level, and selling price. Problems of vehicles in distribution process will disturb directly distribution time. From these examples we can state that dealing with uncertainties is a very important theme in SCM.

1.2 Significance of considering uncertainty in SCM

Uncertainty may induce disturbances in SCM. If we do not consider uncertainty in planning of supply chain activities, it will not carry on in the way we expected. Uncertainty impacts performance of supply chain in different dimensions. [Vorst et al. \(1998\)](#) stated that SCM should be concerned with reduction or even elimination of uncertainty to improve performance of supply chain. The results of case study suggested that reduction of uncertainty can improve service levels significantly. According to industrial survey conducted by Protiviti and APICS (American Production and Inventory Control Society), 66% of respondents considered supply interruption as one of the most significant concerns among all the supply chain related risks. [Mula et al. \(2006\)](#) indicated that models for production planning which do not recognize the uncertainty can be expected to generate inferior planning decisions as compared to models that explicitly account for the uncertainty. [Koh & Saad \(2003\)](#) suggested diagnosing uncertainties to help get the optimum performance of delivery. Therefore, we can observe the sense of considering uncertainty in SCM. [Yu & Li \(2000\)](#) stated that a critical role of

a logistic manager was how to make an optimization decision under uncertain, noisy, and incomplete information.

1.3 Research review about uncertainty in supply chain

Despite of wide range of activities SCM covers, the primary task is often described as uncertainty reduction (Davis, 1993; Mason-Jones & Towill, 1998). Risk and uncertainty are synchronous. Even they are seen as synonymous (Helliard *et al.*, 2001). Risk may be seen as a consequence of uncertainty (Lalwani *et al.*, 2006). Knight (1921). In his seminal work on risk and uncertainty, he ascertained that change in itself is not a risk but that the future uncertainties associated with change may well be risky. Risk is defined as the possibility of bringing about misfortune or loss while uncertainty is associated with those things that are not able to be accurately known or predicted (Collins Dictionary, 1996). According to this definition, uncertainty is not certain to bring misfortune to supply, but it is certainly risky. When there is a large deviation between reality and expectation, performance of results may not be consistent with plan. Even though reality is better than our expectation, they do not certainly bring benefits. For example, when order quantity is larger than that of forecasts, sales quantity may not increase as inventory level is set according to forecast value.

There has already been a lot of research about uncertainty in different sections of supply chain, even though the researchers do not analyze uncertainty from the angle of supply chain. We give an overall overview about it in following sub sections. Relatively, less research of uncertainty is on the standpoint of the whole supply chain. Different clusters of sources of uncertainty are identified and for each source of uncertainty, several improvement principles are identified in the work of Vorst *et al.* (1998). Study of applying different and balanced forms of flexibility to cope with uncertainty in turbulent environments was discussed by Dreyer & Grønhaug (2004). They focus on empirical studies of practical industry, i.e., fish processing plants in Norway. Although it is demonstrated a successful strategy, it may conflict with other evaluation criterias. Ottesen & Grønhaug (2002) stated that, disadvantage of vertical integration, their promising strategy to reduce uncertain supply, is that it may come at the expense of flexibility.

The two researches are on the same fish industry. It is observed that a strategy demonstrated appealing may not always be suitable. [Ho *et al.* \(2005\)](#) deployed a structural approach to measure supply chain uncertainty and their results for an e-commerce system produce a validated uncertainty scale that can help in diagnosing supply chain problems. However, the concrete approach of monitoring and assessing supply chain performance is only on way of envisaging.

We classify uncertainty in supply chain according to function of various stages. For a certain supply chain, firstly we decompose it into different phases. For a typical supply chain, it consists of initial supply of material, manufacturing, distribution, and consumer market. We hence category literature about uncertainty in supply chain as follows: uncertainty in demand, supply, manufacturing, and distribution. Besides these four preliminary sorts of uncertainty, we also refer to other kinds, which are detailed in one certain scope in supply chain.

1.3.1 Uncertainty in supply

We can define supply from two aspects. One is as mentioned in our work, in the first phase of supply chain, supply of materials, parts, or semi-finished products to manufacturers. This kind of supply is of the narrow sense. The other can be considered as all kinds of supplies to demanders in any relationship of supply-demand. Such as, retailers of goods to final customers, supplier of a certain medicament to a clinic, wholesalers to distributors, are all on the side of supply. This kind of supply is of the broad sense. Literature on uncertain supply are mostly focusing on supply with broad sense. Most research of supply uncertainty is on investigating impact of supply uncertainty to performance of organizations ([Boonyathan & Power, 2007](#); [Deo & Corbett, 2010](#)). In research of [Boonyathan & Power \(2007\)](#), results of analysis of a survey of two kinds of industries, product organization and service organization, show that in both industries, supply uncertainty is a more significant determinant of performance than demand uncertainty. Influence of uncertain supply and uncertain demand to performance of supply chain are compared. The implication is to make supply chain manager decide to focus on which section of supply chain.

Moreover, decision making under uncertain supply is also studied. [Anupindi & Akella \(1993\)](#) suggested different supply strategy for material supply. They

address the operational issue of quantity allocation between two uncertain suppliers and its effects on the inventory policies of the buyer. Based on the type of delivery contract a buyer has with the suppliers, they suggest three models for the supply process. [Shou *et al.* \(2009\)](#) studied three scenarios of coordination of supply chains and gave propositions from three different levels' strategy, the operational level, design level and strategic level. Under supply uncertainty and supply chain competition, there are different optimization decisions of order quantity in different scenarios. They treated uncertain supply as a quantified value. Decision of allocation of scarce resource under uncertain supply was studied by [Deo & Corbett \(2010\)](#). Their model of clinics is discussed to apply into other intertemporal resource allocation decisions.

From the view of supply chain, [Wilding *et al.* \(1998\)](#) demonstrated that internal supply uncertainty can be generated from parallel interactions when members at the same tier interact because of supply disruption. [Lee *et al.* \(1997\)](#); [Sterman \(1989\)](#); [Towill *et al.* \(1992\)](#) have also found that supply is uncertain because of the supplier performance. There will be chain reaction of uncertain supply to the whole supply chain. However, when we analyze impact of uncertain supply, it is intuitive to observe its direct influence to its down-stream companies. There is neither little study on the impact of uncertain supply to the whole supply chain. Therefore, we can conclude that research of uncertain supply should concentrate on the first denotation of supply we mentioned above. Our work about uncertainty in manufacturing and uncertain yield in newsboy problem, which we introduce in consecutive sections, is also based on this standpoint.

Thereby, for supply in the broad sense, we cannot uniformly discuss its impact, its cause and method to cope with. Concrete problems should be treated differently. For example, for supply of a supermarket, suppliers are distributors, or factory with direct supply. Uncertain supply manifests quantity, quality, and delivery time of goods. Cause of the uncertainty may be different, such as error of supplier, natural disaster in transportation, delay of supplier of upper level, shortage of goods, etc. While for a wholesaler, whose supplier is always manufacturer, supply uncertainty is mainly caused by problems in procedure of fabrication. For the uncertainty in manufacturing, we will discuss later.

For supply of narrow sense, its direct impact is affecting product planning of manufacturer. The preliminary cause is shortage of resource. The best way to

1. UNCERTAINTY IN SUPPLY CHAIN

reduce this source is to find substitution for scarce resource. Another cause is competition in resource market. General treatment is to keep a certain level of inventory and profitable contract with both suppliers and adversaries.

1.3.2 Uncertainty in demand

Although [Boonyathan & Power \(2007\)](#) state that supply uncertainty is a more significant determinant of performance than demand uncertainty from the result of survey in both industries of products and service. From the point of SCM, it is easy to find that demand uncertainty is more difficult to treat than supply uncertainty. In supply chain, demand is market, which is dynamic and cannot be controlled.

1.3.2.1 Factors causing uncertainty in demand

Similar to supply, we also have different definitions for demand. In order to avoid reduplicative analysis as in previous section of uncertain supply, we would like to directly define demand as demand in consumer market. Uncertainties in demand are mainly oscillations and surges of demand. Because market is dynamic, uncertainty is an inherent characteristic of demand. A common theme in literature is that internal demand fluctuations are the dominant source of uncertainty in supply chains ([Mason-Jones & Towill, 1998](#); [Taylor, 2000](#); [Towill *et al.*, 1992](#)). Consumer is the primary factor causing demand fluctuation. Consumers' necessities, desire and anticipation of consummation, value of consuming, tendency, belief in the production, manner of consummation, as well as the degree of infection between consumers can all influence the quantity of consummation. Another factor impacting demand is the external environment, such as the policy, advertisement, accuracy degree of searching information, production and its life cycle, and so on.

1.3.2.2 Impact of uncertainty in demand on supply chain

Uncertainties in demand affect easily inventory level of the upstream enterprises in supply chain, supply of raw materials, manufacturers, retailers, etc. Some researches verify that impact of uncertainty of demand to the retailer is larger than that to the manufacturer. Because of demand uncertainty and inaccurate and

asymmetric information, there is a very universal phenomenon called “Bullwhip Effect”, which causes hard measurable consequences of poor customer service level. Meanwhile, this phenomenon deteriorates in the process of broadcasting. The distance of the broadcasting is longer, the augment of the uncertainty increases. Between the two ends of a supply chain, the material and the consumer, the deviation is the largest.

1.3.2.3 Conventional methods to cope with uncertainty in demand

As dealing with uncertainties in demand is so urgent, many researchers have considered it in SCM. In literature, conventional methods of demand estimation and inventory control are discussed most (Campuzano *et al.*, 2010; Choi *et al.*, 2005; Kevork, 2010; Reiner & Fichtinger, 2009; Strijbosch & Moors, 2006). Nevertheless, the main disadvantage of traditional methods is that they concentrate in a small scope of optimization. Although make to order and demand-pull manner is superior to mass process, for many products, like daily consumer goods, their demand quantity change dynamically, the best way is still mass production and keeping enough inventory. In this case warehouse is needed and production quantity can only be determined according to a forecasting value.

In practice, production planning is usually made according to demand forecasting. David & Peter (1994) demonstrated the importance of good forecasting in a multi-product/multi-plant production/distribution system. The importance of demand forecasting is also reflected in other social problems, like infrastructure investment, such as transportation system, concert hall, stadiums, museums, exhibit centers, etc. All these projects are executed on a planning scheme, in which demand forecasting is necessary. There have been immense researches contributed to development of demand forecasting. Lots of effective methods of demand forecasting have been proposed, survey of buyers’ intentions, Delphi method, expert opinion, smoothing models, time series methods, judgmental approach, etc. Forecasting is difficult to master (Ascher, 1979). Demand forecasts remained remarkably inaccurate for decades (Ascher, 1979; Flyvbjerg, 2005; Flyvbjerg *et al.*, 2005). Flyvbjerg (2008) stated that despite all claims of improved forecasting models, better data, etc., no improvement in forecasting accuracy seems to have taken place. In the research about “bullwhip” of Chen *et al.* (2000), demand forecasting is considered one of the two most important factors causing “bullwhip”

1. UNCERTAINTY IN SUPPLY CHAIN

effect. Accuracy degree of forecasts depends not only on choice of forecasting model and quality of collected data, but also impacted by other factors, like psychological action of forecasters, bias induced by political-economic impactation, strategic misrepresentation, and so on. Reference class forecasting described by [Flyvbjerg \(2008\)](#) seems to have considered more practical factors of forecasters than conventional forecasting method. But we can see that outside view of situation is actually another subject action, different in problems. Some other kinds of combined forecast are illustrated superior to single method in improving accuracy ([Bates & Granger, 1969](#); [Granger & Ramanathan, 1984](#); [Mahmoud, 1984](#)). Other experts ([Collopy & Armstrong, 1992](#)) have shown that rule-based forecasts produce more accurate results than combined forecasts. We can conclude that no forecasting method developed is general to all problems. The trend is to choose an optimal one among them. This is also the strategy of many firms of consultant in forecasting.

[Kimball \(1988\)](#) described the mechanics of a single stage that operates a base stock policy in the face of random but bounded demand. Deployment of inventory as safety stock for addressing demand uncertainty was examined by [Graves & Willems \(2003\)](#). [Yano & Robert \(1987\)](#) used safety stock as protection against demand variations. Although it is maintaining desirable levels of customer service, rescheduling the material requirement planning system may impact safety stock. They indicated that safety stock may change when rescheduling the system and increasing safety stock may actually result in degraded performance when rescheduling is frequent. [Sridharan & Lawrence LaForge \(1989\)](#) surveyed that one approach suggested in the literature to reduce schedule instability is to introduce safety stock at the master production schedule (MPS) level to act as a buffer against differences in actual and forecast requirements. System's performance is sensible with quantity of safety stock. Compared to the alternative of no safety stock, small amount of safety stock improved schedule stability. However, further increases in the safety stock level often lead to increases in schedule instability and a higher cost penalty. Determining appropriate stocks in stochastic multi-state production/distribution systems is a very difficult task ([Inderfurth, 2002](#)). Dynamic programming algorithm for solving the safety stock optimization problem was developed by [Inderfurth \(2002\)](#). Moreover, uncertainty in supply chain can also impact determination of safety stock. The joint effect of lead time and

demand uncertainties, as well as the effect of “fair shares ”allocation, on safety stocks is studied by Schwarz (2000). Kelle & Silver (1990) stated that the amount of safety stock required depends upon, among other factors, the average value and variability of the length of the replenishment lead time. Because of additional cost of stock, managers are always preferable to reduction of safety stock under the premise of guarantee to meet customers’ needs. Kelle & Silver (1990) used a strategy of order splitting to reduce safety stock amounts. Besides determination of amounts of safety stock, another core problem is placement of safety stock (Graves & Willems, 2000, 2003).

There are close relationship between the two common strategies. On one hand, in most cases the two interact and can impact on each other. Sridharan & Lawrence LaForge (1989) suggest that efforts to reduce setup costs and improve forecasting accuracy may be useful alternatives to increasing safety stock in dealing with the schedule instability problem. On the other hand, decision of amount of safety stock is always based on demand forecasting (David & Peter, 1994; Eppen & Martin, 1988). David & Peter (1994) analyzed safety stock levels for a multi-product/multi-plant production/distribution system with seasonal stochastic demand which is based on demand forecasting.

Demand forecasting and strategy of safety stock are both strategies of plan ahead. However things always carry on in a track differing with plan. Control in action is needed in practice. In recent years, strategies of robustness and flexibility have become hot. Some researchers have tried to form a robust supply chain to make it immune to the uncertainties of demand. However, most of them is just a fantastic idea and hard to realize. Flexible and agile systems have also been much tried to improve the ability to cope with uncertainties in demand. Barad & Even (2003) considered flexibility as the ability of the manufacturing system to cope with internal and external variation with high competitive competency and high economic profitability. Swafford *et al.* (2008) presented an approach to achieve supply chain agility through IT integration and flexibility. In their opinion, supply chain flexibility represents operational abilities within the supply chain functions and supply chain agility represents the speed of the aggregate supply chain to adapt in a more customer-responsive manner. Tang (2006) considered in his research robust strategies for mitigating operational and disruption risks and enhancing the efficiency and resiliency of supply chain management.

1.3.3 Uncertainty in manufacturing

Different to uncertain external environment like demand uncertainty, uncertainties in manufacturing is internal uncertainties, which are caused by the staff, machines or some other internal elements. Comparing with external uncertainties, the internal ones are rather more dependent on the structures and planning schedules of the company or factory. Although the intuitional concept of internal uncertainties seems easier to solve than that of external ones, disturbances of uncertainty in manufacturing often interrupt manufacturing process of one product or even more related products, consequently causing more lead time, and consequently delaying delivery time. Uncertainties in process of manufacturing mainly include (Barad & Even, 2003): machine breakdown; staffing/operator problems; unexpected orders; cancelation or modification of existing orders; early or late arrival of raw materials; modification of release and due dates; uncertainty in the duration of processing of activities.

1.3.3.1 Complexity of keeping stability and flexibility in modern manufacturing system

Rapid development of technologies, global competitions, variation of customers' tendencies, and shorter product cycle time are the main factors impacting manufacturing enterprizes' external environment. Availability of materials, staff, and machines are the bases to keep operations of production. Moreover, manufacturing system is becoming more complex with development of technology and the multifunctional need of products. At present, the growing complexity is one of the most significant characteristics of manufacturing, which is manifested not only in manufacturing system, but also in the products to be manufactured, in the processes, and the company structures (Wiendahl & Scholtissek, 1994). To our knowledge, the more complex is the system, the less stable is it, i.e., it is more difficult to keep system's stability. Stability is directly related to continuity and efficiency of production. High stability can reduce uncertainty of manufacturing system from aspect of system performance. Even for a manufacturing system with good performance, it may be disturbed by external uncertainty. Like variation of products, we need a manufacturing system robust and flexible. Flexible manufacturing system (FMS) emerged exactly in the context of products diversification.

However, FMS is with a more complicated structure than conventional manufacturing system. Therefore, FMS is usually with a lower stability. We can observe that it is not easy to reduce external and internal uncertainties simultaneously. We should cope with different uncertainty with different strategy.

1.3.3.2 Advanced manufacturing system

From the perspective of SCM, considering realizing the most efficient manufacturing manner and responding to production dynamics caused by disruption of uncertainty, there are some promising strategies and concepts to make production adaptable to consumer market, such as demand driven manufacturing, Kanban system, lean production, etc. The ideal systems, such as the material requirement planning (MRP), manufacturing resource planning (MRPII) and enterprise resource planning (ERP) are recommended to get the most efficiency of resources of the companies and to realize minimization of costs and shortest lead time of manufacturing. MRPII focuses on management of resources of human, wealth and equipment within enterprise. This is a weakness in present strong competition. Modern business of manufacturing relies on the superiority of technique and cooperation between the suppliers, customers and distributors as an entire supply chain. Therefore, traditional MRPII is not satisfied in this environment. Based on MRP, MRPII, ERP, lean production (LP), computer integrated manufacturing system (CIMS), agile manufacturing, and some other management theories are developed. Moreover, thanks to advanced manufacturing technologies (AMT), such as flexible manufacture system (FMS), computer numerical control (CNC), computer aided design (CAD), computer aided manufacturing (CAM), etc., production is more efficient. The rapid developed internet technology, mechanical engineering technique, electronic technique, and automatic technique, all contribute much to the modern manufacturing. The low level of these equipments and machines are all to help to realize the high level strategy and decision. They are the basis of realizing advanced theory in manufacturing.

However, none of these existing theories above considers uncertainties in process of manufacturing. These years many scholars and researchers have paid attention to uncertainties in manufacturing. The normal uncertainties, external late supply, internal late supply, planned set-up time exceeded, machine breakdowns, labor unavailability, tooling unavailability, demand batch size enlargement

1. UNCERTAINTY IN SUPPLY CHAIN

and customer design changes, were discussed by [Koh & Saad \(2003\)](#). They used parts delivered late (PDL) and finished products delivered late (FPDL) as the criteria of delivery performance of MRP-controlled manufacturing environment, and demonstrate the influence degree of identified uncertainties by experiments of simulation. They suggested enterprises to implement the optimum use of buffer or slack. Also in the domain of MRP-controlled manufacturing, [Minifie & Robert \(1990\)](#) developed a dynamic MRP-controlled manufacturing system simulation model to study the interaction effects of demand and supply uncertainties. [Brennan *et al.* \(1994\)](#) examined the performance of MRP-controlled manufacturing environment under demand and lead time uncertainties. [Kanet & Sridharan \(1998\)](#) examined late delivery of raw materials, variations in process lead-times, interoperation move times and queue waiting times in MRP-controlled manufacturing environment. It can be concluded that in the area of exploring uncertainties in the MRP-controlled manufacturing environment, the simulation modeling appears to be the most common research methodology used.

1.3.3.3 Research on strategic level to consider uncertainty in manufacturing system

Almost all the manufacturing companies must prepare for two kinds of business model: lot size production, multi-product and small batch. The variety of production decides the complexity of structure, and consequently induces the instability of the production system. [Burns & Stalker \(2009\)](#) posited that as a firm's environment becomes more complex and/or unpredictable, there is a need for a more organic structure. Thus, firms in relatively certain and predictable environments would have a mechanistic structure with greater subdivision of tasks and simpler jobs. In contrast, firms in uncertain and unpredictable environments would have more organic structures, with less specialization and more complex jobs.

Our first task is to increase stability of system, and then the flexibility to cope with different uncertainties emerging in the production process. Flexibility is considered a multi-dimensional construct. [Pagell & Krause \(1999\)](#) focused on the following three types of flexibility: product mix, new product introduction and modification. Concerning on the flexibility in production, there are some distinct views. In general, many researchers deemed that there is an obvious

relation between the flexibility level, environmental uncertainties and the performance of company. Such as Gerwin (1993), suggests that manufacturers that are facing increasingly uncertain environments often respond with increased operational flexibility; and Swamidass & Newell (1987), suggest that increases in manufacturing flexibility lead to increases in firm performance. Flexibility is often examined at the strategic level to help managers make decision. Pagell & Krause (1999) discussed the relationship between flexibility at the operational level and the environmental uncertainties. They concluded a quite different result through a mail survey of North American Manufacturers: no relationship was found between the measures of environmental uncertainty and operational flexibility; no relationship was found between a firm's performance and its effort to align the level of operational flexibility with its external environment. All these methodologies are working on dealing with the external uncertain environment. This is like the demand uncertainty, which we treated in the proceeding chapters. Here, we aim to solving the uncertainties in the firm itself, the manufacturing uncertainties, which is considered as the internal uncertainty. In despite of the results discussed in the past, we believe there is a relationship among the internal uncertainty of manufacturing, the operational flexibility, and the firm's performance.

Flexibility is seen as a way for manufacturing organizations to adapt to uncertain external environments (Pagell & Krause, 1999). Swamidass & Newell (1987) noted that increases in flexibility were generally linked to increased performance. Moreover, they concluded that one way to cope with increased environmental uncertainty is through increased manufacturing flexibility. Gerwin (1993) presented a model that posits that environmental uncertainty leads to manufacturing strategy and hence the flexibility requirements of the system. The structural contingency theory makes the measurement of uncertainties and flexibilities more important. The decision makers often employ different strategies according to their perception of the environment. As to the measurement of environment, Duncan *et al.* (1972) proposed six perceptual items to the environmental uncertainties, such as actual users of products of the firm, competitors of supply of raw materials, competitors of customers, government regulation, etc.

1.3.3.4 Research on operational level to consider uncertainty in manufacturing system

Besides research of uncertainty on strategic level, there are also some studies on operation level to cope with uncertainty. Early in 90s in last century, the approaches to manage changes and uncertainties in manufacturing have emerged. [Kádár & Monostori \(1998\)](#) proposed a distributed, multi-agent holonic-like system and it is hoped to reach a dynamic behavior through increased autonomy of agents in dynamic changing conditions. A rolling horizon approach was proposed by [Tolio & Urgo \(2007\)](#), which applied a two-stage stochastic programming method against the occurrence of multiple uncertain events, and the need of resources was modeled through a scenario based formulation. It is concluded by many scholars that the effect of uncertainties can be reduced through the rescheduling of the planning or orders, or softened by the changes of MRP parameters, such as the safety stock, safety lead time, planned lead time, lot-sizing rules, freezing or planning horizon. [Morel *et al.* \(2003\)](#) proposed a model using the principle of Holonic Manufacturing System. [Vandaele & De Boeck \(2003\)](#) developed software dedicated to high level tuning under input and output uncertainties. The aim is to find a reduced lead time, optimal lot-sizing and the utilization levels of the system in order to guarantee a high customer service level. [Koh & Saad \(2003\)](#) presented a business model to diagnose the underlying causes of uncertainties. Another approach that appears is the use of fuzzy model to deal with uncertainties. That is how [Mula *et al.* \(2006\)](#) worked on both demand and lead time uncertainties. [Grabot *et al.* \(2005\)](#) dealt with demand uncertainty for a system with multi-product and multi-level.

It can be briefly summarized that for coping with uncertainty in manufacturing system, the promising strategy is to firstly plan ahead and then control in actions. An advanced manufacturing mode should be applied, to keep excellent cooperation with all parts in firms. For operational detail, within the pure production, both production plans and technological procedure play important roles, either in aspects of reducing uncertainty and increasing production efficiency.

1.3.4 Uncertainty in distribution

Distribution in supply chain is a process with multi participants. This characteristic brings strong uncertainty. Problems in the distribution process will not only affect distribution activity itself, but also reduce supply chain performance, and may even cease operation of the supply chain. Before discussing uncertainty in distribution, we decompose it in details to recognize better the procedure of distribution. It includes two major parts: handling and transportation. Handling is the picking, loading and unloading procedure of goods, between factory or warehouse and transportation vehicles. We can see that handling is internal procedure, which can be better controlled compared to external procedure, transportation. Transportation can be impacted by many external factors, like the weather, traffic condition. Uncertainty in external environment is difficult to handle and always takes more interests of researchers.

1.3.4.1 Research priorities of uncertainty in distribution

Uncertainty in distribution mostly concentrates on tardy delivery time (Ray *et al.*, 2005; Weng & McClurg, 2003) and delivery frequency (Frey & Rhodes, 1998; Lalwani *et al.*, 2006). It is interesting to find that uncertain delivery time is always considered together with uncertain demand in literature. The efficiency of supplier-buyer coordination in coping with the uncertainty in delivery time and demand was discussed by Ray *et al.* (2005); Weng & McClurg (2003). Ray *et al.* (2005) discussed decision making of supply chain affected by the business characteristic, demand uncertainty and delivery time variability. Lalwani *et al.* (2006) found that impact of uncertainties associated with stock holding costs and delivery frequencies to distribution network is more substantial than that of the intuitive factors, customer volume changes and transport tariffs. Different uncertainties' effects on delivery date were discussed by Koh & Saad (2003).

From results of literature review, we observe that research about uncertainty in distribution is not too much. As mentioned above, we decompose distribution procedure into handling and transportation. We can analyze uncertainty in distribution from these two aspects respectively.

Uncertainty in handling process origins from following sources:

1. UNCERTAINTY IN SUPPLY CHAIN

- Characteristic of handling equipment. Handling equipment is always with certain reliability. For some handling equipment with oversize or overweight, disassembly is needed and this may impact handling efficiency.
- Working environment. Because of transmission attributes of handling procedure, there is always not enough space for executing handling. This needs handling scheme planned before execution, to coordinate workers on different handling equipment. High handling efficiency needs smooth handling channel, including good road condition and enough working space.

We can specify uncertainty in handling process into scope of equipment and facilities planning. To our knowledge, there is no research on this regard. The major reason is probably that it is biased in favor of practical application, such as material handling path planning in factory. Therefore it does not need much research in theoretical research.

1.3.4.2 Research of uncertainty in transportation system

Uncertainty in transportation system for people's travel, e.g., Metropolitan Planning, has recently received some attention ([Krishnamurthy & Kockelman, 2003](#); [Mahmassani, 1984](#); [Pradhan & Maria Kockelman, 2002](#)), mainly focuses on consideration of uncertainty of travel demand, inputs and parameters of models, political and technical environment. Different to transportation for people's travel, planning for transportation in supply chain always consider uncertainty in procedure of path planning. For distribution routing planning, there are two kinds of models widely used, Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP). Uncertainty is paid attention in routing planning with the two models ([Alfa, 1987](#); [Laporte *et al.*, 1992](#)). Like demand quantity, the most widely used approach for treating uncertainty of distribution time is based on representation of probability distribution for it ([Fu, 2002](#); [Gendreau *et al.*, 1996](#); [Haghani & Jung, 2005](#)).

Sources of uncertainty in distribution path planning mainly include: uncertainty in vehicles, uncertainty of routes, and uncertainty of clients. There is some research treating uncertainty from these aspects. Uncertainty of vehicles refers to uncertain condition of vehicle, like breakdown and traffic accidents. In a series of research of [Li *et al.* \(2007\)](#), they contributed to rescheduling problem with

disruption of vehicles' breakdown. [Mu *et al.* \(2010\)](#) proposed a new class of VRP, disrupted VRP, and using two algorithms to generate new routes for disrupted VRP plan. Situation of routes contribute much to traveling time. E.g., when a vehicle sinks into traffic jam, all following schedules could be influenced. Even delayed time cannot be forecasted. Routes affected by weather like in fog or rainy days, travel speed may slow down. A schedule re-optimized was suggested by [Xiang *et al.* \(2008\)](#). [Huisman *et al.* \(2004\)](#) proposed an dynamic vehicle scheduling approach in order to avoid trips starting late in environments characterized by significant traffic jams. Traffic congestion was coped with in dial-a-ride by [Fu \(2002\)](#). Although we expect that all clients carry on according to reservation, there are always some unavoidable cases where request changes. Such as absence of clients, cancelation of requests, new arrival of request, etc. Sometimes the location and size of a customer order is not known deterministically until vehicle arrives. Dynamic VRP for covering all orders was solved by [Chen & Xu \(2006\)](#), using a dynamic column generation algorithm. Random demand was considered in stochastic VRP ([Gendreau *et al.*, 1996](#); [Xiang *et al.*, 2008](#)).

1.3.5 Other kinds of uncertainty

Besides the four main kinds of uncertainties we discuss above, there are some other sorts studied and defined in literature:

- Uncertainty in logistic was studied by [Yu & Li \(2000\)](#). In their work, the heavy burden of computation of conventional stochastic programming ([Mulvey & Ruszczyński, 1995](#); [Mulvey *et al.*, 1995](#)) for scenario study sorts out through adding variables into linear programming. Although they have reduced computation burden compared to previous methods for the same kind of problem, the limitation of their method is obvious that scenario-based research depends too much on parameters in scenarios and at the application of linear model.
- Uncertainty in supply chain relationship. Researchers generally agree that uncertainty is a major driving force behind the effective establishment of supply chain relationships. [Williamson \(1979\)](#) clearly stated when he classified types of organizational relationships thus: “the three critical dimensions for characterizing transactions are: 1) uncertainty, 2) the frequency with

1. UNCERTAINTY IN SUPPLY CHAIN

which transactions recur, and 3) the degree to which durable transaction-specific investments are incurred. Of these three, uncertainty is widely conceded to be a critical attribute”. The importance of supply chain relationships has been identified by Handfield *et al.* (1999) when they state that “without a foundation of effective supply chain organizational relationships, any efforts to management the flow of information or materials across the supply chain are likely to be unsuccessful”.

- Supply chain risk uncertainty. Operation of supply chain is based on firm-to-firm cooperation. It consists of information and resource sharing, within which there is a supply chain project investment. For any kind of investment, there is some risk. Estimation of risk in supply chain is already an appealing and important research area in SCM, especially in the preliminary planning of supply chain. It refers to much knowledge in economy area. Decision making under conditions of supply chain risk uncertainty is of great importance, but there is a lack of investigations that center on supply chain investment decisions when facing high levels of risk uncertainty (Hult *et al.*, 2010). In their work, different real options are investigated for related supply chain projects under high supply chain risk.
- Information uncertainty. Information sharing is considered as an important role in reducing demand uncertainty in supply chain. However, there is also uncertainty in information. Information uncertainty exists mainly in incompleteness, distortion, and amplification of information. The most universe phenomenon is “information silos”, i.e., lack of reciprocity among enterprize information systems. In context of competition, enterprizes are always self-closed in resources, both in material and information resource. Cooperation among enterprizes is always limited in temporary trades. Information sharing is almost executed only internal the enterprize. Poor level of information sharing is a major cause of information uncertainty. Another factor inducing uncertain information is information transfer manner. In conventional supply chain, information is progressively transferred, from low stream firms to upstream firms. “Bullwhip” effect is exactly caused by information asymmetry in this transmission. Integrated supply chain mode

is obviously superior to conventional mode. In integrated supply chain system, all supply chain firms can share demand information of consumers and can benefit for catching earlier more accurate information. Therefore, in order to reduce information uncertainty, supply chain cooperation mechanism and information sharing technique are needed.

- **Forecasting uncertainty.** Loss resulting from forecasting uncertainty is obvious. The future is always unknown. Although many scholars and researchers have spent much work on developing method of forecasting, which can be seen from literature about demand forecasting in section 1.3.2, it has the inherent characteristic of uncertainty. Efficiency of forecast relates to methods of forecasting, and also depends upon forecast horizon. Long-term forecasting is with larger uncertainty than short-term forecasting caused by the distant future (Al-Saba & El-Amin, 1999). Order forecast horizon was considered the first and main cluster of sources of uncertainty by Vorst *et al.* (1998). Forecasting is used throughout the supply chain, from demand forecasting to prediction of availability of supply. Many decisions are made on the base of forecasting, e.g., inventory level is based on forecasting of production yield, lead time and demand; pricing is based on forecasting of market share, assessment of competitors' capacity, investment return rate, inflation, etc. Al-Saba & El-Amin (1999) applied method of Artificial Neural Network for long-term forecast, which was characterized with large uncertainty, to get accurate results. Forecast uncertainty is increasingly paid attention in research of SCM. Giordani & Söderlind (2003) studied the inflation uncertainty reported by individual forecasters in a survey and results showed that forecasters underestimate inflation uncertainty.
- **Cost uncertainty.** Financial activities account much in supply chain operation. There are various types of cost in supply chain, materials cost, production cost, stock holding costs, transportation cost, wage rates, etc. Even there are some marginal costs to investment. Because of diversification of calculation manner of costs, consideration point of cost differs in firms. As its complication refers to economics and specialty, we will not spend much effort in this regard. We would like to concern about research from this respective which is general in SCM. Hartman (1972) examined

effects of uncertain output price, wage rates and investment costs on quantity of investment undertaken by a firm. Obvious effect of stock holding costs on distribution network was found by [Lalwani *et al.* \(2006\)](#).

1.4 Conclusions

The sense of taking uncertainty into account in SCM is stated by many researchers. It is obvious that we should pay attention to unavailability of resources in supply chain. We aim to get a complete analysis of uncertainty in SCM. Analyzing uncertainty in different stages of supply chain will almost cover all potential cases. From literature review, we can find that although there is immense research on uncertainty in supply chain, there is no systematic research of SCM with uncertainty in consideration.

Most of work in literature is limited in a narrow scope of research point through focusing on scenarios study. We are not to negate the function of scenario study. Actually it is found that scenarios planning is an effective method to learn about the future by understanding the nature and impact of the most uncertain and important driving forces affecting the world. But it is not yet demonstrated the best way for research of uncertainty in SCM. Therefore, other strategy should be attempted. The methods for treating problems are also appropriate for certain case they concentrate. In our work, we aim to propose an general way to solve uncertainty in supply chain. This helps supply chain managers to give complete consideration of uncertainty in the procedure of decision making.

Chapter 2

Coping with uncertain demand in supply chain

Uncertain demand is one of the most important kinds of uncertainty in supply chain. We have concluded in precedent chapter that the two preliminary traditional methods, safety stock and demand estimation, are with disadvantage of improvement. These two methods are on the operational level to treat uncertainty. They work well in a certain extent. Different from them, from strategic level we propose to apply an intuitive and rather simple approach, postponement strategy. Postponement has been appreciated in recent decades, mainly in manufacturing period of realizing mass customization and decoupled system. With postponement strategy, we could address demand with different quantity flexibly. Based on assumption of ideal cooperation among all the enterprises in the same supply chain, a linear programming model is generated, with objective of satisfying demand of consumer markets while minimizing supply cost. Through results tested in a numeric example, it is demonstrated feasible to schedule supply procedure in supply chain regardless of quantity of demand and to supply different replenishment strategy for decision maker.

2.1 Introduction of postponement strategy

Originally, postponement was known as late customization or delayed product differentiation, which was first discussed by W. Alderson (1957) ([Alderson \(2006\)](#)). Since then, postponement strategy has been applied in many industries, including

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

high-tech industry, food industry, garments industry, etc. It is necessary to recognize that postponement strategy is a double-sided sword. It can bring benefits to enterprise, such as reduced inventory, pooling risk, accurate forecast. Meanwhile, the disadvantages also exist, like high cost of designing and manufacturing of the common components, cost of reconfiguration of the supply chain structure, etc. Therefore, it can be stated that postponement strategy is not suitable to all situations. It depends upon the real situation. There is a trade-off between additional costs and the benefits. Some researchers also indicated this point. [Huang & Li \(2008\)](#) suggested firms to choose the suitable postponement decision according to their business environment, static decision or dynamic decision, to cope with external environmental changes. Although postponement is often used by suppliers, it is as well used by demanders. [Graman \(2010\)](#) implied an order postponement in a supply chain. He showed that both manufacturer and retailer gained when the order was placed later under some conditions. Many factors may impact effects of applying postponement strategy, products price, cost of each stage in supply chain, packaging, assembling, inventory cost, service-level, etc. [Ma et al. \(2002\)](#) found that a key factor for commonality and postponement decisions is interaction between processing time and component procurement lead time.

The approach of postponement is concreted according to the practical problem by different authors, to achieve coping with distinct problems. [Graman \(2010\)](#) proposed a partial-postponement decision cost model and demonstrated its application in determining inventory level of finished-goods and postponement capacity. The problem was solved through using a non-linear programming formulation. He also illustrated the relationship and interaction between the related factors and the expected costs and the postponement capacity. [Zeng et al. \(2006\)](#) developed a systematic approach to determine the optimal timing for staged order commitment, with categorizing attributes and aggregation of processes to reduce complexity.

Postponement is proved an effective method to treat demand uncertainty by some researchers. [Cvsa & Gilbert \(2002\)](#) proposed a two-tier supply chain model to demonstrate that below a threshold level of demand uncertainty the supplier as well as the buyers can benefit from providing early purchasing opportunities

2.2 Postponement applied to address uncertain demand in supply chain

versus postponement. As defined by [Graman \(2010\)](#), while certain parts of demands are solved through make-to-stock strategy, a combination of this strategy and postponement is called “partial ” or “tailored” postponement. The partial postponement strategy is a flexible method to respond to demand uncertainty. In the scenario that demand is independent of time and stochastic, [Aviv & Federgruen \(1999\)](#) indicated that benefits of postponement were confined into two factors, statistic economies of scale and risk pooling via common buffers.

Before attempt of applying postponement strategy, we would like to explain its meaning clearly. Although postponement is similar to delay, it is necessary to distinguish the difference between them. In fact, the term “delay” is always regarded detrimental, especially, delay in production and delay in transportation. It is exactly a type of uncertainty in supply chain. [Sipahi & Delice \(2010\)](#) proposed a differential equation to analyze impact of three types of delay on inventory behavior and to obtain an ordering policy to make inventory variation insensitive to the detrimental effects of delay. Here, postponement is a subjective strategy, rather than an objective delay phenomenon in supply chain process.

2.2 Postponement applied to address uncertain demand in supply chain

In most cases, conventional sense of supply chain is actually supply chain network. Each phrase in supply chain may consist of several companies with the same function. Relationship among them is competition and cooperation. We can state that from the angle of cooperation, integration should be emphasized for the plan on strategic level. While for decision on tactical and operational level, such as concrete manner of cooperation and execution of strategy, decomposition is necessary. In our work, we focus on allocation of supply. It is obvious that decomposition of supply chain is needed during calculation. Based on this concept, we transfer the complexity planning problem of supply chain network into resolution of several sub systems ([Zheng & Mesghouni, 2011a,b](#))

2.2.1 Decomposition of supply chain

We concentrate on a normal supply chain in manufacturing industry modeled in Figure 2.1. It is obvious that quantity of goods prepared in each stage should be decided according to demand quantity in last node, consumer market. To solve this problem in the whole supply chain, firstly, we simplify the structure of supply chain as in Figure 2.2. Through the process of structure simplification, research of the complicated supply chain network is turning to subsystems of supply chain. There is only one level of demand-supply relation in a subsystem. Our main idea is when demand occurs, according to the total inventory level of all the suppliers, we allocate supply task of equal quantity of demand to certain suppliers.

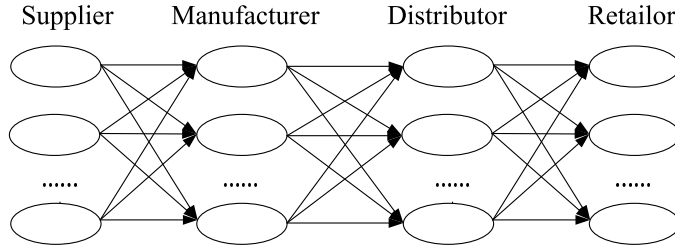


Figure 2.1: Normal supply chain structure

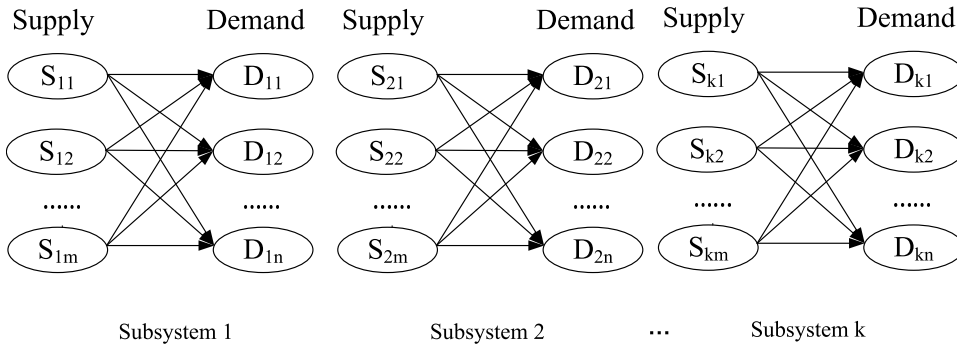


Figure 2.2: Simplified supply chain structure

In literature viewed, postponement used in managing demands in period of supply is much fewer than that in manufacturing. In our work, we aim to apply postponement strategy in supply section, which meets directly uncertain demand in supply chain. When demand quantity exceeds expected value, i.e., inventory level, we postpone the quantity which can not be satisfied immediately with stock. In literature, the work most similar to ours is that of [Iyer et al. \(2003\)](#).

They analyzed demand postponement as a strategy to handle demand surges and showed that postponement strategy may lead to reduced investment in initial capacity. But the model was limited in a single period of postponement demands. In our work, based on the model of [Iyer *et al.* \(2003\)](#), we consider the practical condition that includes both the regular period and the postponed period.

2.2.2 Description of approach of application of postponement

Postponing unsatisfied demand means that it disregards to uncertain quantity of demand. It works under the environment where the hardware in the supply chain does not change, like the capacity of inventory or manufacturing efficiency. We respond to demand surges after the demands having occurred. What the suppliers should do before demand unfolds is keeping the normal safe stock level and negotiating a good cooperation contracts among them. Our approach is feasible in an absolute cooperative environment, from the standpoint of the whole supply chain.

Following the direction of information, i.e., from consumer market to material supply, firstly we calculate sub system 1 in [Figure 2.2](#), which is at the end of supply chain and with demand from consumer market as input data. Computation results of sub system 1 can then be used as input data for its precedent sub system 2. Iteration of the same kind of computation carry on until we get all planning for the entire supply chain. As in [Figure 2.2](#), three iterations are needed. Spirit of our approach of postponement is that we do not concern demand distribution or prior planning of supply. We focus on scheduling of supply in a subsystem of supply-demand described in [Figure 2.2](#), to make clear the flow of goods.

After occurring of uncertainty of demand, demand quantity of a demander i , D_i , is identified. Firstly, we concentrate on the question of deciding quantity supplied to each demander with stock. β is given to represent the ratio of quantity of demand postponed, thereby $1 - \beta$ is the part of demand satisfied with stock immediately. We denote that postponed demand carry in a postponement period, while serviced parts of demand supplied in regular period. α_{ij} is set to describe the ratio of demand i serviced by supplier j in regular period. This step is called scheduling process. The next step is to complete the unsatisfied demand, i.e. the postponed part β , with β_{ij} to describe the ratio of demand i satisfied by supplier

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

j in postponement period. We call this step a rescheduling process of supply in this sub system. At this point we have completed scheduling for a sub system. Iterating procedure of scheduling for the whole supply chain is described as in Figure 2.3.

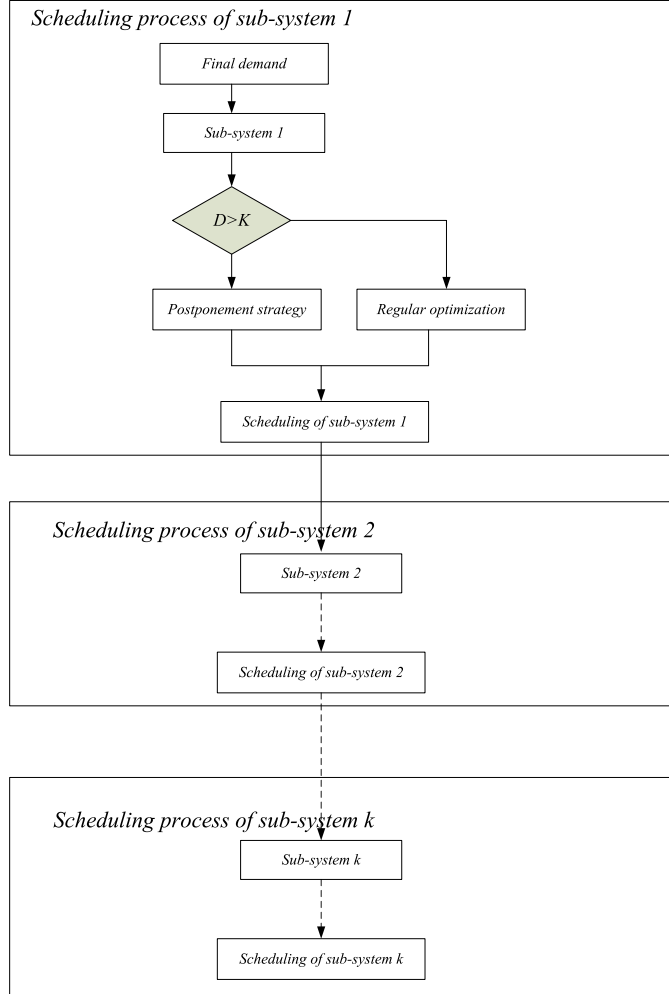


Figure 2.3: Procedure of the scheduling with the postponement strategy

As described by Iyer *et al.* (2003), the specific manner in which demand postponement occurs can follow the following two possible schemes: (a) Postpone a fraction of demand for each customer: every unit of demand is split with β delivered in the regular period and $1 - \beta$ delivered in the postponement period. In this scheme, every customer is affected and has a fraction of his demand postponed; (b) Postpone all demands for a fraction of customers: a fraction $1 - \beta$

2.2 Postponement applied to address uncertain demand in supply chain

of the demand is postponed and thus delivered entirely in the postponement period, and then the remaining fraction β of the demand is delivered in the regular period. Note that in this case, any given customer may see his demand delivered entirely in the regular period or entirely in the postponement period depending on whether his demand was postponed or not. In our work, different to [Iyer et al. \(2003\)](#), we consider that the postponement is planned after demand unfolds.

Resumptively, our strategy of postponement is executed in three stages:

- 1) Determine optimal fraction of total postponed quantity of demand β ;
- 2) Calculate optimal fraction α_{ij} for each supply-demand relation in the regular period.

- 3) Calculate the optimal fraction β_{ij} for each supply-demand relation in the postponement period.

Before we detail the three steps, we give notations used in following mathematical models.

Notations:

β - Optimal fraction of total postponed demand.

α_{ij} - Ratio of demand i satisfied by supplier j in regular period.

β_{ij} - Ratio of demand i satisfied by supplier j in postponement period.

For subsystem k ,

c_1 - Unit cost of production of inventory.

c_2 - Unit cost of new manufacturing in postponed period, including all the costs of manufacturing, cost of material, processing, assembly, etc.

c_3 - Unit cost of compensation paid by suppliers to demanders for postponement, which is assumed to be equivalent to all demanders.

c_4 - Unit cost of conservation between the two delivery times.

c_5 - Unit cost of transportation.

D_i - Demand of i^{th} demander.

D - Total demand, $D = \sum_{i=1}^n D_i$.

K - Total inventory level of all suppliers, $K = \sum_{j=1}^m k_j$.

k_j - Stock of supplier j .

m - number of suppliers.

n - number of demanders.

p_j - Transportation time of j^{th} supplier in the postponement period.

r_{ij} - Distance between supplier i and the demander j .

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

s_j - Supply capacity of j^{th} supplier in the postponement period.

S - Total supply capacity of supplier in the postponement period.

t_j - Manufacturing time for supply of j^{th} supplier in the postponement period.

t - Expected manufacturing time constant.

T - Allowable postponing time.

ξ - Threshold of amount for delivery .

In order to reduce the complexity of calculating, we assume that the unit cost of conversation, c_1 , the unit cost of manufacturing, c_2 , and the unit compensation for postponing to demanders, c_3 , are all identical to each supplier. The allowable lead time of delivery T is also equivalent to suppliers.

2.2.2.1 Optimal fraction of total postponed demand

In regular period, $(1 - \beta)$ fraction of demand is satisfied. Total stock of all the suppliers must be capable of supply task. We have assumed that information of suppliers is already known. Their inventory level is constant. We get hence an inventory constraint as follows:

$$(1 - \beta) \sum_{i=1}^n D_i \leq \sum_{j=1}^m k_j \quad (2.1)$$

In postponement period, demand is satisfied with new manufacturing. According to the manufacturing capacity (supply capacity) of the suppliers, we can get the manufacturing constraint:

$$\beta \sum_{i=1}^n D_i \leq \sum_{j=1}^m s_j t_j \quad (2.2)$$

In inequality above, t_j must be controlled in the allowable postponing time T . Furthermore, the sum of t_j and p_j can not exceed T .

$$t_j + p_j \leq T \quad (2.3)$$

Although t_j is a decision variable, which can be independent, to simplify calculation of β , we choose an expected constant t , we note,

$$S = t \sum_{j=1}^m s_j \quad (2.4)$$

According to formulations above, we hence obtain

$$1 - \frac{K}{D} \leq \beta \leq \frac{S}{D} \quad (2.5)$$

Total expected cost of supply, including both regular period and postponement period, is

$$\begin{aligned} V_1(\beta) &= c_1 \sum_{j=1}^m k_j + c_2 \beta \sum_{i=1}^n D_i + c_3 \beta \sum_{i=1}^n D_i + c_4 \left(\sum_{j=1}^m k_j - (1 - \beta) \sum_{i=1}^n D_i \right) \\ &= c_1 K + \beta D (c_2 + c_3 + c_4) + c_4 (K - D) \end{aligned} \quad (2.6)$$

The first term of the formulation above is the cost of the production of inventory; the second term is the new manufacturing cost for satisfying the postponed demands; the third part is compensation for postponing paid to demanders; the last part is conservation costs. As transport cost is related to the single amount of delivery and the calculation is rather complicated, we do not consider it in the period of calculation of β .

From the function of cost, we find that the cost is proportional to the postponement fraction β . Therefore, the minimum cost of supply could be obtained with the minimum β .

According to formulation 2.5, the optimal value of β is:

$$\beta^* = 1 - \frac{K}{D} \quad (2.7)$$

Accordingly, the minimum expected cost is

$$\begin{aligned} V_1^*(\beta) &= c_1 K + (D - K)(c_2 + c_3 + c_4) + c_4 (K - D) \\ &= c_1 K + (D - K)(c_2 + c_3) \end{aligned} \quad (2.8)$$

2.2.2.2 Optimal fraction of supply quantity to each supplier

After the total postponement fraction has been determined, optimal fraction to each supplier in regular period α_{ij} and that in postponement period β_{ij} can be calculated. Firstly, we discuss calculations of the two parts separately, then we integrate them to execute the calculation of optimization.

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

Optimal fraction of supply to each supplier in regular period

In the relationship of modern enterprises, the long-term cooperation is appreciated. Goods are usually sent to the familiar customers. In our work, we suppose an ideal situation of the cooperation among the enterprises in the same supply chain. Demand is allocated just according to the objective of minimization of cost and the maximization of service level.

As the cost of production, conservation, compensation for postponing paid to demanders is concerned with total postponement fraction, here we only have to consider the distance and cost of transportation with α_{ij} . Transport cost concerns mainly with the distance of delivery r_{ij} :

$$\min V_2(\alpha_{ij}) = \min(c_5 \sum_{i=1}^n \sum_{j=1}^m r_{ij} \cdot D_i \cdot \alpha_{ij}) \quad (2.9)$$

Unit cost of transporting c_5 is probably inversely proportional to the amount of delivery. Therefore, for the sake of low cost, suppliers deliver goods only when they have a reasonable amount. For example, the threshold of the delivery amount is ξ , when quantity of goods $q \leq \xi$, suppliers do not want to carry on deliver. Without consideration of carpool, there is a delivery amount constraint:

$$D_i \alpha_{ij} \geq \xi \quad (2.10)$$

Demand satisfied in regular period is

$$\sum_{i=1}^n \sum_{j=1}^m D_i \alpha_{ij} = (1 - \beta) \sum_{i=1}^n D_i \quad (2.11)$$

Demand satisfied in the regular period is serviced with stock, that is

$$\sum_{i=1}^n D_i \alpha_{ij} \leq k_j, \forall j = 1, 2, \dots, m. \quad (2.12)$$

The natural attribution of the rate of distribution is:

$$0 \leq \alpha_{ij} \leq 1 \quad (2.13)$$

From the formulations above, we can get the fraction of demand postponement allocated to each supplier.

Optimal fraction of supply to each supplier in postponement period

After the total postponement fraction and the optimal fraction of supplying of each supplier in the regular period have been determined, the optimal fraction of each supplier in the postponement period can be calculated. Different from calculating the total cost of postponement, the allocation of postponement is more complicated. As the allocation of demand in regular period, the cost of transporting concerns mainly with the distance of delivery:

$$\min V_3(\beta_{ij}) = \min(c_5 \sum_{i=1}^n \sum_{j=1}^m r_{ij} \cdot D_i \cdot \beta_{ij}) \quad (2.14)$$

Transport amount constraint:

$$D_i \beta_{ij} \geq \xi \quad (2.15)$$

The total quantity of postponed demand allocated to suppliers:

$$\sum_{i=1}^n \sum_{j=1}^m D_i \beta_{ij} = \beta^* \sum_{i=1}^n D_i \quad (2.16)$$

The postponed demand is satisfied by the new supply capacity (from supply of upstream enterprize or manufacturing itself):

$$\sum_{i=1}^n D_i \beta_{ij} \leq t \cdot s_j, \forall j = 1, 2, \dots, m. \quad (2.17)$$

Demand constraints are:

$$\sum_{i=1}^n \beta_{ij} = 1 - \sum_{i=1}^n \alpha_{ij}, \forall j = 1, 2, \dots, m. \quad (2.18)$$

Natural attribution of the rate of distribution is:

$$0 \leq \beta_{ij} \leq 1 \quad (2.19)$$

From the calculation of the formulations above, we can get the fraction of demand postponement allocated to each supplier.

Integrated calculation

If we use the separated calculation for both regular period and postponement period, constraints are not considered simultaneously. Consequently we may get solutions infeasible. Therefore, we integrate the formulations in the two periods to solve them simultaneously.

We get the integrated formation for optimizations as follows:

$$\begin{aligned} \min V_4(\alpha_{ij}, \beta_{ij}) = & \min(c_5 \sum_{i=1}^n \sum_{j=1}^m r_{ij} \cdot D_i \cdot \alpha_{ij} \\ & + c_5 \sum_{i=1}^n \sum_{j=1}^m r_{ij} \cdot D_i \cdot \beta_{ij}) \end{aligned} \quad (2.20)$$

All the constraints, [2.10](#), [2.12](#), [2.13](#), [2.15](#), [2.16](#), [2.17](#), [2.18](#), and [2.19](#), in the two periods must be satisfied.

2.3 Instance of application of the approach of postponement

To demonstrate the feasibility and effectiveness of our approach dealing with uncertain demand in supply chain, we apply it to the example in [Gumus *et al.* \(2009\)](#).

2.3.1 Description of model from the original SC network

The instance used in ([Gumus *et al.*, 2009](#)) is a supply chain network design presented for a reputable multinational company in alcohol free beverage sector. Existing supply chain, the cost and capacity data refer to ([Gumus *et al.*, 2009](#)).

In the model shown in [Figure 2.4](#), 2 factories (F_1, F_2), 3 warehouses (W_1, W_2, W_3) and 6 distributors ($D_1, D_2, D_3, D_4, D_5, D_6$) are selected from the company's system in order to explain existing design of the network, considering that the product flow is followed by only one type of product of the company. The problem to solve is to decide and design optimal SC network to satisfy demand, simultaneously to minimize the supply cost.

2.3 Instance of application of the approach of postponement

Firstly, we simplify the supply chain network as two subsystems as in Figure 2.5.

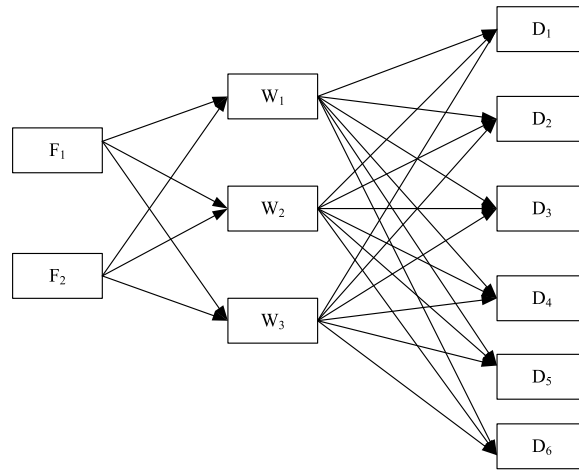


Figure 2.4: Supply chain network consisting of factories, warehouses and distributors

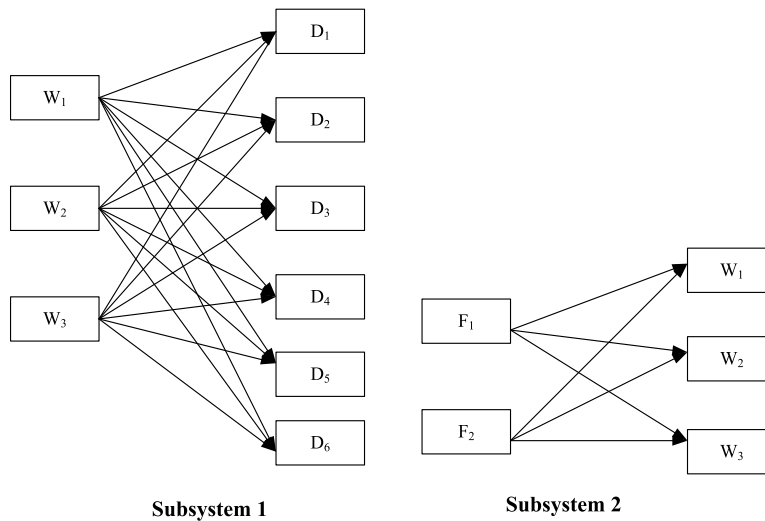


Figure 2.5: Simplified subsystems

Besides applied in the case where inventory of suppliers can not satisfy current demands, our approach is also an effective scheduling method in allocation of demand in the case where stock is enough to satisfy demands. To demonstrate this point, we apply our method in both cases. The two cases correspond to our instance are just the one with estimated demand and the other one with unexpected demand.

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

Data in Table 2.1, Table 2.2, Table 2.3, Table 2.4 and Table 2.5 is the original data obtained from literature. In order to use our methodology, we adjust some parameters. The concept of transportation distances are replaced by unit transport costs. Therefore, $c_5 = 1$, r_{ij} refers to transport cost.

As we do not know exactly inventory level, we assume that inventory is equal to warehouse's capacity. Thus, corresponding the data of capacity of the factories and warehouses in our model, in subsystem 1, $k_1 = 3,785,630$, $k_2 = 1,564,479$, $k_3 = 346,094$, $K = \sum_{j=1}^3 k_j = 5,696,203$; In subsystem 2, $k_1 = 3,011,970$, $k_2 = 1,298,716$, $K = \sum_{j=1}^2 k_j = 4,310,686$.

Table 2.1: Transport costs from factories to warehouses (cent/case)

Factories	Warehouses		
	W1	W2	W3
F1	0.01	1.15	0.41
F2	1.15	0.01	0.74

Table 2.2: Transport cost from warehouses to distributors (cent/case)

Warehouses	Distributors					
	D1	D2	D3	D4	D5	D6
W1	0.48	0.65	0.63	0.71	0.45	0.42
W2	0.60	0.36	0.55	0.52	0.72	0.76
W3	0.13	0.25	0.17	0.39	0.06	0.05

Table 2.3: Capacities of factories and warehouses

Factories/Warehouses	Capacity
F1	3011970
F2	1,298,716
W1	3,785,630
W2	1,564,479
W3	346,094

Table 2.4: Estimated demand of distributors (case)

distributors	demand
D1	116,803
D2	55,425
D3	74,668
D4	9,660
D5	81,539
D6	56,820

Table 2.5: Random demand of distributors (case)

distributors	demand
D1	1, 116,803
D2	955,425
D3	1,774,668
D4	1,509,660
D5	1,581,539
D6	856,820

2.3.2 Results of calculation for the case with estimated demand

Different to the work in [Gumus *et al.* \(2009\)](#), we do not focus on demand estimation. Here we use estimation value of demand as the real occurring demand. The problem waiting to be solved is a linear programming problem. We use LINDO 6.1 to resolve it.

In order to simplify calculation, we ignore the constraint of transport amount, which is assumed to satisfy the transportation principle, using some methods such as out-sourcing, car pooling and so on.

2.3.2.1 Calculation results of subsystem 1

For subsystem 1, from the data of estimated demand quantity in [Table 2.4](#), we obtain $D = \sum_{i=1}^6 D_i = 394915$. We have got that $K = 5696203$ in subsystem 1. As $D < K$, we need not use the postponement strategy for rescheduling the SC network, i.e., $\beta = 0$. The optimization method is enough for scheduling in this case.

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

From calculation results for subsystem 1, we get allocation of demand of distributors to each warehouse is specified in Table 2.6. The objective value of supply cost is 58605.25.

Table 2.6: Allocation of the demand of distributors to each warehouse in the case with estimated demand

Warehouses	Distributors					
	D_1	D_2	D_3	D_4	D_5	D_6
W_1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
W_2	0.000000	0.880848	0.000000	0.000000	0.000000	0.000000
W_3	1.000000	0.119152	1.000000	1.000000	1.000000	1.000000

2.3.2.2 Calculation results of subsystem 2

From the results in subsystem 1, we get demand quantity in subsystem 2 as in Table 2.7.

Table 2.7: Allocation of demand of warehouses to each factory in the case with estimated demand

distributors	demand
D1	0
D2	65771
D3	329144

$D = \sum_D^i = 394915$, as we get $K = 4310686$ for subsystem 2, so $D < K$. It is still not necessary to use the postponement strategy. $\beta = 0$. From calculation results we get allocation of demand of warehouses to each factory of subsystem 2 seen in Table 2.8.

Table 2.8: Allocation of demand of warehouses to each factory in the case with estimated demand

Factories	Warehouses		
	W_1	W_2	W_3
F_1	0.000000	0.034962	1.000000
F_2	0.000000	0.965038	0.000000

2.3.3 Results of calculation for the case with unexpected demand

In uncertain demand environment, where demand quantity exceeds stock, the postponement strategy is just appropriate to cope with the unexpected demand. We can get similar calculation results as the ones above.

2.3.3.1 Calculation results of subsystem 1

Compared with algorithms in literature, superiority of our algorithm is that we can deal with unexpected demands. Quantity of demand in this section we deal with is beyond inventory level of suppliers.

We calculate total quantity of demand in subsystem 1 with the data in Table 2.5: $D = \sum_{j=1}^m D_j = 7794915$. As indicated in section 2.3.1, in subsystem 1 $K = 5696203$, then we get $D > K$. Thereby $\beta = \beta^* = 1 - \frac{K}{D} = 0.27$.

With calculation result we get the ratio of supply for each warehouse in the regular period and postponement period as shown in Table 2.9 and Table 2.10 respectively.

Table 2.9: Allocation of demand of distributors to each warehouse for subsystem 1 in the case with unexpected demands in regular period

Warehouses	Distributors					
	D1	D2	D3	D4	D5	D6
W1	1.0000	0.0000	0.129865	0.0000	1.0000	1.0000
W2	0.0000	0.057377	0.0000	1.0000	0.0000	0.0000
W3	0.0000	0.0000	0.195019	0.0000	0.0000	0.0000

Table 2.10: Allocation of the demand of distributors to each warehouse for subsystem 1 in the case with unexpected demands in postponement period

Warehouses	Distributors					
	D1	D2	D3	D4	D5	D6
W1	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
W2	0.0000	0.942623	0.480097	0.0000	0.0000	0.0000
W3	0.0000	0.0000	0.195019	0.0000	0.0000	0.0000

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

2.3.3.2 Calculation results of subsystem 2

We use the calculation results of subsystem 1 as input data for calculation of subsystem 2. The upstream supply for the factory is assumed to be enough, hence supply capacity is the manufacturing capacity. In our example, the total products needed by the warehouses are much less than the stocks. Therefore, in the case where factories only need to supply demand in the postponement period of the warehouses, we need not use the postponement strategy in subsystem 2. However, we still use the optimization model to get the optimal allocation of supply. Furthermore, empty warehouse should be replenished. We can calculate the cost of replenishing the inventory. There exit two other cases: the second case is that factories only need to send quantity of safe stock to the warehouse, and the third case is that factories need to fulfill the need of warehouses in the postponement period, and simultaneously need to replenish the inventory of the warehouses. We execute the calculations under the three cases separately. Sometimes, manager must make decision of choosing the optimal manner. Through comparison of calculation results for the three cases above, we can find which cost least. The one with the lowest cost is the optimal proposal.

Case 1: Factories only need to supply the need in the postponement period of the warehouses.

In this case, postponement strategy is not needed. We use calculation of the regular period. We get the objective value: $\min V_2(\alpha_{ij}) = 392580$.

The optimal allocation of demand is as in Table 2.11.

Table 2.11: Optimal allocation of demand of warehouses to each factory in case 1

Factories	Warehouses		
	W1	W2	W3
F1	0.0000	0.258978	1.000000
F2	0.0000	0.741022	0.000000

For replenishing the inventory, here, $D = 5696203$, $K = 4310686$. $K < D$, postponement strategy is needed. We get objective value: $\min V_2(\alpha_{ij}, \beta_{ij}) = 113330$.

The optimal allocation of demand for the regular period is as in Table 2.12, for the postponement period is as in Table 2.13.

2.3 Instance of application of the approach of postponement

Table 2.12: Optimal allocation of demand of warehouses to each factory in regular period

Factories	Warehouses		
	W1	W2	W3
F1	0.795632	0.000000	0.000000
F2	0.000000	0.830127	0.000000

Table 2.13: Optimal allocation of demand of warehouses to each factory in postponement period

Factories	Warehouses		
	W1	W2	W3
F1	0.204368	0.000000	1.000000
F2	0.000000	0.169873	0.000000

The sum of separate supply for demand of warehouses and for replenishing the inventory of warehouses is 505910.

Case 2: Factories only need to send quantity of safe stock to the warehouse to satisfy the need of warehouses in the postponement period.

In this case, we use the contrary allocation of the supply to demand. We get: $\min V_2(\alpha_{ij}) = 256220$. Allocation of supply of factories to each warehouse is as in Table 2.14.

Table 2.14: Optimal allocation of the demands of warehouses to each factory in case 2

Factories	Warehouses		
	W1	W2	W3
F1	0.000000	0.150693	0.849307
F2	0.000000	1.000000	0.000000

Case 3: Factories need to fulfill the need of warehouses in the postponement period, and simultaneously need to replenish the inventory of the warehouses.

In this case, $D = 7794915$, $K = 4310686$. $K < D$, postponement strategy is needed.

Objective value $\min V_2(\alpha_{ij}, \beta_{ij}) = 681630$. Optimal allocation of demand for the regular period is as in Table 2.15, for the postponement period is as Table 2.16.

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

Table 2.15: Optimal allocation of demand of warehouses to each factory in regular period in case 3

Factories	Warehouses		
	W1	W2	W3
F1	0.422688	0.216952	1.000000
F2	0.000000	0.391524	0.000000

Table 2.16: Optimal allocation of demand of warehouses to each factory in postponement period in case 3

Factories	Warehouses		
	W1	W2	W3
F1	0.577312	0.000000	0.000000
F2	0.000000	0.391524	0.000000

2.3.4 Discussions

According to the result of ANN simulation in (Gumus *et al.*, 2009), the first and second factories, and the first and second warehouses are open, but the third warehouse is closed. On the other hand, analytical method gives a solution in which all the factories and warehouses are open. While ANN simulation finds 182,021 dollars as the minimum cost, analytical method's result is 167,231 dollars. Dealing with the same quantity of demands, our results show the optimal scheduling is that, the first and second factories, the second and third warehouses are open, while the first warehouse is not used. The minimum cost is 196833.45 dollars. It is not as good as compared to the results in (Gumus *et al.*, 2009), however, we have conquered the limit of their methods, the constraint that the capacity of the warehouses should be equal or more than the demand of the distributor. This is just what we want to deal with, the case where demand quantity is beyond warehouse capacity.

Furthermore, another advantage of our method is that it can quickly get the best replenishment strategy after emptying of stocks which is used to satisfy the demands in regular period. There are usually several strategies to choose, we can execute our postponement strategy under different cases separately. We can compare performance of different replenishment strategies to find the one with least cost as the proposal.

2.4 Conclusions

In this chapter, we have proposed using postponement strategy in scheduling of supply chain network to cope with uncertainties in demand, based on the hierarchal subsystems of the supply chain network and the ideal cooperation of the agents in supply chain. It is actually a method transforming uncertainty to certainty. Simplification of supply chain network to demand-supply subsystems is to simplify computation of large scale of variables. A linear programming model is employed to get the optimal allocation of the supplier to the demand, with objective of minimization of supply cost, which concludes manufacturing cost, compensation cost, manufacturing cost and transport cost. It is demonstrated feasible and powerful in scheduling of supply chain through numerical example. We found that, even in the cases where inventory is capable of satisfying demand, our optimization model is also appropriate. The postponement strategy is only necessary when the total inventory cannot satisfy unexpected demand. We have compared the results of treating the same demands to the results in (Gumus *et al.*, 2009). It is completely competitive.

Inevitably, some drawbacks and limits exist in our research. We have not considered the physical position relationship among members of supply chain. In that case, we need more data, this makes the scheduling more complicated. In our future study, we can take it into account to complete practical scheduling, to avoid the phenomenon of roundabout. As to the products in the logistics, we only have treated the flow of finished products. The treatment of materials and parts will be more interesting and complex. Another drawback is in the calculation. In fact, in order to get the parameters needed in calculation of linear programming in LINDO 6.1, we have done a lot of preparing work by hands, using programming in software will bring much convenience. As well, the usage of the linear programming is limited in small scale of calculation. For larger scale of calculation, a heuristic algorithm should be more appropriate. If all the calculations are integrated in software or a tool box, it will be much more convenient and simpler for the managers to use our method. It is worthy to realize a visual process of all the design and calculation procedures.

2. COPING WITH UNCERTAIN DEMAND IN SUPPLY CHAIN

Chapter 3

Flexible job shop scheduling problem under uncertainty environment

Uncertainty in manufacturing includes mainly unavailability of machines, new arrival tasks and uncertain processing time of products. In our work, we focus on flexible job shop, which is an appropriate manner for modern consumer market. We suggest using condition based maintenance (CBM) to reduce unavailability of machines in manufacturing system. Different to conventional preventive maintenance, CBM makes scheduling for manufacturing dynamic, without predicted moment of maintenance task. In order to solve flexible job shop scheduling problem with CBM, two stages are needed. Firstly, we use method for solving ordinary flexible job shop scheduling (FJSP) to give a preschedule for manufacturing plan, then when maintenance tasks needed we add them into the preschedule. For the second stage of adding maintenance tasks, we propose an inserting algorithm, which is demonstrated suitable for treating new arrival of jobs. In the section of discussing uncertain processing of jobs, we observe that in different existing schedule, it is important to analyze impact degree of processing time of operations.

3.1 Reducing unavailability of machines in FJSP

Unavailability of machines, is the preliminary kind of uncertainty in manufacturing system. Flexible job shop, as a representative and popular manner of manu-

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

facturing, attracts our attention to use it as our research objective. We suggest using condition based maintenance (CBM), a category of preventive maintenance (PM), to reduce unavailability of machines in flexible job shop. Our problem is modeled as scheduling problem in flexible job shop with CBM. Application of CBM makes manufacturing system scheduling dynamic. Because in CBM, maintenance task is determined by monitoring, we cannot predict the exact moment when maintenance task is necessary. Occurring of breakdown of machines are random in that condition. It is obvious that in most time of production, machines are available, under this circumstance, the problem is an ordinary flexible job shop scheduling problem (FJSP). We solve ordinary FJSP to get a preschedule. When need of maintenance task emerges, we need to add them into the preschedule. We propose an Inserting Algorithm (IA). Because of the originality of the problem, there is no benchmark for us to demonstrate effectiveness of our algorithm. Hence we concentrate on conventional FJSPPM. In order to solve FJSPPM, firstly we attempt to find promising method for solving FJSP. Three approaches, a hierarchical Genetic Algorithm, an integrated Genetic Algorithm, and an integrated Ant Colony Optimization, are proposed. The best approach among the three is adopted in solving FJSPPM. To illustrate effectiveness of IA, we compare it with the simultaneous scheduling algorithm (SSA) in literature on benchmark of FJSPPM.

3.1.1 Introduction and literature on FJSPPM

We have concluded the factors inducing uncertainties in manufacturing system. Although manufacturing subject to less disturbance than the end stage in supply chain, such as demand, complexity of manufacturing system may increase possibility of uncertainty occurring. Different manufacturers adopt distinct manufacturing manners, which depend upon class of products, scale and capacity of company, etc. Therefore, to do research on uncertainty in manufacturing system, we should focus on a classic manufacturing manner. Job shop is a manufacturing manner suitable for consumer market with attribution like species diversity and small batch size. It is popular in manufacturing industry. Flexible job shop is an extension of job shop, which is more flexible in producing diversified products and making full use of machines.

3.1.1.1 Flexible Job-shop Scheduling Problem (FJSP)

Flexible Job-shop Scheduling Problem (FJSP) extends job-shop scheduling problem (JSSP) with alternative machines routings, by assuming that a machine is capable of performing more than one type of operation (Hussain & Joshi, 1998; Najid *et al.*, 2002; Nasr & Elsayed, 1990). That means for any given operation, there is at least one machine capable of performing it. The first model is referred as job shop scheduling with alternative machine tool routings, which was first addressed by Iwata *et al.* (1978). The same model was later addressed by Brandimarte (1993) as flexible job shop scheduling problem (FJSP). Brucker & Schlie (1990) first addressed FJSP by a polynomial algorithm, which was applied with two jobs. FJSP can be considered as a generalization of JSSP and parallel machines problem. It concludes two sections: assignment of available machines to operations and sequence scheduling of all jobs.

There are two kinds of flexibility, total flexibility and partial flexibility. Both of them are studied by Kacem *et al.* (2002a). They developed two new approaches: the approach by localization and an evolutionary approach controlled by the assignment model. By hybridizing particle swarm optimization and simulated annealing, Xia & Wu (2005) proposed a hybrid approach to solve the multi-objective flexible job-shop scheduling problem, in which, the particle swarm optimization is to deal with the assignment problem, and simulated annealing scheduling algorithm for sequence scheduling.

To solve FJSP which includes two sub problems, both being NP-hard problems, there are two approaches: hierarchical approach and integrated approach. The former one treats the assignment of machines and sequencing scheduling separately, while the latter one considers the two problems simultaneously. Brandimarte (1993), who was the first to use decomposition method in FJSP, applied hierarchical approach, both sub problems are tackled by Tabu Search (TB). After him, Kacem *et al.* (2002b); Saidi-Mehrabad & Fattahi (2007); Xia & Wu (2005), etc., all use hierarchical approach to solve the problem, with different or the same heuristic to solve the two sub problems. In contrast, there is less literature for the integrated approach, Dautère-Pérès & Paulli (1997) defined a neighborhood structure for the problem where there was no distinction between the two sub problems. Gambardella & Mastrolilli (1996) presented two neighborhood func-

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

tions. [Fattahi *et al.* \(2007\)](#) compared the two approaches and concluded that hierarchical approach have better performance than integrated algorithms.

3.1.1.2 Preventive Maintenance

Most literature working on job-shop scheduling problem (JSSP) does not consider unavailability of machines. However, in most practical manufacturing environment, there are usually some sorts of uncertainty inducing unavailability of machines, such as the unavailability of staff, operational errors of staff, machine breakdown, and so on. The reasons of staff and others subjective aspects are usually not considered as optimization section. Meanwhile, the objective aspects, like the machines' performances, are always focused in research. Machine's performance depends on its parameters, which cannot be changed or improved after machine going out of the factory. In contrary, it decrease with time in its lifetime. Besides the final scrap, breakdown cannot be avoided, especially in term of modern machine, which is always with a sophisticated structure. In most cases, breakdown is caused by very small errors, imprecision between the two joint parts, or attrition of some parts, etc. Therefore, ensuring machines performing in good condition attracts many researchers and practitioners. Furthermore, preventive maintenance (PM) is widely studied among them.

PM is obviously more effective than breakdown maintenance, which is a kind of widely used maintenance before, for machines in small batch production, where the interruption is not very severe. PM is also superior to the periodic maintenance, in the aspect of avoiding over maintenance and insufficient maintenance. PM is to avoid interruption by performing maintenance activity before breakdown happens. It is expected that after maintenance, machine is restored to a good working condition in a period, which may be fixed or unfixed. Correspondingly, there are two kinds of PM, the one with fixed period and the one with unfixed period. The former is for machines with fixed time to scrap, and the latter is appropriate to the structured machines, which is more complex and without fixed time to scrap. In fact, the processing condition or material difference may provoke distinction of lifetime between the same kinds of parts. Thereby, the fixed period of maintenance are actually unfixed, with an interval. In this case, it can also be concluded in the unfixed period of maintenance.

PM is an effective method to increase availability of machines. Another reason for which PM is paid attention is its sharing resource directly with production. Most studies concerning maintenance consider maintenance periods as constraints, i.e., maintenance is privileged to production (Liao *et al.*, 2006). In fact, the priority depends on concrete case. For example, when PM is not urgent, production takes priority in order to maximize production, otherwise, maintenance takes priority. When maintenance is urgent, if it does not carry out immediately, breakdown may occur, and then series of consequence may be provoked. The significance of PM is to guarantee continuity of production. Therefore, relationship between PM and production must be treated well. Stochastic approach is more appropriate to deal with conflict between maintenance and production. However, there is little literature on stochastic approach. The related works (Kaabi-Harrath, 2004; Xu *et al.*, 2008) still favor maintenance to production. The goal of PM is to maximize the availability of production system and to decrease cost of unexpected failures. As it is opposite to the ultimate goal of maximizing production, a trade-off between PM and production should be found to get the maximum profitable point of production system.

3.1.1.3 Flexible Job-shop Scheduling Problem with Preventive Maintenance

There is not much research on JSSP considering maintenance activities. We have referred several researchers working on JSSP integrated with preventive maintenance (PM)(Gao *et al.*, 2006; Lei, 2010a; Moradi *et al.*, 2011; Wang & Yu, 2010). Other similar works studies influence of maintenance activity in some other production modes, like parallel machines (Berrichi *et al.*, 2010; Liao *et al.*, 2006).

Two different scheduling horizons are investigated for the problem of scheduling jobs on two parallel machines which are not continuously available for processing, the long-term and short-term horizons (Liao *et al.*, 2006). Maintenance is considered as ε -almost periodic in a parallel machine scheduling problem (Xu *et al.*, 2008). Berrichi *et al.* (2010) proposed an integrated bi-objective model for parallel machine problem using reliability models to take the maintenance aspect into consideration. The intervals of maintenance and the sequence of production are optimized in the model. A visual interactive simulation model was

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

constructed to show how the state dependent rescheduling technology is used (Eric Li & Shaw, 1998). A heuristic which relies only on predicted downstream machine failure times has been refined to include job-shop state variable information.

For FJSP with machine maintenance in consideration, a hybrid genetic algorithm is proposed by Gao *et al.* (2006) to solve FJSP with non-fixed availability constraints, which used partial representation method to represent only a part of a solution candidate and leaves the rest part to be decided by the heuristic method to strengthen the inheritability of the solution candidate. Moradi *et al.* (2011) investigated integrated FJSP with preventive maintenance activities under multi-objective optimization approaches, where four multi-objective optimization methods are compared to find the Pareto-optimal solution.

3.1.1.4 Condition Based Maintenance

Despite PM has been studied in FJSP to increase availability of machines and reliability of the entire production system, the maintenance activity interval is mainly given as a constant or the maintenance must be executed in a predicted interval. And the theoretic basis of the maintenance interval is not specified, that is, PM is only an abstract activity.

The type of PM we use in FJSP is Condition Based Maintenance (CBM). In the groundbreaking report of Neal *et al.* Neale *et al.* (1979), difference in maintenance strategies (e.g., breakdown, planned, etc.) were illustrated and CBM was suggested. Since 1990s condition monitoring techniques has been increasingly used to aid planning replacement Aven (1996) and preventive maintenance Christer *et al.* (1997). CBM has become widely accepted as one of the drivers to reduce maintenance costs and increase plant availability Al-Najjar (1991), Bengtsson (2002). The main idea of CBM is executing maintenance activity in the period of potential machine failure, in order to avoid malfunction of machines. Malfunctions refer to the mechanical failures, which induce the machine breakdown, such as slipping clutch, jump file transmission, generation power does not work, etc. Potential failure is the failure which has not happened yet, but may happen in one moment in future. It is the hidden faults, which exist commonly. The moment when the failure happen depends on the system itself. For detailed introduction and application about CBM, can refer to Sethiya (2006).

The theoretical basis of CBM is the $P - F$ curve, which describes the deterioration process of machine, shown in Figure 3.1.

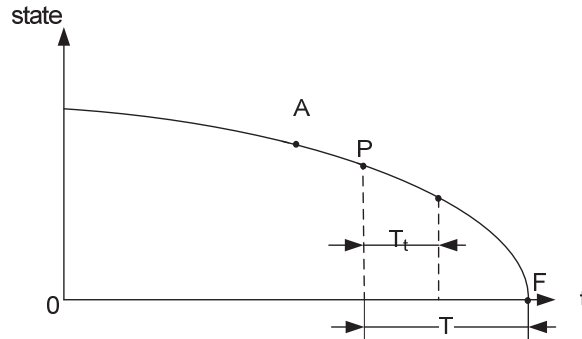


Figure 3.1: P-F curve

In Figure 3.1, A : the moment when failure began;

P : the moment when hidden failure is detected;

F : the moment when malfunction occurs;

T : the interval of $P - F$, the process of the hidden failure developing to malfunction.

To prevent malfunction, executing time of maintenance should be before the point F and after P , to use maximally the effective lifetime. To find the right moment to execute maintenance is the essence of CBM.

Advantage of CBM is that it transforms the state of maintenance from passiveness to activeness. It gets rid of the disadvantage of the cyclic maintenance, which may induce inadequate maintenance or over maintenance. CBM chooses an appropriate time to perform maintenance to avoid breakdowns and reduce the maintenance cost simultaneously. It is based on analysis of failure mechanism of machines. The main obstacle of applying CBM is high cost of installation of observer and detector for discovering potential failure of machines. In spite of the costly installation, increase of reliability of machine is the most important motive of application. CBM and the Reliability-Centered Maintenance are the primary maintenance strategies in future.

As CBM is also a kind of PM, we note the problem as flexible job shop scheduling problem with preventive maintenance (FJSPPM). The attribution of real-time of CBM makes this kind of FJSPPM dynamic. We can conclude this problem as dynamic FJSPPM (DFJSPPM). Liu *et al.* (2007) classified attempts

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

to scheduling in presence of disruptions in manufacturing system into two groups. One group with completely reactive job dispatching scheduling, and the second group offers control strategies to aid the system recovery from disruptions with consideration of an initial schedule. The main difference between the two groups is that no schedule is generated in advance in the complete reactive scheduling, but decisions are made on real time using priority dispatching rules. On the other hand, the second group uses a predetermined schedule called preschedule or predictive schedule to optimize a certain performance measure and is implemented until some unforeseen disruption occurs in the system. DFJSPPM is different to conventional FJSPPM, where PM is determined in a fixed period or at a fixed moment. Before data of PM obtained by CBM, the problem is a classic FJSP. Job shop carries on production according to a preschedule, result of solving FJSP. After obtaining data of PM, we add PM into existing preschedule. At this moment, we can reschedule it as solving a new FJSPPM if we just have a perfect moment when all ongoing job operations are completed and PM task is not arriving. However, if we cannot find the perfect moment, but just a processing period, we cannot reschedule all jobs with new arriving PM tasks. In order to solve this real time problem with disruption, we propose an inserting algorithm (IA). IA can be considered as a reactive dispatching scheduling for adding PM into existing preschedule, which is different to the two groups concluded by [Liu *et al.* \(2007\)](#). We introduce IA in details in following section.

3.1.2 Mathematical modeling for FJSPPM

We study the situation that scheduling period of FJSP coincides with the $P-F$ interval T of CBM. That is, maintenance activity is executed within the scheduling period. FJSP is already NP-hard problem. Added with maintenance execution, the problem becomes more complicated.

Because DFJSPPM depends on concrete problem, the first step of solving DFJSPPM is to specify the time windows of PM tasks. This step transfers the problem into FJSPPM. In subsequent section we do comparative study with existing benchmark of FJSPPM in literature to demonstrate our proposed algorithm.

FJSPPM is described as follows: n jobs are to be scheduled on m machines. Each job i represents a number of n_i non-preemptable ordered operations. The execution of each operation k of job i (noted as O_{ik}) requires one machine selected

from a set of available machines, called A_{ik} , and occupy that machine t_{ikj} time units until the operation is completed. There are L_j maintenance tasks which has to be processed on machine j during the planning horizon. The maintenance task corresponds to a predefined time window T , within which the starting time of the maintenance task can be moved. We assume that:

- (1) All the n_i ordered operations of the i^{th} job have to be processed;
- (2) Activity of each operation O_{ik} requires one machine selected from a set of available machines, called A_{ik} ;
- (3) Every machine processes only one activity (job operation or maintenance task) at a time;
- (4) Set-up and unloading time for operations are machine-independent and are included in processing time of operation;
- (5) Maintenance task is considered as a special job, duration of which is included in makespan of jobs;
- (6) Machine is restored to good working condition after maintenance.
- (7) Jobs are processed before their due dates. Therefore, there is no penalty of tardiness and storage cost. Production cost concerns only with processing cost.

Notations:

- Indices

i, h : index of jobs, $i, h = 1, 2, \dots, n$;

j : index of machines, $j = 1, 2, \dots, m$;

k, g : index of operation sequence, $k, g = 1, 2, \dots, n_i$;

l : index of maintenance tasks, $l = 1, 2, \dots, L_j$.

- Parameters

n : total number of jobs;

m : total number of machines;

n_i : total number of operations of Job i ;

L_j : total number of maintenance tasks on Machine j ;

O_{ik} : the k^{th} operation of Job i ;

PM_{jl} : l^{th} potential maintenance on Machine j ;

p : maximum number of maintenances needed on one machine;

A_{ik} : set of available machines for Operation O_{ik} ;

t_{ikj} : processing time of O_{ik} on Machine j ;

CM_j : unit processing cost on machine j ;

p_{jl} : duration of Maintenance task PM_{jl} ;

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

$[t_{Ejl}, t_{Ljl}]$: time window associated with maintenance, where t_{Ejl} is the earliest starting time, and t_{Ljl} is the latest starting time of Maintenance task PM_{jl}

- Decision variables

$$x_{ikj} = \begin{cases} 1, & \text{if Machine } j \text{ is selected for Operation } O_{ik}, \\ 0, & \text{otherwise;} \end{cases}$$

c_{ik} : completion time of the Operation O_{ik} ;

y_{jl} : completion time of Maintenance task PM_{jl} .

Our model is given as follows:

$$\min F1 = \max(\max_{1 \leq i \leq n} c_{in_i}, \max_{1 \leq j \leq m} y_{jL_j}) \quad (3.1)$$

$$\text{s.t.} [(c_{hg} - c_{ik} - t_{hgj})x_{hgj}x_{ikj} \geq 0] \vee [(c_{ik} - c_{hg} - t_{ikj})x_{hgj}x_{ikj} \geq 0], \\ \forall (i, k), (h, g), j \quad (3.2)$$

$$[(y_{jl} - c_{ik} - p_{jl})x_{ikj} \geq 0] \vee [(c_{ik} - y_{jl} - t_{ikj})x_{ikj} \geq 0], \forall (i, k), (j, l) \quad (3.3)$$

$$\sum x_{ikj} = 1, j \in A_{ik}, \forall i, k \quad (3.4)$$

$$t_{Ejl} \leq y_{jl} \leq t_{Ljl}, \forall l, j \quad (3.5)$$

$$x_{ikj} \in 0, 1, \forall i, k, j \quad (3.6)$$

$$c_{ik} \geq 0, \forall i, k \quad (3.7)$$

$$y_{jl} \geq 0, \forall j, l \quad (3.8)$$

The objective function (3.1) is minimization of makespan of jobs and preventive maintenances. Inequality (3.2) ensures no-overlapping constraints between operations on the same machine. Inequality (3.3) ensures no-overlapping constraints between preventive maintenance tasks and operations on the same machine. Equation (3.4) states that only one machine should be selected from the set of available machines for each operation. Inequality (3.5) states that the preventive maintenance tasks have to be executed within their time windows. (3.6) is integer constraint of decision variable. (3.7) and (3.8) ensure the feasibility of the two variables.

3.1.3 Solution approach for FJSPPM

We decompose FJSPPM into two stages, FJSP and adding PM. From literature of FJSP, we find that most studies focus on arrangement of machines using

meta heuristic and decoding procedure for sequence scheduling. We would like to compare this policy with the hierarchical method, which treat the two sub problems directly and separately. Among the immense meta heuristics, we are interested in GA and ACO, which are used frequently in literature. Both GA and ACO are promising algorithms in permutation optimization. In our first stage of solving FJSP, we use three different approaches, hierarchical genetic algorithm (HGA), integrated genetic algorithm (IGA) and integrated ant colony optimization (IACO). Although [Fattahi *et al.* \(2007\)](#) stated that hierarchical algorithm is superior to integrated algorithm in solving FJSP, he just used Simulated Annealing (SA) and Tabu Search (TS) in searching structures. Their conclusions may not be appropriate to other heuristics, like GA and ACO. We compare performance of these three approaches and pick out the better one to be used in following stage of solving FJSPPM.

Based on the approach to solve FJSP, PM activities are added to the program through two different methods: simultaneous scheduling algorithm (SSA)([Gao *et al.*, 2006](#)), inserting algorithm (IA).

We detail these approaches in following sections.

3.1.3.1 Hierarchical Genetic Algorithm for FJSP

Since Genetic Algorithm (GA) was introduced by Holland in 1975, it has been proved powerful in optimization problem and has been used by many researchers and scholars. As we mentioned in proceeding section, there are two difficult problems in FJSP: the allocation of operations on machines and operation sequence scheduling. GA has been widely used for JSSP, also for FJSP. [Hussain & Joshi \(1998\)](#) proposed a two pass GA for JSSP with alternative routing. In fact it is also a hierarchical approach for FJSP, GA for the first sub problem and Non Linear Programming (NLP) for the second sub problem. [Jawahar *et al.* \(1998\)](#) proposed a GA-based heuristic algorithm for flexible manufacturing systems with alternative routing, in which machines were selected randomly. Many researchers proposed different hybrid GA to improve the performance of GA. Two different chromosomes are used to represent the machine assignment and operation sequence separately by [Kim *et al.* \(2003\)](#). Local search with two kinds of neighborhood is hybridized with the genetic algorithm to enhance the search ability in [Gao *et al.* \(2006\)](#).

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

From literature about solving FJSP with GA, we find that much attention is paid to the part of machine assignment, while sequence scheduling is rather ignored, only with certain scheduling rules represented in decoding procedure. Take the work of [Kacem *et al.* \(2002a\)](#) for example. They concentrated on machine assignment, which is obtained with an approach of localization (AL), with chromosome representing machine assignment. The crossover and mutation procedures also contribute to changing machines. For sequence scheduling, starting and ending time of operations are computed according to scheduling algorithm.

In HGA, two consecutive GA procedures are constructed for machine assignment and sequence scheduling respectively. In the first GA, minimization of total processing time and work load of machines are proposed as both objectives and the fitness function. In the second GA, the sum of average of workload of machine and makespan works as fitness function while minimization of makespan is objective, which is also the objective of the whole FJSP. To our knowledge, in literature of JSSP, workload is considered as fitness function only when it plays the role of objective. Although it is not new that fitness function is different from objective function, it is interesting to test and verify effect of this attempt. Flowchart of HGA is shown in [Figure 3.2](#).

GA-1: the first GA for machine assignment

The overall structure of GA-1 is described as follows:

(1) Encoding: genes of chromosome represents machine assignment of operations, with size (n, n_i) ;

(2) Initial population: It is initialized that machine for each operation is randomly selected from the set of available machines, A_{ij} , to guarantee its feasibility. Consider the example with four machines and four jobs, where each job requires four operations ([Gao *et al.*, 2006](#)). For the part of FJSP, the initialized chromosome is as in [Table 3.1](#). It is a matrix with size $(4, 4)$.

(3) Offspring generation: Crossover and mutation are to realize variety of population and to avoid local optimal solution. In crossover procedure, we use entire row or column crossover, to keep feasibility of individuals. Firstly, randomly select two individuals as one pair of parents. Secondly, randomly select the manner of crossover, either row crossover or column crossover. Finally, choose randomly

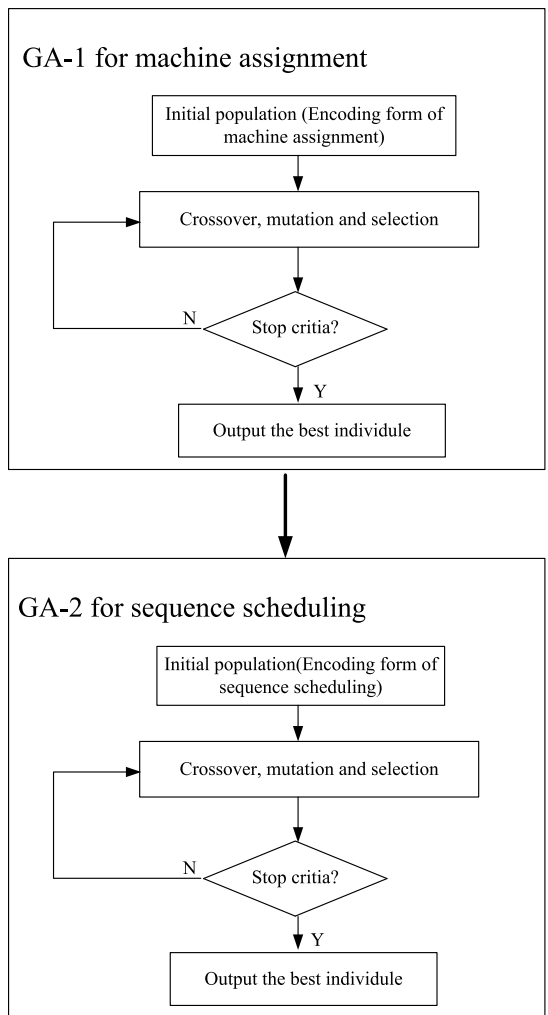


Figure 3.2: Hierarchical Genetic Algorithm (HGA) for FJSP

Table 3.1: Machine assignment to operations

job \ operation	1	2	3	4
	1	4	3	3
2	2	4	1	4
3	3	1	2	1
4	2	4	4	3

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

the cut position of row or column and carry on crossover to generate two new individuals. In mutation procedure, individual and its mutation position is selected randomly and within the mutation probability. In order to ensure feasibility of solutions, the mutated value is also in the set of available machines.

(4) Fitness evaluation: total processing time and workload of machine are calculated for each chromosome in current generation. The two objectives are weighted together as $\text{Fitness} = w_1 \cdot \text{total processing time} + w_2 \cdot \max(\text{machine workload})$. We set $w_1 = w_2 = 0.5$.

(5) Selection: Individuals in parents join in competition with offspring in terms of keeping good individuals. $(2 \cdot N)$ individuals are generated until this step. N (Population size) individuals are selected from $(2 \cdot N)$ ones by selection method. The two widely used methods of selection are roulette wheel and tournament. In the work in literature, the two selection methods is chosen randomly, without clear clarification of reasons. In our work, after comparing the effectiveness of the two method through experiment, the better one is used finally. We modify the conventional tournament selection which is proposed by [Goldberg *et al.* \(1992\)](#). In ordinary tournament, two individuals are chosen randomly from the population, and then the fitter one in the two will be chosen if a random value r is smaller than a probability value k , otherwise, the other one is chosen where k is a parameter. Because in our work, $(2 \cdot N)$ individuals join in the tournament, which can guarantee the diversity of population, we need not to use the probability value k . We compare the effectiveness of the two selection methods in the following section.

(6) Stop criteria: the program stops when fixed number of generation is reached. The best chromosome, together with corresponding schedule, is outputted as results. Otherwise, the program iterates steps (3)-(5).

Test of comparing tournament and roulette wheel in GA-1

We take the example of J15M10 in [Xia & Wu \(2005\)](#) to compare the effectiveness of the two selection methods. It is a FJSP with total flexibility, 15 jobs with 56 operations processed on 10 machines. We execute the program 10 times, the results shown in Table 3.2. All our experiments are carried on a computer with Intel(R) Core(TM) 2 CPU (2.66GHz; 2.67GHz), GA program is realized on

3.1 Reducing unavailability of machines in FJSP

Matlab R2008a. The parameters used in GA in our simulation are listed in Table 3.3. Following experiments of GA use the same parameters as well.

Table 3.2: Result of comparing tournament and roulette wheel in GA-1

	best value	mean value	mean executing time (cpu: second)
tournament	51	51.15	293.09
roulette wheel	75	81.15	814.02

Table 3.3: Parameters of GA

Parameters	value
Population size (N)	2000
Generation (M)	200
Crossover probability (Pc)	0.9
Mutation probability (Pm)	0.1

We find that tournament is superior to roulette wheel both in fitness value and executing time. Therefore, we use tournament as selection method in GA-1.

GA-2: the second GA for sequence scheduling

This part is exactly solving JSSP, based on the proceeding part of machine assignment. GA for JSSP has been studied by many researchers (Dorndorf & Pesch, 1995; Park *et al.*, 2003; Yamada & Nakano, 1997).

The structure of GA-2 is similar to GA-1, but with different chromosome representation and different formats of genetic operators.

(1) Chromosome: since operations assigned to each machine have already been fixed through GA-1, the order of them is the unique factor needing to be decided. Because here only an initial sequence is needed. We adopt the widely used priority rule to get a initial sequence scheduling. For the example in Table 3.1, an initial sequence of operations on each machine is the emergence position of operations as shown in Table 3.4, with a rule of sequencing from top to bottom in the table.

Chromosome exists as a matrix with size $(m, 2r)$, where r represents the maximum number of operations assigned on one machine. The first half of the chromosome, from column 1 to column r , represent index of job; the second half, from

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

Table 3.4: Sequence scheduling

M1	3	2	1	3	
M2	2	4	3		
M3	3	1	1	4	
M4	1	2	4	4	2

column $(r + 1)$ to column $2r$, represent index of operation of related job. Combination of the two halves compose the total representation of operations. e.g., in the same row, the value of 1^{th} column, i , with j at $(r + 1)^{th}$ column, represent operation O_{ij} . Chromosome representation of the sequence scheduling in Table 3.4 is represented as:

```

3 2 1 3 0 2 3 4 4 0
2 4 3 0 0 1 1 3 0 0
3 1 1 4 0 1 2 3 4 0
1 2 4 4 2 1 2 2 3 4

```

Population is initialized with random permutation of all operations on each machine. To avoid infeasible solution, operations of the same job must obey constraint of processing order.

(2) Crossover: [Park et al. \(2003\)](#) has applied different crossover procedures in JSSP and demonstrated that different crossover is suitable to different problems, depending upon the scale of problem. We adopt the same crossover procedure as in GA-1. The difference is that column crossover is not suitable.

(3) Mutation: in order to keep diversity of solution, one point is selected randomly and the value of which is changed with its neighbor.

(4) Fitness evaluation: makespan is the evaluation criteria for sequence scheduling.

(5) Selection: We use tournament as selection method as it is demonstrated promising in GA-1.

3.1.3.2 Integrated Genetic Algorithm for FJSP

Different to hierarchical approach, in which machine assignment and sequence scheduling are treated separately, in integrated approach, the two sub problems are integrated in one GA procedure. Flowchart of integrated approach of GA is described in Figure 3.3.

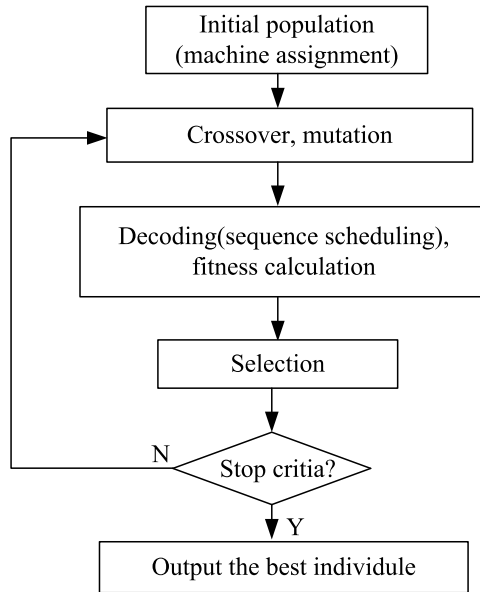


Figure 3.3: Integrated Genetic Algorithm (IGA) for FJSP

Chromosome is the same as that in GA-1 in section 3.1.3.1, keeping the same approach of offspring generation. Objective is minimization of makespan, so fitness value can also be makespan. Because makespan is the maximum makespan among all jobs, it is obvious that the scheme with minimum makespan needs that maximum workload on all machines is optimal as well. We have executed some experiments with different fitness representations types, makespan, makespan with mean workload of all machines, and makespan with maximum workload among all machines. We find that using $makespan + mean(workloads)$ as fitness value is the best manner. The two selection methods, tournament and wheel roulette, are also compared on experiments to select the better one. In decoding procedure, scheduling algorithm is used to get sequence scheduling and then makespan is computed. Operations on the same machine are sequenced according to the position of occurrence. When the program stopped and the best chromosome is obtained, the sequence scheduling of the best chromosome is calculated again in the procedure of decoding. As sequence scheduling is essential for decoding procedure to calculate makespan, we detail it as follows.

Sequence scheduling: Firstly, according to processing sequence to schedule all operations of all jobs, e.g., the first operation of each job is firstly scheduled, and then the second operation, and so on, until all operations are scheduled. For

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

scheduling operations on the same machine, there are two traditional methods. One is scheduling operations according to the sequence of number of jobs (Mesghouni, 1999), e.g., in the example in Table 3.1, operations O_{21} and O_{41} are both assigned to machine 2, O_{21} will be scheduled before O_{41} . Decoding procedure is described in Figure 3.4. The other one is giving a vector of priority of operations, as a part of chromosome, and then sequencing operations on the basis of the priority (Gao *et al.*, 2006). In our work, we try to find a promising sequencing method for operations on the same machine, on comparing the four scheduling sequence methods: (a) order of number of jobs; (b) inverse order of number of jobs; (c) random order; (d) order of available time of jobs. Performance of these four methods is compared on two instances of FJSP next.

```
Procedure: Priority-based Decoding
Input: chromosome X
Output: an active schedule
begin
  for i=1 to m
    Q1←X(:,1) //the machines used for the first operation of each job
    schedule the first operation of each job, in the case where more than one operation using the same machines, according to operations priority, assign operations on the machine.
  for i=1 to m
    for k=2 to n
      Q2←X(:,k) //the machines used for the kth operation of each job
      schedule the rest 2 to n operations of each job, initialize the starting time of each operation as the end time of its preceding operation; if the initialized starting time is earlier than the end time of other operations proceeded on the same machine, set its starting time as this end time.
    Output the active schedule
  end
```

Figure 3.4: Decoding procedure

Test of comparing sequence scheduling methods

We take the example of J8M8 and J15M10 in Xia & Wu (2005) to compare the efficiency of the four sequence scheduling methods, with results shown in Table 3.5 and Table 3.6.

From results in Table 3.5, we can see that scheduling sequence method (b) is superior to the others. But in Table 3.6 sequence method (d) is the best. That may be corresponding to size of problem. We can not arbitrarily define the best sequence scheduling method, but it is obvious (b) and (d) perform relatively better among the four. Therefore, we use order of available time of jobs as scheduling sequence method for large scale problem, while for small scale problem inverse order of jobs is preferred as sequence scheduling method.

3.1 Reducing unavailability of machines in FJSP

Table 3.5: Result of comparing scheduling sequence methods in integrated GA on example J8M8

	best value	mean value	mean executing time (cpu: second)
(a) order of number of jobs	15	15.4	229.63
(b) inverse order of number of jobs	14	14	260.61
(c) random order of jobs	14	15.3	578.55
(d) order of available time of jobs	15	15.2	567.32

Table 3.6: Result of comparing scheduling sequence methods in integrated GA on example J15M10

	best value	mean value	mean executing time (cpu: second)
(a) order of number of jobs	12	13.5	386.15
(b) inverse order of number of jobs	13	13.9	433.29
(c) random order of jobs	13	14.1	833.85
(d) order of available time of jobs	12	12.9	866.27

3.1.3.3 Integrated Ant Colony Optimization for FJSP

Ant Colony Optimization (ACO), also a population-based approach, was developed from the Ant Algorithm proposed to solve Travelling Salesman Problem (TSP) firstly by [Colorni *et al.* \(1994\)](#). Later it is developed for various formats (ACO, ant systems (AS), Max-Min ant system (MMAS), Ant Colony System, ACS, Elitist ant system (EAS), Rank-Based Ant System (RBAS), and applied for several NP-hard combinatorial optimization problems ([Bullnheimer *et al.*, 1999](#); [Dorigo & Gambardella, 1997](#); [Gambardella & Dorigo, 1997](#); [Stützlea & Hoosb, 2000](#)). [Colorni *et al.* \(1992\)](#) was the first one to apply ACO to JSP. Various developed ACO were compared by [Heinonen & Pettersson \(2007\)](#) in JSP with different visibility studies. They demonstrated that MMAS is superior to others. Hybrid algorithms with ACO were developed to improve the solution quantity: ACO combined with local search proposed by [Heinonen & Pettersson \(2007\)](#); ACO combined with tabu search by [Huang & Liao \(2008\)](#). ACO was also applied for FJSP ([Girish & Jawahar, 2009](#); [Ponnambalam *et al.*, 2010](#); [Rossi & Dini, 2007](#)). We use the approach of [Ponnambalam *et al.* \(2010\)](#), in which two pheromone

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

trails are used for machine assignment and sequence scheduling separately.

Solution construction of IACO

In this approach, the two sub problems of FJSP are integrated. It is assumed that the ant colony depose two kinds of pheromone, $\tau_{-}m_{ijk}$ and $\tau_{ijj'j'}$, to control the two sub problems, machine assignment and sequence scheduling separately.

(1) Machine assignment

Machine assignment is executed in the first stage. An ant choose machine k for operation O_{ij} with probability:

$$P_{ijk} = \frac{\tau_{-}m_{ijk}^{\alpha_{-}m} \cdot \eta_{ijk}^{\beta_{-}m}}{\sum_{k=1}^{A_{ij}} \tau_{-}m_{ijk}^{\alpha_{-}m} \cdot \eta_{ijk}^{\beta_{-}m}} \quad (3.9)$$

Where $\alpha_{-}m$ and $\beta_{-}m$ are parameters to control weights of fitness of pheromone and heuristic separately. η_{ijk} represents the rule of choosing machines. $\eta_{ijk} = 1/T_{ijk}$. T_{ijk} is the processing time of operation O_{ij} on machine k . A_{ij} is the set of available machines for operation O_{ij} .

(2) Sequence scheduling

Sequence scheduling is executed after machine assignment. Take an example of 3 jobs and 3 machines. Machine assignment is obtained from the proceeding stage: operations O_{13} , O_{32} , O_{33} and O_{23} are executed on machine 1; O_{11} , O_{31} and O_{22} will be executed on machine 2; O_{21} and O_{12} are executed on machine 3.

Set R includes the available jobs which wait to be executed, initially, $R = \{O_{11}, O_{21}, O_{31}\}$. Set $Tabu$ represents the operations which have already been scheduled, initially, $Tabu = \{\emptyset\}$. The first operation is chosen from set R randomly. Here, we pick up O_{11} for example. Simultaneously, update Set R and $Tabu$: $R = \{O_{12}, O_{21}, O_{31}\}$, $Tabu = \{O_{11}\}$. The ant chooses next operation in accordance with probability:

$$P_{ijj'j'} = \frac{\tau_{ijj'j'}^{\alpha} \cdot \eta_{ijj'j'}^{\beta}}{\sum_{i=1}^n \sum_{j=1}^{n_i} \tau_{ijj'j'}^{\alpha} \cdot \eta_{ijj'j'}^{\beta}} \quad (3.10)$$

Where, α and β are two parameters to control the weights of fitness of pheromone and heuristic separately. $\eta_{ijj'j'}$ represents the rule of sequence scheduling. Different rules in literature of FJSP can be used:

- Shortest processing time (SPT), the operations with the shortest processing time have higher priority;
- Longest processing time (LPT), the operations with the longest processing time have higher priority;
- Most work remaining (MWR), the jobs with the Most work remaining have higher priority;
- Length of unscheduled tasks in job (LTJ), the jobs with the most remaining work than others have higher priority;
- Shortest starting time of operation (SST), the operations that can start earlier than others have higher priority.
- First In First Out (FIFO), the jobs start earlier have higher priority. When considering the flow time of jobs, this rule is suitable.

In the early days of our research work, we adopt the two popular methods, SPT and MWR, as alternatives. Our experiments show that MWR outperforms SPT. Therby we use MWR as scheduling rule.

Sequence scheduling procedure continues until all operations are scheduled, that is $A = \{0\}$, and $Tabu = \{O_{11}, O_{12}, O_{13}, O_{21}, O_{22}, O_{23}, O_{31}, O_{32}, O_{33}\}$. The entire scheduling can be considered in a digraph shown in Figure 3.5.

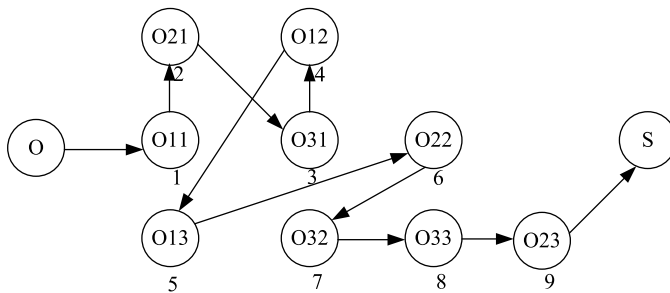


Figure 3.5: Digraph of sequence scheduling in ACO

The starting and ending time are simultaneously scheduled, according to the un-overlapping rule in the model in section 2.

(3) Feasible solution

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

We get a feasible solution for our problem after the two proceeding stages, including the machines used and processing sequence of all operations. A maximum iteration number is defined to terminate the program. Like the number of ants, the number of iteration is also determined according to the size of problem.

Pheromone trail design of IACO

τ_m_{ijk} indicates the pheromone trail for representing desirability that operation O_{ij} choose Machine k to executing the processing. $\tau_{ij'j'}$ represents the pheromone trail for desirability that operation O_{ij} executes after operation $O_{i'j'}$. All feasible schemes are initialized to 0.1.

We use Max-Min ant system to update pheromone, which is demonstrated to outperform other formats of ant system by [Heinonen & Petterson \(2007\)](#). That is, after one iteration, only the pheromone of the best ant in the iteration is updated. Assume that the example in [Figure 3.5](#) is the best ant in current iteration. The pheromone trails will be updated as follows. All the pheromone will decrease over time as evaporation. Simultaneously, the pheromone trails, $\tau_m_{112}, \tau_m_{123}, \tau_m_{131}, \tau_m_{213}, \tau_m_{222}, \tau_m_{231}, \tau_m_{312}, \tau_m_{321}, \tau_m_{331}$, will increase with $\Delta\tau_m$; the pheromone trails, $\tau_{2111}, \tau_{3121}, \tau_{1231}, \tau_{1312}, \tau_{2213}, \tau_{3222}, \tau_{3332}, \tau_{2333}$, will increase by $\Delta\tau$.

Pheromone after current iteration tn will be updated:

$$\tau_m_{ijk}(tn + 1) = \rho \cdot \tau_m_{ijk}(tn) \quad (3.11)$$

$$\tau_{ij'j'}(tn + 1) = \rho \cdot \tau_{ij'j'}(tn) \quad (3.12)$$

For the pheromone of the best ant,

$$\tau_m_{ijk}(tn + 1) = \tau_m_{ijk}(tn + 1) + \Delta\tau_m \quad (3.13)$$

$$\tau_{ij'j'}(tn + 1) = \tau_{ij'j'}(tn + 1) + \Delta\tau \quad (3.14)$$

$$\Delta\tau_m = \Delta\tau = \frac{1}{f(ibest)} \quad (3.15)$$

3.1 Reducing unavailability of machines in FJSP

Where, ρ is evaporation rate, ranging in $[0, 1]$. $f(ibest)$ is the makespan of iteration best. Similar to iteration best, someone used global best. To avoid premature convergence, iteration best is preferred.

The spirit of MMAS is to avoid stagnation of iteration on pheromone updating. The value of pheromone is limited in a range $[\tau_{min}, \tau_{max}]$. The limits of the two kinds of pheromone are determined as the same value as follows:

$$\tau_{max} = \frac{1}{1 - \rho} \cdot f(ibest) \quad (3.16)$$

$$\tau_{min} = \frac{\tau_{max}}{y} \quad (3.17)$$

Where y is a parameter defining the space between τ_{max} and τ_{min} . We can see that their values change when new iteration best is obtained.

Parameters applied to ACO is shown in Table 3.7.

Table 3.7: Parameters of ACO

Parameter	value
Number of ants (M_ant)	400
Generation (NC_max)	500
Space range parameter (y)	10
Pheromone evaporation rate (ρ)	0.1
Control parameter of pheromone of operation (α)	1
Control parameter of heuristic of operation (β)	2
Control parameter of pheromone of machine (α_m)	1
Control parameter of heuristic of machine (β_m)	2
Strength of pheromone (Q)	10

3.1.3.4 Comparing effectiveness of the three approaches for FJSP

As mentioned in proceeding section that our method of solving FJSPPM is based on the preschedule obtained from conventional model of FJSP, we would like to find out the best one in the three approaches above. We test our methods on three classic examples of FJSP in [Xia & Wu \(2005\)](#): J8M8, instance of partial flexibility, 8 jobs with 27 operations processed on 8 machines; J10M10, instance of total flexibility, 10 jobs with 30 operations processed on 10 machines; J15M10, instance of total flexibility, 15 jobs with 56 operations processed on 10 machines.

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

Original data of the three examples is in Table 3.8, Table 3.9 and Table 3.10 respectively, where symbol X indicates that the assignment is impossible. Results of experiments on the three examples through executing the programme 10 times are shown in Table 3.11. The best value of the three examples obtained from Xia & Wu (2005) is also shown in Table 3.11, with * for recognition. Gantt chart of the optimal solution of the three examples is shown in Figure 3.6, Figure 3.7 and Figure 3.8 respectively.

Table 3.8: Problem J8M8 with 27 operations (partial flexibility)

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8
J1	O_{11}	5	3	5	3	3	X	10	9
	O_{12}	10	X	5	8	3	9	9	6
	O_{13}	X	10	X	5	6	2	4	5
J2	O_{21}	5	7	3	9	8	X	9	X
	O_{22}	X	8	5	2	6	7	10	9
	O_{23}	X	10	X	5	6	4	1	7
	O_{24}	10	8	9	6	4	7	X	X
J3	O_{31}	10	X	X	7	6	5	2	4
	O_{32}	X	10	6	4	8	9	10	X
	O_{33}	1	4	5	6	X	10	X	7
J4	O_{41}	3	1	6	5	9	7	8	4
	O_{42}	12	11	7	8	10	5	6	9
	O_{43}	4	6	2	10	3	9	5	7
J5	O_{51}	3	6	7	8	9	X	10	X
	O_{52}	10	X	7	4	9	8	6	X
	O_{53}	X	9	8	7	4	2	7	X
	O_{54}	11	9	X	6	7	5	3	6
J6	O_{61}	6	7	1	4	6	9	X	10
	O_{62}	11	X	9	9	9	7	6	4
	O_{63}	10	5	9	10	11	X	10	X
J7	O_{71}	5	4	2	6	7	X	10	X
	O_{72}	X	9	X	9	11	9	10	5
	O_{73}	X	8	9	3	8	6	X	10
J8	O_{81}	2	8	5	9	X	4	X	10
	O_{82}	7	4	7	8	9	X	10	X
	O_{83}	9	9	X	8	5	6	7	1
	O_{84}	9	X	3	7	1	5	8	X

3.1 Reducing unavailability of machines in FJSP

Table 3.9: Problem J10M10 with 30 operations (total flexibility)

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
J1	O_{11}	1	4	6	9	3	5	2	8	9	5
	O_{12}	4	1	1	3	4	8	10	4	11	4
	O_{13}	3	2	5	1	5	6	9	5	10	3
J2	O_{21}	2	10	4	5	9	8	4	15	8	4
	O_{22}	4	8	7	1	9	6	1	10	7	1
	O_{23}	6	11	2	7	5	3	5	14	9	2
J3	O_{31}	8	5	8	9	4	3	5	3	8	1
	O_{32}	9	3	6	1	2	6	4	1	7	2
	O_{33}	7	1	8	5	4	9	1	2	3	4
J4	O_{41}	5	10	6	4	9	5	1	7	1	6
	O_{42}	4	2	3	8	7	4	6	9	8	4
	O_{43}	7	3	12	1	6	5	8	3	5	2
J5	O_{51}	7	10	4	5	6	3	5	15	2	6
	O_{52}	5	6	3	9	8	2	8	6	1	7
	O_{53}	6	1	4	1	10	4	3	11	13	9
J6	O_{61}	8	9	10	8	4	2	7	8	3	10
	O_{62}	7	3	12	5	4	3	6	9	2	15
	O_{63}	4	7	3	6	3	4	1	5	1	11
J7	O_{71}	1	7	8	3	4	9	4	13	10	7
	O_{72}	3	8	1	2	3	6	11	2	13	3
	O_{73}	5	4	2	1	2	1	8	14	5	7
J8	O_{81}	5	7	11	3	2	9	8	5	12	8
	O_{82}	8	3	10	7	5	13	4	6	8	4
	O_{83}	6	2	13	5	4	3	5	7	9	5
J9	O_{91}	3	9	1	3	8	1	6	7	5	4
	O_{92}	4	6	2	5	7	3	1	9	6	7
	O_{93}	8	5	4	8	6	1	2	3	10	12
J10	O_{101}	4	3	1	6	7	1	2	6	20	6
	O_{102}	3	1	8	1	9	4	1	4	17	15
	O_{103}	9	2	4	2	3	5	2	4	10	23

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

Table 3.10: Problem J15M10 with 56 operations (total flexibility)

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
J1	O_{11}	1	4	6	9	3	5	2	8	9	4
	O_{12}	1	1	3	4	8	10	4	11	4	3
	O_{13}	2	5	1	5	6	9	5	10	3	2
	O_{14}	10	4	5	9	8	4	15	8	4	4
J2	O_{21}	4	8	7	1	9	6	1	10	7	1
	O_{22}	6	11	2	7	5	3	5	14	9	2
	O_{23}	8	5	8	9	4	3	5	3	8	1
	O_{24}	9	3	6	1	2	6	4	1	7	2
J3	O_{31}	7	1	8	5	4	9	1	2	3	4
	O_{32}	5	10	6	4	9	5	1	7	1	6
	O_{33}	4	2	3	8	7	4	6	9	8	4
	O_{34}	7	3	12	1	6	5	8	3	5	2
J4	O_{41}	6	2	5	4	1	2	3	6	5	4
	O_{42}	8	5	7	4	1	2	36	5	8	5
	O_{43}	9	6	2	4	5	1	3	6	5	2
	O_{44}	11	4	5	6	2	7	5	4	2	1
J5	O_{51}	6	9	2	3	5	8	7	4	1	2
	O_{52}	5	4	6	3	5	2	28	7	4	5
	O_{53}	6	2	4	3	6	5	2	4	7	9
	O_{54}	6	5	4	2	3	2	5	4	7	5
J6	O_{61}	4	1	3	2	6	9	8	5	4	2
	O_{62}	1	3	6	5	4	7	5	4	6	5
J7	O_{71}	1	4	2	5	3	6	9	8	5	4
	O_{72}	2	1	4	5	2	3	5	4	2	5
J8	O_{81}	2	3	6	2	5	4	1	5	8	7
	O_{82}	4	5	6	2	3	5	4	1	2	5
	O_{83}	3	5	4	2	5	49	8	5	4	5
	O_{84}	1	2	36	5	2	3	6	4	11	2
J9	O_{91}	6	3	2	22	44	11	10	23	5	1
	O_{92}	2	3	2	12	15	10	12	14	18	16
	O_{93}	20	17	12	5	9	6	4	7	5	6
	O_{94}	9	8	7	4	5	8	7	4	56	2
J10	O_{101}	5	8	7	4	56	3	2	5	4	1
	O_{102}	2	5	6	9	8	5	4	2	5	4
	O_{103}	6	3	2	5	4	7	4	5	2	1
	O_{104}	3	2	5	6	5	8	7	4	5	2
J11	O_{111}	1	2	3	6	5	2	1	4	2	1

Continued on next page

3.1 Reducing unavailability of machines in FJSP

Table 3.10 – continued from previous page

		M_1	M_2	M_3	M_4	M_5	M_6	M_7	M_8	M_9	M_{10}
J12	O_{112}	2	3	6	3	2	1	4	10	12	1
	O_{113}	3	6	2	5	8	4	6	3	2	5
	O_{114}	4	1	45	6	2	4	1	25	2	4
	O_{121}	9	8	5	6	3	6	5	2	4	2
	O_{122}	5	8	9	5	4	75	63	6	5	21
	O_{123}	12	5	4	6	3	2	5	4	2	5
J13	O_{124}	8	7	9	5	6	3	2	5	8	4
	O_{131}	4	2	5	6	8	5	6	4	6	2
	O_{132}	3	5	4	7	5	8	6	6	3	2
	O_{133}	5	4	5	8	5	4	6	5	4	2
J14	O_{134}	3	2	5	6	5	4	8	5	6	4
	O_{141}	2	3	5	4	6	5	4	85	4	5
	O_{142}	6	2	4	5	8	6	5	4	2	6
	O_{143}	3	25	4	8	5	6	3	2	5	4
J15	O_{144}	8	5	6	4	2	3	6	8	5	4
	O_{151}	2	5	6	8	5	6	3	2	5	4
	O_{152}	5	6	2	5	4	2	5	3	2	5
	O_{153}	4	5	2	3	5	2	8	4	7	5
	O_{154}	6	2	11	14	2	3	6	5	4	8

Table 3.11: Result of three approaches applied to three examples of FJSP

	J8M8	J10M10	J15M10
HGA			
best makespan	16	7	14
mean makespan	16.1	7.9	17.4
Mean executing time (cpu time: second)	433.03	481.35	917.50
IGA			
best makespan	14	7	12
mean makespan	15.7	7.2	13.5
Mean executing time (cpu time: second)	250.91	251.56	386.15
IACO			
best makespan	15	7	16
mean makespan	15.4	7.9	17.9
Mean executing time (cpu time: second)	290.99	344.86	694.19
best solution in literature (makespan)	15*	7*	12*

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

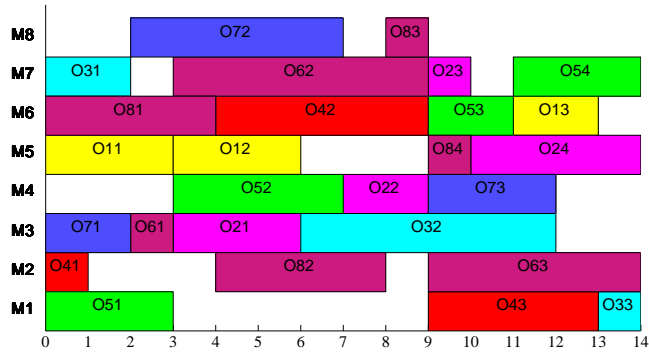


Figure 3.6: Gantt chart of best solution of J8M8

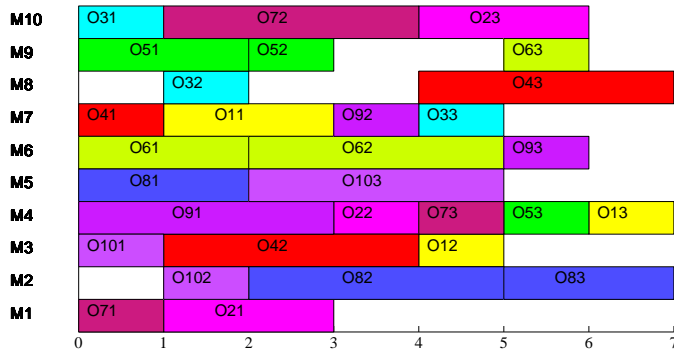


Figure 3.7: Gantt chart of best solution of J10M10

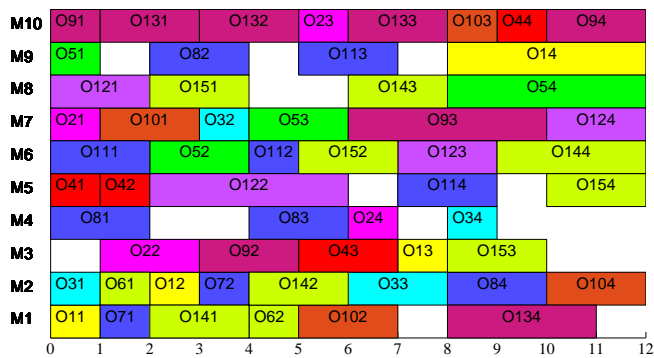


Figure 3.8: Gantt chart of best solution of J15M10

From the results of experiments above, we can find that IGA is superior to the other two approaches in all the three examples. IGA can obtain the best values as in literature. For the example of J8M8, we found a better result than that in literature. HGA performs better than IACO in larger scale problem, but worse in smaller problem in obtaining the best value. IGA needs less time than the other two, followed by IACO, while HGA needs the least time.

3.1.3.5 Complete approach for FJSPPM

Based on the approach of solving FJSP, we add PM in the program. We use two different approaches to solve FJSP with PM. One is Simultaneous Scheduling Algorithm (SSA), the approach of [Gao et al. \(2006\)](#), where jobs and PM tasks are scheduled simultaneously. The second is our new proposed Inserting Algorithm (IA), to insert PM after all jobs have been scheduled. Both are based on the same initialization of starting time of PM which is set at the latest moment of time window. Flowchart of the two algorithms is shown in Figure 3.9.

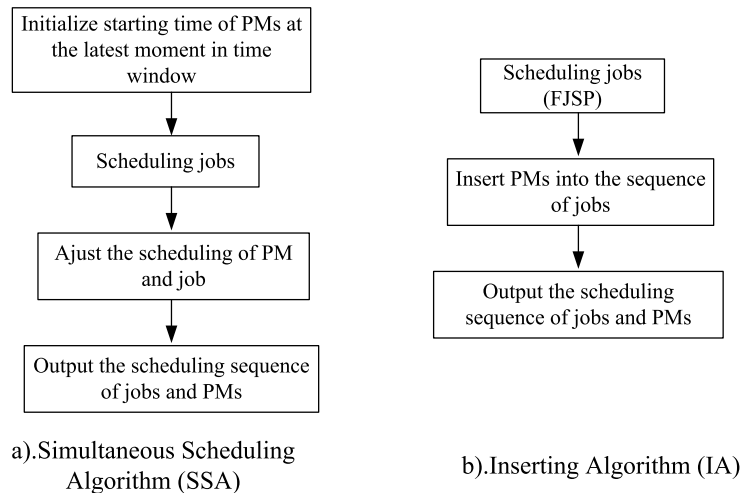


Figure 3.9: Two algorithms of solving FJSPPM

Simultaneous Scheduling Algorithm (SSA)

Although SSA is already used by [Gao et al. \(2006\)](#), we would like to examine the effectiveness of their algorithm. We propose another two methods to compare with their algorithm.

- (1) Algorithm of compacting PM at left in literature ([Gao et al., 2006](#)).

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

Firstly, all PM tasks are initialized to start at the latest moment in time windows. Then begin to schedule jobs. When one operation of a job meets a PM, i.e., a collision occurs, compact the PM task to the left side as possible, and then range the operation after PM. The procedure of compacting PM for treating collision of PM and job is illustrated in Figure 3.10.

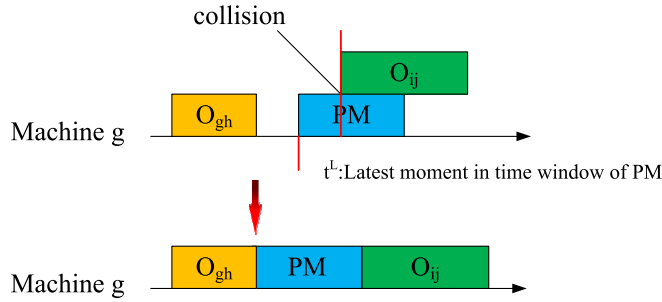


Figure 3.10: Compact PM to left when PM is initialized to latest moment

(2) Initializing starting time of PM at the latest moment in time windows and compact PM to right side.

Based on the algorithm in literature, firstly we initialize PM tasks, but at the earliest moment of their time window. When an operation meets a task of PM, delay PM to right side and just after the operation. The activity of delay is surely constrained in time window of PM. Illustration of this method of treating collision of PM and job is shown in Figure 3.11.

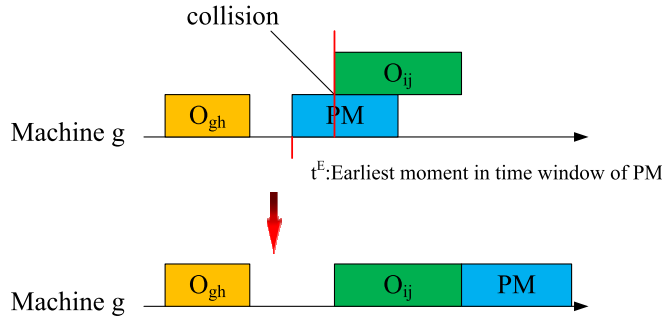


Figure 3.11: Compact PM to right when PM is initialized to earliest moment

(3) Change machines for jobs when there are collisions with PM tasks.

Firstly initialize PM tasks, either at the latest or earliest moment in time window. In our example, we take the latest moment of time window. The difference to the two algorithms above is the policy of treating collision of PM tasks and

jobs. Unlike the two methods above, in which operations still use the machine, another policy of treating the collision of PM and job is to change machine of processing the job. That is to say, PM remains where it is initialized, but job choose another machine. Take the example in Figure 3.12. Operation O_{ij} arranged on machine g meets a task of PM. We need not to move PM, but to find another machine available, e.g. machine g' for O_{ij} .

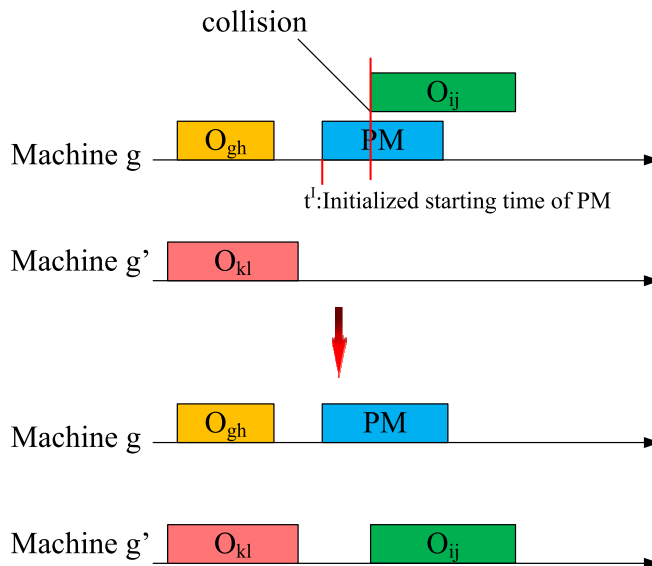


Figure 3.12: Change machine to treat collision of PM and job

For choosing a new machine for a job having collision with PM task, we can use different rules:

- (a) Randomly choose a machine available;
- (b) Choose the machine with the least processing time for the operation;
- (c) Choose the machine with the earliest available moment. Machines' available moments are the ending time of last operation at current moment;
- (d) Take the machine with a least sum of processing time and idle time for the operation. Idle time occurs when the job's available moment is later than available moment of machine.

The methods corresponding to the four rules are summarized as to choose random machine, choose machine with minimum processing time, choose machine with earliest available time, choose machine with least idle time, respectively. In these 4 methods, we initialize the starting time of PM at the latest moment of time window. The test of comparison of these 6 methods of SSA is executed on

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

example J8M8, the same as testing example J8M8 in preceding section. IGA is used, with the same parameters in preceding testing examples. Data of PM refer to literature. We execute the programme of each method 10 times. Mean value and best value of makespan are compared as well. Parameters are the same as in preceding test of GA. The results are shown in Table 3.12, from which we can see that initializing starting time of PM at the end of time windows is a good choice. Moreover, we have tried to use IACO to find an optimal initialized starting time of PM, the results are not good as the one used, neither. The performance of methods of (b) and (d) with changing machines is better than methods of moving PM used in literature. Therefore, in following tests, starting time of PM initialized at the latest moment of time window, meanwhile we adopt the three good performing methods as three different kinds of SSA: traditional method in literature without changing machines; choose new machine with minimum processing time; choose new machine with minimum sum of processing time and idle time.

Table 3.12: Comparison of different methods of SSA

	best value	mean value
machines do not change		
PM initialized starting at t^E	19	19.3
PM initialized starting at t^L	17	17.2
choose a new machine		
(a) random machine	20	20.6
(b) machine with minimum processing time	17	17
(c) machine with earliest available time	18	18.5
(d) machine with minimum idle time	17	17

Inserting Algorithm (IA)

In IA, PM tasks are inserted into idle intervals of jobs after all of them have been scheduled. We aim to make full use of the idle intervals, which always exist and are unavoidable in scheduling. IA is described as follows:

- (1) Find effective idle time intervals from left to right on the scheduling sequence of each machine, in the range of time windows of PM task.

(2) If the maximal effective idle time interval cannot satisfy the duration time of the PM task, perform PM task at the beginning of the maximal idle time interval, and then delay all its posterior sequence of operations.

(3) For the preschedule where there is no useful idle time for inserting PM tasks, insert it at the moment close to the latest moment of time window and then push the following tasks.

Complete approach for FJSPPM

The two algorithms above must be combined with the approach for FJSP to solve FJSP with PM. We propose to use the following combination: Integrated GA with SSA; Integrated GA with IA; Integrated ACO with SSA. As we mentioned in section above, three different kinds of SSA can be used in it. Strictly, there are seven different approaches in total. We compare and differentiate the 7 approaches in the section of experiments.

- (1) IGA with SSA:
 - (1a) IGA with SSA1, without changing machine;
 - (1b) IGA with SSA2, choosing new machine with minimum processing time;
 - (1c) IGA with SSA3, choosing new machine with minimum sum of processing and idle time.
- (2) IGA with IA;
- (3) IACO with SSA:
 - (3a) IACO with SSA1, without changing machine;
 - (3b) IACO with SSA2, choosing new machine with minimum processing time;
 - (3c) IACO with SSA3, choosing new machine with minimum sum of processing and idle time.

3.1.4 Numerical experiments of FJSPPM

In order to test the effectiveness and efficiency of our proposed approaches, we compare the seven approaches as described above on the examples in [Gao *et al.* \(2006\)](#), in which part of FJSP are the examples of [Xia & Wu \(2005\)](#), the same as testing examples of FJSP we used in preceding section. The three examples of FJSPPM are: J8M8PM, with one maintenance task on each machine; J10M10PM, with one maintenance task on each machine; J15M10PM, with one or two maintenance tasks on each machine. Data of PM tasks originates from

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

(Gao *et al.*, 2006), detailed in Table 3.13, Table 3.14 and Table 3.15 respectively.

Table 3.13: PM tasks in J8M8PM

		PM_{11}	PM_{21}	PM_{31}	PM_{41}	PM_{51}	PM_{61}	PM_{71}	PM_{81}
Time Window	t_{jl}^E	5	6	10	9	3	8	4	7
	t_{jl}^L	10	9	15	17	10	16	14	13
Duration		4	3	5	3	3	5	3	4

Table 3.14: PM tasks in J10M10PM

		PM_{11}	PM_{21}	PM_{31}	PM_{41}	PM_{51}	PM_{61}	PM_{71}	PM_{81}	PM_{91}	PM_{101}
Time Window	t_{jl}^E	2	2	1	2	3	2	2	3	2	3
	t_{jl}^L	4	7	6	5	7	6	5	7	5	6
Duration		2	1	1	2	1	2	2	3	2	3

Table 3.15: PM tasks in J15M10PM

		PM_{11}	PM_{21}	PM_{31}	PM_{32}	PM_{41}	PM_{51}	PM_{61}	PM_{71}	PM_{81}	PM_{82}	PM_{91}	PM_{101}
Time Window	t_{jl}^E	2	3	1	5	3	2	1	3	1	7	2	3
	t_{jl}^L	5	7	3	11	10	8	6	7	5	11	5	8
Duration		1	1	1	2	3	2	1	1	1	1	1	1

Parameters are used as the same as the approaches for solving FJSP, in Table 3.3. Results of comparing the seven approaches on the three examples are shown in Table 3.16. Solution obtained by hGA with SSA is in Gao *et al.* (2006). Gantt charts of the best solutions we obtained are shown in Figure 3.13, Figure 3.14 and Figure 3.15 respectively.

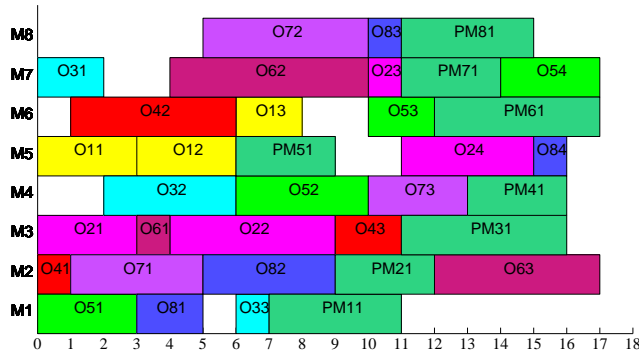


Figure 3.13: Gantt chart of best solution of J8M8PM

3.1 Reducing unavailability of machines in FJSP

Table 3.16: Result of seven approaches applied on examples of FJSPPM

		J8M8PM	J10M10PM	J15M10PM
(1) IGA with SSA				
(1a) IGA with SSA1 (not change machines)	makespan	17	8	12
	executing time	541.10	556.31	915.72
(1b) IGA with SSA2 (choose new machine with minimum processing time)	makespan	17	9	14
	executing time	1903.79	1981.43	2273.34
(1c) IGA with SSA3 (choose new machine with minimum sum of idle and processing time)	makespan	17	9	12
	executing time	1867.85	2105.32	3254.13
(2) IGA with IA				
	makespan	18	9	13
	executing time	251.91	252.56	387.15
(3) IACO with SSA				
(3a) IACO with SSA1 (not change machines)	makespan	18	9	18
	executing time	400.15	513.22	942.36
(3b) IACO with SSA2 (choose new machine with minimum processing time)	makespan	18	8	16
	executing time	931.60	1000.64	1188.34
(3c) IACO with SSA3 (choose new machine with minimum sum of idle and processing time)	makespan	17	9	17
	executing time	835.70	923.20	1318.75
hGA with SSA (best solution in literature)	makespan	17*	8*	12*

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

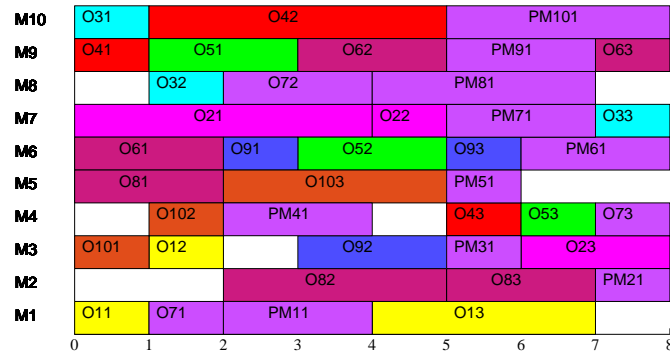


Figure 3.14: Gantt chart of best solution of J10M10PM

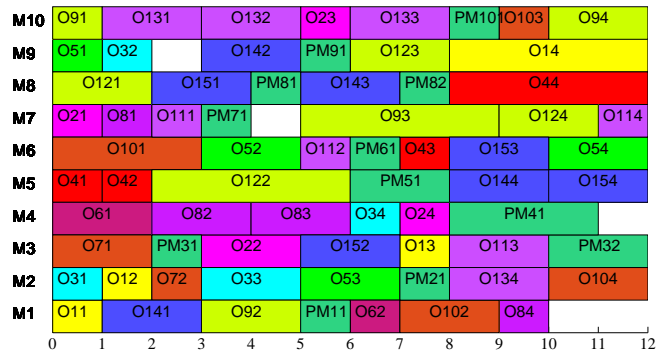


Figure 3.15: Gantt chart of best solution of J15M10PM

3.1.4.1 Results analysis

From results in Table 3.16, we can see that in most cases performance of IACO is inferior to IGA, but IACO cost less executing time than IGA. Result obtained with our approach is comparable with the best value obtained in literature. Our proposed approaches, SSA2 and SSA3, generally perform better than SSA1 in literature, especially combined with IACO. Moreover, it is obvious that our proposed IA has a great advantage in executing speed. High executing speed may bring significant convenience when the programm embedded with other management software like ERP.

3.1.4.2 Discussions

In our work we suggest to use CBM as preventive maintenance to reduce unavailability of machines. As we known, in most cases machines are available. Because CBM is not with fixed period, we are uncertain about when to execute maintenance task until detecting equipment send some results of maintenance. Combining with $P - F$ curve in Figure 3.1, we illustrate the situation of manufacturing.

Take example in Figure 3.16. Before we detected hidden failure (point P), we do not predict maintenance task in scheduling problem. We execute manufacturing according to a preschedule of classic FJSP. When arriving at point P , we have to consider adding maintenance tasks, and need a scheduling solution of FJSPPM. Thereby, a real-time scheduling is needed for this dynamic environment. At this moment, if we apply Simultaneous Scheduling Algorithm (SSA) for FJSPPM, we have to stop the ongoing task, like job i and job g in Figure 3.16, and then to reschedule the resting tasks. Hence, for the next rescheduling stage, we have to consider the stopped jobs additionally, which may increase complexity of scheduling problem. However, if we apply Inserting Algorithm (IA) for adding PM into the scheduled scheme for normal FJSP, we do not need to reschedule FJSPPM. From section 3.1.4.1, we have demonstrated the good performance of IA rather competitive with other approaches for FJSP. Even though the results of IA for treating emerging maintenance task are not so good as that of SSA, IA is obviously more suitable for FJSP with CBM. Compared to SSA, another advantage of IA is less modification to the original preschedule. Preschedule relates much with facility planning of factory. Once facility is fixed, it should not be

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

changed frequently. Operations can be delayed, but it is better to be processed on the same machine. There is a problem of workpiece path planning, where material handling is involved.

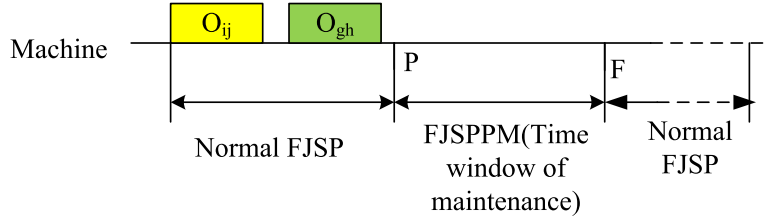


Figure 3.16: Disruption of maintenance arrives at an existing preschedule of FJSP

3.2 FJSP with dynamic arrival jobs

There is not much research about uncertain job arrivals in FJSP. [Berkoune \(2005\)](#), who worked also in our research group, proposed two different methods of inserting orders forecasted to existing jobs in FJSP. One is static method, in which urgent jobs forecasted are inserted into empty intervals of machines. This is similar to our Inserting Algorithm (IA) for PM, which was called strategy of real demand in his thesis. For dynamic inserting algorithm, ordinary jobs are delayed for guaranteeing due time of urgent jobs. This was a real time strategy. There is some research on new job arrivals in other manufacturing modes, such as flow shop, where arrival time of jobs is generated from discrete uniform distribution in research of [Sung & Kim \(2002\)](#), with determined ranges. Similarly, dynamic job arrivals are considered by [Yao *et al.* \(2011\)](#) in flow shop scheduling. The stochastic time of job arrivals is considered in a known uniform distribution.

On the base of the work of [Berkoune \(2005\)](#), we consider the situation of demand unpredictable, i.e., urgent jobs. When an urgent job arrives, it must be added into actual scheduling scheme to ensure its due date. We propose two methods to add urgent arrival jobs into ongoing scheduling scheme: one is inserting algorithm like IA of maintenance in section 3.1.3.5; the other is rescheduling resting operations of actual scheme and new jobs, which is similar to the dynamic inserting method in ([Berkoune, 2005](#)). The difference is that in some case we do not utilize the inserting algorithm, but a rescheduling.

3.2.1 Inserting algorithm of new arrival job

Insertion of job is similar to that of maintenance, only with different constraint of due date of jobs to that of time window of maintenance. Hence, we can apply our Inserting Algorithm of maintenance to the problem of inserting urgent job shop. Taking the instance in Figure 3.17, new job arrive at moment 9. Firstly, we can schedule new job independently on the available machines, ensuring its due date, like in Figure 3.18. And next we insert scheduling of new arrival job into scheme of ongoing task. Like IA of maintenance in section 3.1.3.5, in case of collision of old jobs and new jobs, we give priority to new arrival jobs and delay operations of old jobs, shown in Figure 3.19. The difference to IA of maintenance is that we need not to find idle time firstly, because scheduling new job at idle time may not assure its due date.

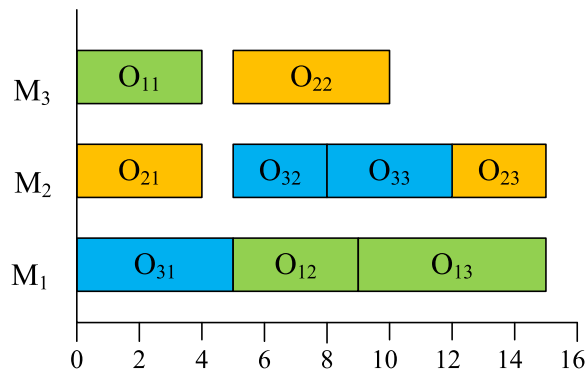


Figure 3.17: Ongoing scheduling scheme before new job arrival

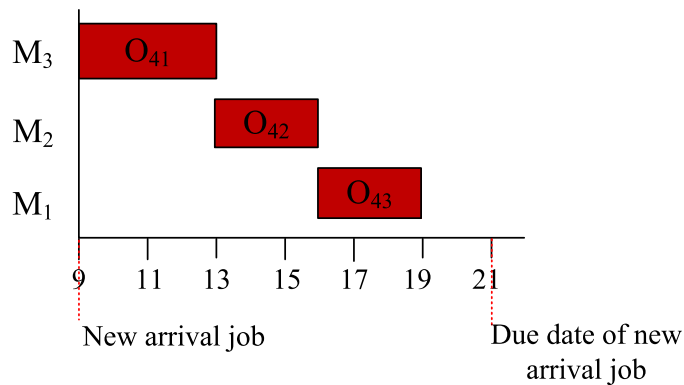


Figure 3.18: Scheduling independently for new arrival job

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

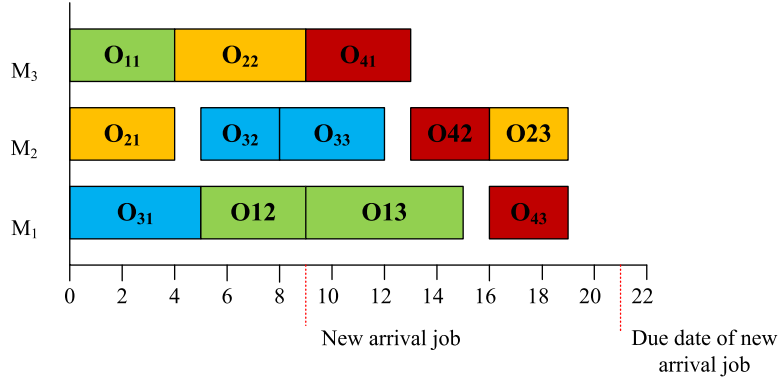


Figure 3.19: Inserting algorithm of new arrival job

3.2.2 Rescheduling resting operations with new arrival jobs

For the same instance in Figure 3.17. We try to reschedule resting operation from the moment of new job arriving. It should be concerned that ongoing tasks can not be interrupted once they start, like O_{33} in the instance. Therefore, resting operations in the example when new job arrives are O_{13} and O_{23} . We thus reschedule them together with new arrival job to find an optimal solution, displayed in Figure 3.20.

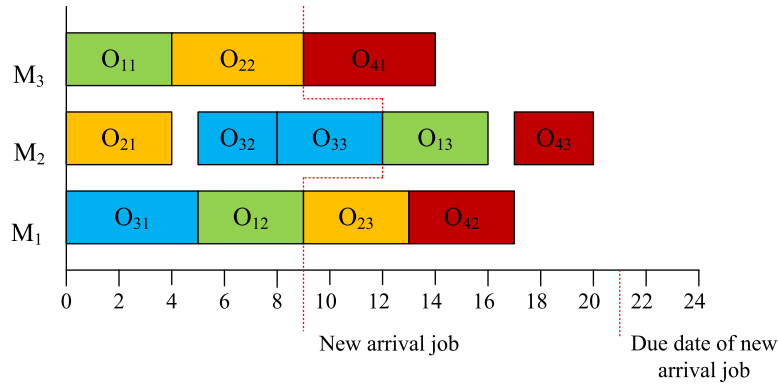


Figure 3.20: Rescheduling resting operations with new arrival job

Because of the limitation of time of research, we could not demonstrate and compare these two methods through numerical examples. Because the similarity with the work of Berkoun (2005), we can refer to his thesis for detailed illustration of the methods for treating added jobs.

3.3 Impact of uncertain processing time of jobs to FJSP

Like dynamic arrival time of jobs in job shop scheduling, uncertain processing time is fewly studied in literature. Discrete processing times are generated from the discrete uniform distribution by [Sung & Kim \(2002\)](#). Fuzzy processing time considered in JSSP is analyzed by [Lei \(2010a\)](#) and that considered in FJSP is treated by [Lei \(2010b\)](#). Triangular fuzzy numbers are used to represent fuzzy processing time. In the research of using variable neighborhood search for dynamic job shop scheduling of [Zandieh & Adibi \(2010\)](#), job arrivals are Poisson distribution, mean time between failure (MTBF) and the mean time to repair (MTTR) of machines also follow exponential distribution. Simulation is executed in Artificial Neural Network.

Different to discussions of representation of uncertain processing time in job shop scheduling in literature, we discuss the impact of uncertain processing time to job shop scheduling.

Although at present uncertain processing time is paid much attention on dynamic scheduling, it is not clearly declared in literature how is its impact to scheduling if it is treated statistic. We would like to give some discussions on impact of uncertain processing time to job shop scheduling.

We use the example in [Figure 3.17](#). If O_{11} cost 5 time units, which is more than expected ordinary value 4, it will affect the following operations of the same job 1, O_{12} and O_{13} , and consequently operations on the same machine, O_{22} . With the same analogy, O_{12} and O_{13} may influence operations on the same machine of them, and O_{22} may delay its following operation of the same job. In the example of [Figure 3.17](#), because of idle time on machine M_2 is just exactly 1 unit time, only O_{22} is influenced and should be delayed 1 time unit. It has no influence on overall scheduling makespan. The impact of more processing time on scheduling is shown in [Figure 3.21](#).

Similarly, if O_{11} costs 3 time units, which is less than ordinary value 4, it may also influence its related operations, like the operations of the same job, O_{12} and O_{13} , and the operations on the same machine, O_{22} . In the example, it will only affect O_{22} , but does not influence overall makespan of scheduling. The scheduling impacted by this changed processing time is shown in [Figure 3.22](#).

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

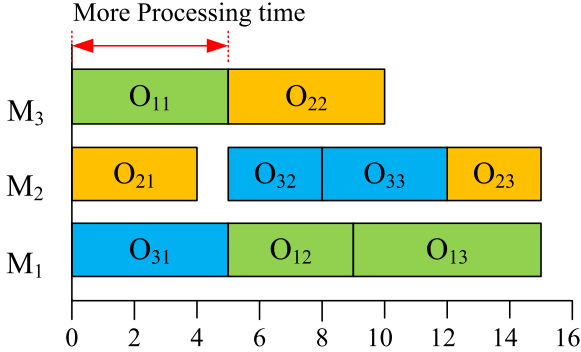


Figure 3.21: Impact of more processing time on job shop scheduling

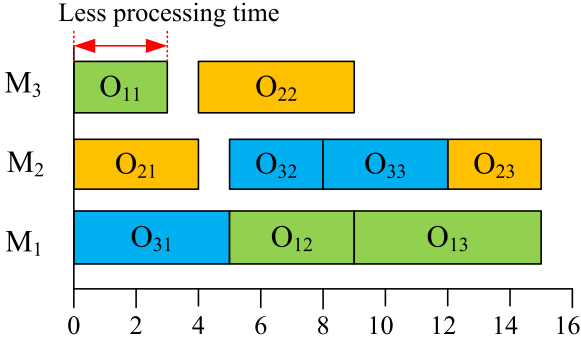


Figure 3.22: Impact of less processing time on job shop scheduling

According to analysis above, we can find that not every operation's uncertain processing time disturbs the overall scheduling. Moreover, if uncertain processing time does influence makespan of overall scheduling, impact degree is still uncertain. If the influence is small, we can ignore it. We note the operation which impacts much the overall scheduling as key operation. For the key operation, we can pay more attention to forecast its processing time. Take the scheduling scheme of Figure 3.6 as an example. In order to find the key operation, we increase the processing time of each operation to see how is the impact to overall makespan of scheduling.

Impact of increasing processing time of each operation in Figure 3.6 on makespan is shown in Figure 3.23 and Figure 3.24, corresponds to increase of 1 and 2 time units respectively. From the results, we can find that operations O_{22} , O_{23} , O_{24} , O_{33} , O_{42} , O_{43} , O_{51} , O_{52} , O_{53} , O_{54} , O_{61} , O_{62} , O_{63} , O_{71} , O_{81} , O_{82} , O_{83} , and O_{84} are key operations. It is not hard to observe that the key operations we found are just the ones after which there is no empty space until the next operations on the same machine. Moreover, for some operations, like O_{72} , when the real processing time increases 1 time units, it does not impact the overall schedule, but while it increases 2 time units, it does. Hence we can give some floating range to these operations. For O_{72} , its floating range is $[0, 1]$, which is exactly the empty space between it and its next operation O_{83} . We call this float free float. Furthermore, for the operations like O_{11} , when it increases 1 time unit, it does not delay the overall schedule, but it will delay its next operation O_{12} , we call these operations with a total float. The floating range of O_{11} is $[0, 3]$. The concept of floating comes from the critical path method (CBM), which is a project modeling technique developed in the late 1950s by Kelley Jr & Walker (1959).

Similarly, we can also find key operations for other scheduling schemes. For instance, for the same instance of FJSP, J8M8, in addition to the scheduling scheme in Figure 3.6, there are several different optional solutions, like that in Figure 3.25, Figure 3.26, and Figure 3.27. All these three optional solutions achieve the same minimum value of makespan, 14. Since the empty intervals between operations in scheduling scheme play the role of redundancy of processing time, which is a slack for tolerating uncertain processing time, the scheme with more empty intervals (except the empty interval at the beginning of schedule on

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

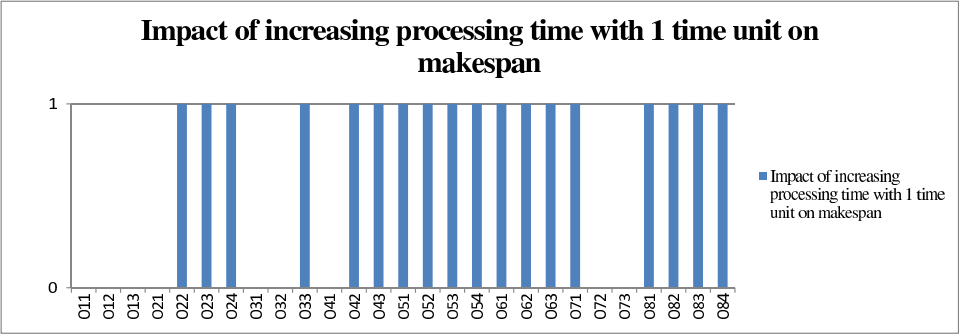


Figure 3.23: Impact of increasing processing time with 1 time unit to J8M8

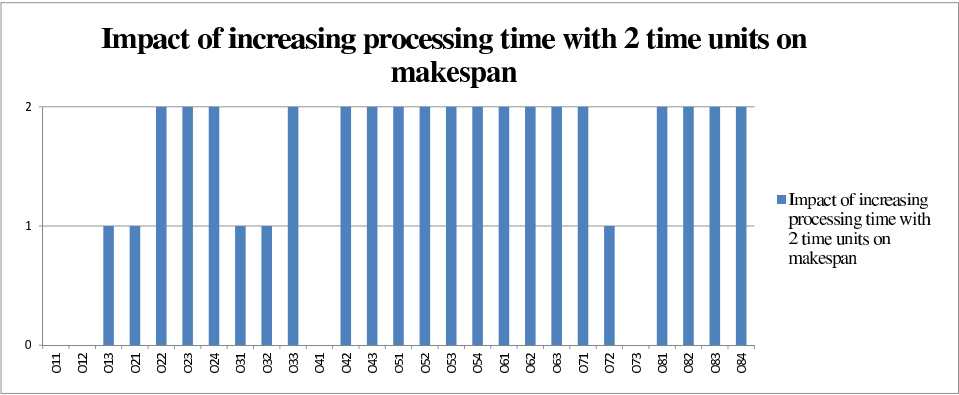


Figure 3.24: Impact of increasing processing time with 2 time units to J8M8

3.3 Impact of uncertain processing time of jobs to FJSP

machines) is preferred. For the four different schemes of J8M8 in Figure 3.6, Figure 3.25, Figure 3.26 and Figure 3.27, the number of empty intervals (time units) is 26, 18, 18 and 22 respectively. Therefore, from the point of view of minimization of makespan and redundancy of processing time, the scheme in Figure 3.6 is the best solution for J8M8.

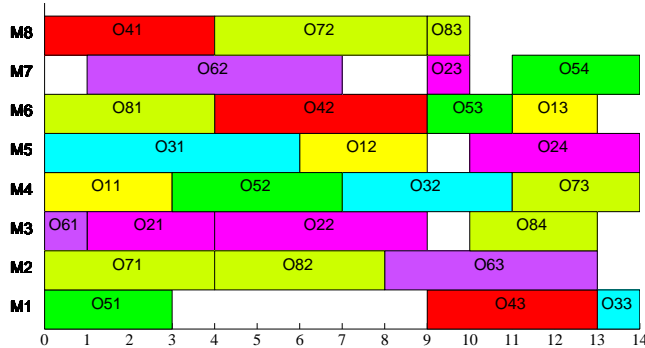


Figure 3.25: Optional solution 1 for J8M8

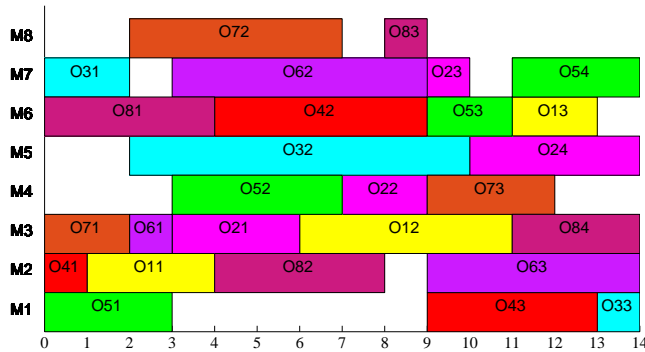


Figure 3.26: Optional solution 2 for J8M8

Because the key operations have much impact on makespan of overall scheduling, prediction and assurance of their processing time on the related machines should be paid more attention than that operations. Precise forecasting of processing time of the key operations is needed if we adopt the scheduling scheme in Figure 3.6. This concept reduces the workload of forecasting and makes contribution to management of jobs' uncertain processing time.

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

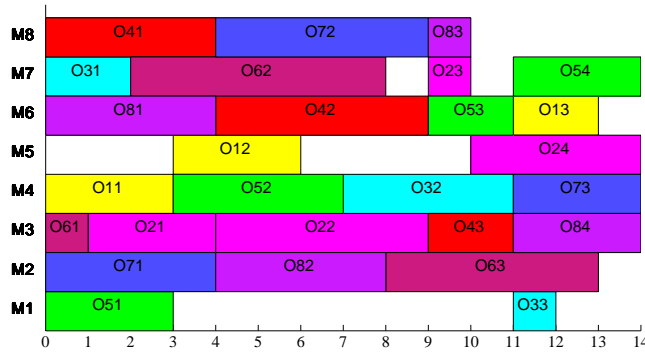


Figure 3.27: Optional solution 3 for J8M8

3.4 Conclusions

In our study of uncertainty in manufacturing system, we concentrate on the flexible job scheduling problem (FJSP). In order to ensure availability of machines, we add condition based maintenance (CBM), a kind of preventive maintenance (PM), into scheduling problem. CBM is on a theoretic base of $P - F$ curve, and can make full use of resources, machines for processing job, materials and staff to maintain machines.

The procedure to sort out FJSP with CBM conclude two parts, getting scheduling scheme for ordinary FJSP as a preschedule and add PM tasks into existing schedule. For the first part, to get optimal result of the problem, the minimum makespan of jobs and maintenances, firstly we propose to find the best solution for FJSP through comparing hierarchical approach and integrated approach. Three different approaches are proposed: Integrated Genetic Algorithm (IGA), Hierarchical Genetic Algorithm (HGA) and Integrated Ant Colony Optimization (IACO). Different to conclusions of some researchers, stating that hierarchical approach is superior to integrated approach, we find that IGA is the best among the three. We get promising results for benchmark of FJSP. For an instance of FJSP, we gain better result than that in literature. For the second part, we propose an Inserting Algorithm (IA) and improve the Simultaneous Scheduling Algorithm (SSA) in literature with different heuristics. We discover that our two proposed SSA, for treating collision of job and PM, the one with choosing new machine with minimum processing time (SSA2) and the other one with choosing new machine with a minimum sum of processing time and idle time

(SSA3) perform well. Combining the approach for FJSP and the four different algorithms to add PM tasks to scheduling procedure of job shop, we apply seven different approaches: IGA with three different kinds of SSA, IGA with IA and IACO with the three different kinds of SSA. Numerical experiments demonstrate effectiveness of our proposed algorithms. Our proposed IA performs much better in executing speed. With IA, we try to use the empty interval between jobs. It is a module independent from the module of getting solution for FJSP. We can change easily either of them to improve the solution. Unfortunately, it is a little inferior to SSA in terms of objective value. Furthermore, IGA with SSA in literature without changing machines when job meets PM (SSA1) and IGA with SSA3 perform a little better than other combinations. The results are comparable with that in literature.

In addition to research on reducing unavailability of machines in flexible job shop, we discuss algorithms for treating new arrival of jobs as well. We observe that IA used in FJSPPM is also suitable to solve this problem. Another feasible strategy is rescheduling all jobs when new jobs arrive. The third part in this chapter is studying impact of uncertain processing time on flexible job shop scheduling. The necessity of treating uncertain processing time is declared. On the basis of experiments, we come to believe that not all operations in a certain scheduling scheme will impact makespan. It is important to search the key operations having severe impact on overall schedule. Furthermore, we find that empty intervals among operations in scheduling play the role of redundancy for tolerating uncertain processing time. If utilization rate of machines is considered, it is necessary to trade off it with the concept of redundancy.

3. FLEXIBLE JOB SHOP SCHEDULING PROBLEM UNDER UNCERTAINTY ENVIRONMENT

Chapter 4

Distribution problem under uncertain environment

After having discussed uncertainty in demand and manufacturing system in precedent chapters, in this chapter we would like to introduce our research about uncertainty in distribution problem. Transportation is the preliminary part in distribution. Uncertainty in transportation is mainly induced by external factors, as it contacts with outside world. With respect to allocation of staff and management of transport system, vehicle routing gets more attention. Vehicle routing problem is a hot research topic in last several decades. It refers to two problems, scheduling problem of routes for distribution and decision of number of vehicles. In our work, we concentrate on Vehicle Routing Problem with Pickup and Delivery (VRPPD), with uncertain partnership of suppliers and demanders, i.e., unpaired VRPPD, which is a promising strategy to treat uncertainty of clients in transport.

4.1 Uncertainty of clients in distribution

Ultimate objective of supply chain is to satisfy request of clients, which is completed by distribution, the direct stage contacting with consumer market. Unfortunately, there are some uncertain factors which make the execution procedure not coincide with our plan. Although [Mason-Jones & Towill \(1998\)](#) illustrated that improving reliability in the four main segments in supply chain, demand side, manufacturing process, supplier side, and control system, may shrink the Uncertain Circle, as the procedure with direct relation to customers, accurate de-

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

livery is specially needed to be guaranteed. Uncertainty of distribution time has been studied a lot in previous research of practitioners and scholars. [Ray *et al.* \(2005\)](#) considered uncertain delivery time in tailored supply chain decision making, but randomness of distribution time is actually ignored. [Xiang *et al.* \(2008\)](#) proposed to re-optimize schedule when new events occur. [Alfa \(1987\)](#) examined the traveling salesman problem (TSP) with time-varying (but not stochastic) travel time. Like demand quantity, the most widely used approach for treating uncertainty of delivery time is based on representation of probability distribution for it ([Fu, 2002](#)). Normal distribution is used widely, as its simple representation, with a mean value and a standard deviation, and popular suitability for stochastic events. Stochastic travel time was studied by [Laporte *et al.* \(1992\)](#). Scenario analysis of variant travel time applied by [Huisman *et al.* \(2004\)](#). The dynamic VRP considering online requests and uncertain travel times was solved with exact method by [Chen & Xu \(2006\)](#); [Yang *et al.* \(2004\)](#), heuristic by [Fleischmann *et al.* \(2004\)](#); [Regan *et al.* \(1996\)](#), with metaheuristic by [Gendreau *et al.* \(1996\)](#); [Haghani & Jung \(2005\)](#).

Uncertain distribution time in practice is generally caused by external interference, like change of situation of routes, vehicles' unexpected emergence, drivers' faults, influence of other clients, etc. The three main aspects inducing uncertainty in distribution are: uncertainty in vehicles, uncertainty of routes, and uncertainty of clients. It is obvious that availability of vehicle is problem of hardware, which can be obtained through inspection before utilization. Uncertainty of routes refers to situation of route like congestion, traffic accidents and so forth, which can neither be changed or improved by individual efforts. Uncertainty of clients mainly refers to quantity or delivery time of requests changed and cancelation of demand. We center on uncertainty of clients as its impact can be reduced if there are some good response measures. For example, when we are informed just at the moment before arriving clients that their requests are canceled, how to treat the products already prepared for the original clients with demand changed? We find that the model of unpaired VRPPD (vehicle routing problem with pickup and delivery) is a good respond measure to uncertainty in clients. We give explanations in section [4.3.1.2](#).

4.2 Vehicle routing problem

In order to analyze distribution procedure, we decompose it in details. The diagram of subdivision of distribution is shown in Figure 4.1. We can see that

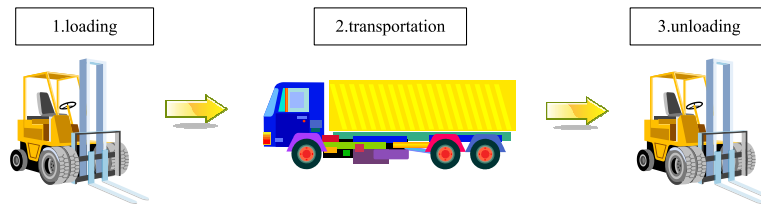


Figure 4.1: Distribution procedure

transportation procedure plays an important role in distribution, as handling part in loading and unloading is more certain than transportation. Thanks to developed technique of conservation and equipment handling, quantity and quality of goods in distribution procedure can be guaranteed. Unavoidably, there may be some errors caused by drivers or handling workers. Overall, compared to delivery time, uncertainty of quantity and quality in distribution procedure is much less. Thereby, quantity and quality of goods are little considered in optimization problem of distribution. Similarly, our work also focuses on delivery time. Delivery time consists of handling time and transportation time. Handling time is rather easy to calculate and it accounts a relatively small proportion in the whole delivery time. Therefore, transportation time is the key factor. Moreover, besides quantity and quality of demand, delivery time is another part in demand contents. However, in practice, we cannot always serve clients one by one. There are always some other constraints, like utility of resources, consideration of distribution cost, etc. Therefore, we would like a delivery planning which can satisfy delivery time of clients meanwhile with reasonable cost. For this kind of problem, there are two kinds of models, Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP).

TSP seeks an optimal route for a salesman to run through a group of cities to finish his sales project within minimum time, i.e., shortest distance for a Hamiltonian cycle. The original mathematical formula of TSP was firstly studied by Karl Menger (1931) and the name is introduced by Hassler Whitney (1934). A detailed treatment of the connection between Menger and Whitney as well as the growth in the study of TSP can be found in the paper of Schrijver (2005). VRP

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

is factually an extension of TSP, with several salesman, but the groups of cities are not determined in advance. Moreover, assumption of infinite capacity in TSP are relaxed with capacity constraint of vehicle. In order to keep generality of problem, we focus on VRP.

In some literature, VRP is also called Vehicle Routing and Scheduling Problem (VRSP) (Desrosiers *et al.*, 1986; Solomon, 1987), or Vehicle Scheduling Problem (VSP) (Foster & Ryan, 1976; Waters, 1989). VRP is an NP-hard problem in combinatorial optimization. It is extension of TSP, which is proved to be NP-hard by Johnson & Garey (1979). It was firstly proposed by Dantzig & Ramser (1959). In VRP, it seeks to service a number of clients with a fleet of vehicles. The objective is to satisfy demands of all clients under constraints of capacity of vehicles, limit of routes, etc. Meanwhile in most cases it aims to achieve objective of minimizing number of vehicle and least time-consuming.

4.2.1 Practical application of VRP

According to Gregory (2010), studying VRP is useful for several reasons:

- i. It is a difficult real-world problem in which planners are still relatively weak.
- ii. There are existing benchmarks for which we can assess the performance of planners against existing techniques.
- iii. Technological developments that have made VRP solvers effective could also improve the performance of planners.

Many practical problems can be modeled as VRP, like collection of household waste, school bus problem, gasoline delivery trucks, mail service system, goods distribution, etc. VRP plays an important role in logistic and distribution problem. Huge research has been contributed on it since it was proposed.

Casco *et al.* (1988) reported that solving a model of VRP with combining deliveries and pickups has led to industry wide savings in distribution costs upwards of \$160 million a year. Wen *et al.* (2010) considered a real-life dynamic multi-period and multi-objective routing problem encountered by a large distributor operating in Sweden. They proposed a three-phase heuristic embedded within a rolling horizon scheme. Their results were compared with the solutions produced by the platform of company. The comparison showed that their method improved upon those solutions in terms of travel time, customer waiting and daily workload balance, with gains of 0.2%, 24% and 35%, respectively. Garaix *et al.*

(2010) considered a multigraph for alternative routes for vehicle routing problem. Computational experiments on realistic data issued from an On-Demand Transportation system in the French Doubs Central area underline the cost savings brought by the proposed methods, with a gap varied between 6% and 25%.

Since it is an effect model for optimization in distribution problem, we have great interest to focus on it.

4.2.2 Classic model of VRP

Although there are different forms of VRP, the base is still the classic model.

4.2.2.1 Definition of classic VRP

According to definition of Laporte (1992b), VRP is described as follows:

Let $G = (V, A)$ be a graph where $V = 1\dots n$ is a set of vertices representing cities with the depot located at vertex 1, and A is the set of arcs. Every arc $(i, j), i \neq j$ is associated a non-negative distance matrix $C = (c_{ij})$. In some contexts, c_{ij} can be interpreted as travel cost or as travel time. When C is symmetrical, it is often convenient to replace A by a set E of undirected edges. In addition, assume there are m available vehicles based at the depot, where $m_L < m < m_U$. When $m_L = m_U$, m is said to be fixed. When $m_L = 1$ and $m_U = n - 1$, m is said to be free. When m is not fixed, it often makes sense to associate a fixed cost f on the use of a vehicle. The VRP consists of designing a set of least-cost vehicle routes in such a way that:

- i. each city in $V \setminus \{1\}$ is visited exactly once by exactly one vehicle;
- ii. all vehicle routes start and end at the depot;
- iii. some side constraints are satisfied.

VRP can then be formulated as follows:

Let $x_{ij}(i \neq j)$ be a binary variable equal to 1 if and only if arc (i, j) of A appears in the optimal solution.

$$\text{Minimize } \sum_{i=j} c_{ij} x_{ij} \tag{4.1}$$

Subject to:

$$\sum_i x_{ij} = 1, \forall i \in V, \tag{4.2}$$

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

$$\sum_j x_{ij} = 1, \forall j \in V, \quad (4.3)$$

$$\sum_{i,j \in S} x_{ij} \leq |S| - v(S) \quad (S \subseteq V \setminus \{1\}; |S| \geq 2) \quad (4.4)$$

$$x_{ij} \in 0, 1, \forall i, j \in E, i \neq j \quad (4.5)$$

In the formulation, 4.1, 4.2, 4.3 and 4.5 define a modified assignment problem (i.e. assignments on the main diagonal are prohibited). Constraint 4.4 are subtour elimination constraints: $v(S)$ is an appropriate lower bound on the number of vehicles required to visit all vertices of S in the optimal solution.

4.2.2.2 Solution approach for classic VRP

There is considerable research contributed to development of algorithm for VRP and its various versions. We review some algorithms, both in exact algorithms and heuristics.

Following the survey of [Laporte & Nobert \(1987\)](#), exact algorithms for the classic VRP can be classified into three broad categories: (i). direct tree search methods; (ii). dynamic programming; (iii). integer linear programming. For each category, there are different concrete approaches. Branch-and-bound was a widely used and efficient approach. [Christofides *et al.* \(1981\)](#) use branch-and-bound scheme successfully solved VRPs ranging from 10 to 25 vertices; [Laporte *et al.* \(1986\)](#) use it to solve a VRP with 260 vertices. Meanwhile, the nearest neighbour algorithm, insertion algorithms and tour improvement procedures developed for VRP: tabu search heuristic was applied by [Laporte \(1992a\)](#) for TSP, which is then found also suitable for VRP [Gendreau *et al.* \(1994\)](#). Later, attention were paid increasingly on developed version of VRP. We discuss it in following sections.

4.2.3 Classification and extension of VRP

There are various versions of VRP developed. We pick out the ones researched considerably to review in details.

4.2.3.1 Capacitated VRP (CVRP)

Different to classic VRP, routes in CVRP is defined as a least cost simple cycle of graph G passing through depot and such that the total demand of the vertices visited does not exceed the vehicle capacity. The most promising exact algorithm for solving CVRP is branch-and-cut (Baldacci *et al.*, 2004; Fukasawa *et al.*, 2006; Lysgaard *et al.*, 2004). Traced back to the work of Wren & Carr (1971) and Wren & Holliday (1972), we find that sweep algorithm has been applied in CVRP so early. The method is commonly attributed to Gillett & Miller (1974) who gave it its name.

4.2.3.2 VRP with Time Windows (VRPTW)

VRPTW is an extension of VRP with constraints of time windows. In VRPTW, besides constraints in VRP, constraint of time window must be satisfied. There are two kinds of time windows: hard time window and soft time window. The former request vehicles arriving in time windows, vehicles must wait when arriving earlier and refused when arriving later; in the latter one, time windows do not need to be satisfied strictly, but there is punishment for vehicles arriving beyond time windows.

Solomon (1987) stated that approximation methods seem to offer the most promise for practical size problems and different heuristic performs well in different environment. Various researchers have investigated the VRPTW using exact and approximation techniques. The work of Kohl (1995) is one of the most efficient exact methods for the VRPTW; it succeeded in solving various 100-customer size instances. However, no algorithm has been developed to date that can solve to optimality all VRPTW with 100 customers or more (Ombuki *et al.*, 2006).

Research on combinatorial optimization based on metaheuristics has gained popularity especially. Metaheuristics, such as genetic algorithms (GA) (Potvin & Bengio, 1996; Zhu, 2000), evolution strategies (Hombberger *et al.*, 1999; Tan *et al.*, 2006), simulated annealing (Chiang & Russell, 1996; Czech & Czarnas, 2002), tabu search (Cordeau *et al.*, 2001; Gendreau *et al.*, 1994). Since Solomon (2003) constructed benchmark for VRPTW, there has been increasing research on heuristic approach focusing one VRPTW to find better solutions (Ombuki *et al.*, 2006). Surveys can refer to (Braysy & Gendreau, 2005; Cordeau *et al.*, 2005; Gendreau *et al.*, 2008).

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

4.2.3.3 VRP with Pick-Up and Delivery (VRPPD)

Problems that need to be solved in real-life situations are usually much more complicated than the classic VRP, like variation in the type of request. The versions of VRP discussed in previous sections, type of demand of clients are all identical, to sell goods to clients or to collect goods from them. There are some cases where the clients have two different kinds of requests, pickup or delivery or both. This kind of problem is named VRPPD.

According to definition of [Parragh *et al.* \(2008\)](#), Vehicle Routing Problems with Pickups and Deliveries (VRPPD) refer to problems where goods are transported between pickup and delivery locations. Delivering merchandizes from suppliers to determined demanders is obviously categorized to paired type VRPPD, which is also called static VRPPD by [Parragh *et al.* \(2008\)](#). The first attempt to generalize the Pickup and Delivery Problem (PDP) in unified notation was proposed in ([Savelsbergh & Sol, 1995](#)), covering all possible versions of the PDP, including the dial-a-ride problem (DARP) ([Zidi *et al.*, 2010](#)). There has been lots of research on VRPPD ([Desaulniers *et al.*, 2002](#); [Dumas *et al.*, 1991](#); [Mitrovic-Minic, 1998](#)). Like other optimization problems, there are exact methods, heuristics and metaheuristics developed for solution approach. Exact method was used in early years, mainly concluding branch and cut algorithm ([Ruland & Rodin, 1997](#)) and column generation ([Dumas *et al.*, 1991](#)). The early work of pickup and delivery constraints was considered in TSP ([Kalantari *et al.*, 1985](#)). Heuristics are always proposed to combine with exact method for optimization ([Lu & Dessouky, 2006](#); [Xu *et al.*, 2003](#)). Metaheuristics become attractive in recent years: Genetic Algorithm in ([Jung & Haghani, 2000](#)); parallel tabu search in ([Caricato *et al.*, 2003](#)); Simulated Annealing in ([Bent & Hentenryck, 2006](#)); neighborhood search in ([Ropke & Pisinger, 2006](#)). From conclusion of [Parragh *et al.* \(2008\)](#), recent new best results have been presented by [Ropke & Pisinger \(2006\)](#) and [Bent & Hentenryck \(2006\)](#).

4.2.3.4 VRP with Stochastic Demand (VRPSD)

While the classic view of VRP is static and deterministic, in many practical problem there are significant constraints which make the problem dynamic and stochastic.

In VRPSD, demands of customer are stochastic variables $\xi_i, i = 1, \dots, n$ independently distributed with known distributions. The actual demand of each customer is only known when the vehicle arrives at the customer's location. It is also assumed that ξ_i does not exceed the capacity of vehicle (Bianchi *et al.*, 2004). There are some other naming styles for VRPSD. It is called probabilistic vehicle routing problem (PVRP) by Bertsimas *et al.* (1991) and cyclic heuristic was introduced to solve it. It was illustrated in examples performing better than re-optimization heuristic. Yang *et al.* (2000) named it stochastic vehicle routing problem (SVRP) and proposed two heuristic algorithms. Metaheuristic was demonstrated outperforming cyclic heuristic in paper of Bianchi *et al.* (2004). As demand is uncertain, vehicle's capacity may be unsatisfactory, re-stock strategy appears to be promising (Bertsimas *et al.*, 1991; Yang *et al.*, 2000). Re-stock strategy allows vehicles to return to depot and then continue visiting rest clients. When to return is an added decision variable.

4.2.3.5 Other types of VRP

For other types of VRP, we introduce them briefly. The VRP where the length of any route may not exceed a prescribed bound L is referred to as DVRP Laporte (1992b). VRP with due times (VRPDT) pursuits best service time, in which the lower bounds of time windows are relaxed (Kang *et al.*, 2008). In VRP with multi use of vehicles (VRPM), the same vehicle can be assigned to several routes during a giving planning period (Taillard *et al.*, 1996). FSVRP refers to fleet size and mix vehicle VRP, where the fleet size if fixed and vehicles may have different capacities (Gang, 2010). Multi Depot VRP (MDVRP) add the assignment of customers to depots (Lim & Wang, 2005). Split Delivery VRP (SDVRP) is a relaxation of the classic VRP where it is allowed that the same customer be served by different vehicles if it reduces overall costs (Archetti *et al.*, 2006). Even there are many kinds of variants combining some of the types we discussed above, like Capacitated VRP with Time Windows (CVRPTW), Multi Depot VRP with Time Windows (MDVRPTW), etc.. In fact, almost all research on VRP is CVRP, like in the definition of both VRPTW and VRPPD of Desrochers *et al.* (1987), capacity constraint is always considered. VRPTW studied by Alvarenga *et al.* (2007) considered also capacity constraint.

4.3 Unpaired Vehicle Routing Problem with Pickup and Delivery

In the classic VRPPD, requests of pickup and delivery are paired, unpaired VRPPD is a subclass of VRPPD, where units of goods picked up can be delivered to any location of delivery. Moreover, the relationship of clients is not restricted in one-to-one mapping. Goods picked up from one location may serve several requests of delivery. Obviously this kind of partnership is more flexible, but increasing complexity of the problem. Paired VRPPD is suitable for modeling determinate delivering problem, like that of courier company, where merchandize is delivered from an origin to a certain destination. For delivery problem within a supply chain, in which all companies cooperate with a common objective of satisfying demands of clients, origins and destinations for demands are not allocated into pairs in advance. This is exactly unpaired VRPPD in which we are interested. The characteristic of unpaired VRPPD is that: the relationship of pick-up and delivery is not fixed and the goods picked up at one node of pick-up can be used to supply several clients with deliver demand.

With respect to paired VRPPD, unpaired type receives less attention. Unpaired TSP with pickup and delivery (TSPPD) ([Anily & Bramel, 1999](#); [Hernández-Pérez & Salazar-González, 2004](#)) is also studied more than unpaired VRPPD. Rather less research focus on VRPPD, [Dror *et al.* \(1998\)](#) proposed a mixed integer programming formulation for the redistribution of self-service electric cars, and Lagrangian relaxation methodology applied to solve it. To our knowledge, there has not been metaheuristic approach for solving unpaired VRPPD. In our work, we use grouping genetic algorithm (GGA), which was introduced by [Falke-nauer \(1998\)](#) and has been demonstrated able to find high quality solution in the work of [Pankratz \(2005\)](#), which works on a paired VRPPD. Although our problem is different, we modify GA procedure to make it adaptable to our problem.

In following sections, firstly we explain the motivation or studying unpaired VRPPD, and then give a detailed problem description and mathematic formulation, after that introduce our algorithm for solving the model, at last the algorithm is applied on numerical experiments.

4.3.1 Motivation of studying unpaired VRPPD

Besides its adaptation to practical problem and our aim to fulfill the gap of research, there are two other motivations. One is that studying unpaired VRPPD is extension of our previous work on treating demand uncertainty in supply chain in chapter 2. The other one is to cope with uncertainty of clients.

4.3.1.1 Model of unpaired VRPPD for distribution stage in supply chain

In chapter 2, through strategy of postponement, we have obtained optimal solution of allocation of merchandizes, in regular period and postponed period. As merchandizes are considered with large quantity, they can be delivered directly from supplier to demander with special line transportation. Unavoidably, there are always some rest goods, which cannot just fully fill the vehicle, i.e., demand is inferior to capacity of vehicle. In order to make full use of capacity of vehicle, we would like search an optimal solution for scheduling vehicles' routing. Unpaired VRPPD is suitable for modeling our problem with the aim of spending minimum costs in transportation. It helps to integrate resources of transportation, including vehicles, drivers and time.

4.3.1.2 Coping with uncertainty of clients

As we mentioned in section 4.1, there are three general kinds of uncertain cases in clients. Emergency request may happen in the case where clients would like more than the quantity that they have reserved. In this case, supplier is not obligatory to accept this potential order. However what the supplier expected is that there are excess goods and then the added demand can be satisfied. Another normal kind of uncertainty is cancelation or reduction of demand, which probably happens occasionally although it disobeys contract of business. We consider the case where these two kinds of uncertainty happen simultaneously. It is better that the quantity requested emergently does not exceed reduced quantity. For a normal VRP scheduling scheme, the quantity of goods does not change when the vehicle departures from the node of pick-up. Thereby when demand of a client of delivery increases, the added quantity cannot be satisfied or it is satisfied at the cost of decreasing supply to other clients. While for the client with decreased

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

demand in another routing, there will be surplus of goods which bring a wastage of resource.

Example:

Figure 4.2 is a normal VRP scheduling scheme for distribution, while Figure 4.3 is the model of unpaired VRPPD. The capacity of vehicle is assumed to be 15. When demand of clients changes, e.g., demand of client 4 increases, from original quantity 1 to a new quantity 2, it cannot be satisfied in the normal scheduling scheme. And the reduction of demand of client 9 in routing of vehicle 2 will bring a surplus of goods after the procedure of distribution. However, if we adopt the unpaired VRPPD model, the surplus caused by reduction of client 9 can be just used for the increasement of client 4. This is a great advantage of the unpaired VRPPD model in coping with uncertainty of clients. It is obvious to observe that another advantage of the unpaired VRPPD is the integration of resources, where only one vehicle is needed.

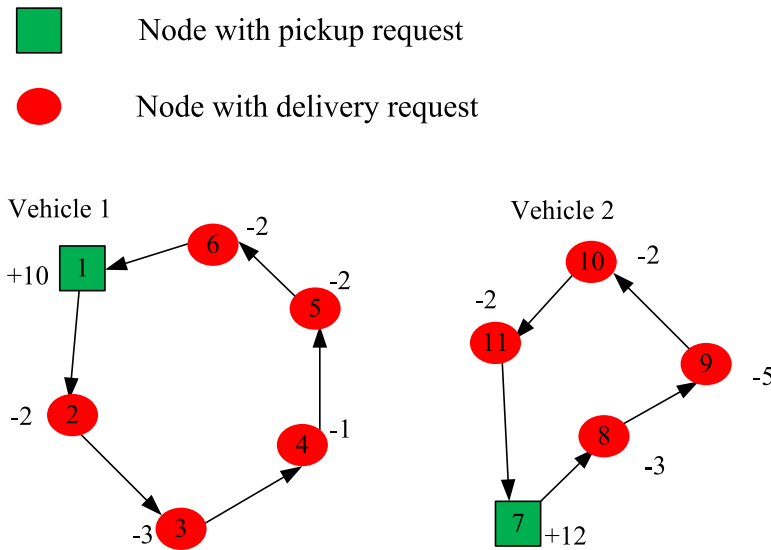


Figure 4.2: Normal VRP scheduling scheme

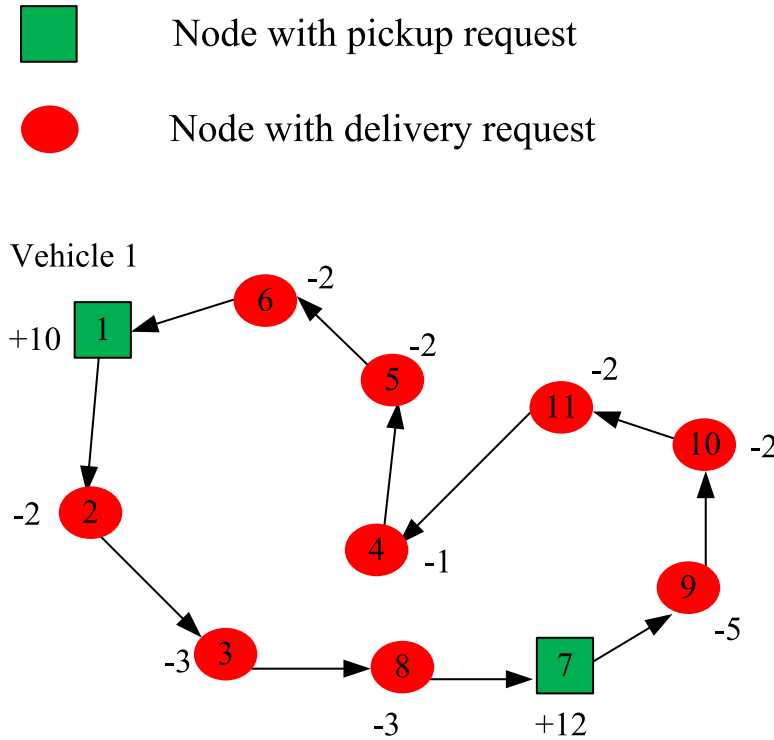


Figure 4.3: Unpaired VRPPD model

4.3.2 Description of mathematic model

4.3.2.1 Model of distribution problem

We try to solve distribution problem in supply chain, which is execution stage and extension of approach of treating uncertain demand in supply chain management in chapter 2, described briefly as follows: The problem focuses on integrating merchandizes and then allocating them to demanders. Through strategy of postponement, we have obtained optimal solution of allocation of merchandizes, in regular period and postponed period. Merchandizes in the problem are assumed with a large quantity. Take one numeric result of our preceding research in chapter 1 for example: in sub system warehouse-distributor, allocation of merchandizes is as in Figure 4.4. Sub figure 4.4(a) indicates allocations in regular period. In regular period, demands are satisfied by inventory; Sub figure 4.4(b) indicates allocations in postponement period, where demand is satisfied at a delayed date, by new products. D_1 to D_6 are distributors, as the aspect of demanders. W_1 , W_2 and W_3 are warehouses, as the aspect of suppliers. D_1 , D_3 , D_5 and D_6 are supplied by W_1 ; D_2 and D_4 are supplied by W_2 ; D_3 is supplied by W_3 .

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

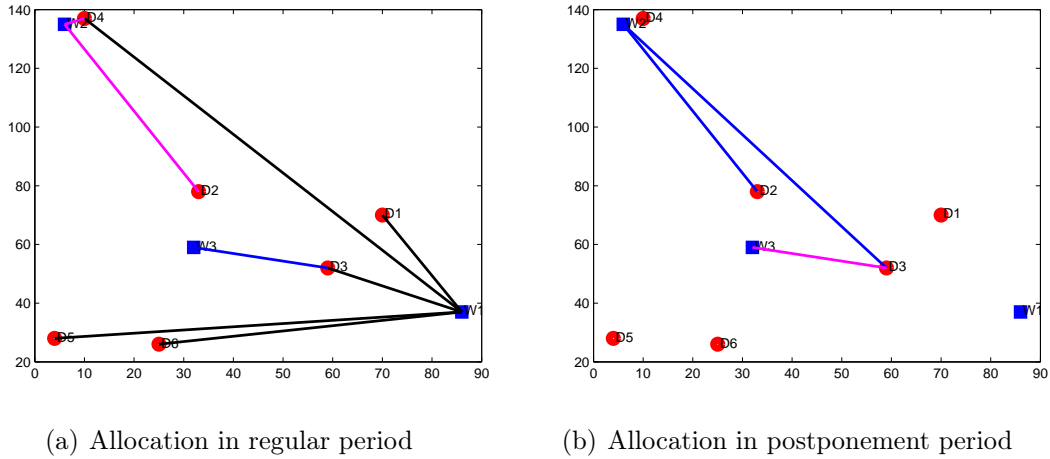


Figure 4.4: Original allocation of delivering merchandizes

As merchandizes are considered with large quantity, for each pair of partners with relationship of demand-supply in the two periods, merchandizes can be delivered directly from supplier to demander with special line transportation. Unavoidably, there are always some cases with rest goods, which cannot fill the vehicle exactly fully, i.e., demand is inferior to capacity of vehicle. In order to make full use of capacity of vehicle, integrating resources of transportation, we would like to spend minimum resources to deliver the resting goods. We model this distribution problem as unpaired VRPPD we described above. Allocation of delivery in Figure 4.4 can be transferred in Figure 4.5. We have allocated suppliers for each demander in original schedule. In order to optimize the solution, we can change the relationship of suppliers and demanders, i.e., demanders can be served by any supplier. This is a procedure of re-allocation of demand. It is obvious that constraints of capacity of suppliers should be considered. We can assemble merchandizes from different warehouses and then distribute to demanders. The nodes of warehouses and distributors make up the network. Visit of vehicles at each node of warehouse is to pick up merchandizes, while that of distributors is to deliver merchandizes. Each vehicle can only departure from and return to node of warehouses. Corresponding to the model of VRPPD, we can see that in our problem, distributors play the role of clients, while warehouses play the role of both clients and depots.

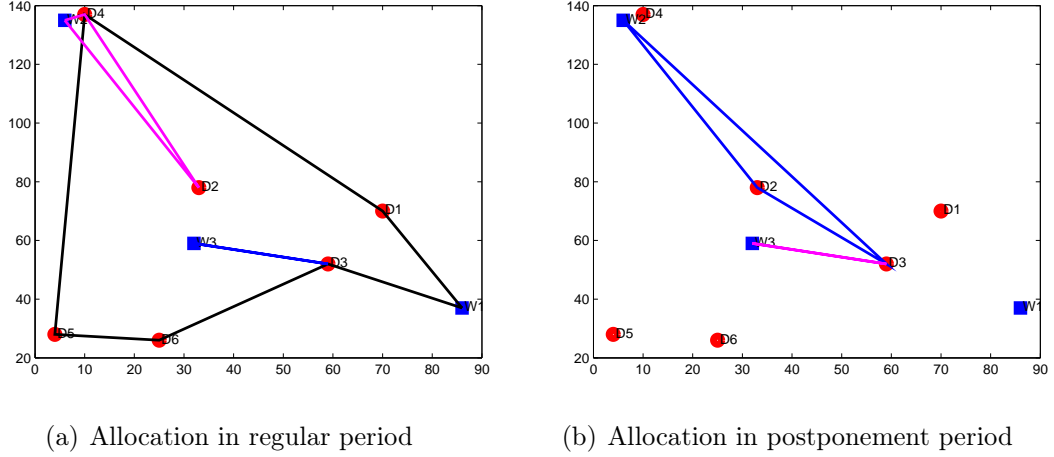


Figure 4.5: Unpaired VRPPD model for distribution problem

4.3.2.2 Formulation for unpaired VRPPD

Denote set of warehouses as W , set of distributors as D , hence set of clients $C = W \cup D$, set of depots $P \supseteq W$. Set of vehicle is also noted as V . Variable Q_{ik} denotes the resting goods on vehicle k after it has served customer C_i . q_{ik} is representation of quantity of customer C_i served by vehicle k . $q_{ik} \geq 0$ represents collecting activity at customer of warehouse by vehicle k , while $q_{ik} \leq 0$ represents delivery activity. After visiting warehouse, the quantity of goods on vehicle increases; while after visiting distributors, goods on vehicle decreases.

In order to simplify computation, we assume that:

- i. All available vehicles are with the same capacity;
- ii. Traveling of vehicle with the same unit cost w_1 ;
- iii. All vehicles have the same utilization cost w_2 .

The problem can be modeled mathematically as follows:

Objective function:

$$\min \sum_{k \in V} T_k \cdot w_1 + \sum_{k \in V} w_2 \quad (4.6)$$

Physical constraints:

$$\sum_{j \in C} \sum_{k \in V} x_{ijk} = 1, \forall i \in D \quad (4.7)$$

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

$$\sum_{i \in C} \sum_{p \in P} x_{pik} = 1, \forall k \in V \quad (4.8)$$

$$\sum_{j \in C} \sum_{k \in V} x_{ijk} \geq 1, \forall i \in W \quad (4.9)$$

$$\sum_{i \in C} x_{ipk} = 1, \forall p \in P, \forall k \in V, \quad (4.10)$$

Constraint 4.7 states that each customer of warehouse must be assigned exactly to one vehicle and visited only once. Constraint 4.8 indicates that each route of vehicle departures from only one depot and only once, from this we can obtain that each customer of distributor, who also serves as depot, are visited at least once, which is represented in Constraint 4.9. Constraint 4.10 ensures each route of vehicle returns a depot chosen.

Constraint of capacity of vehicle:

When $x_{ijk} = 1$,

$$y_{ik} + q_{jk} = y_{jk}, \forall j \in W, q_{jk} \geq 0; \forall j \in D, q_{jk} \leq 0, \sum_{k \in V} q_{jk} = q_j \quad (4.11)$$

$$\sum_{i \in C} \sum_{j \in C} q_{ik} x_{ijk} \leq q, \forall k \in V \quad (4.12)$$

Constraint of workload of vehicle:

$$T_k < wl, \forall k \in V \quad (4.13)$$

Constraint 4.13 origins from consideration of driver's legal working time. This constraint of time can be transformed to constraint of travel distance in calculation procedure.

Constraint of integer:

$$x_{ijk} \in \{0, 1\}, i, j \in C, k \in V \quad (4.14)$$

Notations:

C_i : customer i , where $i = 1, 2, \dots, N$.

N : number of client, including both warehouses and distributors.

P : number of depot, including only distributors.

q_i : demand of customer C_i .

q_{jk} : quantity of goods at node j served by vehicle k .

q : capacity of vehicle.

R_k : vehicle route k , $k = 1, 2, \dots, U$.

T_k : travel time of vehicle k , $k = 1, 2, \dots, U$.

U : total number of vehicles used.

V : set of vehicles used, $\{k = 1, 2, \dots, U\}$.

wl : workload constraint of vehicle.

w_1 : unit cost of transportation.

w_2 : unit cost of punishment for arriving earlier beyond time windows.

x_{ijk} : decision variable to indicate vehicle k visits node j after having served node i .

y_{jk} : capacity of vehicle k after having served client j .

4.3.3 Solution algorithm

Procedure of GGA applied to solve our problem is described in this section.

Encoding method

Each chromosome represents a solution for the problem, including clusters of all clients, with a fleet of vehicles. Each vehicle relates to a cluster with a group of clients. The length of chromosome, i.e., the number of genes, is variable and depends on the number of vehicles needed by a given solution. Figure 4.6 shows an encoding form for an example with 13 clients, in which there are 5 warehouses (nodes 1 – 5) and 8 distributors (nodes 6 – 13). 3 vehicles are used.

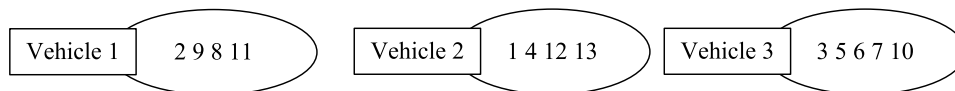


Figure 4.6: Encoding form for chromosome

Different to the chromosome representation style in the work of [Pankratz \(2005\)](#), we include the routing part of solution in the chromosome. For initialization of population, to keep feasibility of individuals, choose the first client with demand of pickups, in the set of warehouses, the following clients can be randomly

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

selected, but the physical constraints, workload constraints and constraints of capacity of vehicles indicated above must be satisfied.

Crossover

Our crossover method is based on order crossover (OX) and the general group-oriented crossover scheme presented by [Falkenauer \(1998\)](#). The crossover procedure is illustrated in [Figure 4.7](#), in five steps:

(1) Specify a crossover section by randomly selecting two cross points in each parent;

(2) Replace the clusters in the same place in the first parent as the cross point in the second parent with cross section of the second parent.

(3) Nodes in other places in the first parent may duplicate with the new parts. In this case, remove the duplicated nodes originally belonging to the second parent.

(4) When some clients may not be assigned to any cluster, reinsert them into the newly generated individual, applying an insertion heuristic. This may require adding a new vehicle if necessary, to assure feasibility of offspring.

(5) Generate the second offspring by repeating steps (2) – (4) with reserved roles of parents.

Mutation

The group-oriented mutation operator in [Pankraz \(2005\)](#) is applied: firstly select a cluster in an individual and then remove it from the solution, finally reinsert the removed clients into the individual by insertion heuristic, which is the same with that in crossover procedure, new vehicle added when necessary.

Selection

Select N (population size) best individuals from the mating pool of all the parents and offsprings, with a roulette wheel method. Fitness function is the objective function of cost of individual.

4.3 Unpaired Vehicle Routing Problem with Pickup and Delivery

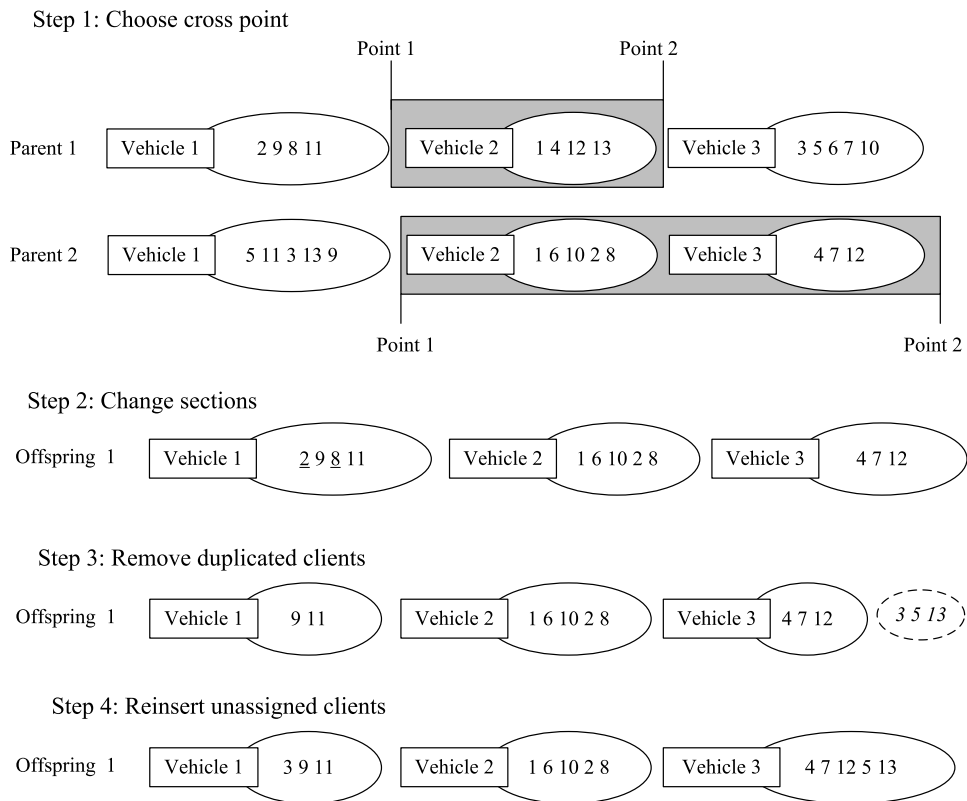


Figure 4.7: Crossover procedure

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

Insertion heuristic

Different to the work of [Pankratz \(2005\)](#), we do not insert a node to a cluster with minimum cost, but to insert it to a randomly selected cluster. On one hand, because pickup and delivery request are not paired, under the constraint of vehicle's capacity and workload, it is always more difficult to get a feasible solution than that of the paired requests in classic PDP. On the other hand, random choice of vehicle for clients will keep variety of solution, to prevent premature convergence of GGA. In order to keep feasibility of solutions, we propose a special insertion heuristic for our problem with three steps:

(1). Repair the modified cluster in offspring. As we delete the duplicated clients with that in the original section, the cluster may become unfeasible. Take the offspring in [Figure 4.7](#), where the first cluster of offspring 1 has been modified. As each route must begin with a pickup request. Client 9 cannot be the first node in a cluster, with delivery request. Therefore, we should repair it to keep feasibility of individual.

(2). Add the unassigned nodes into existing feasible cluster, in which there exist some clusters with rest workload. We can add some nodes into it to make full use of resource of vehicle, which also contributes to minimizing number of vehicles used.

(3). Add vehicles for unassigned request if necessary. When there are no more clusters into which we can add nodes, we have to add new vehicles.

4.3.4 Experiment of numerical example

The solution approach, GGA, described in [section 4.3.3](#) has been implemented in Matlab R2008, and ran on a computer with Intel(R) Core(TM) 2 CPU (2.66GHz 2.67GHz). The parameters used in GA in our experiments are: Population size (N) = 100; Generation (M) = 200; Crossover probability (Pc) = 0.9; Mutation probability (Pm) = 0.1. We use an example of 1-PDTSP in ([Hernández-Pérez & Salazar-González, 2004](#)), similar to the TSPPD instances used in ([Mosheiov, 1994](#)). They generated coordinates in $[-500, 500] \times [-500, 500]$, each one corresponding to the location of a customer with a random demand in $[-10, 10]$. Compared to problem description in [section 4.3.2](#), we have other parameters in unpaired VRPPD. We add workload $wl = 3000$; unit cost of transportation

$w_1 = 10$; Cost of utilization of each vehicle $w_2 = 2000$. Through several tests, we get our best solution shown as Figure 4.8.

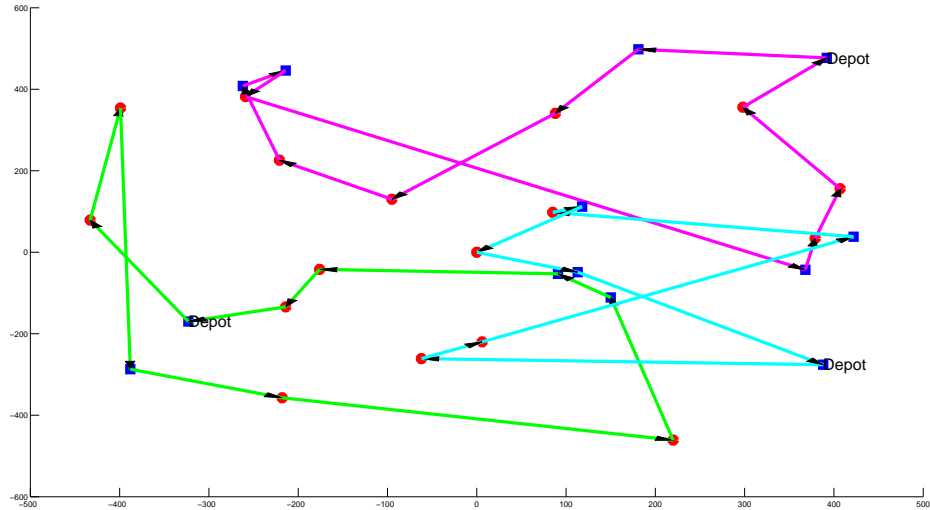


Figure 4.8: Solution for an example with 30 clients

The objective function of our problem is the entire cost, including transportation cost and utilization cost of vehicles, which is different to that in TSPPD in (Hernández-Pérez & Salazar-González, 2004). They have obtained approximate solution for the same example with objective of min travel distance. The results of using two heuristics are 6439 and 6403. In the solution we obtained, there are 3 vehicles used, with a whole cost as 75851, travel distance is 7285. We have added 882 compared to their result, caused by increase of routes. In TSPPD, there is only one route, but in ours there are 3. We can observe that the increase is reasonable.

4.4 Conclusions

In this chapter, the unpaired Vehicle Routing Problem with pickup and delivery (VRPPD) is modeled for distribution problem in supply system obtained in Chapter 2. It is a promising measure for treating uncertainty in clients in distribution.

4. DISTRIBUTION PROBLEM UNDER UNCERTAIN ENVIRONMENT

Our work is a tentative research on using metaheuristic to solve unpaired VRPPD, which is a innovative method application. We use Group Genetic Algorithm (GGA) as a preliminary. Different to classic GA, each gene in GGA represents a group of objects instead of a single object. Each chromosome is a feasible solution for the problem. Besides constraints of general ones in VRPPD, there is one more that making vehicles empty at the end of routes. Our crossover procedure is based on order crossover (OX) and the general group-oriented crossover scheme presented in literature. An insertion heuristic is also used in crossover procedure, but different to that for paired VRPPD. An numerical example is applied to demonstrate efficiency of our approach. Result of experiment show the feasibility of our algorithm. As the originality of the example, no comparative work can be executed. For future research, we will apply another metaheuristic, Artificial Bee Colony (ABC), on our problem and compare efficiency of the two approaches through more examples.

Chapter 5

Uncertainty of demand and yield in bi-level newsboy problem

In previous chapters, we have discussed uncertainty in different stages in supply chain, uncertainty of demand in Chapter 2, uncertainty in manufacturing in Chapter 3, and uncertainty in distribution in Chapter 4. In this chapter, we take into account two kinds of uncertainty simultaneously in bi-level newsboy problem, which is a miniature of supply chain. In bi-level newsboy problem, newsboy is considered together with his supplier. The two sides are with a good cooperation relationship with each other. Research of bi-level newsboy problem is critical and fundamental to the research of supply chain management. Unknown need of market is considered as the most important factor causing difficulty of solving the newsboy problem. In our research, besides uncertain need, we consider uncertain supply as well, i.e., yield of the manufacturer, uncertainty of which is caused mainly by uncertain qualification ratio of products. In this double uncertain environment, deciding the appropriate ordering quantity becomes more complicated than that in classic newsboy problem. We adopt two popular algorithms to solve this kind of newsboy problem, the Bayesian approach and fuzzy hybrid intelligent algorithm.

5.1 Introduction of uncertainty in newsboy problem

The classic newsboy problem intends to observe an optimal ordering policy in a dynamic market with stochastic demand. It is also called the newsvendor problem. The typical problem is characterized by fixed price and uncertain demand for a perishable product. Noting inventory level as q , thereby demand quantity exceeding q will be lost, while unsold copies will be worthless. The mathematical problem appears to date from (Edgeworth, 1888) where the central limit theorem was used to determine the optimal cash reserves to satisfy random withdrawals from depositors (Gallego, 1995).

Profit function in the standard newsboy problem is as follows:

$$\pi = E[p \cdot \min(q, D)] - c \cdot q \quad (5.1)$$

where D is a random variable for representing demand, with probability distribution F ; each unit is sold with price p and purchased with price c ; E is the expectation operator. The solution to the optimal stocking quantity of the newsvendor which maximizes expected profit is:

$$q = F^{-1}\left(\frac{p - c}{p}\right) \quad (5.2)$$

where F^{-1} denotes the inverse cumulative distribution function of D .

A lot of research, such as inventory management, is based on the model of the newsboy problem. It has deserved unabated attentions since it emerged. Most of recent study focuses on extension and generalization of the classic model. Bi-level newsboy problem is a new branch of extension. It bring the ideal of SCM into newsboy problem, i.e., from the overall profit of the whole supply chain, rather than only one point as in classic newsboy problem.

Uncertain demand and restricted inventory capacity make it difficult to derive optimal solutions in newsboy problem. Although uncertainty is an intuitive attribution and the most important factor in newsboy problem, in the considerable literature, there is no systematic research on uncertainty. In order to replenish this gap, we concentrate on studying uncertainty in newsboy problem.

In our work, we consider two kinds of uncertainty in bi-level newsboy problem, that of demand and that of yield. Most literature of newsboy problem is around uncertainty of demand. Moreover, demand is mostly modeled stochastic over a period (Gallego, 1995), with determinate type of probability distribution, like normal distribution, which is the most widely used. For treating with uncertainty of demand, two-stage ordering decision is demonstrated better than Quick Response decision model (Liu, 2006). Besides, compound distribution in demand forecasting is widely used in recent work. As accurate forecasting is hard and costly, usage of statistic method, like time-series forecasting method, mixed with demand information updating is developing, e.g., the Bayesian approach, or with multi-stage policy. There are some widely used probability distribution to describe the stochastic and statistic characteristic of demand: such as normal distribution, uniform distribution, Poisson distribution, etc. However, in some situation, we cannot get a definitive distribution of demand. Type of distribution is unknown, or parameters of the distribution are unknown. The parameters may be stochastic, for instance, also following a usual distribution function, distinct or not to the original distribution type (Kamath & Pakkala, 2002).

Uncertainty of yield is rather less studied than that of demand. Uncertainty of yield comes mainly from supplier or manufacturer, due to uncertainty in manufacturing process, imperfect inspection, defective of products, the deterioration in transportation or in storage, etc. Such kinds of uncertainty in yield are always random and have negative effects to enterprize. Especially in the case of Quick Response policy, the negative influence is evident. Khouja (1999) synthesized the research about random yield in newsboy problem. Defective units or available production capacity is considered as random variable (Ciarallo *et al.*, 1994; Jain & Silver, 1995), but with known probability (Ehrhardt & Taube, 1987; Karlin, 1958). Diversification was recommended to cope with the supplier with random yield (Parlar & Wang, 1993). But to some small-scale wholesalers, they cannot diversify suppliers, which will reduce the profit from volume discount. In recent study on newsboy problem, there is not much focusing on random yield. The Gardener Problem is designated to cover the random yield by Abdel-Malek *et al.* (2008). Their developed methodologies are applicable to general probability distribution functions. Supply yield is modeled using a uniform distribution considering both the minimum ordering guarantee and the maximum yield (Tiwari

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

et al., 2011). In the review of Yano & Lee (1995), three important issues relating random yields are: the modeling of costs impacted by presence of random yields; the modeling of yield uncertainty; measures of performance. There have been enormous effects on the modeling of uncertain yields. However, they are limited to certain application cases. Commonly observed yield distribution is needed but difficult to derive.

For the problem with the two sorts of uncertainty, there is rather little study. The effects of demand uncertainty and yield uncertainty are investigated by Wang (2009) in the environment of decentralized supply chain. It indicated that higher uncertainty leads to smaller optimal production and ordering quantities of manufacturer and distributor. Gavirneni *et al.* (1998) present several well-performing heuristics for solving the periodic inventory problem with random yield and demand. The myopic heuristics proposed are still the best method available for solving the joint random yield problem. However, some computational investigations reveal that the performance of the heuristics may become quite poor if service levels are high and exceed those values for which results are reported in the original study (Inderfurth & Transchel, 2007). Tiwari *et al.* (2011) considered using two stage ordering policy and demand forecast update to derive an optimal ordering quantity, but the unreliable yield percentage is assumed a uniform distribution and considered both a minimum ordering guarantee and maximum yield.

Although uncertain timing of yields is suggested to be considered in some researches (Yano & Lee, 1995), we can consider yield quantity in a certain period to simplify the question with uncertain timing. This transformation makes the uncertain timing to be included in the problem of uncertain quantity. Effect of delayed time caused by distribution is discussed in our future work, uncertain distribution. Thereby, in our research, we consider the yield quantity in determined time intervals to avoid effects of timing.

We assume that uncertain yield is mainly caused by defective, which is classified into two kinds. One kind is due to fabrication, and the other one due to transportation. Supplier is considered responsible to the transportation. Hence, these two kinds of defective both affect directly the profit of supplier. Inspection is not executed before transportation, although it is recommended by some researchers. Because immediate inspection is not appropriate to all cases, e.g.,

repetition of inspection may be costly and may cause some damages; there may be only one inspection procedure, which is just executed when products arrive.

5.2 Mathematical model for bi-level newsboy problem with uncertain demand and supply

In the classic newsboy problem, the newsboy's expected profit is considered as the objective function, but the profit of supplier is not taken into account. This decentralized planning is not good to the supply chain integration. In practice, supplier and newsboy always need to make some contracts on price to obtain an optimal policy for both sides, called the win-win strategy. This cooperation is necessary for a long-term business. Although there are probably several newsboys around a supplier and there is even competition among them, we assume the situation more cooperate than competitive. We apply the newsboy model for general supply chain in manufacturing industry, with manufacturer as the role of supplier while wholesaler as newsboy. The simplified model with one manufacturer and one wholesaler is used in our work, where both sides are affected by uncertain demand and yield. For manufacturer, he needs an optimal initial production quantity to prepare for production, such as labors, materials and so on. For the wholesaler, optimal ordering quantity needs to be decided, to make maximal profit or minimal loss. However, for preliminary research, we focus on the problem with only one layer of demand-supply. The problem becomes too complicated if there are too many unknown variables. Therefore, we assume that the initial production capacity of manufacturer is given. We concentrate on the problem of deciding the optimal ordering quantity of wholesaler.

Although defective products are always returned to manufacturer to change for good ones, there is timing effect for the newsboy then to the manufacturer. As mentioned in the former section that the timing effect can be transformed into quantity effect in a determined planning period. We consider uncertain quantities for demand and yield.

We assume that:

- 1) For the model with several wholesalers, each wholesaler in the model is allocated a definitive fraction of yields from the manufacturer. So for the model

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

with only one wholesaler, the yield is just equal to the quantity delivered to wholesaler from manufacturer.

2) Sale period is known in advance, the model is defined in the sale period.

3) Production capacity of manufacturer, i.e., the initial production quantity T is given.

4) Unit production cost, wholesale price, retail price and salvage value are all known in advance.

We study the integrated supply chain with one product, facing both uncertain demand and uncertain yield.

Notations:

c -unit production cost;

Q -ordering quantity;

q -realized quantity of wholesaler received from manufacturer, i.e. $q = \min(y, Q)$;

r -unit retail price to consumer;

T -initial production quantity;

u -product qualification ratio;

v -unit lost value after salvage;

w -unit wholesale price to wholesaler;

x -realized demand;

y -realized yield, $y = T \cdot u$.

If realized demand exceeds realized yield, i.e., $x \geq y$, supply chain loses the opportunity to make a profit on $x - y$ units of products. If $x < y$, supply chain salvages $y - x$ units of products at a unit salvage value and the unit lost value is v .

The objective of the newsboy problem is to determine the optimal ordering quantity of wholesaler to maximize profit (Liu *et al.*, 2006; Nahmias, 2005) or to minimize loss or cost (Abdel-Malek *et al.*, 2008; Boulaksil *et al.*, 2009; Tiwari *et al.*, 2011). For the integrated supply chain, similarly, we utilize minimization model to determine the optimal ordering quantity of wholesaler. For our problem with given initial production capacity, potential loss of wholesaler is represented as equation 5.3:

$$f(q, x) = \begin{cases} (x - q) \cdot (r - w) & \text{when } q < x \\ (q - x) \cdot v & \text{when } q \geq x \end{cases} \quad (5.3)$$

5.2 Mathematical model for bi-level newsboy problem with uncertain demand and supply

where $q = \min(y, Q)$.

Potential loss of manufacturer is represented as:

$$f(Q, x) = \begin{cases} (y - Q) \cdot c & \text{when } Q < y \\ (Q - y) \cdot (w - c) & \text{when } Q \geq y \end{cases} \quad (5.4)$$

Combining the two parts, we get potential loss of the whole supply chain as equation 5.5:

$$f(Q, x, y) = \begin{cases} (y - Q) \cdot c + (x - Q) \cdot (r - w) & \text{when } Q < y \text{ and } Q \leq x \\ (y - Q) \cdot c + (Q - x) \cdot v & \text{when } x < Q < y \\ (Q - y) \cdot (w - c) + (x - y) \cdot (r - w) & \text{when } Q \geq y \text{ and } x \geq y \\ (Q - y) \cdot (w - c) + (y - x) \cdot v & \text{when } x < y \leq Q \end{cases} \quad (5.5)$$

As $y = T \cdot u$, where u is a random variable, we get the formulas as equation 5.6:

$$f(Q, x, u) = \begin{cases} (T \cdot u - Q) \cdot c + (x - Q) \cdot (r - w) & \text{when } Q < T \cdot u \text{ and } Q \leq x \\ (T \cdot u - Q) \cdot c + (Q - x) \cdot v & \text{when } x < Q < T \cdot u \\ (Q - T \cdot u) \cdot (w - c) + (x - y) \cdot (r - w) & \text{when } Q \geq T \cdot u \text{ and } x \geq T \cdot u \\ (Q - T \cdot u) \cdot (w - c) + (T \cdot u - x) \cdot v & \text{when } x < T \cdot u \leq Q \end{cases} \quad (5.6)$$

The optimal decision model of the whole supply chain can be described as equation 5.7:

$$\min E[f(Q, x, u)] \quad (5.7)$$

s.t. $Q > 0$, Q is integer.

We use two methods to describe the uncertainty of the two variables, stochastic and fuzziness. When there is enough historical data from which we can get the probability distribution of yield and demand, we can use stochastic, otherwise, we can only get an interval from estimation of experts, then fuzziness is more appropriate. For the stochastic representation, we consider double uncertainty of the two variables and utilize Bayesian approach to specify uncertainty. Accordingly, we propose a hybrid intelligent algorithm for the case with two fuzzy variables.

5.3 Bayesian approach for representing double uncertainty of stochastic variables

As mentioned in previous section, unknown demand and yield are estimated by specialists. They are estimated primarily according to the knowledge to the industry and experiences of specialists. Unavoidably, there are some discrepancies to the practical condition. In immense literature, Bayesian approach is used recently to update prior distribution.

5.3.1 Description of Bayesian approach

The rule of Bayesian approach is as follows: Given prior distribution of a random variable, θ_j , is $P(\theta_j)$, supplemental information according to new investigations is e_k . Conditional distribution (degree of likelihood) of e_k is $P(e_k|\theta_j)$. Hence distribution of θ_j , under the condition of given information of e_k , i.e. the post distribution $P(\theta_j|e_k)$, is represented with Bayes formula:

$$P(\theta_j | e_k) = \frac{P(\theta_j) \cdot P(e_k | \theta_j)}{\sum_{j=1}^n P(\theta_j) \cdot P(e_k | \theta_j)} \quad (5.8)$$

It is intuitive that the Bayesian formula is appropriate to discrete distribution. For continuous distribution, it is also paid enormous attention (Choi *et al.*, 2006; Kamath & Pakkala, 2002; Yelland, 2010).

5.3.2 Modeling of stochastic demand and yield

Demand is assumed stochastic with PDF (probability density function) $g(x)$ and CDF (cumulative distribution function) $G(x)$ defined over the continuous interval $[0, \infty)$. $F(x)$ is differential, invertible and strictly increasing over I . Before the sale season begins, the capacity of production is determined, with quantity T . Yield y is random and proportional to T , i.e. $y = T \cdot u$, where u is stochastic product qualification ratio, independent of T . The CDF, $G(u)$, and PDF, $g(u)$, of u are in a space \wedge . $G(u)$ is assumed differential, invertible and strictly increasing over \wedge (Wang, 2009).

5.3.2.1 Product qualification ratio

In some research, the substandard products can be sorted out in time during the production process (Chan *et al.*, 2003; Chiu, 2006). In our work, we assume that inspection executes after the batch production. In the case where distribution of defective products can be obtained from historical data, the uncertainty of defective rate can be represented with stochastic variable. The usually used families of distribution, such as normal distribution, uniform distribution, Poisson distribution, Gamma distribution, etc, are considered to represent the probability distribution of uncertain demand. We utilize normal distribution in our work. As we known, normal distribution (also called Gaussian distribution) is often used as a first approximation to describe the real-valued random variables that tend to cluster around a single mean value. It is considered the most prominent probability distribution in statistics. There are several reasons: Firstly, the normal distribution is analytically tractable, that is, a large number of results involving this distribution can be derived in explicit form; Secondly, the normal distribution arises as the outcome of the central limit theorem, which states that under mild conditions the sum of a large number of random variables is distributed approximately normally; Thirdly, the “bell” shape of the normal distribution makes it a convenient choice for modeling a large variety of random variables encountered in practice.

Moreover, the normal distribution is a good representation even in the case of lack of historical data. We assume that the product qualification ratio follows a normal distribution with a mean μ_u and a variance σ_u^2 : $u \sim f_N(\mu_u, \sigma_u^2)$.

5.3.2.2 Uncertain demand

Different combination of demand and product qualification ratio distribution are used in literature. There are some commonly used combinations of demand and product qualification ratio distribution: {uniform, uniform} (Gavirneni *et al.*, 1998; Tiwari *et al.*, 2011; Wang, 2009); {gamma, uniform} (Boulaksil *et al.*, 2009). In the work of Tiwari *et al.* (2011), some propositions obtained from the model of uniform distribution are also supported by extensive numerical experiments for normal and lognormal distribution.

For preliminary study, we can use the form {normal, normal} to explain the calculation process.

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

Similar to the product qualification ratio, demand follows a normal distribution with a mean μ_x and a variance σ_x^2 : $x \sim f_N(\mu_x, \sigma_x^2)$.

5.3.3 Bayesian approach to represent double uncertainty of variables

As the distribution assumed in previous sections, the prior distribution is obtained according to historical data and experience of experts. We consider the parameters of the distribution described above, the mean and variance of normal distribution, μ_u, σ_u^2 and μ_x, σ_x^2 , which are for uncertain product qualification ratio and demand respectively, are also uncertain. We call the uncertainty of parameters as the second-level uncertainty. We adopt Bayesian approach to represent the entire uncertainty of variables.

The core spirit of Bayesian approach is information updating. Through information updating, we get the posterior distribution of uncertain variable. There are mainly two kinds of information updating: the direct information updating with new data and the indirect information updating.

5.3.3.1 Direct information updating

Direct information updating is the case where new data can be obtained to modify directly the prior distribution of uncertain variable.

Take the defective ratio for example. We can get the distribution of defective ratio according to the prior distribution which is obtained from historical data. From the pre-production or trial production, we can executive random sampling inspection. According to this information of inspection, the prior distribution can be modified and updated. The demand information can be updated similarly. When the sale data of pre-seasonal products collected from the market is close to seasonal product, we can use this data to update the distribution by Bayesian approach.

Example:

A retailer orders electronic components from a supplier of radio. According to historical experiences, the probability distribution of variety of qualification ratio is as shown in the third row of Table 5.1. Now before the new ordering, there

5.3 Bayesian approach for representing double uncertainty of stochastic variables

is information that the qualification ratio rises. Taking a random sampling of 10, from the finished products, it is founded that there is no defective product. Therefore, according to this information, update the probability distribution of product qualification ratio of the factory.

Table 5.1: Calculation of posterior distribution with direct information updating

Qualification ratio	0.95	0.90	0.85	0.80
defective ratio θ_j	0.05	0.10	0.15	0.20
Prior distribution $P(\theta_j)$	0.1	0.4	0.4	0.1
Likelihood $P(e_0 \theta_j)$	0.599	0.349	0.197	0.107
$P(\theta_j) \cdot P(e_0 \theta_j)$	0.0599	0.1359	0.0788	0.0107
Posterior distribution $P(\theta_j e_0)$	0.207	0.483	0.273	0.037

Under the conditional probability, the probability of the event (e_0) that there is 0 defective product in the sample of 10 obeys the binomial approximation. The likelihood can be calculated according to equation 5.9:

$$P(e_0|\theta_j) = C_1 0^0 p_j^0 (1 - p_j)^{10} \quad (j = 1, 2, \dots, 4) \quad (5.9)$$

where, $p_j = P(\theta_j)$.

The fourth row in Table 5.1 is the results of the formula above. Then we can calculate the posterior distribution according to Bayesian Formula mentioned in section 5.3.1, the results as in the final row of Table 5.1.

5.3.3.2 Indirect information updating

Different to direct information updating, in the case of indirect information updating, the newly collected data does not work directly on the prior distribution. Indirect information is more complex and universal than direct information updating. Thereby, we focus on the indirect information updating.

Assuming that parameters of normal distribution, both the mean μ_u and variance θ_u^2 are random variables, with normal distribution $N(\mu_1, \tau_1^2)$ and $N(\mu_2, \tau_2^2)$, respectively, called the prior distribution of μ_u and θ_u^2 .

In section 5.3.2, the normal distribution of product qualification ratio is denoted with $f_N(\mu_u, \theta_u^2)$. We call it the conditional distribution of u , based on certain mean μ_u and variance θ_u^2 . The prior distribution of product qualification

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

ratio with uncertain mean and variance is represented as $f(u)$:

$$\begin{aligned} f(u) &= \int_0^\infty \int_0^\infty g(u) \cdot f(\mu_u) f(\sigma_u^2) d(\mu_u) d(\sigma_u^2) \\ &= \int_0^\infty \int_0^\infty f_N(u|\mu_u, \sigma_u^2) \cdot f_N(\mu_u|\mu_1, \tau_1^2) \cdot f_N(\sigma_u^2|\mu_2, \tau_2^2) d(\mu_u) d(\sigma_u^2) = N(\mu_1 + \mu_2, \tau_1^2 + \tau_2^2) \end{aligned} \quad (5.10)$$

We use the newly collected value of \hat{u} , which can be obtained by a dynamic simulation of market, time-series forecasting method, or observed directly from the pre-seasonal market.

The posterior distributions of μ_u represented as

$$\hat{f}(\mu_u) = \frac{g(\hat{u}) \cdot f(\mu_u)}{f(\hat{u})} \quad (5.11)$$

where $g(\hat{u})$ and $f(\hat{u})$ can be derived from the conditional distribution and prior distribution with \hat{u} .

Finally, the posterior distribution of product qualification ratio u is updated:

$$\hat{f}(u) = \int_{-\infty}^\infty g(u) \cdot \hat{f}(\mu_u) d(\mu_u) \quad (5.12)$$

Besides the {normal, normal} combination distribution for the uncertain parameters, we can also use other types of distribution. E.g., inverse-gamma distribution is applied for the uncertain variance in (Choi *et al.*, 2006). The exponential distribution, gamma distribution, and Poisson distribution, are widely used as well. Some combination types may be complicated. It is hard to get an explicit expression for the posterior distribution. After information is updated, posterior distribution may keep the same kind of distribution as the prior one, just with the parameters changed, this case called conjugate distribution. The calculation is rather simple. Sometimes, after the information is updated, the type of distribution also changes, with an unusual distribution type, or even sometimes impossible to get the probability density function.

To facilitate calculation, the conjugate distribution is adopted in our work. We assume that after information updating, the posterior distribution of product qualification ratio is still a normal distribution.

Similarly, for probability distribution of demand with uncertain parameters,

the second level of uncertainty, i.e. the uncertain parameters, we calculate the prior distribution $h(x)$ and posterior distribution $\hat{h}(x)$, which are conjugate distributions.

5.3.4 Model of describing the problem with stochastic variables

Different from the model of (Wang, 2009), we consider the potential loss of both wholesaler and manufacturer. Since we focus on the decision variable, ordering quantity of wholesaler, Q , with the mathematical model of demand and product qualification ratio, the expected loss is expressed as a function of Q :

$$\begin{aligned}
 P(Q) &= E[f(Q, x, u)] \\
 &= \int_0^{Q/T} \left(\int_0^{uT} [(w - c)(Q - uT) + v(uT - x)]f(x)dx + \right. \\
 &\quad \left. \int_{uT}^{\infty} [(w - c)(Q - uT) + (r - w)(x - uT)]f(x)dx \right)g(u)du + \\
 &\quad \int_{Q/T}^{\infty} \left(\int_0^Q [c(uT - Q) + v(Q - x)]f(x)dx + \right. \\
 &\quad \left. \int_Q^{\infty} [c(uT - Q) + (r - w)(x - Q)]f(x)dx \right)g(u)du
 \end{aligned} \tag{5.13}$$

Strictly, the expected value of the potential loss of the supply chain expressed as the formula above is based on the theory as follows:

If the integrand $f(x)$ satisfies the condition that integral $\int_{-\infty}^{\infty} xf(x)dx$ is absolutely convergent, the expected value of x can be calculated by:

$$E[x] = \int_{-\infty}^{\infty} xf(x)dx \tag{5.14}$$

In another word, the integrand in equation above should satisfy the convergent condition. We assume that the integrands satisfy the condition. However, it is difficult to calculate the exact condition which parameters should satisfy. We keep the hypotheses to continue subsequent computation.

For this kind of problem, the best approach is using mathematical formulas to calculate directly the decision variable if it is in appropriate condition. Hence,

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

firstly, we validate attribution of the function, convexity, differentiability and so on.

Taking the first derivative of equation 5.13 w.r.t. Q , we get:

$$\begin{aligned} \frac{dP(Q)}{dQ} = & (w - c)(F(\infty) - F(0)) \int_0^{Q/T} g(u)du + \\ & [(c - v)(F(\infty) - F(0)) - (r - w)(F(\infty) - F(Q))] \int_{Q/T}^{\infty} g(u)du \end{aligned} \quad (5.15)$$

Generally, the usually used *CDF* types of demand (referring to the plots of the *cdf* of simulated demand in (Mostard *et al.*, 2005)), Normal, Lognormal and uniform distribution, are all with $F(\infty) = 1$, and $F(0) = 0$. Therefore, we simplify the equation above to:

$$\frac{dP(Q)}{dQ} = (w - c) \int_0^{Q/T} g(u)du + [(c - v) - (r - w)(1 - F(Q))] \int_{Q/T}^{\infty} g(u)du \quad (5.16)$$

The second derivative of equation 5.13 w.r.t Q is:

$$\frac{dP^2(Q)}{dQ^2} = (2w + v - r) \frac{1}{T} g\left(\frac{Q}{T}\right) \quad (5.17)$$

If $\frac{dP^2(Q)}{dQ^2} < 0$, $P(Q)$ is concave, otherwise $P(Q)$ is convex. Hence, we have to discuss the relation of the four parameters of price, c , w , v , r .

There is no definitive data for the relationship of the four kinds of price. It differs in case of different merchandize, industry, country, etc. The general principle is: for the products with low price or difficult to manage, the difference between wholesale price and retail price is rather lager than those with higher price. This makes variety of retail enterprize roughly have the same profit level. On average, the profit margin of merchandize is about 30%. We get some data from the internet. For example, from a survey of a Chinese teacher in July 2008, the retail price of vegetable in Hangzhou (a city in the east of China, close to Shanghai) is almost twice of the wholesale price. This difference is mainly caused by the inconvenient distribution channel of China. In the developed country, the difference of retail and wholesale price must be less than that in the developing country. We can easily estimate the price difference of merchandize in other industry with a higher price and longer life. Hence, we can infer that the average

price difference may be at the level of 30%, i.e. $w = r \cdot 70\%$.

Therefore, we can obtain: $\frac{dP^2(Q)}{dQ^2} > 0$, $P(Q)$ is convex.

$$\frac{dP(0)}{dQ} = [(c - v) - (r - w)(1 - F(Q))] \int_0^\infty g(u) du \quad (5.18)$$

$$\frac{dP(\infty)}{dQ} = (w - c) \int_0^\infty g(u) du \quad (5.19)$$

It is easily found that $\frac{dP(\infty)}{dQ} > 0$, as it is obvious that $w > c$ and $\int_0^\infty g(u) du > 0$.

Proposition 5.1 *Under the condition where $\frac{dP(0)}{dQ} < 0$, there exists a unique and finite $Q^* \in (0, \infty)$ that minimize $P(Q)$,*

Proof It is already proven that $P(Q)$ is convex and second-order derivative. If the first derivative of $P(Q)$, the minimum value of $P(Q)$ must exist and is unique.

We denote $a = 1 - F(Q)$, since $0 < F(Q) < 1$, we get $0 < a < 1$.

5.3.4.1 Discussion of relationship among different parameters of price

We discuss the relationship of each pair of two adjacent price parameters separately, i.e., the two kinds of price are in adjacent stages in supply chain. Before the discussion, we introduce some concepts used widely in price decision.

List price: is the price given before discounts, before rebates are subtracted and taxes added.

Net price: is the price after all discounts and rebates are subtracted from the list price.

In our work, to facilitate computation, we do not consider discounts. i.e., the price is independent of ordering quantity.

Retail price = Wholesale price \times (1 + markup percent).

Gross margin percent = markup/retail price.

Generally, the “margin” that we talk about is gross margin. Wholesaler and retailers usually have much more margin than manufacturer.

1) Manufacturing cost c and wholesale price w . As we know, generally, for manufacturer, 1 ~ 3% is low profit ratio; 3 ~ 5% is middle profit ratio; 5 ~ 8% is high profit ratio; and above 10% is profiteering (sudden huge profit). Some other industries may have higher profit ratio than this, such as garment typically between 10 ~ 15%, drugs with average 15%, etc. Of course, there are some

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

special industries that can earn much more than others, for example, the grand brand of luxury, jewelry, car, watch, etc. And also, the data differs in different country and region. In order to get universal data, we concentrate on consumer staples. Therefore, for general industry, e.g., drugs, electrical products, food, we give the price relationship separately, which is shown in Table 5.2. In order to give an intuitive example, we take drug for example. For drugs, $c = w \cdot 85\%$.

2) Wholesale price and retail price. Although there are usually some median distributors between wholesalers and retailers, we consider the case where retailers order merchandizes from wholesalers directly. There is a traditional formula for retailers to determine retail price: *retail price* = *wholesale price* \times 2. i.e., the gross margin percent is 50%. Because there are usually discounts promotions and some other reasons for decrease price, finally, the realized price may be less than initial one. Some quick searching turns up a couple of results indicating that typical retail markup is 40%, while for wholesale, average 30% margin on goods. Most grocery stores work on around 30% profit margin on their selling cost. For drugs, $w = r \cdot 85\%$, for other industries, refer to Table 5.2.

3) Retail price and salvage value. Salvage value (also named as residual value) is surely connected to the current market value of products. We can calculate it by multiplying current market value by Salvage Value Percentage. Salvage value percentage has large difference for distinct products. There is still not definitive value. Even for the same product, Salvage Value Percentage varies in different companies. For example, Salvage value percentage for fresh fruits and vegetables is 0, while for electronic equipment is about 10 ~ 20%. The salvage value of unsold merchandize is kind of different from the salvage value of depreciation products. In some degrees, the salvage value of unsold products is higher than that of depreciation products, for example, at the point of scrap value, the materials of unsold products which junk dealer can make use of are more valued than that of depreciation products. Moreover, in flea market, the unsold products can get better price than depreciation products. In addition, the unsold products can be resold in the discount season after the sale season. In that case, they can be resold with a price much higher than the salvage value. For example, some garments are resold with 30%, 50% or some other percentage in the next year in the discount season. There is no document indicating the

5.3 Bayesian approach for representing double uncertainty of stochastic variables

general partition of unsold products, either being resold or recycled. For drugs, the salvage value is typically 20 ~ 30%, i.e., $v = r \cdot 25\%$.

Table 5.2: Price relationship for different industries *

	Drug	Garment	Electrical product
$c - w$	$c = w * 85\%$	$c = w * 80\%$	$c = w * 70\%$
$w - r$	$w = r * 85\%$	$w = r * 50\%$	$w = r * 70\%$
$r - v$	$v = r * 25\%$	$v = r * 10\%$	$v = r * 20\%$

* result above is from drug statistic data from Internet.

5.3.4.2 Computation based on our hypothesis

With the estimation of relationship of prices in drug industry described above, we represent the other three kinds of price, v , c , w with r as: $c = 0.72r$; $w = 0.85r$; $v = 0.25r$. Therefore, equation 5.18 becomes:

$$\frac{dP(0)}{dQ} = (0.47r - 0.15r \cdot a) \int_0^\infty g(u) du \quad (5.20)$$

Since $0 < a < 1$, it is obvious that $\frac{dP(0)}{dQ} > 0$.

Unfortunately, the results are not as what we expected. Hence, we find that in the situation of our assumption, we cannot use the traditional method for calculating the extremum of function to calculate the optimal ordering quantity of wholesaler. However, in the situation opposite to our assumption, we can get the expected results $\frac{dP(0)}{dQ} < 0$, where $c - v < (r - w) \cdot a$.

Under the condition $c - v < (r - w) \cdot a$, we can obtain Proposition 5.1.

Denote $k = (c - v) - (r - w) \cdot a$, $k < 0$.

Set $\frac{dP(Q)}{dQ} = 0$, we get:

$$(w - c)[G(\frac{Q^*}{T}) - G(0)] = -k[G(\infty) - G(\frac{Q^*}{T})] \quad (5.21)$$

Similar to $F(\infty)$ and $F(0)$, we define $G(\infty) = 1$, $G(0) = 0$. Then,

$$G(\frac{Q^*}{T}) = -k/(w - c - k) \quad (5.22)$$

where

$$k = (c - v) - (r - w) \cdot a, k < 0 \quad (5.23)$$

$$F(Q^*) > (r - w)/(c - v) \tag{5.24}$$

$\because w - c > 0$ and $k < 0$

$\therefore -\frac{k}{w-c-k} \in (0, 1)$

i.e. $G(\frac{Q^*}{T}) \in (0, 1)$, so, there exist an unique Q^* to make $\frac{dP(Q)}{dQ} = 0$, which is represented in equation 5.22.

In order to calculate the optimal initial production capacity T^* , from equation 5.22, it is found that the distribution of demand $F(x)$ and distribution of yield loss $G(u)$ are needed. The two probability distributions can use the results of Bayesian approach, which completely represent double uncertainty of the two variables.

5.3.4.3 Discussion

In fact, when equation 5.23 is not satisfied, we substitute the original distribution of uncertain demand and qualification ratio to calculate the expression of expected loss, $E[f(Q, x, u)]$. We have tried both the normal distribution and continuous uniform distribution. Unfortunately, we cannot get the explicit expression for function of the expected loss. i.e., we cannot use the exact algorithm to derive the optimal ordering quantity. Therefore, we obtain the result:

Only under the condition, where $c - v < (r - w) \cdot a, 0 < a < 1$, we can use the exact mathematical method to calculate the optimal ordering quantity of wholesaler.

For the case where the assumption does not hold, we can use simulation approach to calculate the optimal ordering quantity of wholesaler, which is illustrated in the following section.

5.4 Uncertainty represented with fuzzy variable

In previous section, uncertain demand and product qualification ratio are both represented with random variable with distributions of known type. Nevertheless, it is founded that using Bayesian approach to forecast demand or qualification ratio is rather costly. Sometimes there are even lots of constricts in computation for its application. In addition, in most practical cases, there is not enough or reliable historical data, product qualification ratio can only depends on the rough

range estimated by some specialists. Therefore, we prefer to represent uncertain variables with fuzziness, which is studied a lot recently.

To deal with the decision problem with fuzzy information, the fuzzy set theory proposed by Zadeh (1965) and the credibility theory proposed by (Liu, 2006) are widely used.

5.4.1 Credibility theory

Zadeh (1978) proposed possibility theory as extension of his fuzzy set theory and fuzzy logic. There are two measures including possibility and necessary measure. As we know, a fuzzy event may fail even though its possibility achieves 1, and hold even though its necessity is 0 (Ji & Shao, 2006). However, in the credibility theory proposed by Liu (2006), the fuzzy event must hold if its credibility is 1 and fail if its credibility is 0.

Credibility theory proposed by Liu (2006) is a new branch of mathematics for studying the behavior of fuzzy phenomena. Since we use it for the calculation in later section, we introduce it briefly here.

5.4.1.1 Credibility measure and credibility space

From the credibility theory of Liu (2006), the possibility measure is the credibility measure, rather than probability measure. It is on the basis of the following five axioms.

Let Θ be a nonempty set, and let $P(\Theta)$ be the power set of Θ (i.e., all subsets of Θ). Each element in $P(\Theta)$ is called an event.

- 1) $Cr\{\Theta\} = 1$.
- 2) Cr is increasing, i.e., $Cr\{A\} \leq Cr\{B\}$ whenever $A \subset B$.
- 3) Cr is self-dual, i.e., $Cr\{A\} + Cr\{A_c\} = 1$ for any $A \in P(\Theta)$.
- 4) $Cr\{U_i A_i\} \wedge 0.5 = \sup_i Cr\{A_i\}$ for any $\{A_i\}$ with $Cr\{A_i\} \leq 0.5$.
- 5) Let Θ_k be nonempty sets on which Cr_k satisfies the first four axioms, $k = 1, 2, \dots, n$, respectively, and let $\Theta = \Theta_1 \times \Theta_2 \times \dots \times \Theta_n$. Then: $Cr\{(\theta_1, \theta_2, \dots, \theta_n)\} = Cr_1\{\theta_1\} \wedge Cr_2\{\theta_2\} \wedge \dots \wedge Cr_n\{\theta_n\}$, for each $(\theta_1, \theta_2, \dots, \theta_n) \in \Theta$.

5.4.1.2 Fuzzy simulation

Fuzzy simulation, developed by (Liu, 1998, 1999; Liu & Liu, 2002), was defined as a technique for conducting sampling experiments on models of fuzzy systems. Numerous numerical experiments showed that fuzzy simulation indeed works well for handling fuzzy systems (Liu, 2006).

Liu (2006) introduced the technique of simulation for computing credibility, finding critical values, and calculating expected value. Some researchers have applied this technology to numerical examples to analyze its effectiveness (Ji & Shao, 2006; Shao & Ji, 2006).

Let ξ be a fuzzy variable with membership function $\mu(u)$. According to the credibility theory of Liu (2006), the possibility, necessity, credibility measure of the fuzzy event $\xi \geq r$ can be represented respectively by:

$$Pos\{\xi \geq r\} = \sup_{u \geq r} \mu(u) \quad (5.25)$$

$$Nec\{\xi \geq r\} = 1 - \sup_{u < r} \mu(u) \quad (5.26)$$

$$Cr\{\xi \geq r\} = \frac{1}{2}[Pos\{\xi \geq r\} + Nec\{\xi \geq r\}] \quad (5.27)$$

We introduce the application of expected value, which is used in subsequent section.

Suppose that f is a function and $\boldsymbol{\xi} = (\xi_1, \xi_2, \dots, \xi_n)$ is a fuzzy vector with membership function μ . Randomly generate \mathbf{u}_k from the ε -level set of $\boldsymbol{\xi}$ for $k = 1, 2, \dots, N$. Then for any number $r \geq 0$, the credibility value $Cr\{f(\boldsymbol{\xi}) \geq r\}$ and $Cr\{f(\boldsymbol{\xi}) \leq r\}$ for any number $r < 0$ may be estimated by using the samples. After that, we may employ simulation to calculate the integral,

$$E[f(\boldsymbol{\xi})] = \int_0^{+\infty} Cr\{f(\boldsymbol{\xi}) \geq r\} dr - \int_{-\infty}^0 Cr\{f(\boldsymbol{\xi}) \leq r\} dr \quad (5.28)$$

Applying the equation of definition of credibility here, for any number $r \geq 0$, $Cr\{f(\boldsymbol{\xi}) \geq r\}$ can be estimated by equation 5.29:

$$Cr\{f(\boldsymbol{\xi}) \geq r\} = \frac{1}{2} \left[\max_{k=1,2,\dots,N} \{\mu_k | f(\boldsymbol{\xi}, \mathbf{u}_k) \geq r\} + 1 - \max_{k=1,2,\dots,N} \{\mu_k | f(\boldsymbol{\xi}, \mathbf{u}_k) < r\} \right] \quad (5.29)$$

For any number $r < 0$, $Cr\{f(\xi) < r\}$ can be estimated by equation 5.30:

$$Cr\{f(\xi) < r\} = \frac{1}{2} \left[\max_{k=1,2,\dots,N} \{\mu_k | f(\xi, \mathbf{u}_k) \leq r\} + 1 - \max_{k=1,2,\dots,N} \{\mu_k | f(\xi, \mathbf{u}_k) > r\} \right] \quad (5.30)$$

5.4.2 Solutions with fuzzy variables

For the model of equation 5.6 described in section 5.2, different from the representation with stochastic variables, the two variables, uncertain demand x and product qualification ratio u are both fuzzy numbers. To facilitate calculation, we consider both of them represented with triangular fuzzy numbers. Optimal ordering quantity Q is still the decision variable. Objective function is minimization of potential loss of the whole supply chain.

To solve the model with fuzzy variables, we combine genetic algorithm with fuzzy simulation to get a hybrid intelligent algorithm. The programs are as follows:

Step 1 For wholesalers, initialize the chromosome population of the first generation $Q = (Q_1, Q_2, \dots, Q_p)$ and validate the feasibility of chromosome, where, p is the population number.

Step 2 For every chromosome $Q_j (j = 1, 2, \dots, p)$, apply the fuzzy simulation to calculate the related profit $E(f_j)$, i.e. the fitness of every chromosome.

Step 3 According to fitness of chromosomes, we select them with the roulette wheel, and then apply the operations of cross and mutation to get a new generation.

Step 4 Repeat step 2 to step 3, and break out until the generation number G is achieved.

Step 5 Compare the fitness in the last generation, select the chromosome Q with the largest fitness value, which is exactly the best value obtained for the solution of ordering quantity of wholesaler.

In step 2, to calculate the fitness value $E(f_j)$, fuzzy simulation is used for the fuzzy variable's expected value. We refer to the fuzzy simulation of Liu (2002, 2003), which are used and illustrated by Ji & Shao (2006) and Shao & Ji (2006). The two papers applied fuzzy variable to address uncertain demand. Different from them, we have two different fuzzy variables, uncertain demand and uncertain product qualification ratio.

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

For our model with two fuzzy variables, the fuzzy simulation procedure described as follows:

- 1) For chromosome Q_j , set its fitness $E(f_j) = 0, j = 1, 2, \dots, p$;
- 2) Generate uniformly x_m from the range of fuzzy need x to make its possibility $Pos\{x_m\} \geq \varepsilon$ (where ε is a small enough number), and denote $v_m = Pos(x_m)(m = 1, 2, \dots, M)$; M is simulation generation number which corresponds to the intervals of demand variables; similarly generate uniformly u_l from the range of fuzzy product qualification ratio u to make its possibility $Pos\{u_l\} \geq \varepsilon$ (where ε is a small enough number), denote $v_l = Pos(u_l)(l = 1, 2, \dots, M)$.
 $\mu_m = x_m \wedge u_l$;
- 3) Set $a = \min_{1 \leq m, l \leq M} \{f(x_m, u_l, Q_j)\}$, $b = \max_{1 \leq m, l \leq M} \{f(x_m, u_l, Q_j)\}$;
- 4) Generate uniformly $r_n(n = 1, 2, \dots, N)$ from $[a, b]$, where N is a constant to subdivide the intervals;
- 5) If $r_n \geq 0$, compute the credibility

$$Cr\{f(x_m, u_l, Q_j) \geq r\} = \frac{1}{2}(\max_{1 \leq m, l \leq M} \{\mu_m | f(x_m, u_l, Q_j) \geq r\} + \min_{1 \leq m, l \leq M} \{1 - \mu_m | f(x_m, u_l, Q_j) < r\})$$
and set $E(f_j) \leftarrow E(f_j) + Cr\{f(x_m, u_l, Q_j) \geq r\}$;
if $r_n < 0$, the credibility

$$Cr\{f(x_m, u_l, Q_j) < r\} = 1/2(\max_{1 \leq m, l \leq M} \{\mu_m | f(x_m, u_l, Q_j) < r\} + \min_{1 \leq m, l \leq M} \{1 - \mu_m | f(x_m, u_l, Q_j) \geq r\})$$
and set $E(f_j) \leftarrow E(f_j) - Cr\{f(x_m, u_l, Q_j) < r\}$;
- 6) Set $E(f_j) \leftarrow \max(a, 0) + \min(b, 0) + E(f_j) \cdot (b - a)/N$.

5.4.3 Operations of genetic algorithm

In previous section, we have mentioned that we used genetic algorithm combined with fuzzy simulation to solve the problem. We explain the explicit operations of genetic algorithm.

1) Encoding of chromosome. We apply real value coding for chromosome. For this study, genes in chromosome represent directly demand quantity and qualification ratio.

2) Selection of chromosome. Since in this work, we keep the number of individuals in mating pool fixed as the population number, we adopt roulette wheel as selection method, which is good at choosing good performing individuals for generating offsprings.

3) Crossover of chromosome. We apply the Golden Selection method. Set Golden coefficient as θ . Select two chromosomes of wholesaler Q_k and Q_l to execute crossover operation, then the newly generated chromosomes are:

$$Q_m = \theta \cdot Q_k + (1 - \theta) \cdot Q_l$$

$$Q_n = \theta \cdot Q_l + (1 - \theta) \cdot Q_k$$

4) Mutation of chromosome. We use the constraints of upper and lower bounds to guarantee the feasibility of chromosome. Execute mutation operation for chromosome Q_m . Set the upper and lower bounds of demand for wholesaler is ξ_{max} and ξ_{min} respectively. To guarantee the feasibility of variables, which need to be scattered in the interval between upper and lower bounds, mutation procedure is executed as follows:

$$Q_n = \xi_{max} + \xi_{min} - Q_m$$

5.5 Numerical examples

The instance we apply is similar to that in [Shao & Ji \(2006\)](#). As the originality of the problem, there is no benchmark. Hence we initialize the data we need to complete the examples. Demand of market is considered as a fuzzy triangular variable $D = [310, 350, 380]$ (cases), fuzzy product qualification ratio with triangular variable $R = [0.9, 0.95, 1.0]$. The other parameters are as follows: $c = 28\text{€}$, $r = 40\text{€}$, $v = 10\text{€}$, $w = 34\text{€}$, $T = 400$ (cases).

As the parameters of prices do not satisfy the condition of applying Bayesian approach in section [5.3.2](#), we apply fuzzy simulation method to solve it. Through application on the examples, we demonstrate the effectiveness of fuzzy simulation method. We use Matlab R2007b to program, performed on a personal computer configured with Intel Core 2 CPU 2.13 GHz.

Initial generation population is 100; generation number is 200; with 200 random number in fuzzy simulation.

Results of computation show that the best value of ordering quantity of wholesaler is 345 cases, with the expected potential loss is almost 1114€. The convergence curve is as shown in [Figure 5.1](#).

Because the result of fuzzy simulation is random, the final result of potential loss is not constant. We execute the program 100 times to investigate the difference. Results are shown in [Figure 5.2](#). we can see that the optimal ordering

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

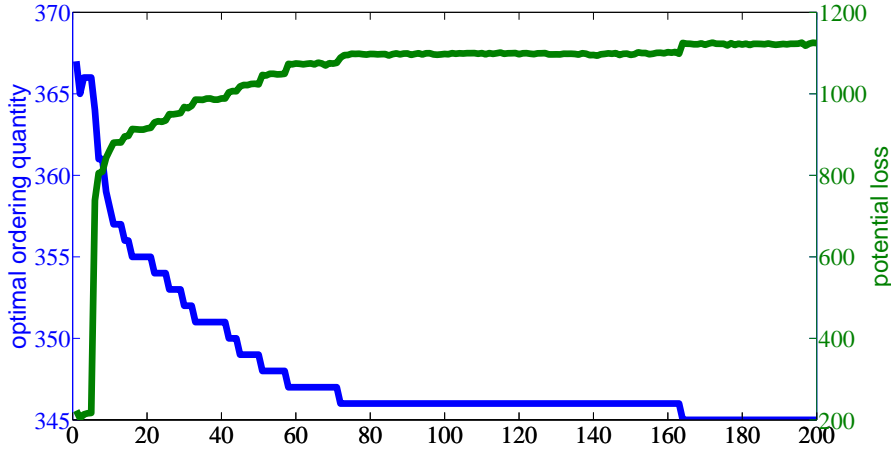


Figure 5.1: Results of computation with GA

quantity does not change much while potential loss varies between 1100 and 1200. The averages are 345.2 and 1126.7 separately.

Next, we change the prices to analyze their impacts to our results. When one parameter changes, the other parameters keep the default value given above. For all of the following experiments, we execute the program 100 times to get an average value of the optimal ordering quantity and potential loss.

1) Change wholesale price w .

Keeping the other parameters as default value, when wholesale price decreases, wholesaler's profit will increase, but manufacturer's profit will decrease. Therefore, we do not know the change of the summation of potential loss of the two. That is, we cannot obtain directly the relationship between potential loss and wholesale price. Results of experiments are shown in Figure 5.3 and Table 5.3. We test 9 different wholesale prices, from 30 to 38. With each value of wholesale price, we execute the program to the optimal ordering quantity and potential loss. From the results, we can see that optimal ordering quantity value changes little between 345 and 346, potential loss between 1100 and 1140. Both of them do not change much. Moreover, the overall trend of potential loss is smaller with increase of wholesale price; on the contrary, ordering quantity is larger.

2) Change retail price r . From the formula of our model, we can see that potential loss is proportional to retail price. When other parameters keep constant and retail price decreases, the potential loss will decrease. When retail price

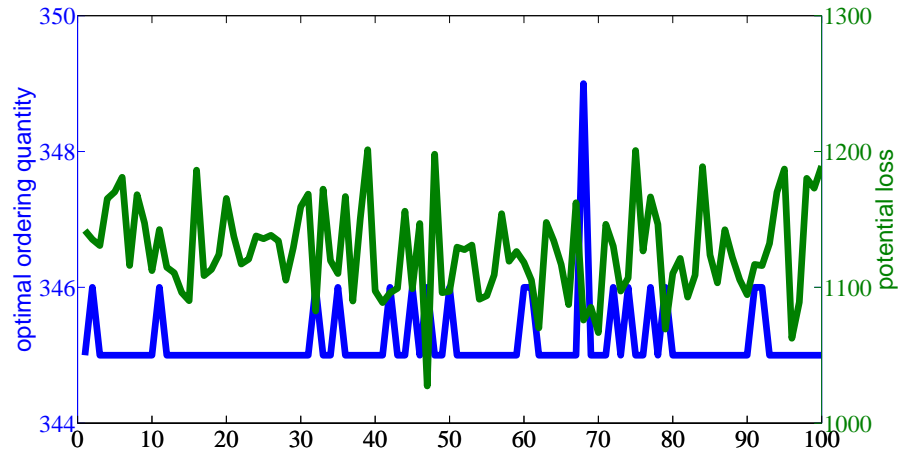


Figure 5.2: Results of executing 100 times

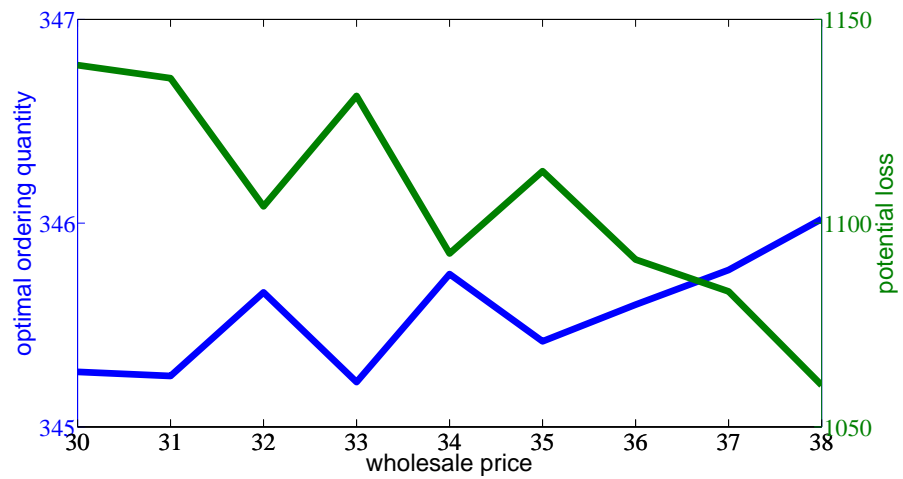


Figure 5.3: Change with different wholesale price

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

Table 5.3: Results of optimal ordering quantity and potential loss with different wholesale price

Wholesale price	Potential loss	Ordering quantity
30	1138.8	345.3
31	1135.6	345.3
32	1104.1	345.7
33	1131.2	345.2
34	1092.6	345.8
35	1112.8	345.4
36	1091.1	345.6
37	1083.2	345.8
38	1060.2	346.0

increases, the potential loss will increase. But we do not know the change of ordering quantity in advance. The results or experiments of increasing r from 38 to 46 are shown in Figure 5.4 and Table 5.4, from which we can observe that potential loss increases with increasement of retail price. Like that in experiment 1, the trend of potential loss is contrary to that of ordering quantity.

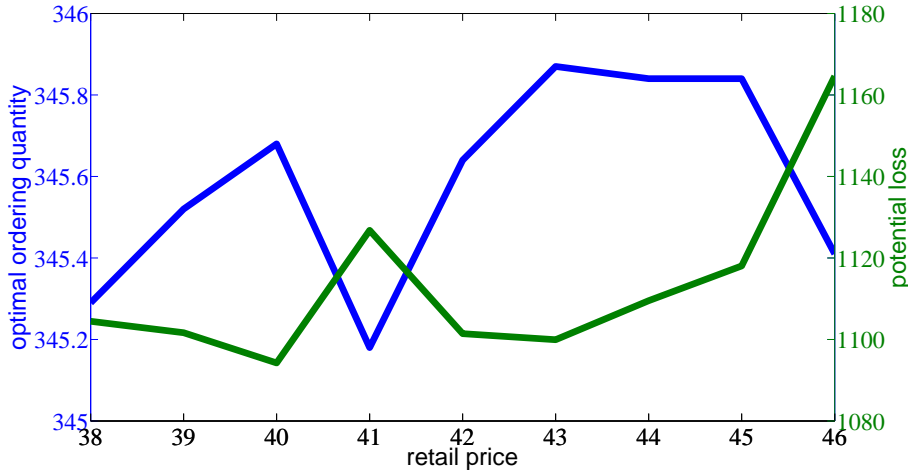


Figure 5.4: Change with different retail price

3) Narrow the range of variation of demand D . It means the variance of fuzzy demand is smaller than the original one used in precedent experiment. We test with different values of fuzzy number D : $D_1 = [290350380]$, $D_2 = [300350380]$, $D_3 = [310350360]$, $D_4 = [310350370]$, $D_5 = [310350380]$, $D_6 = [310350390]$, $D_7 = [310350400]$, with unit being cases. We expect that the optimal

Table 5.4: Results of optimal ordering quantity and potential loss with different retail price

Retail price	Potential loss	Ordering quantity
38	1104.5	345.3
39	1101.7	345.5
40	1094.2	345.7
41	1126.8	345.2
42	1101.4	345.6
43	1099.9	345.9
44	1109.5	345.8
45	1118.1	345.8
46	1164.6	345.4

ordering quantity will increase with larger range of demand. Result of simulation illustrated in Figure 5.5 and Table 5.5. From the results, we can find that when the range increases, the optimal ordering quantity also increases, which coincides with our expectation. The trend of potential loss is also contrary to that of optimal ordering quantity.

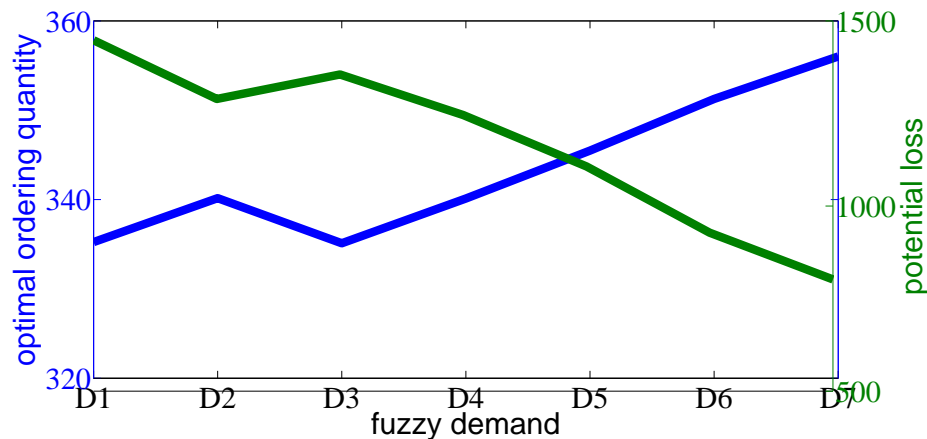


Figure 5.5: Comparison with different fuzzy demand

4) Change the fuzzy qualification ratio of product R . From the formula of our model, although we cannot find out the relationship of the results with qualification ratio of products, we can infer that when other parameters keep constant and qualification ratio increases, potential loss of manufacturer will grow because of excess production. We test with different values of R : $R_1 = [0.88, 0.95, 1]$, $R_2 = [0.89, 0.95, 1]$, $R_3 = [0.90, 0.94, 1]$, $R_4 = [0.9, 0.95, 1]$, $R_5 = [0.91, 0.95, 1]$,

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

Table 5.5: Results of optimal ordering quantity and potential loss with different fuzzy demand

Fuzzy demand	Potential loss	Ordering quantity
D1=[290 350 380]	1447.7	335.2
D2=[300 350 380]	1289.1	340.2
D3=[310 350 360]	1355.4	335.1
D4=[310 350 370]	1245.7	340.1
D5=[310 350 380]	1106.9	345.5
D6=[310 350 390]	927.8	351.3
D7=[310 350 400]	801.7	356.0

$R_6 = [0.92, 0.95, 1]$, $R_7 = [0.93, 0.95, 1]$. Results of experiments are shown in Figure 5.6 and Table 5.6. From the results, we obtain that potential loss increase with increase of qualification ratio, which is consistent with our speculation. Similar to precedent experiments, when potential loss increases, optimal ordering quantity decreases.

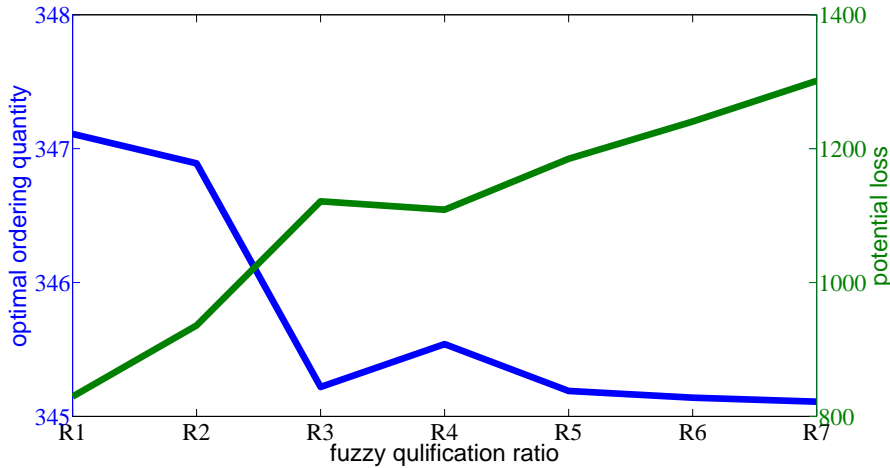


Figure 5.6: Comparison with different qualification ratio

Discussions

We achieve the objective of obtaining optimal ordering quantity. Under the situation where parameters, T , w , r , c , v , and fuzzy variables, D , R , are given, we can calculate the decision variable effectively.

Table 5.6: Results of optimal ordering quantity and potential loss with different qualification ratio

Qualification ratio	Potential loss	Ordering quantity
R1=[0.88 0.95 1]	829.7	347.1
R2=[0.89 0.95 1]	935.9	346.9
R3=[0.9 0.94 1]	1121.3	345.2
R4=[0.9 0.95 1]	1108.8	345.5
R5=[0.91 0.95 1]	1184.8	345.2
R6=[0.92 0.95 1]	1240.5	345.1
R7=[0.93 0.95 1]	1301.2	345.1

From the initial test and all the following experiments above, it is easy to find that the potential loss and optimal ordering quantity are contrary. This coincides with the phenomenon in practice that we need large inventory to obtain good profit and small loss. We expect to obtain less loss and small ordering quantity. Unfortunately, this is impossible. Therefore, a trade-off value is needed. Among the four factors, fuzzy demand influences most the final results, both the potential loss and optimal ordering quantity; followed by fuzzy qualification ratio and retail price; the factor with minimum impact is wholesale price. Therefore, the estimation of demand of market is especially important. The two prices are the factors the decision maker can control; an optimal price policy should be negotiated. The optimal trade-off value is at the point of intersection: the rough values are: $w = 36.8$, $r = 40.6$, $D = [310350380]$, $R = [0.89, 0.94, 1]$, the other parameters are still default. We get again the optimal quantity with 345 cases. The potential loss decreases to 997.2. It seems that the parameters we used here are reasonable. However, we do not consider the relationship between demand and retail price. For further research, we can consider it in problem model.

5.6 Conclusions

In this chapter, we illustrate the procedure of using two different methods to solve the bi-level newsboy problem with uncertain demand and uncertain product qualification ratio. We have demonstrated that Bayesian approach is suitable for representing double uncertainty of variables. Actually, we can say that Bayesian approach is also a kind of forecasting method. It is obvious that it costs more

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

than normal forecasting since it needs information updating. If the potential cost-saving is larger than forecasting cost, we can consider adopting the Bayesian approach; otherwise, we should use directly the prior information. From the research of [Lee \(2008\)](#), there is a threshold value of forecast.

Application of hybrid genetic algorithm with fuzzy simulation in numerical examples demonstrates the effectiveness of this method. We have found the relationship between the different parameters and objective function. Furthermore, we observe that the objective function of potential loss of this bi-level newsboy problem is not completely consistent with decision making in reality. From this point, objective function of maximization of profit is more intuitive. Therefore, we suggest using maximization of profit as objective function.

For future research, we can consider the newsboy problem under situation where there is competition among several newsboys. Then the uncertain product qualification ratio may result from competition. Combination of the two representations of uncertainty, the stochastic and fuzzy method, will also be interesting.

Conclusions and Perspectives

Our work is surrounding uncertainty in supply chain management (SCM). Uncertainty is ignored in conventional SCM, which is not suitable for practical situation. We center on this research to give a systematic research about uncertainty in SCM and attempt to propose a reference for research in this domain.

In any stage in supply chain, there exist uncertainty which may impact performance of activity in supply chain. We focus on uncertainty in three primary stages in supply chain, uncertainty in demand, uncertainty in manufacturing and uncertainty in distribution. For these different kinds of uncertainty, we analyze each of them in detail, their influence, cause, and measure to deal with them when they occur in create problems. Furthermore, we tried to test performance of our approaches proposed through numerical examples. Research of uncertainty in the three different stages is actually not strictly parallel as they are not independent. Certainly distinct sorts of uncertainty are probably independent, e.g., only uncertainty in demand needs to be considered when we focus on analysis of marketing. However, they may interact each other in the case of overall consideration of supply chain, where they should be considered simultaneously and even interaction analysis needed. This point of view is confirmed in the last chapter of this thesis where uncertainty of both demand and supply is taken into account in bi-level newsboy problem. This part is also an attempt of treating uncertainty in concrete supply chain management problem, in which uncertainty in treated concretely, with particular approach to represent uncertainty of decision variables.

In addition to concrete approaches to cope with uncertainty of variables in decision problem, for treating uncertainty in the three main stages in supply chain, we proposed different strategies. For uncertainty in demand, we suggested a postponement strategy to obtain optimal allocation of supply quantity to each supplier in the chain. This prove to be a flexible strategy in allocation of goods to

5. UNCERTAINTY OF DEMAND AND YIELD IN BI-LEVEL NEWSBOY PROBLEM

demanders to satisfy demand. Through experiments, we found that this strategy is also suitable to optimization for normal supply problem. Treating uncertainty in distribution can be regarded as an extension work for executing this strategy. Distribution, as the execution stage of supply, is not easy to control as it contacts much with external world outside of supply chain, such as route condition which we mentioned in fourth chapter of this thesis. The preliminary part in distribution is transportation, in which uncertainty occurs mainly due to uncertainty of clients' request. There are also some other factors causing uncertainty in transport, but we cannot take into account every aspect. We find that in the model of unpaired vehicle routing problem with pickups and deliveries (VRPPD), disadvantage caused by uncertainty of clients' request can be mitigated. For solving the problem, we apply a grouping genetic algorithm (GGA). To our knowledge, this is the first attempt of using metaheuristic to solve unpaired VRPPD. We are very honored to replace this research gap in solving unpaired VRPPD. Obviously, improved algorithm can be endeavored in future research.

For manufacturing, we concentrate on flexible job shop as it is an appropriate mode for demand of modern consumer market. To cope with unavailability of machines, which is the main uncertainty in manufacturing system, we suggest applying condition based maintenance (CBM). CBM is a category of preventive maintenance (PM), with monitoring as data basis. The scheduling problem in this mode of manufacturing system is modeled as FJSSPM (flexible job shop scheduling problem with preventive maintenance). The dynamic attribute of CBM makes the problem suitable for normal period of manufacturing and maintenance execution period as well. Firstly, we obtain a preschedule through solving normal FJSP (flexible job shop scheduling problem). When maintenance is needed, insertion algorithm is applied to add maintenance tasks. Different algorithms are proposed to solve the problem. We obtain a better result than that in literature with our proposed integrated genetic algorithm (IGA) on an experiment of benchmark in FJSP. Performance of other algorithms is also tested. Results of experiments showed that we have obtained effective approach for solving the problem.

The concrete problems we focused on, e.g., FJSPPM and unpaired VRPPD, are NP hard problems. The method we used most to solve the problem is genetic algorithm. As a widely used metaheuristic, it performs well while solving our problems. In solving FJSPPM, it is found better performing than ant colony

optimization (ACO). Recently the growing trend is combining GA with other methods in solving optimization problem. In next research period, we will attempt to improve the approach as well.

Limitation of our research exist unavoidably. As originality of some of our problems, when we use the benchmark we have to change or add some parameters to complete the problem. This makes the problem unique, therefore, we can not compare our result with others. We hope that there are some other researchers interested in our problematic experiment and then we can compare the performance of our approaches.

For future research, we would like to endeavor in the domain of applying our strategy and particularly of treating uncertain variables in some projects of real problems. We hope this theoretical research can contribute to the practical problems in supply chain management. Furthermore, for the problem of calculating supply cost in applying strategy of postponement, the objective function can be improved, other factors can be taken into account; even multi objective model could be considered. For research of uncertainty in distribution, change of clients' requests can be quantified into the problem, and benchmark for experiments is needed.

Bibliography

- ABDEL-MALEK, L., MONTANARI, R. & MENEGHETTI, D. (2008). The capacitated newsboy problem with random yield: The gardener problem. *International Journal of Production Economics*, **115**, 113–127. [143](#), [146](#)
- AL-NAJJAR, B. (1991). On the selection of condition based maintenance for mechanical systems. *Operational Reliability and System Maintenance*, 153–73. [76](#)
- AL-SABA, T. & EL-AMIN, I. (1999). Artificial neural networks as applied to long-term demand forecasting. *Artificial Intelligence in Engineering*, **13**, 189–197. [47](#)
- ALDERSON, W. (2006). Marketing efficiency and the principle of postponement. *A Twenty-First Century Guide to Aldersonian Marketing Thought*, 109–113. [49](#)
- ALFA, A. (1987). A heuristic algorithm for the travelling salesman problem with time-varying travel costs. *Engineering Optimization + A35*, **12**, 325–338. [44](#), [120](#)
- ALVARENGA, G., MATEUS, G. & DE TOMI, G. (2007). A genetic and set partitioning two-phase approach for the vehicle routing problem with time windows. *Computers & Operations Research*, **34**, 1561–1584. [127](#)
- ANILY, S. & BRAMEL, J. (1999). Approximation algorithms for the capacitated traveling salesman problem with pickups and deliveries. *Naval Research Logistics*, **46**, 654–670. [128](#)
- ANUPINDI, R. & AKELLA, R. (1993). Diversification under supply uncertainty. *Management Science*, 944–963. [32](#)

BIBLIOGRAPHY

- ARCHETTI, C., SAVELSBERGH, M. & SPERANZA, M. (2006). Worst-case analysis for split delivery vehicle routing problems. *Transportation Science*, 226–234. [127](#)
- ASCHER, W. (1979). Forecasting, an appraisal for policy-makers and planners. [35](#)
- AVEN, T. (1996). Condition based replacement policies—a counting process approach. *Reliability Engineering & System Safety*, **51**, 275–281. [76](#)
- AVIV, Y. & FEDERGRUEN, A. (1999). The benefits of design for postponement. *International Series In Operations Research and Management Science*, 553–584. [51](#)
- BALDACCI, R., HADJICONSTANTINO, E. & MINGOZZI, A. (2004). An exact algorithm for the capacitated vehicle routing problem based on a two-commodity network flow formulation. *Operations Research*, 723–738. [125](#)
- BARAD, M. & EVEN, S. (2003). Flexibility in logistic systems-modeling and performance evaluation. *International Journal of Production Economics*, **85**, 155–170. [37](#), [38](#)
- BATES, J. & GRANGER, C. (1969). The combination of forecasts. *OR*, 451–468. [36](#)
- BENGTSSON, M. (2002). Condition based maintenance on rail vehicles—a. *IDPMTR*, **2**, 06. [76](#)
- BENT, R. & HENTENRYCK, P. (2006). A two-stage hybrid algorithm for pickup and delivery vehicle routing problems with time windows. *Computers & Operations Research*, **33**, 875–893. [126](#)
- BERKOUNE, D. (2005). *Optimisation de l'ordonnancement prenant en compte les tâches prévisionnelles*. Ph.D. thesis. [108](#), [110](#)
- BERRICHI, A., YALAOUI, F., AMODEO, L. & MEZGHICHE, M. (2010). Bi-objective ant colony optimization approach to optimize production and maintenance scheduling. *Computers & Operations Research*, **37**, 1584–1596. [75](#)

- BERTSIMAS, D., CHERVI, P., PETERSON, M. & OF MANAGEMENT, S.S. (1991). *Computational approaches to stochastic vehicle routing problems*. Sloan School of Management, Massachusetts Institute of Technology. [127](#)
- BIANCHI, L., BIRATTARI, M., CHIARANDINI, M., MANFRIN, M., MASTROLILLI, M., PAQUETE, L., ROSSI-DORIA, O. & SCHIAVINOTTO, T. (2004). Metaheuristics for the vehicle routing problem with stochastic demands. In *Parallel Problem Solving from Nature-PPSN VIII*, 450–460, Springer. [127](#)
- BOONYATHAN, P. & POWER, D. (2007). The impact of supply chain uncertainty on business performance and the role of supplier and customer relationships: Comparison between product and service organizations. In *Proceedings of the DSI Mini Conference on Service Management, Pittsburgh (USA)*. [32](#), [34](#)
- BOULAKSIL, Y., FRANSOO, J. & TAN, T. (2009). Capacity reservation and utilization for a manufacturer with uncertain capacity and demand. *The Netherlands: School of Industrial Engineering, Eindhoven University of Technology*. [146](#), [149](#)
- BRANDIMARTE, P. (1993). Routing and scheduling in a flexible job shop by tabu search. *Annals of Operations Research*, **41**, 157–183. [73](#)
- BRAYSY, O. & GENDREAU, M. (2005). Vehicle routing problem with time windows, part ii: Metaheuristics. *Transportation science*, **39**, 119–139. [125](#)
- BRENNAN, L., GUPTA, S. & TALEB, K. (1994). Operations planning issues in an assembly/disassembly environment. *International Journal of Operations & Production Management*, **14**, 57–67. [40](#)
- BRUCKER, P. & SCHLIE, R. (1990). Job-shop scheduling with multi-purpose machines. *Computing*, **45**, 369–375. [73](#)
- BULLNHEIMER, B., HARTL, R. & STRAUSS, C. (1999). An improved ant system algorithm for the vehicle routing problem. *Annals of Operations Research*, **89**, 319–328. [89](#)
- BURNS, T. & STALKER, G. (2009). The management of innovation. *SSRN eLibrary*. [40](#)

BIBLIOGRAPHY

- CAMPUZANO, F., MULA, J. & PEIDRO, D. (2010). Fuzzy estimations and system dynamics for improving supply chains. *Fuzzy Sets and Systems*, **161**, 1530–1542. [35](#)
- CARICATO, P., GHIANI, G., GRIECO, A. & GUERRIERO, E. (2003). Parallel tabu search for a pickup and delivery problem under track contention. *Parallel Computing*, **29**, 631–639. [126](#)
- CASCO, D., GOLDEN, B. & WASIL, E. (1988). Vehicle routing with backhauls: models, algorithms and case studies. *Vehicle routing: methods and studies*, 127–147. [122](#)
- CHAN, W., IBRAHIM, R. & LOCHERT, P. (2003). A new epq model: integrating lower pricing, rework and reject situations. *Production Planning & Control*, **14**, 588–595. [149](#)
- CHEN, F., DREZNER, Z., RYAN, J. & SIMCHI-LEVI, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management science*, 436–443. [35](#)
- CHEN, Z. & XU, H. (2006). Dynamic column generation for dynamic vehicle routing with time windows. *Transportation Science*, 74–88. [45](#), [120](#)
- CHIANG, W. & RUSSELL, R. (1996). Simulated annealing metaheuristics for the vehicle routing problem with time windows. *Annals of Operations Research*, **63**, 3–27. [125](#)
- CHIU, Y. (2006). The effect of service level constraint on epq model with random defective rate. *Mathematical Problems in Engineering*, **2006**, 1–13. [149](#)
- CHOI, J., REALFF, M. & LEE, J. (2005). Stochastic dynamic programming with localized cost-to-go approximators: Application to large scale supply chain management under demand uncertainty. *Chemical Engineering Research and Design*, **83**, 752–758. [35](#)
- CHOI, T., LI, D. & YAN, H. (2006). Quick response policy with bayesian information updates. *European journal of operational research*, **170**, 788–808. [148](#), [152](#)

- CHRISTER, A., WANG, W. & SHARP, J. (1997). A state space condition monitoring model for furnace erosion prediction and replacement. *European Journal of Operational Research*, **101**, 1–14. [76](#)
- CHRISTOFIDES, N., MINGOZZI, A. & TOTH, P. (1981). Exact algorithms for the vehicle routing problem, based on spanning tree and shortest path relaxations. *Mathematical programming*, **20**, 255–282. [124](#)
- CIARALLO, F., AKELLA, R. & MORTON, T. (1994). A periodic review, production planning model with uncertain capacity and uncertain demand-optimality of extended myopic policies. *Management Science*, 320–332. [143](#)
- COLLOPY, F. & ARMSTRONG, J. (1992). Rule-based forecasting: Development and validation of an expert systems approach to combining time series extrapolations. *Management Science*, 1394–1414. [36](#)
- COLORNI, A., DORIGO, M., MANIEZZO, V. *et al.* (1992). An investigation of some properties of an ant algorithm. In *Proceedings of the Parallel Problem Solving from Nature Conference (PPSN 92)*, 509–520, Elsevier Publishing. [89](#)
- COLORNI, A., DORIGO, M., MANIEZZO, V. & TRUBIAN, M. (1994). Ant system for job-shop scheduling. *Belgian Journal of Operations Research, Statistics and Computer Science*, **34**, 39–53. [89](#)
- CORDEAU, J., LAPORTE, G. & MERCIER, A. (2001). A unified tabu search heuristic for vehicle routing problems with time windows. *Journal of the Operational Research Society*, 928–936. [125](#)
- CORDEAU, J., GENDREAU, M., HERTZ, A., LAPORTE, G. & SORMANY, J. (2005). New heuristics for the vehicle routing problem. *Logistics systems: design and optimization*, 279–297. [125](#)
- CVSA, V. & GILBERT, S. (2002). Strategic commitment versus postponement in a two-tier supply chain. *European Journal of Operational Research*, **141**, 526–543. [50](#)
- CZECH, Z. & CZARNAS, P. (2002). Parallel simulated annealing for the vehicle routing problem with time windows. In *Parallel, Distributed and Network-based*

BIBLIOGRAPHY

- Processing, 2002. Proceedings. 10th Euromicro Workshop on*, 376–383, IEEE. [125](#)
- DANTZIG, G. & RAMSER, J. (1959). The truck dispatching problem. *Management science*, 80–91. [122](#)
- DAUZÈRE-PÉRÈS, S. & PAULLI, J. (1997). An integrated approach for modeling and solving the general multiprocessor job-shop scheduling problem using tabu search. *Annals of Operations Research*, **70**, 281–306. [73](#)
- DAVID, C. & PETER, L. (1994). Modeling the evolution of demand forecasts with application to safety stock analysis in production/distribution systems. *IIE transactions*, **26**, 17–30. [35](#), [37](#)
- DAVIS, T. (1993). Effective supply chain management. *Sloan management review*, **34**, 35–35. [31](#)
- DEO, S. & CORBETT, C. (2010). Dynamic allocation of scarce resources under supply uncertainty. [32](#), [33](#)
- DESAULNIERS, G., DESROSIERS, J., ERDMANN, A., SOLOMON, M. & SOUMIS, F. (2002). Vrp with pickup and delivery. *The vehicle routing problem*, **9**, 225–242. [126](#)
- DESROCHERS, M., LENSTRA, J., SAVELSBERGH, M. & SOUMIS, F. (1987). Vehicle routing with time windows: Optimization and approximation. Tech. rep., Department of Operations Research and System Theory, Centrum voor Wiskunde en Informatica. [127](#)
- DESROSIERS, J., SOUMIS, F., DESROCHERS, M. & SAUVÉ, M. (1986). Vehicle routing and scheduling with time windows. *Netflow at Pisa*, 249–251. [122](#)
- DORIGO, M. & GAMBARDILLA, L. (1997). Ant colony system: A cooperative learning approach to the traveling salesman problem. *Evolutionary Computation, IEEE Transactions on*, **1**, 53–66. [89](#)
- DORNDORF, U. & PESCH, E. (1995). Evolution based learning in a job shop scheduling environment. *Computers & Operations Research*, **22**, 25–40. [85](#)

- DREYER, B. & GRØNHAUG, K. (2004). Uncertainty, flexibility, and sustained competitive advantage. *Journal of Business Research*, **57**, 484–494. [31](#)
- DROR, M., FORTIN, D., ROUCAIROL, C. *et al.* (1998). Redistribution of self-service electric cars: A case of pickup and delivery. [128](#)
- DUMAS, Y., DESROSIERS, J. & SOUMIS, F. (1991). The pickup and delivery problem with time windows. *European Journal of Operational Research*, **54**, 7–22. [126](#)
- DUNCAN, O., FEATHERMAN, D. & DUNCAN, B. (1972). Socioeconomic background and achievement. Seminar Press New York. [41](#)
- EDGEWORTH, F. (1888). The mathematical theory of banking. *Journal of the Royal Statistical Society*, **51**, 113–127. [142](#)
- EHRHARDT, R. & TAUBE, L. (1987). An inventory model with random replenishment quantities. *International Journal of Production Research*, **25**, 1795–1803. [143](#)
- EPPEN, G. & MARTIN, R. (1988). Determining safety stock in the presence of stochastic lead time and demand. *Management Science*, 1380–1390. [37](#)
- ERIC LI, Y. & SHAW, W. (1998). Simulation modeling of a dynamic job shop rescheduling with machine availability constraints. *Computers & industrial engineering*, **35**, 117–120. [76](#)
- FALKENAUER, E. (1998). *Genetic algorithms and grouping problems*. John Wiley & Sons, Inc. [128](#), [136](#)
- FATTAHI, P., SAIDI MEHRABAD, M. & JOLAI, F. (2007). Mathematical modeling and heuristic approaches to flexible job shop scheduling problems. *Journal of Intelligent Manufacturing*, **18**, 331–342. [74](#), [81](#)
- FLEISCHMANN, B., GNUTZMANN, S. & SANDVOSS, E. (2004). Dynamic vehicle routing based on online traffic information. *Transportation science*, **38**, 420–433. [120](#)

BIBLIOGRAPHY

- FLYVBJERG, B. (2005). Measuring inaccuracy in travel demand forecasting: methodological considerations regarding ramp up and sampling. *Transportation Research Part A: Policy and Practice*, **39**, 522–530. [35](#)
- FLYVBJERG, B. (2008). Curbing optimism bias and strategic misrepresentation in planning: Reference class forecasting in practice. *European Planning Studies*, **16**, 3–21. [35](#), [36](#)
- FLYVBJERG, B., HOLM, M. & BUHL, S. (2005). How (in) accurate are demand forecasts in public works projects?: The case of transportation. *Journal of the American Planning Association*, **71**, 131–146. [35](#)
- FOSTER, B. & RYAN, D. (1976). An integer programming approach to the vehicle scheduling problem. *Operational Research Quarterly*, 367–384. [122](#)
- FREY, H. & RHODES, D. (1998). Characterization and simulation of uncertain frequency distributions: Effects of distribution choice, variability, uncertainty, and parameter dependence. *Human and Ecological Risk Assessment*, **4**, 423–468. [43](#)
- FU, L. (2002). Scheduling dial-a-ride paratransit under time-varying, stochastic congestion. *Transportation Research Part B: Methodological*, **36**, 485–506. [44](#), [45](#), [120](#)
- FUKASAWA, R., LONGO, H., LYSGAARD, J., ARAGÃO, M., REIS, M., UCHOA, E. & WERNECK, R. (2006). Robust branch-and-cut-and-price for the capacitated vehicle routing problem. *Mathematical programming*, **106**, 491–511. [125](#)
- GALLEGO, G. (1995). The newsvendor problem. *IEOR course of Columbia University*. [142](#), [143](#)
- GAMBARDELLA, L. & DORIGO, M. (1997). Has-sop: Hybrid ant system for the sequential ordering problem. [89](#)
- GAMBARDELLA, M. & MASTROLILLI, M. (1996). Effective neighborhood functions for the flexible job shop problem! *Journal of Scheduling*, **3**, 3. [73](#)
- GANG, C. (2010). A pso-ga method to solve a partial shipment and scheduling problem. In *Computer Application and System Modeling (ICCSM), 2010 International Conference on*, vol. 10, V10–330, IEEE. [127](#)

- GAO, J., GEN, M. & SUN, L. (2006). Scheduling jobs and maintenances in flexible job shop with a hybrid genetic algorithm. *Journal of Intelligent Manufacturing*, **17**, 493–507. [75](#), [76](#), [81](#), [82](#), [88](#), [99](#), [103](#), [104](#)
- GARAIX, T., ARTIGUES, C., FEILLET, D. & JOSSELIN, D. (2010). Vehicle routing problems with alternative paths: an application to on-demand transportation. *European Journal of Operational Research*, **204**, 62–75. [122](#)
- GAVIRNENI, S., BOLLAPRAGADA, S. & E MORTON, T. (1998). Periodic review stochastic inventory problem with forecast updates: Worst-case bounds for the myopic solution. *European journal of operational research*, **111**, 381–392. [144](#), [149](#)
- GENDREAU, M., HERTZ, A. & LAPORTE, G. (1994). A tabu search heuristic for the vehicle routing problem. *Management science*, 1276–1290. [124](#), [125](#)
- GENDREAU, M., LAPORTE, G. & SÉGUIN, R. (1996). A tabu search heuristic for the vehicle routing problem with stochastic demands and customers. *Operations Research*, 469–477. [44](#), [45](#), [120](#)
- GENDREAU, M., POTVIN, J., BRÄUMLAYSY, O., HASLE, G. & LØKKETANGEN, A. (2008). Metaheuristics for the vehicle routing problem and its extensions: A categorized bibliography. *The Vehicle Routing Problem: Latest Advances and New Challenges*, 143–169. [125](#)
- GERWIN, D. (1993). Manufacturing flexibility: a strategic perspective. *Management science*, 395–410. [41](#)
- GILLETT, B. & MILLER, L. (1974). A heuristic algorithm for the vehicle-dispatch problem. *Operations research*, 340–349. [125](#)
- GIORDANI, P. & SÖDERLIND, P. (2003). Inflation forecast uncertainty. *European Economic Review*, **47**, 1037–1059. [47](#)
- GIRISH, B. & JAWAHAR, N. (2009). Scheduling job shop associated with multiple routings with genetic and ant colony heuristics. *International journal of production research*, **47**, 3891–3917. [89](#)

BIBLIOGRAPHY

- GOLDBERG, D., DEB, K. & CLARK, J. (1992). Genetic algorithms, noise, and the sizing of populations. *Complex Systems Champaign*, **6**, 333–333. [84](#)
- GRABOT, B., GENESTE, L., REYNOSO-CASTILLO, G. & VÉROT, S. (2005). Integration of uncertain and imprecise orders in the mrp method. *Journal of Intelligent manufacturing*, **16**, 215–234. [42](#)
- GRAMAN, G. (2010). A partial-postponement decision cost model. *European Journal of Operational Research*, **201**, 34–44. [50](#), [51](#)
- GRANGER, C. & RAMANATHAN, R. (1984). Improved methods of combining forecasts. *Journal of Forecasting*, **3**, 197–204. [36](#)
- GRAVES, S. & WILLEMS, S. (2000). Optimizing strategic safety stock placement in supply chains. *Manufacturing & Service Operations Management*, **2**, 68–83. [37](#)
- GRAVES, S. & WILLEMS, S. (2003). Supply chain design: safety stock placement and supply chain configuration. *Handbooks in Operations Research and Management Science*, **11**, 95–132. [36](#), [37](#)
- GREGORY, P. (2010). New planning benchmarks: Vehicle routing problem variants. In *The 4th Italian Workshop on Planning and Scheduling*. [122](#)
- GUMUS, A., GUNERI, A. & KELES, S. (2009). Supply chain network design using an integrated neuro-fuzzy and milp approach: A comparative design study. *Expert Systems with Applications*, **36**, 12570–12577. [60](#), [63](#), [68](#), [69](#)
- HAGHANI, A. & JUNG, S. (2005). A dynamic vehicle routing problem with time-dependent travel times. *Computers & operations research*, **32**, 2959–2986. [44](#), [120](#)
- HANDFIELD, R., NICHOLS, E. & ERNEST, L. (1999). *Introduction to supply chain management*. prentice Hall Upper Saddle River, NJ. [46](#)
- HARTMAN, R. (1972). The effects of price and cost uncertainty on investment. *Journal of economic theory*, **5**, 258–266. [47](#)

- HEINONEN, J. & PETTERSSON, F. (2007). Hybrid ant colony optimization and visibility studies applied to a job-shop scheduling problem. *Applied Mathematics and Computation*, **187**, 989–998. [89](#), [92](#)
- HELLIAR, C., LONIE, A., POWER, D. & SINCLAIR, D. (2001). Attitudes of uk managers to risk and uncertainty. *Balance Sheet*, **9**, 7–10. [31](#)
- HERNÁNDEZ-PÉREZ, H. & SALAZAR-GONZÁLEZ, J. (2004). A branch-and-cut algorithm for a traveling salesman problem with pickup and delivery. *Discrete Applied Mathematics*, **145**, 126–139. [128](#), [138](#), [139](#)
- HO, C., TAI, Y., TAI, Y. & CHI, Y. (2005). A structural approach to measuring uncertainty in supply chains. *International Journal of Electronic Commerce*, **9**, 91–114. [32](#)
- HOMBERGER, J., GEHRING, H. *et al.* (1999). Two evolutionary metaheuristics for the vehicle routing problem with time windows. *Infor-Information Systems and Operational Research*, **37**, 297–318. [125](#)
- HUANG, K. & LIAO, C. (2008). Ant colony optimization combined with taboo search for the job shop scheduling problem. *Computers & Operations Research*, **35**, 1030–1046. [89](#)
- HUANG, Y. & LI, S. (2008). Suitable application situations of different postponement approaches: Standardization vs. modularization. *Journal of Manufacturing Systems*, **27**, 111–122. [50](#)
- HUISMAN, D., FRELING, R. & WAGELMANS, A. (2004). A robust solution approach to the dynamic vehicle scheduling problem. *Transportation Science*, **38**, 447–458. [45](#), [120](#)
- HULT, G., CRAIGHEAD, C. & KETCHEN JR, D. (2010). Risk uncertainty and supply chain decisions: a real options perspective. *Decision Sciences*, **41**, 435–458. [46](#)
- HUSSAIN, M. & JOSHI, S. (1998). A genetic algorithm for job shop scheduling problems with alternate routing. In *Systems, Man, and Cybernetics, 1998. IEEE International Conference on*, vol. 3, 2225–2230, IEEE. [73](#), [81](#)

BIBLIOGRAPHY

- INDERFURTH, K. (2002). *Production planning for product recovery management*. Univ., FEMM. [36](#)
- INDERFURTH, K. & TRANSCHEL, S. (2007). Technical note on heuristic heuristics for the random yield problem. *Operations Research*, **55**, 1183–1186. [144](#)
- IWATA, K., MUROTSU, Y., OBA, F. & UEMURA, T. (1978). Optimization of selection of machine tools, loading sequence of parts and machining conditions in job-shop type machining systems. *Annals of the CIRP*, **27**, 447–451. [73](#)
- IYER, A., DESHPANDE, V. & WU, Z. (2003). A postponement model for demand management. *Management Science*, 983–1002. [52](#), [53](#), [54](#), [55](#)
- JAIN, K. & SILVER, E. (1995). The single period procurement problem where dedicated supplier capacity can be reserved. *Naval Research Logistics (NRL)*, **42**, 915–934. [143](#)
- JAWAHAR, N., ARAVINDAN, P. & PONNAMBALAM, S. (1998). A genetic algorithm for scheduling flexible manufacturing systems. *The International Journal of Advanced Manufacturing Technology*, **14**, 588–607. [81](#)
- JI, X. & SHAO, Z. (2006). Model and algorithm for bilevel newsboy problem with fuzzy demands and discounts. *Applied Mathematics and Computation*, **172**, 163–174. [159](#), [160](#), [161](#)
- JOHNSON, D. & GAREY, M. (1979). Computers and intractability: A guide to the theory of np-completeness. *Freeman&Co, San Francisco*. [122](#)
- JUNG, S. & HAGHANI, A. (2000). Genetic algorithm for a pickup and delivery problem with time windows. *Transportation Research Record: Journal of the Transportation Research Board*, **1733**, 1–7. [126](#)
- KAABI-HARRATH, J. (2004). *Contribution à l'ordonnancement des activités de maintenance dans les systèmes de production..* Ph.D. thesis, Université de Franche-Comté. [75](#)

- KACEM, I., HAMMADI, S. & BORNE, P. (2002a). Approach by localization and multiobjective evolutionary optimization for flexible job-shop scheduling problems. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, **32**, 1–13. [73](#), [82](#)
- KACEM, I., HAMMADI, S. & BORNE, P. (2002b). Pareto-optimality approach for flexible job-shop scheduling problems: hybridization of evolutionary algorithms and fuzzy logic. *Mathematics and computers in simulation*, **60**, 245–276. [73](#)
- KÁDÁR, B. & MONOSTORI, L. (1998). Agent based control of novel and traditional production systems. In *Proceedings of ICME98, CIRP International Seminar on Intelligent Computation in Manufacturing Engineering, July*, 1–3. [42](#)
- KALANTARI, B., HILL, A. & ARORA, S. (1985). An algorithm for the traveling salesman problem with pickup and delivery customers. *European Journal of Operational Research*, **22**, 377–386. [126](#)
- KAMATH, K. & PAKKALA, T. (2002). A bayesian approach to a dynamic inventory model under an unknown demand distribution. *Computers & Operations Research*, **29**, 403–422. [143](#), [148](#)
- KANET, J. & SRIDHARAN, V. (1998). The value of using scheduling information in planning material requirements*. *Decision Sciences*, **29**, 479–496. [40](#)
- KANG, K., LEE, B., LEE, Y. & LEE, Y. (2008). A heuristic for the vehicle routing problem with due times. *Computers & Industrial Engineering*, **54**, 421–431. [127](#)
- KARLIN, S. (1958). One stage inventory models with uncertainty. *Studies in the mathematical theory of inventory and production*, 109–135. [143](#)
- KELLE, P. & SILVER, E. (1990). Safety stock reduction by order splitting. *Naval Research Logistics (NRL)*, **37**, 725–743. [37](#)
- KELLEY JR, J. & WALKER, M. (1959). Critical-path planning and scheduling. In *Papers presented at the December 1-3, 1959, eastern joint IRE-AIEE-ACM computer conference*, 160–173, ACM. [113](#)

BIBLIOGRAPHY

- KEVORK, I. (2010). Estimating the optimal order quantity and the maximum expected profit for single-period inventory decisions. *Omega*, **38**, 218–227. [35](#)
- KHOUJA, M. (1999). The single-period (news-vendor) problem: literature review and suggestions for future research. *Omega*, **27**, 537–553. [143](#)
- KIM, Y., PARK, K. & KO, J. (2003). A symbiotic evolutionary algorithm for the integration of process planning and job shop scheduling. *Computers & Operations Research*, **30**, 1151–1171. [81](#)
- KIMBALL, G. (1988). General principles of inventory control. *Journal of manufacturing and operations management*, **1**, 119–130. [36](#)
- KNIGHT, F. (1921). Risk, uncertainty and profit,(reissued by university of chicago press, chicago, il, 1971). *Haughton Mifflin Co, Chicago*. [31](#)
- KOH, S. & SAAD, S. (2003). Mrp-controlled manufacturing environment disturbed by uncertainty. *Robotics and Computer-Integrated Manufacturing*, **19**, 157–171. [30](#), [40](#), [42](#), [43](#)
- KOHL, N. (1995). *Exact methods for time constrained routing and related scheduling problems*. Ph.D. thesis, Technical University of Denmark. [125](#)
- KRISHNAMURTHY, S. & KOCKELMAN, K. (2003). Propagation of uncertainty in transportation land use models: Investigation of dram-empal and utpp predictions in austin, texas. *Transportation Research Record: Journal of the Transportation Research Board*, **1831**, 219–229. [44](#)
- LALWANI, C., DISNEY, S. & NAIM, M. (2006). On assessing the sensitivity to uncertainty in distribution network design. *International Journal of Physical Distribution & Logistics Management*, **36**, 5–21. [31](#), [43](#), [48](#)
- LAPORTE, G. (1992a). The traveling salesman problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, **59**, 231–247. [124](#)
- LAPORTE, G. (1992b). The vehicle routing problem: An overview of exact and approximate algorithms. *European Journal of Operational Research*, **59**, 345–358. [123](#), [127](#)

- LAPORTE, G. & NOBERT, Y. (1987). Exact algorithms for the vehicle routing problem. *Annals of Discrete Mathematics*, **31**, 147–184. [124](#)
- LAPORTE, G., MERCURE, H. & NOBERT, Y. (1986). An exact algorithm for the asymmetrical capacitated vehicle routing problem. *Networks*, **16**, 33–46. [124](#)
- LAPORTE, G., LOUVEAUX, F. & MERCURE, H. (1992). The vehicle routing problem with stochastic travel times. *Transportation science*, **26**, 161–170. [44](#), [120](#)
- LEE, C. (2008). A bayesian approach to determine the value of information in the newsboy problem. *International Journal of Production Economics*, **112**, 391–402. [170](#)
- LEE, H., PADMANABHAN, V. & WHANG, S. (1997). The bullwhip effect in supply chains¹. *Sloan management review*, **38**, 93–102. [33](#)
- LEI, D. (2010a). Fuzzy job shop scheduling problem with availability constraints. *Computers & Industrial Engineering*, **58**, 610–617. [75](#), [111](#)
- LEI, D. (2010b). A genetic algorithm for flexible job shop scheduling with fuzzy processing time. *International Journal of Production Research*, **48**, 2995–3013. [111](#)
- LI, J., MIRCHANDANI, P. & BORENSTEIN, D. (2007). The vehicle rescheduling problem: Model and algorithms. *Networks*, **50**, 211–229. [44](#)
- LIAO, C., CHEN, C. & LIN, C. (2006). Minimizing makespan for two parallel machines with job limit on each availability interval. *Journal of the Operational Research Society*, **58**, 938–947. [75](#)
- LIM, A. & WANG, F. (2005). Multi-depot vehicle routing problem: A one-stage approach. *Automation Science and Engineering, IEEE Transactions on*, **2**, 397–402. [127](#)
- LIU, B. (1998). Minimax chance constrained programming models for fuzzy decision systems. *Information Sciences*, **112**, 25–38. [160](#)
- LIU, B. (1999). Dependent-chance programming with fuzzy decisions. *Fuzzy Systems, IEEE Transactions on*, **7**, 354–360. [160](#)

BIBLIOGRAPHY

- LIU, B. (2002). Random fuzzy dependent-chance programming and its hybrid intelligent algorithm. *Information Sciences*, **141**, 259–271. [161](#)
- LIU, B. (2003). Uncertainty theory: Toward axiomatic foundations. *Lecture Note, Tsinghua University*. [161](#)
- LIU, B. (2006). A survey of credibility theory. *Fuzzy Optimization and Decision Making*, **5**, 387–408. [143](#), [159](#), [160](#)
- LIU, B. & LIU, Y. (2002). Expected value of fuzzy variable and fuzzy expected value models. *Fuzzy Systems, IEEE Transactions on*, **10**, 445–450. [160](#)
- LIU, B., CHEN, J., LIU, S. & ZHANG, R. (2006). Supply-chain coordination with combined contract for a short-life-cycle product. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on*, **36**, 53–61. [146](#)
- LIU, N., ABDELRAHMAN, M. & RAMASWAMY, S. (2007). A complete multiagent framework for robust and adaptable dynamic job shop scheduling. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on*, **37**, 904–916. [77](#), [78](#)
- LU, Q. & DESSOUKY, M. (2006). A new insertion-based construction heuristic for solving the pickup and delivery problem with time windows. *European Journal of Operational Research*, **175**, 672–687. [126](#)
- LYSGAARD, J., LETCHFORD, A. & EGGLESE, R. (2004). A new branch-and-cut algorithm for the capacitated vehicle routing problem. *Mathematical Programming*, **100**, 423–445. [125](#)
- MA, S., WANG, W. & LIU, L. (2002). Commonality and postponement in multi-stage assembly systems. *European Journal of Operational Research*, **142**, 523–538. [50](#)
- MAHMASSANI, H. (1984). Uncertainty in transportation systems evaluation: issues and approaches. *Transportation planning and technology*, **9**, 1–12. [44](#)
- MAHMOUD, E. (1984). Accuracy in forecasting: A survey. *Journal of Forecasting*, **3**, 139–159. [36](#)

- MASON-JONES, R. & TOWILL, D. (1998). Shrinking the supply chain uncertainty circle. *IOM Control*, **24**, 17–22. [31](#), [34](#), [119](#)
- MESGHOUNI, K. (1999). *Application des algorithmes évolutionnistes dans les problèmes d'optimisation en ordonnancement de la production*. Ph.D. thesis. [88](#)
- MINIFIE, J. & ROBERT, A. (1990). Interaction effects on mrp nervousness. *The International Journal of Production Research*, **28**, 173–183. [40](#)
- MITROVIC-MINIC, S. (1998). Pickup and delivery problem with time windows: A survey. *SFU CMPT TR*, **12**. [126](#)
- MORADI, E., GHOMI, S. & ZANDIEH, M. (2011). Bi-objective optimization research on integrated fixed time interval preventive maintenance and production for scheduling flexible job-shop problem. *Expert Systems with Applications*, **38**, 7169–7178. [75](#), [76](#)
- MOREL, G., PANETTO, H., ZAREMBA, M. & MAYER, F. (2003). Manufacturing enterprise control and management system engineering: paradigms and open issues. *Annual reviews in Control*, **27**, 199–209. [42](#)
- MOSHEIOV, G. (1994). The travelling salesman problem with pick-up and delivery. *European Journal of Operational Research*, **79**, 299–310. [138](#)
- MOSTARD, J., DE KOSTER, R. & TEUNTER, R. (2005). The distribution-free newsboy problem with resalable returns. *International Journal of Production Economics*, **97**, 329–342. [154](#)
- MU, Q., FU, Z., LYSGAARD, J. & EGGLESE, R. (2010). Disruption management of the vehicle routing problem with vehicle breakdown. *Journal of the Operational Research Society*, **62**, 742–749. [45](#)
- MULA, J., POLER, R., GARCIA-SABATER, J. & LARIO, F. (2006). Models for production planning under uncertainty: A review. *International Journal of Production Economics*, **103**, 271–285. [30](#), [42](#)
- MULVEY, J. & RUSZCZYŃSKI, A. (1995). A new scenario decomposition method for large-scale stochastic optimization. *Operations research*, 477–490. [45](#)

BIBLIOGRAPHY

- MULVEY, J., VANDERBEI, R. & ZENIOS, S. (1995). Robust optimization of large-scale systems. *Operations research*, 264–281. [45](#)
- NAHMIA, S. (2005). *Production and operations analysis*. MCGRAW-HILL PROFESSIONAL. [146](#)
- NAJID, N., DAUZERE-PERES, S. & ZAIDAT, A. (2002). A modified simulated annealing method for flexible job shop scheduling problem. In *Systems, Man and Cybernetics, 2002 IEEE International Conference on*, vol. 5, IEEE. [73](#)
- NASR, N. & ELSAYED, E. (1990). Job shop scheduling with alternative machines. *The International Journal Of Production Research*, **28**, 1595–1609. [73](#)
- NEALE, M., ASSOCIATES & FOR TEROTECHNOLOGY, G.B.C. (1979). *A guide to the condition monitoring of machinery*. H.M. Stationery Off. [76](#)
- OMBUKI, B., ROSS, B. & HANSHAR, F. (2006). Multi-objective genetic algorithms for vehicle routing problem with time windows. *Applied Intelligence*, **24**, 17–30. [125](#)
- OTTESEN, G. & GRØNHAUG, K. (2002). Market orientation and uncertain supply in upstream markets: an exploratory study. *European Journal of Purchasing & Supply Management*, **8**, 209–219. [31](#)
- PAGELL, M. & KRAUSE, D. (1999). A multiple-method study of environmental uncertainty and manufacturing flexibility. *Journal of Operations Management*, **17**, 307–325. [40](#), [41](#)
- PANKRATZ, G. (2005). Dynamic vehicle routing by means of a genetic algorithm. *International Journal of Physical Distribution & Logistics Management*, **35**, 362–383. [128](#), [135](#), [138](#)
- PARK, B., CHOI, H. & KIM, H. (2003). A hybrid genetic algorithm for the job shop scheduling problems. *Computers & industrial engineering*, **45**, 597–613. [85](#), [86](#)
- PARLAR, M. & WANG, D. (1993). Diversification under yield randomness in inventory models. *European journal of operational research*, **66**, 52–64. [143](#)

- PARRAGH, S., DOERNER, K. & HARTL, R. (2008). A survey on pickup and delivery problems. *Journal für Betriebswirtschaft*, **58**, 81–117. [126](#)
- PONNAMBALAM, S., JAWAHAR, N. & GIRISH, B. (2010). An ant colony optimization algorithm for flexible job shop scheduling problem. [89](#)
- POTVIN, J. & BENGIO, S. (1996). The vehicle routing problem with time windows part ii: genetic search. *INFORMS journal on Computing*, **8**, 165–172. [125](#)
- PRADHAN, A. & MARIA KOCKELMAN, K. (2002). Uncertainty propagation in an integrated land use-transportation modeling framework: output variation via urbansim. *Transportation Research Record: Journal of the Transportation Research Board*, **1805**, 128–135. [44](#)
- RAY, S., LI, S. & SONG, Y. (2005). Tailored supply chain decision making under price-sensitive stochastic demand and delivery uncertainty. *Management Science*, 1873–1891. [43](#), [120](#)
- REGAN, A., MAHMASSANI, H. & JAILLET, P. (1996). Dynamic decision making for commercial fleet operations using real-time information. *Transportation Research Record: Journal of the Transportation Research Board*, **1537**, 91–97. [120](#)
- REINER, G. & FICHTINGER, J. (2009). Demand forecasting for supply processes in consideration of pricing and market information. *International Journal of Production Economics*, **118**, 55–62. [35](#)
- ROPKE, S. & PISINGER, D. (2006). An adaptive large neighborhood search heuristic for the pickup and delivery problem with time windows. *Transportation Science*, **40**, 455–472. [126](#)
- ROSSI, A. & DINI, G. (2007). Flexible job-shop scheduling with routing flexibility and separable setup times using ant colony optimisation method. *Robotics and Computer-Integrated Manufacturing*, **23**, 503–516. [89](#)
- RULAND, K. & RODIN, E. (1997). The pickup and delivery problem: Faces and branch-and-cut algorithm. *Computers & mathematics with applications*, **33**, 1–13. [126](#)

BIBLIOGRAPHY

- SAIDI-MEHRABAD, M. & FATTAHI, P. (2007). Flexible job shop scheduling with tabu search algorithms. *The International Journal of Advanced Manufacturing Technology*, **32**, 563–570. [73](#)
- SAVELSBERGH, M. & SOL, M. (1995). The general pickup and delivery problem. *Transportation science*, **29**, 17–29. [126](#)
- SCHRIJVER, A. (2005). On the history of combinatorial optimization (till 1960). *Handbook of Discrete Optimization*, 1–68. [121](#)
- SCHWARZ, L. (2000). The design of a jit supply chain: The effect of leadtime uncertainty on safety stock. *Journal of Business Logistics*, **21**. [37](#)
- SETHIYA, S. (2006). Condition based maintenance (cbm). *Secy. toCME/WCR/JBP*. [76](#)
- SHAO, Z. & JI, X. (2006). Fuzzy multi-product constraint newsboy problem. *Applied Mathematics and Computation*, **180**, 7–15. [160](#), [161](#), [163](#)
- SHOU, B., HUANG, J. & LI, Z. (2009). Managing supply uncertainty under chain-to-chain competition. [33](#)
- SIPAHI, R. & DELICE, I. (2010). Stability of inventory dynamics in supply chains with three delays. *International Journal of Production Economics*, **123**, 107–117. [51](#)
- SOLOMON, M. (1987). Algorithms for the vehicle routing and scheduling problems with time window constraints. *Operations research*, 254–265. [122](#), [125](#)
- SOLOMON, M. (2003). Vrptw benchmark problems. *World wide web at <http://web.cba.neu.edu/msolomon/problems.htm>*. [125](#)
- SRIDHARAN, V. & LAWRENCE LAFORGE, R. (1989). The impact of safety stock on schedule instability, cost and service. *Journal of Operations Management*, **8**, 327–347. [36](#), [37](#)
- STERMAN, J. (1989). Modeling managerial behavior: Misperceptions of feedback in a dynamic decision making experiment. *Management science*, 321–339. [33](#)

- STRIJBOSCH, L. & MOORS, J. (2006). Modified normal demand distributions in (*r*, *s*)-inventory control. *European journal of operational research*, **172**, 201–212. [35](#)
- STÜTZLEA, T. & HOOSB, H. (2000). Max–min ant system. *Future Generation Computer Systems*, **16**, 889–914. [89](#)
- SUNG, C. & KIM, Y. (2002). Minimizing makespan in a two-machine flowshop with dynamic arrivals allowed. *Computers & Operations Research*, **29**, 275–294. [108](#), [111](#)
- SWAFFORD, P., GHOSH, S. & MURTHY, N. (2008). Achieving supply chain agility through it integration and flexibility. *International Journal of Production Economics*, **116**, 288–297. [37](#)
- SWAMIDASS, P. & NEWELL, W. (1987). Manufacturing strategy, environmental uncertainty and performance: a path analytic model. *Management Science*, 509–524. [41](#)
- TAILLARD, E., LAPORTE, G. & GENDREAU, M. (1996). Vehicle routeing with multiple use of vehicles. *Journal of the Operational research society*, 1065–1070. [127](#)
- TAN, K., CHEW, Y. & LEE, L. (2006). A hybrid multiobjective evolutionary algorithm for solving vehicle routing problem with time windows. *Computational Optimization and Applications*, **34**, 115–151. [125](#)
- TANG, C. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, **103**, 451–488. [37](#)
- TAYLOR, D. (2000). Demand amplification: has it got us beat? *International Journal of Physical Distribution & Logistics Management*, **30**, 515–533. [34](#)
- TIWARI, D., PATIL, R. & SHAH, J. (2011). Unreliable newsboy problem with a forecast update. *Operations Research Letters*. [143](#), [144](#), [146](#), [149](#)
- TOLIO, T. & URGO, M. (2007). A rolling horizon approach to plan outsourcing in manufacturing-to-order environments affected by uncertainty. *CIRP Annals-Manufacturing Technology*, **56**, 487–490. [42](#)

BIBLIOGRAPHY

- TOWILL, D., NAIM, M. & WIKNER, J. (1992). Industrial dynamics simulation models in the design of supply chains. *International Journal of Physical Distribution & Logistics Management*, **22**, 3–13. [33](#), [34](#)
- VANDAELE, N. & DE BOECK, L. (2003). Advanced resource planning. *Robotics and Computer-Integrated Manufacturing*, **19**, 211–218. [42](#)
- VORST, J., BEULENS, A., WIT, W. & BEEK, P. (1998). Supply chain management in food chains: Improving performance by reducing uncertainty. *International Transactions in Operational Research*, **5**, 487–499. [30](#), [31](#), [47](#)
- WANG, C. (2009). Random yield and uncertain demand in decentralised supply chains under the traditional and vmi arrangements. *International Journal of Production Research*, **47**, 1955–1968. [144](#), [148](#), [149](#), [153](#)
- WANG, S. & YU, J. (2010). An effective heuristic for flexible job-shop scheduling problem with maintenance activities. *Computers & Industrial Engineering*, **59**, 436–447. [75](#)
- WATERS, C. (1989). Vehicle-scheduling problems with uncertainty and omitted customers. *Journal of the Operational Research Society*, 1099–1108. [122](#)
- WEN, M., CLAUSEN, J. & LARSEN, J. (2010). *Rich Vehicle Routing Problems and Applications*. Ph.D. thesis, Ph. d., DTU Management Engineering. [122](#)
- WENG, Z. & MCCLURG, T. (2003). Coordinated ordering decisions for short life cycle products with uncertainty in delivery time and demand. *European Journal of Operational Research*, **151**, 12 – 24. [43](#)
- WIENDAHL, H. & SCHOLTISSEK, P. (1994). Management and control of complexity in manufacturing. *CIRP Annals-Manufacturing Technology*, **43**, 533–540. [38](#)
- WILDING, P., KRICKA, L., CHENG, J., HVICHIA, G., SHOFFNER, M. & FORTINA, P. (1998). Integrated cell isolation and polymerase chain reaction analysis using silicon microfilter chambers. *Analytical biochemistry*, **257**, 95–100. [33](#)

- WILLIAMSON, O. (1979). On the governance of the modern corporation. *Hofstra L. Rev.*, **8**, 63. [45](#)
- WREN, A. & CARR, J. (1971). Computers in transport planning and operation. [125](#)
- WREN, A. & HOLLIDAY, A. (1972). Computer scheduling of vehicles from one or more depots to a number of delivery points. *Operational Research Quarterly*, 333–344. [125](#)
- XIA, W. & WU, Z. (2005). An effective hybrid optimization approach for multi-objective flexible job-shop scheduling problems. *Computers & Industrial Engineering*, **48**, 409–425. [73](#), [84](#), [88](#), [93](#), [94](#), [103](#)
- XIANG, Z., CHU, C. & CHEN, H. (2008). The study of a dynamic dial-a-ride problem under time-dependent and stochastic environments. *European Journal of Operational Research*, **185**, 534–551. [45](#), [120](#)
- XU, D., SUN, K. & LI, H. (2008). Parallel machine scheduling with almost periodic maintenance and non-preemptive jobs to minimize makespan. *Computers & Operations Research*, **35**, 1344–1349. [75](#)
- XU, H., CHEN, Z., RAJAGOPAL, S. & ARUNAPURAM, S. (2003). Solving a practical pickup and delivery problem. *Transportation science*, **37**, 347–364. [126](#)
- YAMADA, T. & NAKANO, R. (1997). Genetic algorithms for job-shop scheduling problems. In *Proceedings of the Modern Heuristics for Decision Support*, 67–81. [85](#)
- YANG, J., JAILLET, P. & MAHMASSANI, H. (2004). Real-time multivehicle truckload pickup and delivery problems. *Transportation Science*, **38**, 135–148. [120](#)
- YANG, W., MATHUR, K., BALLOU, R. *et al.* (2000). Stochastic vehicle routing problem with restocking. *Transportation Science*, **34**, 99–112. [127](#)
- YANO, C. & LEE, H. (1995). Lot sizing with random yields: A review. *Operations Research*, 311–334. [144](#)

BIBLIOGRAPHY

- YANO, C. & ROBERT, C. (1987). Interaction between frequency of rescheduling and the role of safety stock in material requirements planning systems. *International journal of production research*, **25**, 221–232. [36](#)
- YAO, S., ZHAO, M. & ZHANG, H. (2011). Two-stage hybrid flow shop scheduling with dynamic job arrivals. *Computers & Operations Research*. [108](#)
- YELLAND, P. (2010). Bayesian forecasting of parts demand. *International Journal of Forecasting*, **26**, 374–396. [148](#)
- YU, C. & LI, H. (2000). A robust optimization model for stochastic logistic problems. *International Journal of Production Economics*, **64**, 385–397. [30](#), [45](#)
- ZADEH, L. (1965). Fuzzy sets. *Information and control*, **8**, 338–353. [159](#)
- ZADEH, L. (1978). Fuzzy sets as a basis for a theory of possibility. *Fuzzy sets and systems*, **1**, 3–28. [159](#)
- ZANDIEH, M. & ADIBI, M. (2010). Dynamic job shop scheduling using variable neighbourhood search. *International Journal of Production Research*, **48**, 2449–2458. [111](#)
- ZENG, Q., TSENG, M. & LU, R. (2006). Staged postponement of order specification commitment for supply chain management. *CIRP Annals-Manufacturing Technology*, **55**, 501–504. [50](#)
- ZHENG, Y. & MESGHOUNI, K. (2011a). Application of postponement strategy in distribution period for treating uncertain demand in supply chain management. *Engineering Letters*, **19**. [51](#)
- ZHENG, Y. & MESGHOUNI, K. (2011b). Using postponement as a rescheduling strategy in the supply chain management under uncertain demand environment. *Proceedings of the International MultiConference of Engineers and Computer Scientists*, **2**. [51](#)
- ZHU, K. (2000). A new genetic algorithm for vrptw. In *Proceedings of the International Conference on Artificial Intelligence*, Citeseer. [125](#)

ZIDI, I., MESGHOUNI, K., ZIDI, K. & GHEDIRA, K. (2010). A contribution to the modelling and the resolution of a multi-objective dial a ride problem. In *Engineering Systems Management and Its Applications (ICESMA), 2010 Second International Conference on*, 1–7, IEEE. [126](#)

BIBLIOGRAPHY

Le management de la chaîne logistique sous contraintes de disponibilité et d'incertitude

Résumé: Le management de la chaîne logistique concerne un large éventail d'activités. Nombreuses ceux qui ont un caractère incertain apportant souvent des conséquences inattendues. Malgré cela, l'incertitude est fréquemment non considérée dans la gestion de la chaîne logistique traditionnelle. En plus de l'incertitude, l'indisponibilité des ressources augmentera la complexité du problème. En prenant en compte les contraintes d'incertitude et de disponibilité, nous étudions le management de la chaîne logistique selon différents aspects. Cette thèse représente une tentative de recherche afin d'aborder ce problème d'une façon systématique et complète et nous espérons que notre travail contribuera aux futurs travaux de recherche et sera utile aux gestionnaires de la chaîne logistique. Nous nous concentrons sur trois sources classiques de l'incertitude; celle de la demande, celle de la fabrication et celle liée à la distribution. Pour chaque source d'incertitude, nous analysons ses causes et ses impacts sur les performances de la chaîne logistique. L'incertitude est spécifiée dans des problèmes classiques concrets et des approches sont proposées pour les résoudre. Nous nous sommes également focalisés sur le problème bi-niveau du vendeur des journaux qui représente une chaîne logistique miniature, concerné par une double incertitude. Les méthodes utilisées offrent une bonne démonstration du traitement des variables incertaines dans les problèmes de décision.

Mots-clés: Incertitude, Management de la chaîne logistique, Demande, Ordonnement de job shop, tournées de véhicules, Problème bi-niveau de vendeurs des journaux, Métaheuristique.

Supply chain management under availability & uncertainty constraints

Abstract: Supply chain management involves a wide range of activities. Among most of them, uncertainty exists inherently and always brings some consequence not expected. However, uncertainty is not considered much in conventional supply chain management. In the case when availability of resources is not as what we expect, complexity of supply chain management increases. Taking constraints of uncertainty and availability into account, we aim to discuss supply chain management from different aspects. This thesis is an attempt of systematic and complete research from this point and we would like to offer some references to researchers and managers in supply chain.

We focus on three classic sources of uncertainty: demand, manufacturing and distribution. For each source of uncertainty, we analyze its cause and impact to performance of supply chain. Uncertainty is specified into concrete classic problem and approach proposed to solve it. Furthermore, bi-level newsboy problem as a miniature of supply chain, is focused under double uncertain environment. Treating uncertain variables is actually a treatment on operational level. The methods used offer good demonstration in treating uncertain variables in decision problems.

Keywords: Uncertainty, Supply chain management, Demand, Job shop scheduling, Vehicle routing, Bi-level newsboy problem, Metaheuristic.