THE IMPACT OF LINER SHIPPING UNRELIABILITY ON THE PRODUCTION–DISTRIBUTION SCHEDULING OF A DECENTRALIZED MANUFACTURING SYSTEM

XUTING SUN

Ph.D

The Hong Kong Polytechnic University

2018

The Hong Kong Polytechnic University

Department of Industrial and Systems Engineering

The impact of liner shipping unreliability on the production–distribution scheduling of a decentralized manufacturing system

Xuting Sun

A thesis submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy

August 2017

CERTIFICATE OF ORIGINALITY

I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it reproduces no material previously published or written, nor material that has been accepted for the award of any other degree or diploma, except where due acknowledgement has been made in the text.

______________________________(Signed)

Sun Xuting___________________(Name of student)

Abstract

Production and distribution scheduling are two key activities at the operational level in a supply chain. Due to fierce competition in the market and high expectation on the service level from customers, the linkage between production and distribution become more and more close. However, achieving customer satisfaction, as well as controlling the overall cost, is a critical issue. On the one hand, to meet the customized needs from global clients in the competitive market environment, more and more manufacturers are changing their production network from centralized to decentralized. For multi-factory manufacturing systems, production and distribution scheduling problems are much more complicated than the single-factory integrated scheduling problems, because bi-assignment problems are involved. On the other hand, as the connected channel between manufacturers and overseas customers, maritime transport cannot be avoided in global supply chains. However, the regular shipping schedules and the long shipping lead-time dominate the production and distribution decisions made by the manufacturers. When the actual schedules deviate from the published ones, not only the shippers (manufacturers) but also their customers face uncountable losses because of the delays. In reality, schedule unreliability is a common problem in the shipping industry. Both internal and external factors, which are not under the control of the shipping companies, bring about negative impacts on the timely arrivals of vessels. As for the manufacturer with a decentralized production network, there is no doubt that the assignment and scheduling decisions become much more complicated in compensating for the effects of shipping limitations as well as uncertainties. However, most of the literature studied the integrated scheduling problem under a single-factory manufacturing system in a local supply chain without consideration of the limitations

from liner shipping. In addition, almost all the existing studies focus on shipping unreliability from the perspective of the shipping companies. Studies for identifying the impact of shipping uncertainties on the production and distribution scheduling from the perspective of the shippers are quite limited.

This research mainly focuses on the study of the effects of shipping limitations and uncertainties on the production and distribution scheduling for a decentralized manufacturing system and fills the research gaps aforementioned. The main contributions made through this research are as follows:

Firstly, a new and practical deterministic model was proposed for multi-factory job allocation and production–distribution scheduling problems in which inland distance-dependent transportation lead-time and maritime transport limits and variations are taken into consideration. The objective was to minimize the total operating costs, i.e., cost of production, storage, inland and maritime transport, earliness and tardiness. A pure mathematical approach was proposed and formulated into a mixed-integer programming (MIP). A new valid inequality called due-date based cut-off rule (DBC) was exploited to reduce the computational burden of the exact algorithm without removing the optimal solutions. Moreover, a hybrid 2-level fuzzy guided genetic algorithm (H2LFGGA) was developed for more practical and large-scale problems. In this GA, a new mutation operation based on a novel fuzzy controller was introduced. The numerical experiments demonstrated the reliable performance of the proposed integrated model for the variations in external shipment schedules and production cost difference among factories. Managerial insights were obtained in terms of the production scheduling decisions under a multi-factory manufacturing environment. Thirdly, a new stochastic model was proposed for the multi-factory production and

distribution scheduling problem under liner shipping uncertainty. The aim was to make a trade-off between total operating costs and risk costs to achieve more reliable decisions. The closed form of the individual risk cost for any arbitrary probability distribution was formulated corresponding to the loss function composed of both earliness and tardiness penalties. It verified the effects of shipping uncertainty on jobs allocation, production scheduling and shipment selections. The computational and statistical evaluation clearly demonstrated that the new approach can compensate for the amplification effects between the high penalty level and shipping uncertainty. Managerial insights were obtained when facing liner shipping uncertainties.

Publications

Journal Papers:

1. Sun, X.T., Chung, S.H. and Chan, F.T.S., 2015. Integrated scheduling of a multi-product multi-factory manufacturing system with maritime transport limits. *Transportation Research Part E: Logistics and Transportation Review*, *79*, pp.110-127.
2. Sun. X.T., Chung, S.H. and Chan, F.T.S. The impact of liner shipping unreliability on the production–distribution scheduling of a decentralized manufacturing system, *Transportation Research Part E: Logistics and Transportation Review.* (Third round major revision: Reviewer 1 accepted, Review 2 major)

Conference Papers:

3. Sun, X.T., Chung, S.H. and Chan, F.T.S., 2015. An advanced production–distribution scheduling under multi-criteria objectives in a maritime transport network. *The Proceedings of 2015 International Conference on Flexible Automation and Intelligent Manufacturing*, Wolverhampton, UK, June 23-26.
4. Sun, X.T., Chung, S.H. and Chan, F.T.S., 2014. Integrated scheduling of multi-factory supply chain with shipping information. *Proceedings of 2014 International Conference on Technology Innovation and Industrial Management*, Seoul, South Korea, May 28-30.

Acknowledgements

First of all, I would like to express my deepest gratitude to my supervisor, Dr Nick S.H. Chung. During my four-year research journey, his constant encouragement and guidance helped me to explore the nature of doing research. I could not finish this thesis without his trust and patient instruction. I would also like to express my sincere thanks to my co-supervisor, Professor Felix T.S. Chan for his encouragement and enlightenment when my research work was at a low level. Special thanks also go to Professor P. Ji who was the examiner for my registration confirmation. His valuable comments and suggestions inspired me to understand my research work better.

Many thanks also go my dear fellows, Dr. Helen Ma, Dr. Nelson Li, Dr. Jeremy Wang, Dr. Cathy Chen, Dr. Sing Wong, Ms Windy Wen, Mr Allen Chen, Mr Jason Qin, Ms Amy Huo, Ms Esther Fu, Ms, Jenny Pu, Mr Abdou Elsayed Elsayed Eltoukhy and Mr Ibrahim Shaban for their inspiring discussions, suggestions and encouragement for my research work. Special thanks also go to my dear friends, Dr Stella Yang, Dr Shan Guo, Ms Li Chen, Ms Hui Yun, Dr Zhiwei Zhu and Dr Shiyu Shi for their constant support, ideas sharing, encouragement and kind help for my research work as well as my life in the past four years in Hong Kong.

Lastly, I would like to express my thanks in the deepest mind to my parents and my dear friend Mr Sampson Zhang for their understanding, patience and support throughout my four-year research journey.

Table of contents

List of Figures

List of Tables

List of Abbreviations

IP	Integer Programming
MIP	Mixed Integer Programming
MILP	Mixed Integer Linear Programming
GA	Genetic Algorithm
H2LFGGA	Hybrid 2-level fuzzy guided genetic algorithm
CCP	Chance Constrained Programming
DBC	Due-date Based Cut-off rule
MIPD	Multi-factory Integrated Production–Distribution model
MSPS	Multi-factory Separated Production Scheduling
EDD	Earliest Due Date
NEDD	Non-preemptive Earliest Due Date
SPT	Shortest Processing Time
LPT	Longest Processing Time
ATC	Apparent Tardiness cost
RPT	Remaining Processing Time
SEPT	Shortest Expected Processing Time
LEPT	Longest Expected Processing Time
WSPT	Weighted Shortest Processing Time
WSEPT	Weighted Shortest Expected Processing Time
WMDD	Weighted Modified Due Date
WCOVERT	Weighted Cost Over Expected Remaining Time
E/T	Earliness and Tardiness
CDF	Cumulative Distribution Function
JPCIP	Joint Probabilistic Constraint Integer Programming

IPCIP	Individual Probabilistic Constraint Integer Programming
DMIPD	Deterministic Multi-factory Integrated Production and Distribution model

List of Notations

F Set of factories

I Set of production lines

J Set of jobs

S Set of shipments

T Set of terminals

p_{ij} Processing time of job *j* on the production line *i*

q_j Quantity of job *j*

d_j Due date of job *j*

tr_{ft} In-land transportation time from the factory *f* to terminal *t*

a_s Departure time of shipment *s* from terminal

t_s Shipping lead time of shipment *s*

T_{st} = 1, shipment *s* will depart from terminal *t*

= 0, otherwise

T_{fi} = 1, production line *i* belongs to factory *f*

= 0, otherwise

c_{ij}^{pro} Unit production cost of job *j* on production line *i*

$c_j^{w_f}$ Unit storage cost of job *j* in the warehouse w_f which is near to the factory *f* per day

c_{fjt}^{tr} Unit transportation cost from the factory *f* to terminal *t* of job *j*

c_s Unit shipping cost of shipment *s*

c_j^{DC} Unit storage cost of job *j* in DC per day

c_j^{p} Unit penalty cost for tardiness of job *j* per day

μ_s, σ_s Mean and standard deviation of shipping lead-time of shipment *s*

E_j^{DC} Earliness of job *j*

T_j Tardiness of job *j*

x_{ijk} = 1, job *j* is assigned with service immediately preceding job *k* on production line *i*

= 0, otherwise

y_{ijs} = 1, job *j* is produced by production line *i* and delivered by shipment *s*

= 0, otherwise

s_j Starting time for production of job *j*

c_j Completion time for production of job *j*

r_j Arrival time at distribution center of job *j*

c_j^{pro} Unit production cost of job *j*

c_j^{w} Unit storage cost of job *j* in the warehouse

$h_j^{w_f}$ Duration for which job *j* is stored in the warehouse, which is nearby factory *f*

c_j^{tr} Unit inland transportation cost of job *j*

c_j^{s} Unit liner shipping cost of job *j*

β Reliability/confidence level corresponding to the total earliness and tardiness penalties

β_j Reliability/confidence level corresponding to the earliness and tardiness penalties of job *j*

α β-quantile for the total earliness and tardiness penalties

α_j β_j-quantile for the earliness and tardiness penalties of job *j*

Chapter 1 Introduction

In Chapter 1, the research background is briefly discussed in Section 1.1, followed by the scope, objectives and significance of this research in Section 1.2. Lastly, the organization of this thesis is elaborated in Section 1.3.

1.1 Research background

Facing with increasing product diversification and customization demands, more and more manufacturers are adopting the make-to-order business modes. Such kind of manufacturing environment covers a wide range of industries, including electronics products (Li et al. 2005; Stecke and Zhao 2007), fashion manufacturing (Chen and Pundoor 2006), food catering (Chen and Vairaktarakis 2005), electrical appliances/devices, and other fast moving consumer goods (FMCG) industries. Under the fierce market competition, manufacturers try to keep the operating cost as low as possible; on the other hand, they pursue high service quality, i.e., on-time delivery. Therefore, as the key functional activities in the supply chain, production and distribution become intimately linked. The traditional methods, in practice, separate the decisions for production and distribution. The distribution decisions are made after the production scheduling, which is obvious sub-optimal and cannot achieve overall benefit. Therefore, the integrated decisions of production and distribution are essential for make-to-order manufacturers to achieve the trade-off between various costs and service levels.

Most studies discuss the production and distribution scheduling under relative simple manufacturing systems, e.g., single-machine and parallel-machines. (Chen 2009). However, the production and distribution scheduling methods based on the single-factory environment are not suitable any more. With the growing trend of globalization, increasing numbers of manufacturers are extending their production network from single-factory to multiple-factory manufacturing systems, located in different regions and countries. This adds geographical and production flexibility as well as competitiveness to meet the global customers' requirements. Information sharing and coordination planning among the factories are remarkably important when facing the common external constraints. For instance, under a make-to-order business mode, production has close linkage with distribution, which makes it inevitable to take the transport related constraints into consideration to achieve overall benefit. There is no doubt that coordination among factories can further facilitate effective and efficient resource integration and reduce the resource waste in no value-add activities. However, differing from the single-factory scheduling problems, bi-assignment problems are involved under the multi-factory manufacturing environment, i.e., the assignment of each order among different factories, and the assignment of each order to the production line in the factory. The decisions are linked with each other and affect a series of successive decisions. Therefore, under the restriction of production and distribution, how to obtain optimal bi-assignment and scheduling solutions determines how well the resource integration is.

Thanks to the rapid development of the logistic industry, the distribution stage becomes more flexible for the manufacturers, but new challenges emerge as well. Except those companies owning their own vehicle fleet, more and more manufacturers count on the logistics providers, especially, the third-party logistics providers (3PL) for the distribution to their customers (Wang and Lee 2005; Stecke and Zhao 2007; Huo et al. 2010; Agnetis et al. 2014; Azadian et al 2015; Cheng et al. 2015; Li et al. 2015; Guo et al. 2017). Usually, the 3PL provides multiple transport modes, e.g., regular delivery and express delivery. More convenient and efficient means higher transportation cost. Under such a situation, mixed delivery methods, i.e., immediate delivery and batch delivery, may be involved and more complex scheduling decisions are needed.

However, more challenges are faced by the make-to-order manufacturers, when multiple transport modes involve availability restrictions, e.g., rail, air, sea transport (Li et al. 2005; Wang et al. 2005; Li et al. 2006; Leung and Chen 2013; Ma et al. 2013; HaGarciaghaei-Keshteli and Aminnayeri 2014; Mensendiek et al. 2015). As the main support of the international trade, maritime transport is the crucial link in the global supply chain. As for the make-to-order manufacturer with global customers, the characteristics of maritime transport cannot be ignored during production and distribution decision making.

Shipping companies usually publish the expected shipping schedules several months in advance so that shippers can make appropriate decisions, including the departure times from the port, expected shipping lead-times, specific freight rates, etc. However, in reality, schedule unreliability is a common problem in the shipping industry. Both internal and external factors, which are not under the control of the shipping companies, bring about negative impacts on the timely arrivals of vessels. As reported by Notteboom (2006), the actual vessel schedule reliability can be as low as 50% for many shipping routes compared with their expected schedules. In a recent report by Drewry (2015), the statistics showed that only 49% to 55% of ships in three key East–West trade routes arrived within 24 h of the expected time of arrival (ETA), whereas the average deviation from the ETA was 1.9 days and 2.1 days in January 2015 and February 2015, respectively. The situation has not improved much. As reported by Drewry (2016), the reliability of universal average on-time performance according to the shipping schedule in February 2016 was 62.7%, and for Asia–Europe trade, it was less than 60%. The main source of the schedule unreliability arises from the congestion of vessels in ports and the unexpected low handling efficiency at ports/terminals.

In recent years, many researchers have focused on the shipping routing design problems with uncertainties in the shipping operations. Shipping schedules were redesigned or the shipping speed was controlled from time to time to minimize the cost of fuel consumption as well as improve the service reliability (Qi and Song 2012; Wang and Meng 2012). Except for the regular uncertainties (port-related uncertainties), disruptive events (extreme weather conditions, labor strikes) are also involved in maritime transport (Li et al.2015). Although some studies considered the customer service levels as constraints in the fleet deployment and route scheduling problems, their priority was the profitability of the shipping companies. When conflicts cannot be resolved, the shipping companies have to sacrifice the schedule reliability for controlling the total cost. Therefore, how to obtain a more reliable production and distribution decisions are of high concerned to the manufacturers.

All the challenges faced by the make-to-order manufacturer under unprecedented globalization of supply chains motivate this research. The following section mainly discusses the research scope, objectives and significance.

1.2 Research scope, objectives and significance

The scope of this research focuses on the production and distribution problems at the detailed scheduling level, rather than the planning level. The production is required according to the customers' orders rather than the stock level. Therefore, the production and distribution planning and lot scheduling related problems are not discussed in this research. In addition, this research focuses on the supply chain operational risk, other than supply chain disruption risk. According to the challenges faced by the make-to-order manufacturers in the global supply chain, the objectives for this research are established as follows:

1. To develop an exact integrated model for a make-to-order manufacturer with a decentralized production network to determine optimal production and distribution scheduling solutions so as to make trade-off between the total operating cost and delivery timeliness under the consideration of both 3PL and maritime transport.

2. To develop a new application-oriented approach for this multi-factory integrated scheduling model with consideration of both 3PL and maritime transport so as to make it practical in reality.

3. To develop a stochastic model to deal with the operational risk coming from maritime transport for this multi-factory integrated scheduling problem in order to obtain a more reliable integrated scheduling solution in terms of the total operating cost when liner shipping uncertainty cannot be avoided.

In general, this research not only makes contributions to academia but also provides managerial insights to the industry: a) it provides exact mathematical modeling which can be used as a benchmark for the multi-factory integrated scheduling problems with dominated transport modes consideration and just-in-time objectives; b) it provides new ideas on supply chain risk management at the operational level for production and distribution scheduling problems when the uncertainty is coming from the outbound distribution; c) it not only provides useful managerial insights for the manufacturers but also the 3PL companies, forwarders and port related operators and service providers. Further the level of communication among them affects the reliability of the production and distribution scheduling decisions. Moreover, the big data and advanced analytics are essential for risk-averse decisions.

1.3 Organization of the thesis

The thesis is mainly composed of six chapters:

In Chapter 1, the background and challenges of the production and distribution scheduling problems are discussed first. Accordingly, the research objectives are established followed by the significance of this research.

In Chapter 2, a systematic review of the related fields, including the development of the studies of production scheduling, production and distribution scheduling under both simple and complex manufacturing configurations are presented in detail. For the production and distribution scheduling models, besides the common delivery methods, immediate and identical delivery and batch delivery, the models with different delivery methods and multi-factory manufacturing environments are reviewed in the recent literature. It is followed by the related literature on stochastic programming, exact and approximation algorithms for solving production and distribution scheduling models. Finally, a summary of the literature review including research gaps and detailed objectives is presented.

In Chapter 3, a pure mathematical approach is presented for the novel and practical integrated multi-factory production and distribution scheduling model. The detailed modeling is displayed in Chapter 3. In addition, the development procedure of the new proposed valid inequality for accelerating the computational efficiency for the enumerated branch and bound is presented. The superiority of the proposed model and the valid inequality is discussed through numerical experiments.

In Chapter 4, a novel hybrid 2-level fuzzy guided genetic algorithm is developed in detail for application-oriented purposes. The principles of the proposed fuzzy controller are explained. Comparisons between the proposed genetic algorithm and exact algorithm, as well as between the proposed genetic algorithm and simple genetic algorithm, are conducted to verify the effectiveness and efficiency of the proposed heuristic approach.

In Chapter 5, a new stochastic model which is based on the model in Chapter 3 is developed for the integrated multi-factory scheduling problem with shipping uncertainty. The approximate deterministic equivalent is formulated with detailed procedures, in which the closed form of the individual risk cost is proved. The numerical experiments are carried out to verify the effectiveness of the proposed method.

In Chapter 6, overall conclusions including the main contributions and findings are presented. Some recommendation for future work are discussed.

Chapter 2 Literature Review

In Chapter 2, a systematic review of the literature on production scheduling under both a deterministic and stochastic background is firstly presented in Section 2.1. In Section 2.2, a systematic review on the production and distribution scheduling is provided with recent literature. Then it is followed by the related literature on stochastic programming in Section 2.3, exact and approximation algorithms for solving production and distribution scheduling models in Section 2.4 and 2.5. In section 2.6, a summary of the literature review as well as the research gaps and detailed objectives are presented.

2.1 Production scheduling

Production scheduling is defined as the effective and efficient allocation of the limited resources to the activities over time (Graves 1981; Lawler et al. 1993). The problem type can be classified into mainly three fields: machine configuration/environment, job characteristic and performance criteria. The schedule is called optimal if it reaches minimization or maximization, the specific performance criteria. Motivated by the complexity in the real world and the development of scheduling theory, more complex machine configurations are considered. In addition, more irregular performance criteria are proposed for different purposes, which makes the scheduling problems even more challenging. In this section, the content is divided two parts. In the first part, the development of single-factory production scheduling with one-stage machine configurations under both deterministic and stochastic situations is stated through the related literature. In the second part, the literature related to more complex machine configurations, i.e., multiple factories located in different regions, is reviewed.

2.1.1 Single-factory production scheduling

The main machine configurations discussed in the literature, from easy to complex, are:

- Single machine;
- Parallel machines (e.g., identical, uniform, unrelated);
- Open shop;
- Flow shop;
- Jop shop.

Actually, the single machine environment is a special case of the parallel machine environment. For the single machine environment and parallel machines environment, only one-stage operation is involved in the production process for each job. Whereas, multiple operations are required for each job in open shop, flow shop and job shop environments. The open shop is a more general case compared with the flow shop, in which the ordering of the operations of each job is not fixed. The flow shop is a case in which each job has to operate on each machine with a specified processing order. The job shop specifies that each job may have different operations to deal with under its specified ordering. In this section, we mainly focus on the literature related to the scheduling problems under single and parallel machines environment.

The job characteristics mainly indicate the restrictions of the jobs during production, i.e., allowance of preemption or non-preemption, precedence relationship between jobs, release date specified for each job, unit processing requirement or arbitrary nonnegative processing requirement for each job.

The regular performance criteria discussed in most of the literature are the non-decreasing functions of completion times of jobs, i.e.,
sum of weighted completion times: $\sum_{j\in J} w_j c_j$
maximum completion times (i.e., makespan): $C_{max} = \max(c_j, \forall\, j \in J)$
maximum lateness: $L_{max} = \max\big(L_j, \forall\, j \in J\big)$, $L_j = c_j - d_j$
weighted number of tardiness: $\sum_{j\in j} w_j \max\big(c_j - d_j, 0\big) = \sum_{j\in j} w_j T_j$
weighted number of tardy jobs: $\sum_{j\in j} w_j U_j$

However, more and more researchers are starting to consider irregular performance criteria to make the measurement more reasonable due to different problem types, i.e.,
Earliness and tardiness with common due dates: $\sum_{j\in J}(c_j - d)^- + \sum_{j\in J}(c_j - d)^+$
Weighted earliness and tardiness with common due dates: $\sum_{j\in J} w_j (c_j - d)^- + \sum_{j\in J} w_j' (c_j - d)^+$
Weighted earliness and tardiness with distinct due dates: $\sum_{j\in J} w_j (c_j - d_j)^- + \sum_{j\in J} w_j' (c_j - d_j)^+$.

In this subsection, the literature related to the one-stage machine environment, from single to parallel, under both deterministic and stochastic situations are reviewed to demonstrate the development of the scheduling theory in this branch.

Single machine environment

The scheduling problems under a single machine environment are the special cases for all other scheduling problems under complicated machine environments. Due to its simplification, many optimal properties are verified under a specific problem type, which provides insights for the problems under the parallel machine environment. Sidney and Steiner (1986) verified that the Weighted Shortest Processing Time first (WSPT) rule is optimal for the one machine scheduling problem with the objective of weighted total completion times. The Earliest Due Date (EDD) rule was first proposed by Jackson (1955) for the problem to minimize the maximum lateness with common released time 0. However, most problems cannot be solved optimally by using simple dispatch rules. For example, if each job has its specific release time, then the problem $1\left|r_j\right|L_{max}$ become strongly NP-hard (Lenstra, Rinnooy Kan, and Brucker 1977). Karp (1972) verified that the computational complexity of problem $1|\,|\sum_{j\in j} w_j U_j$ is NP-hard. More powerful methods are needed to solve the problems, such as branch-and-bound. Baptiste et al. (2003) proposed a branch and bound algorithm in order to be solved the one machine scheduling problem with arbitrary release time under the objective function to minimize the total number of tardy jobs, i.e., $1\left|r_j\right|\sum_{j\in J} U_j$. The proposed algorithm enabled large-scale problems to be solved by imbedding the elimination rules and strong dominance relations. Bock and Pinedo (2010) proposed a speeding up scheduling algorithm for the NP-hard problem $1\left|r_j,\ p_j\right|\sum_{j\in j} w_j U_j$ by a decomposition scheme. For the problems with the performance criteria minimizing total weighted tardiness, a pseudo-polynomial-time algorithm was proposed by Lawler (1977). However, the computational complexity of the problem to minimize total weighted tardiness was proven as NP-hard (Du and Leung 1990). Potts and van

Wassenhove (1985) proposed a new branch and bound algorithm to solve the single machine total weighted tardiness problem. Fast lower bound calculation was achieved by using a Lagrangian relaxation approach. The subproblems was to minimize the total weighted completion time. A multiplier adjustment method was proposed to substitute the sub-gradient technique.

The above-mentioned problems were all discussed under regular performance measures, that is the objective function was a non-decreasing function of the completion times. However, in reality, more complicated performance criteria are needed such as minimizing the total earliness and tardiness (E/T). It is the case motivated by the just-in-time philosophy. On the one hand, penalties will be induced by late delivery of the orders. On the other hand, storage costs will be induced by early arrival of the orders. Compared with the aforementioned problems, the E/T problems are more difficult to solve, even under single machine environment, and are strongly NP-hard. Baker and Scudder (1990) provided a comprehensive review about problems with E/T. Two key properties of E/T models were proposed in a general form and were often considered under the assumption of a common due date (Bagchi et al.1987; De et al. 1989; Hall and Posner 1991).

In more recent studies, general cases were discussed. Wan and Yen (2002) proposed a Tabu search procedure together with the optimal timing algorithm to solve the single machine E/T scheduling problem with distinct due windows. Hassin and Shani (2005) studied the E/T problems with distinct processing times and distinct due dates given the sequence of tasks. A modified GTW algorithm, which was originated proposed by Garey et al. (1988) for symmetric earliness and tardiness penalties, was developed by the authors to solve the special case of common processing times.

Other advanced single machine scheduling problems including multiple objective problems (Hoogeveen 2005; Wan and Yen 2009), problems with sequence dependent setup times (Allahverdi, Ng, Cheng, and Kovalyov 2008) and problems with batching scheduling (Potts and Kovalov 2000) were also widely explored.

Stochastic single machine environment

Numerous studies have been conducted for stochastic single machine scheduling problems. Rothkopf (1966) undertook one of the very first studies for single machine scheduling problems a under stochastic environment. It was proven that, when the processing time follows exponential distribution and the objective is to minimize the expected total completion time, the problem can be reduced to an equivalent deterministic problem, and the optimal solutions are non-preemptive schedules. However, the result did not hold for the parallel machine environment when preemption was allowed. Therefore, the Weighted Shortest Expected Processing Time (WSEPT) rule is not necessarily optimal for the parallel machine environment. The dynamic allocation indices approach proposed by Gittins (1979) has been extensively studied by many researchers for stochastic scheduling problems under a single machine environment (Pinedo 1983; GLazebrook 1984; Pinedo and Rammouz 1998; Weiss 1992; Seo et al. 2005). Pinedo (1983) studied the single machine scheduling problems with exponential distributed processing times, random release dates as well as random due dates. The performance criteria were the expected weighted sum of completion times and expected weighted number of tardy jobs. The results showed the solutions properties were distinct to those under deterministic situations. No polynomial algorithms were known for these types of problems. Glazebrook (1984) proposed strategies for the single machine scheduling problem where Bernoulli-type breakdowns were involved. The objective was to maximize the total expected reward earned during processing.

Afterwards, different problem types were discussed. The problems with E/T criteria were studied in more general cases (Soroush and Fredendall 1994; Soroush 1999; Soroush 2007). Cai and Tu (1996) proposed a single machine scheduling problem with random processing time and stochastic breakdown and common due date, in which the breakdown occurrence was assumed to follow a general Poisson process. The performance criterion was the sum of the squared deviations of the job completion times from the common due date. The optimal properties were established and a sufficient condition was derived in which the optimal sequences were V-shaped with respect to mean processing times. Jia (2001) discussed a similar problem but with random common due dates. Both the processing time and the due dates were assumed to have exponential distributions. The necessary conditions for optimal schedules were demonstrated to be weighted expected shortest processing time (WESPT). Soroush (2007) proposed a model for random processing times with arbitrary distributions and distinct due dates, aiming at minimizing the total weighted number of early and tardy jobs. An efficient heuristic was proposed for generating optimal schedule candidates due to the NP-hardness of the problem.

Parallel machine environment

As extension research and generalization of the single machine scheduling, many studies have been carried out in parallel machine scheduling. Some dispatching rules have also been proposed for different types of problems. For the simplified problem $\mathrm{Pm}||\sum_{j\in J} c_j$, where Pm represents identical parallel machine environment, the Shortest Processing Time (SPT) rule was proved as the optimal schedule rule. The Longest Processing Time (LPT) rule was applied to the problem $\mathrm{Pm}||C_{max}$ whose worst-case analysis was conducted by Graham (1966) and Hwang et al. (2005). Kawaguchi and Kyan (1986) provided a worst-case bound for the WSPT rule in terms of the identical parallel machine problem with weighted total flowtime $\mathrm{Pm}||\sum_{j\in J} w_j c_j$. Vepsalainen and Morton (1987) proposed more complex priority rules, Apparent Tardiness Cost (ATC) and Weighted Cost Over Expected Remaining Time (WCOVERT) for problems with weighted tardiness related objectives. The superiority of the complex priority rules was demonstrated compared with EDD, S/RPT, WSPT. Leung and Pinedo (2003) discussed a parallel machine scheduling problem with the common performance criterion, i.e., makespan minimization. It was shown that for the situation of unrelated machines, the problem with preemption allowed was strongly NP-hard.

For the situation of identical machines, a polynomial-time algorithm was developed to solve the problem. Li (2006) considered an identical parallel machine scheduling problem with common performance criteria. The main restriction was from machine eligibility. For more general cases, the parallel machine scheduling problem with processing set restrictions were further studied (Lin and Li 2004; Lee et al. 2011). The objective function usually minimized the makespan. Leung and Li (2008) provided a more detailed review on processing set restriction scheduling problems. When considering parallel machine scheduling problems with earliness and tardiness related criteria, no simple dispatched rules could be applied and the general problems are NP-hard.

The literature for parallel machine scheduling problems under E/T objective functions is much less than in a single machine environment. Cheng and Chen (1994) studied a problem of assigning a common due date and sequencing jobs under identical parallel machine environment. The objective was to minimize sum of earliness and tardiness penalties and due date value. The problem was shown as NP-hard, under the special case of an identical processing time, and could be solved in polynomial times. Sivrikaya-Şerifoğlun and Ulusoy (1999) studied a more practical problem, in which distinct due dates, distinct release dates for jobs, different processing rates for machines and sequence-dependent setup times were involved, with the aim at minimizing the total weighted earliness and tardiness penalties. A genetic algorithm (GA) with new proposed crossover operator called multi-component uniform order-based crossover, was developed and verified for its effectiveness and efficiency for solving large-scale problems compared with traditional GA with neighborhood exchange type of search. Later, Radhakrishnan and Ventura (2000) utilized simulated annealing (SA) combined with a local search heuristic to solve almost the same problem but with a different objective function which was to minimize the total absolute deviations of completion times from the corresponding due dates. Ventura and Kim (2003) further considered the problem with additional resource constraints under the assumption of an identical processing time. The problem was formulated into a binary integer programming and solved by a Lagrangian relaxation approach.

Stochastic parallel machine environment

Stochastic scheduling problem under parallel machine environment afterwards got much attention due to its practical applicability. At the very beginning, the studies focused on the discussion on the case of the processing time following exponential distributions. Good and simple optimal schedule policies were verified for some special problem types. Pinedo and Weiss (1979) verified that the LEPT (SEPT) rule was optimal for identical parallel machine scheduling problems with the objective of minimizing the expected makespan (flow time). Weber (1982) generalized the theorem for arbitrary distributions with monotone hazard rates. Emmons and Pinedo (1990) studied a more complex problem in which the due dates were random variables. The objective was to minimize the expected weighted tardy jobs, and optimal polices were obtained under various assumptions. Chang et al. (1992) gave optimal conditions for the LEPT rule to minimize the expected tardiness cost at time t for problems with exponential distributed processing times and random release dates. Cai and Zhou (1999) solve the parallel machine scheduling problem with random breakdown consideration. The objective was to minimize the expected costs for both earliness and tardiness.

When the problems considered become more applied, the optimal properties could be very complicated and the simple dispatching rules could not be optimal and effective any more. More powerful heuristic algorithms and approximation methods were inevitably needed to solve more complicated problems. Al-Kham's and M' hallah (2011) studied a parallel machine scheduling problem to maximize the expected net profit by determining machine capacities, in which the due dates were assumed uncertain. An iterative sampling average approximation method was proposed. Zhang et al. (2012) solved the unrelated machine scheduling problem to minimize the mean weighted tardiness in which the jobs arrived in a Poisson process and the due dates were random. An average-reward reinforcement learning method was proposed to solve this problem. It was demonstrated that the solutions under the policy through learning outperformed WSPT, Weighted Modified Due Date (WMDD), ATC and WCOVERT. Jagtenberg et al. (2013) proved that for the parallel machine scheduling problems with exponential distribution processing time, the lower bound of the worse-case performance of the WSEPT rule was worse than the upper bound of its worse-case performance corresponding to its deterministic counterpart. Xu et al. (2013) discussed an identical parallel machine scheduling problem with uncertain processing time. A robust min-max regret scheduling model was proposed because of limited knowledge of probability distribution. Heuristics were developed to solve the problem. Von Hoyningen-Huene and Kiesmüller (2015) considered the problem with random machine failure. Both preventive and corrective maintenance was involved in the problem. An approximated objective of the expected makespan was proposed for evaluating the schedule in a simplified pattern.

2.1.2 Multiple-factory production scheduling

Due to the increasing trend of globalization, researchers and industrialists have paid attention to multi-factory scheduling problems (Behnamian and Fatemi Ghomi 2014). For the multi-factory scheduling problem, it can be further classified into two categories, i.e., multi-agent and single-agent. The literature reviewed focuses on the single-agent multi-factory scheduling problems. In a multi-factory production scheduling model, the factories can be structured in parallel or in series. A parallel structure model means each factory can produce the finished goods with the same quality that can be supplied to the customers directly (Timpe and Kallrath 2000, Chan et al. 2005a, Chan et al. 2006, Chung et al. 2009a, De Giovanni and Pezzella 2010), while a series structure model means the finished items from one factory become the raw materials or components of another factory for further production. The finished goods will be delivered to customers by the end of production in the last factory in series (Chung et al. 2009b, Chung et al. 2010, Ruifeng and Subramaniam 2011, Karimi and Davoudpour 2015). In the literature, the problems under different machine environments, i.e., single machine, parallel machine, flow shop, job shop and open shop, were discussed. Almost all the studies of this research stream were under a deterministic background. In the following two subsections, the relative literature has been reviewed.

2.1.2.1 Series-structured production network

Thoney et al. (2002) considered a multi-factory scheduling problem in series and showed that the vehicle limit can be the main constraint for the system performance with the due-dates related objectives, in three different scenarios: two factories feeding one, one factory feeding two, three factories in series.

Garcia et al. (2004) considered a scheduling problem of production and distribution planning with no stock process which is called just-in-time scheduling. It was assumed that production costs between the different factories were the same. Therefore, the distribution cost is the only factor in the objective function. An integer programming model was described for small-case problems.

Safaei et al. (2010) studied integrated planning instead of scheduling problem to minimize total operating costs with consideration of limited vehicles in a series-structured multi-factory manufacturing system. Each factory in this system could produce both finished goods which could deliver to local customers directly, and components of the finish goods, which were the input for downstream factory in this system. Two stages of the distribution were considered with limited vehicles.

The machine failure not only affects the production in one factory, but it may induce a chain reaction to other factories in a series-structured multi-factory production network. Chung et al. (2009a) suggested a double tier GA to solve the simultaneous scheduling of perfect and imperfect maintenance during production scheduling in order to maintain the systematic reliability at a revised acceptable level. In general, the measures of customer service level are based on delivery lead time or due dates. Chung et al. (2010) took into account the total delivery lead time without cost for the objective function of the integrated production and distribution model in the multi-factory environment. The authors discussed a multi-factory production scheduling problem where the parallel machines with multiple purpose in each factory took the capacity for producing partial finished goods or finished goods. The objective was to minimize the total makespan, consisting of processing time, distribution time between factories and set-ups time.

2.1.2.2 Parallel-structured production network

For multi-factory or multi-site scheduling problems in a parallel-structure, it usually involves jobs (orders) allocation to the factories and production sequence in each factory.

Timpe and Kallrath (2000) considered a multi-purpose multi-factory manufacturing system in which the factories were geographically dispersed nearby the customers located in different countries. This model was subject to different production modes with changeover times. Moon et al. (2002) solved an integrated process planning and scheduling problem under a multi-factory environment in which each factory strong coordinated and cooperated with each other, like belonging to the same company. Alternative machines and sequences, sequence-dependent set-ups and distinct due dates were taken into account. The objective was to minimize total tardiness. A genetic algorithm based heuristic approach was developed to obtain good approximate solutions. In order to solve for an advanced process planning and scheduling model with precedence constraints under the multi-factory environment, Moon and Seo (2005) developed an evolutionary algorithm to minimize makespan. Jia et al. (2003) proposed a modified genetic algorithm for solving parallel-structured multi-factory scheduling, which can be used to solve various scheduling objectives, including makespan minimization, cost and weighted multiple criteria minimization. Later Jia et al. (2007) further modified the algorithm by integrating the GA with the Gantt chat for deciding on the factory combination and schedule in a distributed manufacturing environment. Multiple objectives, including minimizing makespan, job tardiness and operating cost, could be efficiently solved by the proposed approach for small and medium-sized problem. Chan et al. (2005a) solved a similar distributed scheduling problem in which decisions to be made included job assignment to suitable factories and production scheduling in each factory. An adaptive GA was proposed in which a new crossover operator called dominated gene crossover was developed to enhance the performance of the genetic search. The problem to determine optimal crossover rate was excluded. The numerical experiments indicated significant improvement achieved by the proposed GA, compared with the well-known optimization approaches. Later, Chan et al. (2006) further consider the distributed scheduling problem with machine maintenance constraints, which affected the availability of the machines. The objective was to maximize the system efficiency. A dominant genes GA was proposed to solve the problem with better reliability compared with other existing approaches.

Chen and Pundoor (2006) solved a parallel-machine multiple plant production scheduling problem in a global supply chain. In this problem, multiple plants were located overseas and one distribution center was located locally. For each plant, due to different productivity and labor costs, the processing time and cost of each job differed from the plant assigned to. The decisions to be made included order assignment among plants, production schedule for the jobs in the same plant and shipping schedule of the completed orders from each plant. Four different performance criteria were considered which involved both delivery lead time and total production and distribution cost. The analyses for the computational complexity of the problem under different objectives were carried out. Both exact and heuristic algorithms were proposed to solve the problems. Worst-case analysis for the heuristics were carried out. Randomly generated test instances evaluated the capacity of the heuristics to generate quick near-optimal solutions. Moon et al. (2008) proposed an integrated process planning and scheduling to determine resource selection and operation schedule simultaneously. The objective was to minimize the makespan. The problem was formulated into MILP with sequence and precedence constraints. A new topological sort based evolutionary search approach was proposed to solve this integrated model. The topological sort was used to generate feasible sequences to guarantee the feasibility of the proposed evolutionary search approach. The efficiency of the proposed approach was demonstrated by the numerical experiments for various sizes of problems. De Giovanni and Pezzella (2010) discussed flexible manufacturing systems where each manufacturing cell had multi-purpose machines. In this model, three decisions need to be made: the assignment of jobs to appropriate manufacturing cell, the assignment of job operations to each machine and the processing sequence on each machine in the manufacturing cell. The objective was to minimize the make-span of the whole decentralized manufacturing systems through the 3-level decisions. Kerkhove and Vanhoucke (2014) studied a parallel machine multi-factory scheduling problem with consideration of changeover interference whose objective was to minimize a weighted combination of job lateness and tardiness. The problem came from a real case of a Belgian producer of knitted fabrics. A hybrid meta-heuristic based on both simulated annealing and genetic algorithm was proposed to solve the real-scale scheduling problem. The impact of changeover interference was reduced by 23% compared with the random scenario.

"Production planning results in medium and long-term decisions, whereas production scheduling determines the timing and sequence of operations in the short term." Hooker (2005) proposed a multi-factory production scheduling problem under one-stage parallel machine environment. The problem was divided into parts. The part involving allocating tasks to different facilities with resource constraints were formulated by mixed integer linear programming. The part for tasks scheduling was formulated by constraint programming. These two parts were linked via logic-based benders decomposition. The objective was to minimize cost and makespan in which all tasks had the same release date and deadline. Errdirik-Dogan and Grossmann (2008) solved a simultaneous planning and scheduling problem under one-stage continuous plants with parallel units, aiming at maximizing total profit over multi-period planning horizon. A bi-level decomposition algorithm was proposed to solve upper level planning and lower level scheduling successively. Later, Terrazes-Moreno and Grossmann (2011) solved an integrated production planning and scheduling problem in a production and distribution network that involved short-term as well as long-term decisions. In this production–distribution network, the production sites were responsible for different markets geographically dispersed. A hybrid decomposition method combining the bi-level (Erdirik-Dogan and Grossmann 2008) and spatial Lagrangian decomposition methods was identified to have a faster convergent speed than bi-level decomposition alone.

A popular objective for parallel-structured multi-factory models in very recent studies was minimization of the makespan (Behnamian and Fatemi Ghomi 2013, Lin et al. 2013, Ziaee 2014, Naderi and Ruiz 2014, Xiong et al. 2014). The focus was on the production scheduling under complex processing environment without consideration of transportation constraints. Behnamian and Fatemi Ghomi (2013) modeled each factory with parallel identical machines. A genetic algorithm with a new encoding scheme and local search was developed to find near-optimal solutions. Yazdani et al. (2015) proposed new models and three artificial bee colony algorithms for the same problem proposed in Behnamian and Fatemi Ghomi (2013). The new proposed models significantly outperformed the original one and the proposed metaheuristics performed more effectively. Lin et al. (2013) proposed a modified iterated greedy algorithm for a distributed permutation flow-shop scheduling problem which was simpler and more efficient. A similar problem was solved by Naderi and Ruiz (2014) by a scatter search algorithm which was seldom explored previously in the flow-shop setting. Ziaee (2014) solved a parallel structured scheduling problem in job-shop setting by a fast heuristic algorithm. In the same year, Naderi and Azab (2014) solved a similar distributed job-shop scheduling problem. Two mixed integer linear programming models were proposed for small-scale problems and the newly proposed greedy heuristic could find optimal solutions for small-scale problems efficiently.

Other optimization criteria were also explored. A distributed parallel-factory scheduling problem with transshipment lead time in which each factory had different objective (i.e., processing cost minimization and profit maximization) was recently discussed and solved by a hybrid variable neighborhood search/tabu search algorithm (Behnamian 2013). A hybrid GA with reduced variable neighborhood search was developed to minimize the weighted sum of the makespan and mean completion time for a two-stage assembly scheduling problem (Xiong and Xing 2014). Behnamian (2017) solved a parallel-factory scheduling problem with consideration of transshipment among the factories to minimize the total production cost.

2.2 Production and distribution scheduling

The coordinated production and distribution problems have drawn more and more attention in the last two decades. In order to meet customized needs and stay competitive in the market, more and more companies are adopting the make-to-order business mode. In this way, the finished orders are usually delivered to their customers directly, or shortly after production, without inventory. With the fast development of logistics, such companies have opportunities to realize low cost and high service level by integration of production and distribution planning and scheduling (Thomas and Griffin 1996). More and more researchers are studying production scheduling with transport constraints. Danese and Bortolotti (2014) recently verified that only entire supply chain integration makes a notable benefit for the company rather than partially integrated activities. The majority of the existing literature for integrated production and distribution scheduling problems was modeled in a single-factory production network and focused on the single machine and parallel machine manufacturing environment. In terms of the distribution part, there are mainly three delivery methods, i.e., individual and immediate delivery, batch delivery and other delivery methods provided by 3-party logistics companies. The following subsections review part of the related literature in the research stream of production and distribution scheduling.

2.2.1 Single machine manufacturing environment

Numerous studies on integrated production and distribution scheduling under a single machine manufacturing environment have been conducted. The most common delivery methods considered in such literature are individual and immediate delivery and batch delivery. The former usually occurred when time was the priority and cost was ignored. For batch delivery, it can be further categorized in different situations, i.e., direct shipping and vehicle routing. The jobs belonging to the same customer can be batched together for direct shipping.

On the other hand, the jobs belonging to different customers can be batched together and shipped through vehicle routing. Vehicles available for shipping can have capacity limitation or be without capacity limitation. The former is applicable to the situation where the manufacturer owns its fleet. The latter is for the situation when the distribution part is handled by third-party logistics providers. Except for some special cases, most of the problems were proven to be NP-hard. The following subsections discuss the literature related to single machine integrated scheduling under the common delivery method.

2.2.1.1 Individual and immediate delivery

At the beginning of the development of production and distribution scheduling problems, the constraints in the problems mainly came from the production part. The common constraints included fixed release date, processing time, and delivery time of each job. For the distribution part, homogenous and sufficient vehicles were available. So, the mainly the production part dominated the distribution part. The objective was to minimize the maximum delivery time of all the jobs (Potts 1980; Hall and Shmoys 1992; Hoogevenn and Vestjens 2000; Liu and Cheng 2002).

Potts (1980) was the first study on integrated production and distribution scheduling. The author proposed a heuristic to solve the single machine sequencing problem with release dates and delivery times. It was demonstrated that the deviation of the solutions by the heuristics was no more than 50% from the optimal value. Hall and Shmoys (1992) proposed a similar problem with precedence constraints. A better approximation algorithm was developed based on Jackson's Rule. Hoogevenn and Vestjens (2000) considered an on-line production and distribution scheduling problem where the information about jobs in terms of release dates, processing times, delivery time were not known in advance. An on-line algorithm based on a priority rule was proposed which had a performance bound within 1.62. The author showed that there was no better deterministic on-line algorithm existing for the performance ratio for this problem. Liu and Cheng (2002) considered single machine production and production scheduling with a preemptive penalty where a setup would take place after preemption. NP-hardness was proven by the authors and a dynamic programming was proposed to solve the problem with a polynomial time approximation scheme.

2.2.1.2 Batch delivery

Batch delivery was the common shipping method for the manufacturer to make a trade-off between transportation cost and service level, or to achieve overall efficiency improvement and overall cost reduction under a single machine manufacturing system. It can be further divided into two types, direct shipping and vehicle routing. For batch delivery with direct shipping, the problem may involve single or multiple customers. However, the batch delivery with vehicle routing was only involved in the problems with multiple customers located in distinct geographical regions. The majority of studies on production and distribution scheduling focused on batch delivery with direct shipping (Chen 1996; Hall and Potts 2003; Li and Ou 2005; Pundoor and Chen 2005; Averbakh and Xue 2007; Armstrong et al. 2008; Chen and Lee 2008; Steiner and Zhang 2009; Condotta et al. 2013; Rasti-Barzoki and Hejazi 2013; Tang et al. 2014; Cheng et al. 2015; Gao and Lei 2015; Rasti-Barzoki and Hejazi 2015; Cheng et al. 2017; Karaoğlan and Kesen 2017; Koç et al. 2017). Only a handful of studies discussed the production and distribution problems with vehicle routing (Li et al. 2005; Geismar et al. 2008; Viergutz and Knust 2014; Li et al. 2016; Devapriya et al. 2017).

Chen (1996) undertook one of the very limited studies considering the production and distribution problem with E/T related objective. The author solved a production scheduling problem integrated with batch delivery and common due date assignment for all jobs. There was no limitation assumption on the batch capacity. The cost per batch was independent of the number of finished jobs in the batch. The problem was to determine the job schedules on the single machine and the delivery date of each job so as to minimize the total earliness and tardiness penalties, due date penalty and delivery costs. Polynomial dynamic programming was proposed to solve the problem. Hall and Potts (2003) studied a coordination scheduling problem between one supplier and several manufacturers for a three-stage supply chain. The jobs were first scheduled and formed into batches, delivered to the downstream. Under the total system objective of minimizing the total operating cost, it was demonstrated that total system cost may be reduced by at least 20% through cooperation between the supplier and the manufacturer. Liu and Ou (2005) studied a problem integrating job scheduling with pickup and delivery of the raw material and finished goods. Only one capacitated vehicle was available for both pickup and delivery. The objective function was to minimize the makespan of the whole system's schedule. An efficient heuristic was developed for the general problem. Koç et al. (2017) studied a similar production and distribution problem with both inbound and outbound transportation. In this problem, multiple capacitated vehicles were available. Inventory costs would be induced by unprocessed jobs and finished jobs stored at the facility. The objective was to minimize total transportation costs and inventory holding costs. The problem was proven to be NP-hard and solved by an efficient heuristic.

The common objectives considered are related to delivery time, including minimizing maximum delivery time (Li and Ou 2005; Geismar et al. 2008; Cheng et al. 2015; Karaoğlan and Kesen 2017), sum of delivery times (Li et al. 2005), and maximum lateness (Condotta et al.2013). Many other studies considered the problem with an objective composed of a monotonic function of delivery times and sum of delivery costs, in which the delivery cost was determined by the number of the batches and the job-dependent distances (Pundoor and Chen 2005; Chen and Pundoor 2009). Pundoor and Chen (2005) studied a make-to-order production–distribution system with one supplier and multiple customers. The jobs coming from the same customer could be batched together and shipped by a direct shipment with a capacity limit. The objective was to minimize the maximum delivery tardiness and total distribution cost. A fast heuristic was proposed for solving the general problem. The value of production–distribution integration was evaluated and compared with two sequential approaches. Averbakh and Xue (2007) studied an on-line scheduling problem with the objective of minimizing the total flow time and delivery cost. Preemption was allowed and due dates were not involved in the problem. A on-line two-competitive algorithm was demonstrated to have the best competitive ratio. Chen and Lee (2008) considered a more general problem in which multiple transportation modes were available. The transportation mode was defined by the transportation speed. Higher speed incurs higher cost. The objective was to minimize the total weighted job delivery time and transportation costs.

Polynomial algorithms were developed for special cases and an approximation algorithm was proposed to solve more general cases with performance guarantees. Steiner and Zhang (2009) consider the supply chain scheduling problem with multiple customers, whose jobs had their own due dates. Several jobs coming from the same customer could be delivered in a batch by direct shipping. The objective was to minimize the weighted number of late jobs and total delivery costs. The proposed approximation algorithm was proven to have near-optimal solutions for the original general problem by parametric analysis of its performance ratio. Rasti-Barzoki and Hejazi (2013) considered a similar problem with due date assignment. The objective was to minimize the total weighted number of tardy jobs, total due date assignment costs and total batch delivery costs. The problem was modeled by an integer programming (IP). Two methods, the heuristic algorithm and the branch and bound method were developed and demonstrated for computational efficiency. Later, Rasti-Barzoki and Hejazi (2015) further considered the problem with controllable processing times which was not involved in the former study. A pseudo-polynomial dynamic programming algorithm was proposed to solve the problem.

Some other objectives such as cost oriented were also considered, such as maximizing total demand satisfied (Armstrong et al.2008), minimizing makespan and the number of batches (Tang et al. 2014), minimizing production, delivery and inventory costs in which production cost was proportional to the total production time (Cheng et al.2017).

Some recent studies discussed problems under a batching machine manufacturing system, in which a batch of jobs could be handled at the same time and the processing time was determined by the longest processing time of the job in the batch. Tang et al. (2014) studied a batching machine scheduling problem with batch delivery for steel production. The author considered a system in which the raw material was shipped to the batching machine from the holding area for production by a vehicle. The processing time for production would increase due to the deterioration of the raw material. The objective was to minimize the makespan and the number of batches. The problem was proven to be NP-hard. Both heuristic and exact algorithms based on branch and bound were proposed. The optimal solutions could be obtained for small-scale problems by the exact algorithm. Cheng et al. (2015) proposed a model in which jobs were shipped to the customer after the production under the batching machine. One vehicle with multiple-batch capacity was available for transportation. The objective was to minimize the service span, and a polynomial heuristic was developed. Later, the author further studied the problem with a cost oriented objective and a fast approximation algorithm with less than 2 worst-case ratio was developed (Cheng et al.2017).

A handful of the existing studies under a single machine manufacturing environment integrated scheduling with vehicle routing (Li et al. 2005; Geismar et al. 2008; Devapriya et al. 2017). They studied the problems for perishable products which had short lifespans. The products must be delivered within the lifespan without inventory. In this case, less constraints were involved in terms of the number of the vehicles available.

2.2.2 Parallel machine manufacturing environment

More and more studies on integrated production and distribution scheduling under more complex manufacturing environment, i.e., parallel machine environment, have been conducted due to practicability issues. The most common delivery methods considered were individual and immediate delivery and batch delivery. Due to the NP-hardness of the problems, more heuristics and meta-heuristics have been developed. The following subsections discuss the literature related to parallel machine integrated scheduling under the common deliver methods.

2.2.2.1 Individual and immediate delivery

Similar to the situation under single machine manufacturing systems, the focus of the integrated scheduling problem was mainly on the production part, and the objective was the traditional performance criterion for production scheduling, i.e., makespan. Woeginger (1994) studied a parallel machine scheduling problem with delivery time in which the objective was to minimize the maximum delivery time. Due to NP-hardness of the problem, heuristics based on list scheduling were proposed with worst-case analysis. Gharbi and Haouari (2002) studied an identical parallel machine scheduling problem with release dates and delivery time. The objective was to minimize the makespan for production. A exact algorithm was proposed, imbedded with a preprocessing algorithm, a new tight bounding scheme and a polynomial selection algorithm, to obtain optimal solutions.

In recent studies, different objectives were considered under immediate and identical delivery methods. Garcia and Lozano (2005) considered integrated scheduling with limited vehicles and delivery time windows. The problem was equivalent to a two-stage flow-shop scheduling problem with parallel machines. The objective was to maximize the total profit, equal to the total value of jobs minus earliness and tardiness penalties. The problem was modeled by IP and solved by a tabu search based solution procedure. Gideon et al. (2014) studied a similar problem under an unrelated parallel machine environment. The objective was to minimize the weighted sum of the total weighted job delivery time and the total distribution cost. An ant colony optimization algorithm was proposed for near-optimal solutions which showed the value of integrated scheduling.

2.2.2.2 Batch delivery

For the integrated scheduling problem under a parallel machine manufacturing environment, most studies discussed the problems under typical production scheduling performance criteria, i.e., makespan, maximum tardiness, maximum lateness, number of tardy jobs (Lee and Chen 2001; Chang and Lee 2004; Wang and Cheng 2007; Zhong et al. 2007; Ullrich 2013; Cheng et al. 2015; Liu and Lu 2016; Joo and Kim 2017; Kergosien et al. 2017).

In the problem discussed by Lee and Chen (2001), two types of transportation situations were involved, i.e., delivering semi-finished goods between machines by automated guided vehicles and delivering finished goods from machine to the customer or warehouse. Both transportation capacity and transportation times were considered. The complexity of the problem was analyzed, and polynomial and pseudo-polynomial algorithms were proposed for the problem under certain scenarios. Chang and Lee (2004) proved the NP-hardness of the integrated scheduling problem under three single-vehicle scenarios. A heuristic was proposed with worse-case analysis. Machine availability was further considered for a one customer, one capacitated vehicle problem by Wang and Cheng (2007). The complexity of the problem was analyzed under three scenarios and the heuristics within 2/3 worst-case error bounds was proposed. A similar study was carried out by Liu and Lu (2016), who proposed an approximation algorithm with 3/2 worse-case ratio. Zhong et al. (2007) discussed a one customer, one capacitated vehicle problem in which a job's occupied space during transportation was assumed different. Cheng et al. (2015) consider the integrated problem under an identical batching machine. Both cases of infinite vehicles and limited number of vehicles were proven to be NP-hard and an effective polynomial time algorithm was designed. Most of the studied mentioned above focus on discussion of the complexity of a simple structured problem. Joo and Kim (2017) studied a more practical integrated scheduling problem in which both unrelated parallel machines, multiple customers, heterogeneous vehicles with different capacities and travel times were involved. An optimal solution was obtained by the mathematical model, and the author further proposed a rule-based single-stage GA to solve the problem.

Despite the traditional scheduling performance criteria, a combined objective function, i.e., delivery time related monotonic functions and delivery cost, was also discussed in the literature (Wang and Cheng 2000; Chen and Vairaktarakis 2005; Hall and Potts 2005; Rasti-Barzoki et al. 2013; Gong et al. 2016; Guo et al. 2016). Wang and Cheng (2000) discussed an integrated parallel machine scheduling problem for minimizing the total flow time and delivery cost, in which the delivery cost was dependent on the number of deliveries. The NP-completeness was proven for the two -machine case. Pseudo-polynomial dynamic programming was proposed to solve the problem when the number of machines was fixed the number of the batches had a fixed upper bound. Chen and Vairaktarakis (2005) studied an integrated scheduling model applicable for the computer and food catering service industries. They discussed the problem under two objective functions, respectively. One was to minimize the average delivery times and total distribution cost, the other was to minimize the maximum delivery time of all the jobs and the total distribution cost. The distribution cost was composed of a fixed cost and a distance-dependent cost. The computational results showed that a significant benefit could be achieved by integration, in many situations. Hall and Potts (2005) discussed the coordination of scheduling and batch deliveries with the general objective function combined of scheduling cost and delivery cost. Here, the scheduling cost indicated the regular performance criteria for the production scheduling. In the problem, a fixed number of vehicles without capacity limitation were available. Their results implicated the value of coordination in terms of customer service improvement. Rasti-Barzonki et al. (2013) solved the integrated problem with one customer, one vehicle by a new branch and bound based on analysis of the structure properties of a single machine problem. It was assumed that there was no limit on the capacity of the vehicle. The objective was to minimize the total weighted number of tardy jobs and delivery cost. Recently, Guo et al. (2016) proposed a bi-level mixed integer nonlinear program to solve the integrated problem under an unrelated parallel machine manufacturing environment and batch-based delivery. Two objective functions were involved, i.e., minimizing the total number of tardy batches and minimizing the total cost including labor cost, holding cost, transport cost and tardiness penalty. An optimization approach was developed by integrating a memetic algorithm and heuristic rules which was evaluated by industrial data based numerical experiments. Chen et al. (2015) studied an integrated production scheduling and shipment problem with the bi-objective, which was a weighted combination of production simultaneity and shipment punctuality. The problem was solved by a modified GA.

In addition, the cost oriented objective functions were also discussed for integrated parallel machine scheduling problems in very recent studies (Lee et al. 2014; Masoud and Mason 2016; Fu et al. 2017). Lee et al. (2014) studied an integrated problem with a time window for short-life nuclear medicine. There was an effective time duration after the starting of production and was prohibited to deliver the medicine during or before this duration. Heterogenous vehicles and unrelated parallel machines were involved in the problem. The objective was to minimize the total costs including production cost, fixed vehicle cost and travel cost. Masoud and Mason (2016) considered the integrated problem in an automotive supply chain in which two-stage operations for production and one-stage delivery were involved. Capacitated vehicles were available to deliver the finished parts to meet predefined due dates. The objective was to minimize the total set-up cost, inventory cost, transportation cost and production outsourcing cost. A hybrid simulated annealing algorithm was proposed to get near-optimal solutions.

All the above-mentioned literature in this subsection focused on the integrated problem with batch delivery under direct shipping method. Very limited studies considered integrated parallel machine scheduling with vehicle routing (Ullrich

2013; Fu et al. 2017; Kergosien et al. 2017). Ullrich (2013) considered the integrated problem with machine-dependent ready times as well as the available time of the heterogenous vehicles. The objective was to minimize the total tardiness. Fu et al. (2017) studied an integrated problem met in the metal packaging industry, in which delivery time windows were involved, and sufficient heterogenous vehicles were available for delivery. The problem was solved by a two-phase iterative heuristic. The first phase, responsible for the production part, was to minimize the total set-up cost. The second phase, responsible for the distribution part was to minimize total transportation cost. Both were solved by mathematical models respectively and the benefit of coordination was evaluated. Kergosien et al. (2017) addressed an integrated scheduling for a chemotherapy production and delivery problem, which was treated as a combination of classical parallel machine scheduling with the multi-trip travelling salesman problem. The objective was to minimize the maximum delivery tardiness under the chemical stability duration constraint. A Benders decomposition-based heuristic was proposed to solve the problem.

2.2.3 Other delivery methods

With the rapid development of the third-party logistics companies (3PL), some researchers started to consider the production scheduling problem integrated with 3PL, especially in the increasing trend of make-to-order business modes (Wang and Lee 2005; Stecke and Zhao 2007; Huo et al. 2010; Agnetis et al. 2014; Azadian et al 2015; Cheng et al. 2015; Li et al. 2015; Guo et al. 2017). A handful of studies considered the production scheduling problem with dominated transportation modes, i.e., fixed delivery departure time (Hall et al. 2001; Li et al.

2005; Wang et al. 2005; Li et al. 2006; Leung and Chen 2013; Ma et al. 2013; HaGarciaghaei-Keshteli and Aminnayeri 2014; Mensendiek et al. 2015).

Wang and Lee (2005) studied single machine production and transport logistics scheduling integrated with two transport modes selection. The transport mode was dependent on the transportation time. High cost was induced by a shorter transportation time. No limitation existed on the shipment availability and capacity. The decision involved the job scheduling on the machine and the transportation mode selection. The objective was to minimize the total transportation cost and weighted tardiness cost. A branch and bound algorithm was developed with two effective lower bounds. The efficiency was demonstrated by comparing with the computational running time of Cplex. Stecke and Zhao (2007) considered a similar integrated production and transportation problem for a make-to-order manufacturing company with multiple transport modes consideration provided by 3PL companies such as, FedEx and UPS. The key point was to find the optimal production schedule to leave enough time for a longer shipping lead time and lower cost shipment selection. When allowing partial delivery, the problem could be modeled as an MIP and minimum cost flow network and solved optimally by the NEDD rule under the convex shipping cost function. For the problem without partial delivery, it was proven to be NP-hard. A polynomial heuristic algorithm was proposed for the NP-hard problem. Other scenarios with regard to shipping cost were also analyzed.

Huo et al. (2010) considered production–distribution scheduling under parallel and identical machine manufacturing environments. The delivery time of each job was given at the beginning of the planning horizon. The decision was to select a subset of jobs to produce so as to maximize the total profit. Corresponding to the three scenarios considered: arbitrary profit; equal profit; processing time dependent profit, optimal and near-optimal algorithms were proposed and solved the problem in polynomial time. The bound improvement technique of Kovalyov was utilized to improve the computational efficiency. Li et al. (2015) further considered the problem with identical and parallel batching machines. It was assumed the 3PL picked up jobs on given dates by vehicles with identical capacity. The problem had to decide the delivery time of each job. The objective was to minimize the total profit coming from the on-time delivery jobs. Azadian et al. (2015) considered the integrated production–distribution problem under a more general manufacturing configuration, i.e., unrelated parallel machines. Different shipping options with different costs and transit times were available through 3PL. The objective was to minimize total cost including tardiness penalties. The problem was modeled as a MIP and solved by a decomposition scheme which was composed of an exact dynamic programming and heuristic approach. Cheng et al. (2015) considered the integrated scheduling problem under batching machines. Sufficient identical vehicles were provided by 3PL. The objective was to minimize the total production and distribution cost. The problem was solved by a decomposition method composed of an improved ant colony optimization method and a heuristic method. Guo et al. (2017) proposed a harmony search-based memetic optimization model to solve the integrated scheduling problem for a make-to-order manufacturer with multiple transportation modes. The transportation mode differed according to its specific cost and capacity. It was shown that the proposed memetic optimization process outperformed genetic algorithm-based and traditional memetic optimization process.

Usually, 3PL companies provide more flexible selections in term of transportation cost, time, and usually provide sufficient vehicles responsible for picking up customer's orders at the appointed date and time. However, in reality, dominated transportation modes can be avoided in the supply chain involving shipping schedules, i.e. air, sea, rail transportation. The limited related literature studied the problem under simple machine configurations, i.e., single machine and identical parallel machines. Li et al. (2005) studied an integrated assembly scheduling with air transportation. Different available time, capacity, shipping lead-time with different price was involved for each flight. The problem was solved by a decomposition method. The first sub-problem of multi-destination air transportation allocation was modeled as ILP and solved optimally. The second sub-problem of assembly scheduling was solved based on typical dispatching rules. The objective for the first sub-problem was to minimize the total transportation cost as well as earliness and tardiness penalties. The second sub-problem was to minimize the average waiting cost at the machine. It was shown that considerable cost reduction was achieved compared with exiting method used in industry.

Later, Li et al. (2006) further studied the problem with consideration of the process delays coming from the production part. The scenario that the machine would not be available at the beginning, until some given time, was considered in the sub-problem of assembly scheduling. The objective was changed into minimizing the delivery costs due to adjustment of air transportation allocation. The problem was solved by a decomposition method. Wang et al. (2005) studied a mail processing and distribution scheduling problem with a fixed trucks schedule. The trucks were responsible for different regions with limited capacities.

The processing system was treated as a single machine. The objective was to sequence the mail so as to minimize the total unused truck capacity. The problem was solved based on dispatching rules and heuristics. Leung et al. (2013) studied an integrated one machine scheduling problem with fixed delivery departure dates. Three different objectives with regards to monotonous functions of delivery dates or number of vehicle used were considered and solved by the proposed polynomial algorithm. Ma et al. (2013) studied an integrated production scheduling problem with maritime shipping schedules under a single-factory environment with the objective of minimizing total earliness and tardiness penalties. A two-level GA was proposed to solve the problem. The numerical results demonstrated the significance of shipping information in consideration of integrated scheduling. Hajiaghaei-Keshteli and Aminnayeri (2014) considered an integrated one machine scheduling with rail transportation. In this problem, two kinds of trains were considered, ordinary trains and charter trains. The objective was to minimize the total cost including transportation cost, earliness and tardiness penalties. It was solved by two metaheuristics, i.e., the GA and Keshtel algorithm, which were encoded by specific procedures and heuristics. Mensendiek et al. (2015) considered an integrated scheduling problem with fixed delivery departure dates under a more complex manufacturing configuration, i.e., identical parallel machines. The objective was to minimize the total tardiness. The problem was formulated into mathematical programming and solved by a branch and bound algorithm for small scale problems. A tabu search and a hybrid GA were further developed for large scale problems.

2.2.4 Problems with multi-factory manufacturing environment

Some interesting studies were conducted for multi-factory production and distribution problems. The integrated problem was simplified with the sufficient and identical vehicle assumption (Timpe and Kallrath 2000; Chen and Pundoor 2006). The finished goods could be delivered right after completion. Thoney et al. (2002) showed that vehicle limits can be the main constraint for the system performance with the due-dates related objectives. Garcia at al. (2004) assumed the production costs were the same among the factories, therefore, only transportation cost was involved in the objective function. The objective function was to maximize total profit of the on-time served orders.

Li and Ou (2007) studied a two-machine decentralized production network with heterogenous capacitated vehicles. Each job was composed of two tasks which had to be handled on both machines. The finished parts were bundled together at the distribution center and delivered to customers. The objective was to minimize the total delivery cost and customers total waiting cost. The customer waiting cost was the weighted sum of the delivery times. Most studies on production and distribution scheduling were discussed for just-in-time manufacturing or make-to-order business models. Pundoor and Chen (2009) proposed an integrated model for a cyclic scheduling problem with constant demand. Multiple suppliers producing different products, one warehouse and one customer were involved in the supply chain. The objective was to find joint cyclic production and delivery schedules so as to minimize total production, inventory and distribution cost without backlog.

Kim and Oron (2013) studied an integrated problem for a parallel-structured multi-location production network. In the problem, one vehicle with unlimited capacity was responsible for delivery jobs in batches to the central customer. The objective was to minimize the total delivery cost and weighted sum of tardy jobs. The problem was reduced into a shortest path problem and a corresponding algorithm based on a directed acyclic graph method was proposed to solve small and medium size problems. Other studies focused on integrated scheduling for series-structured multi-site manufacturing system with inner transport consideration (Chan et al. 2013; H'Mida and Lopez 2013; Agnetis et al. 2014; Karimi and Davoudpour 2015; Agnetis et al. 2016). Agnetis et al. (2014) considered a supply chain scheduling problem between factories where the semi-finished products would be delivered in batches from one production site to another production site belong to the same manufacturer. Two transportation modes, i.e., regular transportation with fixed departure time, express transportation with flexible departure time were considered. The objective was to minimize transportation cost. Two situations in which the manufacturer dominated or the 3PL provider dominated were analyzed. Karimi and Davoudpour (2015) considered the integrated problem with both transportation situations, i.e., the transportation among factories and delivery from factory to the customer. The objective was make trade-off between transportation cost and tardiness cost.

2.3 Stochastic programming

Stochastic programming is a framework for modeling optimization problems in which uncertainty is involved (Mínguez et al. 2011). Since uncertainty cannot be avoided in the real world, stochastic programming had got rapid development for its wide range of applications. Stochastic programming is solved based on the probabilistic information of the uncertainty parameters. If the probabilistic information is available, the stochastic programming can be transferred into its deterministic counterpart by taking expected values of the random variables (Rawls and Turnquist, 2010) or by its designed probabilistic constrained programming, which is also called chance constrained programming (CCP).

However, it is difficult to formulate the equivalent deterministic counterparts which are converted from CCP with its distinct structure. Several optimization theories/methods that are based on convex programming cannot be applied because of the non-convexity of the probabilistic constrained programming problems. Therefore, finding good approximation methods becomes significant for solving the CCP. Mainly two types of approaches are proposed for solving the CCP: sampling/scenario based approach (Cao et al. 2010; Wang et al. 2013; Shen 2014; Giovanni et al. 2016) and analytical approximation. Analytical approximations are aimed at converting the CCP problems into their equivalent or approximate deterministic counterparts, which are more reliable than the sample average and scenario-based approximations. To simplify the CCP problems, the linearization of nonlinear deterministic equivalents is inevitable. Based on the proposed linear transformation theorem, Bilsel and Ravindran (2011) solved a multi-objective CCP for the selection of a supplier under uncertainties by using goal programming.

By using discretization and linearization, Wang and Meng (2012) converted the mixed-integer nonlinear convex programming into a mixed-integer programming and solved the problem by a cutting-plane based exact algorithm. Sun et al. (2013)

developed an inexact joint probabilistic left-hand-side chance constrained model and solved by a non-equivalent but sufficient linearization form. Bentaha et al. (2015) converted the original CCP into second order conic programming by piecewise linear approximation for the probabilistic cumulative function. Robust optimization was also used for solving the CCP because of the mild requirement of the probability distribution of the random variables in robust optimization (Li and Li 2015). Borodin et al. (2016) assumed the stochastic component procurement lead-times to follow discrete distributions and reformulated the original joint chance constrained programming into a mixed-integer programming

2.4 Exact algorithm

Researchers have proposed many different optimization methodologies for production and distribution network problems, from linear deterministic models to non-linear stochastic model. Some researchers formulated the problems into mathematical programming, i.e., integer linear programming, mixed-integer linear programing, dynamic programming (Lee and Chen 2001; Lei et al. 2006; M'Hallah and Al-khamis 2012; Bilgen and Celebi 2013). Thereby, the problem can be solved by exact optimization procedures, branch and bound algorithm and dynamic programming algorithm. In this section, some of the literature regarding to branch and bound and dynamic programming algorithms applied for the problem of production and distribution scheduling is discussed.

Branch and bound, as one of the most successfully exact solution procedures for solving constrained optimization problems, has been developed for more than 60 years (Lawler and Mood 1966). The basic idea is based on branching and bounding schemes, especially the lower bounding scheme to search the partial solution step by step on the solution space tree by fathoming the inferior or unfeasible solution space until finding the optimal solution. Therefore, appropriate upper and lower bounding schemes directly determine the search efficiency of the algorithms. In addition, the branching scheme, which determines the search order and direction, also greatly affects the performance of the algorithm. Many researchers, have developed advanced branch and bound methods to even solve large-scale problems, without rigor, in terms of time. Additional pruning rules based on specific properties of the problems were proposed to solve integrated production scheduling problems. Branch and bound mainly adopts a breadth first search strategy. Some researchers used a depth first search strategy in their branch and bound algorithms.

Timpe and Kallrath (2000) formulated a multi-factory supply chain problem into mixed integer programming. They proposed a branch and bound method with directives defined for discrete variables, including factory state, binary tank variables and semi-continuous transport variables. Gharbi and Haouari (2002) proposed a global schedule construction algorithm to determine the upper bound. The lower bounding scheme, called the modified general bound, was proposed based on the so-called general bound proposed by Webster (1996). Wang and Lee (2005) solved a single machine scheduling problem with two transport modes by the branch and bound approach. They utilized the backward sequencing branching rule, i.e. WSPT, to determine the selection order of the unscheduled jobs. Two lower bounds, which were based on the assignment problem and Lagrangian relaxation, were proposed to fathom those inferior solutions. In addition, pruning rules based on dominance properties were further proposed to help fathom inferior branches. Armstrong et al. (2008) proposed a lower bound determined by the proposed heuristics and a branching scheme that ensured the search only branched to feasible schedules. Rasti-Barzoki et al. (2013) studied a one-machine scheduling problem with sufficient vehicles. They proposed a heuristic to determine the upper bound and calculated the lower bound with discussion of different cases of batching of unscheduled jobs. Pruning rules were further developed to decrease the search space. Later, a more complicated problem was solved with due date assignment by a new lower bounding scheme (Rasti-Barzoki and Hejazi 2013). Tang et al. (2014) proposed a branch and bound algorithm which was conducted in a depth-first fashion. The branching order was based on the transportation time of each unscheduled job. The lower bound was calculated by consideration of a fixed number of batches. Karimi and Davoudpour (2015) also applied a depth first search strategy for searching the solution tree. The branching scheme was based on the revised due date of the unscheduled jobs. The lower bounding scheme was based on analyses of the shipment modes. A further pruning scheme was also established.

For most cases, the branch and bound algorithm can only solve simple structured problems or small-scale problems. In order to solve comparative large-scale problems or more complicated ones with exact solutions, the branch and cut method, which is based on the branch and bound method, was proposed. In very recent studies regarding production and distribution scheduling, Karaoğlan and Kesen (2017) developed a new branch and cut algorithm for a single-machine scheduling and vehicle routing problem. The upper bound was iteratively improved during the search process by a simulated annealing based algorithm. A lower bounding and separation algorithm was proposed to separate the solutions violating the valid inequalities. A routing priority based branching scheme was developed for this problem. The authors also provided a detailed review for more implementations of the branch and cut algorithm.

2.5 Approximation algorithm

In order to solve large-scale problems in an efficient and acceptable way, approximation algorithms that determine the near-optimal solutions have had rapid development. Moreover, for some complicated problems which could not be modeled by mathematical programming or solved by exact algorithms, various approximation algorithms were developed. Some recent literature related to production and distribution and multi-factory scheduling problems is discussed here.

Ulusoy at al. (1997) designed a GA with a two-allelic representation scheme and a special uniform crossover operator to solve the simultaneous scheduling of operations on machine centers and automated guided vehicles in a flexible manufacturing system. Jia et al. (2003) presented a modified GA with once gene crossover and twice gene mutation to solve distribution scheduling problems in a multi-factory environment with various objectives which include minimizing makespan, cost and weighted multiple criteria. Later, Jia et al. (2007) proposed a Gantt Chart integrated GA to solve a similar distributed scheduling problem with consideration of multiple objectives. Gen and Syarif (2005) proposed a hybrid GA for a multi period production and distribution problem at planning level. A new technique called spanning tree-based GA was proposed which was hybridized with the fuzzy logic controller to auto-tuning the parameters of the GA. Chan at al. (2005b) proposed a GA embedded with analytic hierarchy process to solve the job allocation problem in a parallel-structured multi-factory system. Chan et al. (2006) and Chung et al. (2009) both proposed a modified GADG (genetic algorithm with dominant genes) based on the GA presented by Chan et al. (2005a), respectively. De Giovanni and Pezzella (2010) proposed an improved GA with a new local search based operator which started from the simple chromosome encoding of MGA proposed by Jia et al. (2003). Behnamian and Fatemi Ghomi (2014) solved a heterogeneous multi-factory production scheduling problem by a novel GA with a new encoding scheme and theorem based local search proposed. Nasiri et al. (2014) developed a Lagrangian relaxation approach which was further solved by GA for a three-echelon multi-site production–distribution problem with stochastic demand. Liu et al. (2014) proposed a GA with a refined encoding operator that integrated probability concepts into a real-parameter encoding method. By the proposed GA, computation space was saved due to reduction on the length of chromosome. Chang and Liu (2015) proposed a hybrid GA for solving a distributed and flexible job-shop scheduling problem. The Taguchi method was utilized to optimize the parameters and a new encoding mechanism was proposed to solve job assignments between factories. Various crossover and mutation operators were adopted in the GA to solve a flexible job-shop scheduling problem. Assarzadegan and Rasti-Barzoki (2016) modeled a single machine integrated scheduling problem into a mixed integer non-linear programming and solved by an adaptive GA and a parallel simulated annealing algorithm (PSA). The crossover and mutation operators were used in the structure of optimal solutions. The results showed the superiority of the proposed GA over PSA. In recent years, GA approaches with different features were proposed for integrated production–distribution scheduling problems with heterogeneous fleet consideration (Zegordi et al. 2010; Ullrich 2013; Low et al. 2014; Hajiaghaei-Keshteli and Aminnayeri 2014; Chen et al. 2015). Zegordi et al. (2010) proposed a gender genetic algorithm which considered non-equivalent structured chromosomes for solving integrated production and distribution scheduling with consideration of different transport speeds and transport capacities.

Other meta-heuristic approaches were also utilized for production–distribution scheduling or planning problems. Varthanan et al. (2013) proposed a multi-criterion integrated production–distribution planning approach. A novel analytic hierarchy process (AHP) based heuristic discrete particle swarm optimization (DPSO) algorithm was developed to solve this multi-period, multi-product and multi-plant model. Chang et al. (2014) used an ant colony optimization heuristic to solve a joint production–distribution schedule with parallel machines and capacitated vehicles by a make-to-order strategy. Toptal et al. (2013) proposed a tabu search heuristic for a joint production and transportation planning problem and Vanhoucke (2014) proposed a hybrid meta-heuristic which combined simulated annealing and genetic algorithms to solve a geographically dispersed parallel machine scheduling problem with limited server availability. Joo and Kim (2017) proposed rule based meta-heuristics using a single-stage GA framework.

2.6 Summary

According to the literature reviewed above, the research gaps were identified as follows:

1. Although the development of production scheduling has been intensively developed for more than sixty years, intensive studies for integrated production and distribution problems under detailed scheduling level has only conducted for two decades (Chen 2009). Most of the studies focused on the single-factory integrated scheduling problems, especially, under a single machine and parallel machine manufacturing environment. The integrated scheduling problem under multi-factory manufacturing environments were quite limited. For the sparse literature, the problems considered either had fewer constraints for the distribution part or considered a series-structured multi-factory manufacturing system. Therefore, a parallel-structured multi-factory scheduling model with consideration of both restrictions from distribution and bi-assignment among factories is proposed to fill the gap.

2. In terms of the delivery methods assumed in the literature, the common delivery methods were immediate and identical delivery and batch delivery under identical transport modes. In recent years, due to the rapid development of third-parity logistics companies, more and more researchers studied the integrated scheduling problem with multiple transport modes selections. For that case, no restriction was assumed for the availability of the shipment. Although some researchers considered more realistic cases, such as air and rail transport, which have high limitations on the available time and transportation time. However, studies on the integrated scheduling problem with maritime transport variation and limitation consideration under global supply chains was quite limited.

3. In terms of the methodology, the proposed methods in the existing literature were applicable for single-factory integrated scheduling problems. For the parallel-structured multi-factory integrated scheduling problem, bi-assignment problems, i.e., job allocation among factories, job assignment on machines in each factory, are involved. A general integrated mathematical model and new meta-heuristics are necessary to solve the integrated scheduling problem in more complicated manufacturing system.

4. Almost all the studies on integrated scheduling problems were analyzed under a deterministic environment. Very limited studies carried out by Sawik (2016) considered disruption risk for an integrated supply, production and distribution scheduling problem. However, the uncertainty in the problem comes from the suppliers. On the other hand, the existing literature discussed the impact of the shipping uncertainty from the perspective of the carriers (Lee et al. 2015; Song et al. 2015; Adulyasak and Jaillet 2016) or the downstream parties (Kouvelis and Li 2012; Kouvelis and Tang 2012; Hung and Hsiao 2013; Heydari 2014; Borodin et al. 2016), but not from the perspective of the upstream parties (i.e., manufacturers), especially for maritime transport.

5. Most of objective functions considered for production and distribution scheduling problems were the regular performance criteria of the production scheduling problems, or a combination of the regular performance criteria and distribution costs. The irregular performance criteria, i.e. E/T related objectives, which are more realistic for the make-to-order business mode with

just-in-time philosophy, were seldom considered for the problem a under deterministic problem background.

To fill the research gaps, firstly a novel deterministic integrated scheduling model for multi-factory job allocation and production–distribution scheduling problems was formulated by mathematical programming to solve the first and second research gaps. Secondly, new methodologies were proposed to solve such a complicated integrated scheduling problem to fill the third research gap. Thirdly, a new stochastic model was proposed to solve the fourth research gap. Finally, new objective functions related to both earliness and tardiness were proposed both in deterministic model and stochastic model to solve the fourth research gap. The research objectives can be summarized as follows:

1. To develop a new deterministic mathematical model for a multi-factory scheduling problem with consideration of E/T related performance criteria and practical transport constraints in global supply chains, i.e., inland distance-dependent transportation lead time and maritime transport limits and variations

2. To develop a problem property-based method to accelerate the enumerate branch and bound algorithm so as to obtain optimal solutions of the complicated integrated model in a reasonable time.

3. To develop a new meta-heuristic to solve the multi-factory integrated scheduling problem with two transport types for more practical and large-scale problems.

4. To develop a new stochastic model for solving the multi-factory integrated scheduling problem with liner shipping uncertainty.

5. To formulate the closed form of the risk cost corresponding to both earliness and tardiness induced by the shipping uncertainty so as to analyze the impact of the liner shipping uncertainty on the multi-factory production–distribution scheduling.

The following chapters describe the development of the modeling and solution methodologies for both deterministic and stochastic problems.

Chapter 3 Development of the valid cuts for computational burden reduction

In this Chapter, firstly the problem description is presented in detail in Section 3.1. The pure mathematical programming, i.e., MIP, is formulated in Section 3.2 for the integrated scheduling problem under multi-factory production network with two types of transportation. A problem property based valid cut is then developed in Section 3.3. Section 3.4 presents the design of the numerical experiments. A discussion of the results is provided in Section 3.5, with a summary in Section 3.6.

3.1 Problem description for the integrated multi-factory production and distribution scheduling

In this study, a job allocation, production and distribution scheduling problem is addressed with consideration of both multi-distance inland transport and maritime transport limits under the multi-factory environment with unrelated parallel production lines in each factory. There are n jobs $J = \{1,2,\dots,n\}$ from the overseas customers and m factories $M = \{1,2,\dots,m\}$ domestically located at different locations with total k production lines $I = \{1,2,\dots,k\}$. The jobs are transported to terminals $T = \{1,2 \dots,t\}$ after completion and shipped by the vessels $S = \{1,2,\dots,s\}$ berthed at the terminals to the overseas customers (see Fig. 3.1).

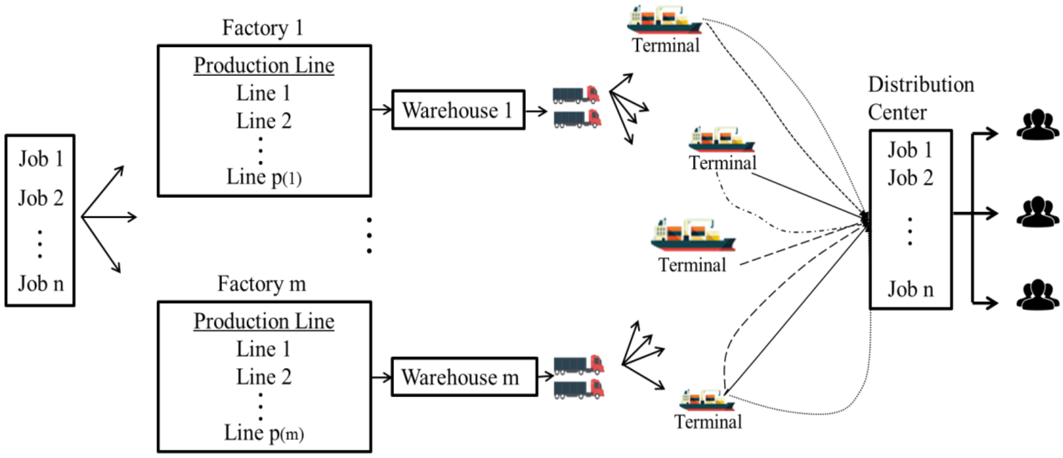

Figure 3.1. The integrated production and distribution model in multi-factory manufacturing system.

In the production part, we consider production lines with different productivity for different factories. The production lines in the same factory are identical and unrelated to those in other factories. Each job $j \in J$ corresponds to a given processing requirement of p_{ij} time units depending on the factory and production line they are assigned to, operated on the production line without interruption and immediately stored in the warehouse near the factory. The delivery time and cost between the factory and warehouse is negligible, compared to the processing time of the jobs in the factory. All jobs and production lines are available at time 0.

In the distribution part, we consider two different transportation situations. Firstly, there are sufficient homogeneous vehicles available at time 0. Here transshipment between the factories does not exist. The travelling cost of each job is determined by the variable quantity travelled and the route, dependent on the factory and terminal to which the job is assigned. Secondly, there are limited shipments with fixed delivery time and shipping lead time at each of the terminals. Each job can be shipped by exactly one shipment while each shipment may deliver several jobs at a time. Each shipment has a specific unit shipping cost. Thereby, the shipping cost of each job is determined by its quantity and the shipment to which it is assigned. The available time of the shipment to which the job is assigned is not earlier than the sum of its departure time from the warehouse and the travelling time spent on the way to the terminal. The job is stored in the warehouse immediately after completion, waiting for its assigned vessel available at the terminal. On the other hand, the job will be saved in the overseas distribution center immediately after the shipment if the due date is not yet met. The delivery time and cost between the distribution center and customers are negligible, compared to the shipping lead time and cost.

3.2 Methodology

In this section, a mathematical approach is developed for this multi-factory integrated scheduling problem.

3.2.1 Mixed integer programming (MIP)

Objective function

$$Z = \text{Min} \sum_{j\in J} q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + \mathrm{c}_j^{s} + c_j^{DC} h_j^{DC} + c_j^{p} l_j), \quad (3.1)$$

where,

$$c_j^{pro} = \sum_{i\in I} \sum_{k\neq j,\in J\cup o(e)} c_{ij}^{pro} x_{ijk}, \quad (3.2)$$

Objective function (3.1) aims at minimizing the sum of the cost of all jobs generated throughout the supply chain, which includes production cost, travelling cost, storage cost in warehouse, shipping cost, storage cost of overseas distribution center, and penalty cost. Eq. (3.2) defines the unit production cost of job j, equal to the unit production cost on the production line i to which job j is assigned.

$$c_j^w = \sum_{i \in I} c_j^{w_i} h_j^{w_i}, \tag{3.3}$$

where,

$$h_j^{w_i} = \max(w_{ij} - c_j, 0), \tag{3.4}$$

where,

$$w_{ij} = \sum_{s \in S} y_{ijs} a_s - \sum_{s \in S} \sum_{t \in T} y_{ijs} T_{st} tr_{it}, \tag{3.5}$$

Eq. (3.3) defines the unit storage cost of job j in warehouse w_i close to the factory with production line i, equal to the unit storage cost of job j per day in the warehouse w_i multiplied by its holding days in that warehouse. If job j is stored in the warehouse w_k, then $h_j^{w_k} \geq 0, h_j^{w_i} = 0,\ \forall\, i \in I,$ where $i \neq k$. Eq. (3.4) defines the holding days of job j in warehouse w_i close to the factory with production line i. If $w_{ij} > c_j$, then the departure time of job j from warehouse w_i is greater than its completion time, thus $h_j^{w_i} > 0$, otherwise $h_j^{w_i} = 0$. If the shipment s is available at terminal t, $T_{st} = 1$, otherwise $T_{st} = 0$. Eq. (3.5) defines the departure time of job j from the warehouse w_i which is close to the factory with production line i, equal to the available time of the shipment s assigned to job j minus the travelling time from the factory with the production line i to the terminal with the shipment s, and is true only if job j is assigned to production line i. Otherwise, $w_{ij} = 0$.

$$c_j^{tr} = \sum_{i \in I} \sum_{t \in T} \sum_{s \in S} y_{ijs} T_{st} c_{ijt}^{tr}, \tag{3.6}$$

$$c_j^s = \sum_{i \in I} \sum_{s \in S} y_{ijs} c_s, \tag{3.7}$$

Eq. (3.6) defines the travelling cost of job j per quantity, equal to the unit travelling cost for the distance from the factory with the production line i to which job j is assigned to terminal t where its assigned shipment s is available. Eq. (3.7) defines the unit shipping cost of job j, equal to the unit shipping cost of shipment s assigned to job j.

$$h_j^{DC} = \max(d_j - r_j, 0), \tag{3.8}$$

$$l_j = \max(r_j - d_j, 0), \tag{3.9}$$

Eqs. (3.8) and (3.9) define the earliness and tardiness of the job as the difference between its arrival time at distribution center and the due date. If $d_j > r_j$, then job j is early, thus $h_j^{DC} > 0$. On the other hand, if $r_j > d_j$, then job j is tardy, thus $l_j > 0$. If $r_j = d_j$, then job j is on time, thus $h_j^{DC} = 0, l_j = 0$.

Constraints:

Two dummy jobs $o(s)$ and $o(e)$ are set in this model as the starting point and ending point of the sequence of jobs scheduled in each production line, whose processing times are zero. The starting point $o(s)$ precedes the 'first' job assigned to the production line, while the ending point $o(e)$ is preceded by the 'last' job assigned to the production line.

$$\sum_{i \in I} \sum_{k \neq j, \in J \cup o(e)} x_{ijk} = 1 \quad \forall j \in J, \tag{3.10}$$

$$\sum_{i \in I} \sum_{j \neq k, \in J \cup o(s)} x_{ijk} = 1 \quad \forall k \in J, \tag{3.11}$$

Constraints (3.10) state that each job is assigned to only one production line and is immediately preceded at most with one other job. If job j is the 'last' job on the production line i, then $x_{ijo(e)} = 1$, otherwise $x_{ijo(e)} = 0$. Constraints (3.11) state that each job is assigned to only one production line and is immediately preceded by at most one other job. If job k is the 'first' job on production line i, then $x_{io(s)k} = 1$, otherwise $x_{io(s)k} = 0$.

$$\sum_{j \in J \cup o(s)} \sum_{n \in J \cup o(e)} (x_{ijk} - x_{ikn}) = 1 \quad \forall k \in J;\ i \in I, \tag{3.12}$$

$$\sum_{k \in J \cup o(e)} x_{io(s)k} = 1 \quad \forall i \in I, \tag{3.13}$$

$\sum_{j \in J \cup o(s)} x_{ijo(e)} = 1 \quad \forall\, i \in I,$ (3.14)

Constraints (3.12) guarantee that each job always has one immediate predecessor and one immediate successor. The immediate predecessor of the 'first' job in the factory is $\mathrm{o}(s)$, and $\mathrm{o}(e)$ is the immediate successor of the 'last' job. Constraints (3.13) limit only one job being assigned as the 'first' job for each factory. If no job is assigned to the production line *i*, then $x_{io(s)o(e)} = 1$. Constraints (3.14) limit only one job being assigned as the 'last' job for each production line.

$x_{ijk} + x_{ikj} \leq 1 \quad \forall\, i \in I;\ j \in J; k \in J, j \neq k,$ (3.15)

Constraints (3.15) reinforce the precedence relations between any pair of jobs *j* and *k*. Either *j* immediately precedes *k* or *k* immediately precedes *j* (if both are scheduled to the same production line), or neither relation holds.

$c_j = s_j + \sum_{i \in I} \sum_{k \neq j \in J \cup o(e)} x_{ijk} p_{ij} \quad \forall j \in J,$ (3.16)

$s_k - s_j \geq \sum_{i \in I} x_{ijk} p_{ij} - N\left(1 - \sum_{i \in I} x_{ijk}\right) \quad \forall\, j \in J; k \in J, j \neq k$ (3.17a)

$s_k - s_j \leq \sum_{i \in I} x_{ijk} p_{ij} + N\left(1 - \sum_{i \in I} x_{ijk}\right) \quad \forall\, j \in J; k \in J, j \neq k,$ (3.17b)

Constraints (3.16) set the completion time of *j* to the sum of its starting and processing time. Constraints (3.17a and 3.17b) relate the starting times of two successive jobs on the same production line. If both *j* and *k* are assigned to the same production line, and *j* immediately precedes *k*, then the starting time of *k* is equal to the sum of the starting time of job *j* and its processing time, which means idle time is not allowed between two consecutive jobs. The constraints do not establish any relationship between s_j and s_k when *j* does not immediately precede *k*, or job *j* and *k* are not scheduled to the same production line. N is a large positive number such that $N \to \infty$.

$\sum_{i \in I} \sum_{s \in S} y_{ijs} = 1 \quad \forall\, j \in J,$ (3.18)

Constraints (3.18) state that each job is finished by exact one production line and shipped by exactly one shipment.

$$r_j = \sum_{i \in I} \sum_{s \in S} y_{ijs}(a_s + t_s) \quad \forall j \in J, \tag{3.19}$$

$$\sum_{i \in I} \sum_{s \in S} y_{ijs} a_s - \sum_{i \in I} \sum_{s \in S} \sum_{t \in T} y_{ijs} T_{st} tr_{it} \geq c_j \quad \forall j \in J, \tag{3.20}$$

Constraints (3.19) set the arrival time of job j at the distribution center to the sum of the available time and shipping lead time of the shipment to which job j is assigned. Constraints (3.20) limit the departure time of each job from the warehouse to be not earlier than its production completion time in the factory.

$$\sum_{k \in J \cup o(e)} x_{ijk} - \sum_{t \in T} \sum_{s \in S} y_{ijs} T_{st} = 0 \quad \forall i \in I;\ j \in J, \tag{3.21}$$

Constraints (3.21) relate the factory with the production line to which job j is assigned with the shipment by which it will be shipped from the terminal. In other words, it links and integrates the production planning with the transportation policy which lead them to have impacts on each other.

3.3 Due-date based primary cut-off rule (DBC)

In order to improve the efficiency of the model and extend the problem scale that can be solved in a reasonable time, a rule is created to cut those unreasonable and less considered shipments so as to shrink the range of the shipping information and increase the efficiency of the original model. The rule is as follows:

Each shipment has its available time and lead time which, to some extent, determine the arrival time of the jobs. Therefore, for each job, its assigned shipment greatly affects the size of its penalty caused by tardiness. In consideration of the customer service level, those shipments which cause huge penalties are not considered. Here, the extent of “huge penalty” is that it is greater than the sum of total other component costs, including production cost, storage cost and transportation cost. In other words, each job may only be considered to be assigned to part of the shipments whose arrival time will not lead to huge penalties for that job at the beginning of scheduling.

It can be demonstrated by

$$c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s} \geq c_j^{p} l_j \quad \forall j \in J. \tag{3.22}$$

Which, in detail, is

$$\sum_{i\in I}\sum_{k\neq j,\in J\cup o(e)} c_{ij}^{pro} x_{ijk} + \sum_{i\in I} c_j^{w_i} * \max(\sum_{s\in S} y_{ijs} a_s - \sum_{s\in S}\sum_{t\in T} y_{ijs} T_{st} tr_{it} - c_j, 0) + \sum_{i\in I}\sum_{t\in T}\sum_{s\in S} y_{ijs} T_{st} c_{ijt}^{tr} + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_s \geq c_j^{p} * \max(r_j - d_j, 0), \quad \forall j \in J. \tag{3.23}$$

Through numerical experiments, it greatly aggravates the computational complexity instead of reducing the runtime which is unacceptable and inefficient. Therefore, a relaxed pattern is developed based on the original rule as follows:

$$maxc^{pro} + \mathrm{maxc}^{w} * \max(\sum_{i\in I}\sum_{s\in S} y_{ijs} a_s - \sum_{i\in I}\sum_{s\in S}\sum_{t\in T} y_{ijs} T_{st} tr_{it} - c_j, 0) + maxc^{tr} + maxc^{s} \geq c_j^{p} * (r_j - d_j) \quad \forall j \in J. \tag{3.24}$$

Here, $mintr_{ft} = min(tr_{ft},\ \forall\, f \in F, t \in T)$, $mint_s = min(t_s,\ \forall\, s \in S)$, are the minimum transportation time and minimum shipping time for each job respectively. After collection, a new restriction for the shipments selection is obtained as follows:

$$(c_j^{p} - \mathrm{maxc}^{w}) \times \sum_{i\in I}\sum_{s\in S} y_{ijs} a_s \leq maxc^{pro} + maxc^{tr} - \mathrm{maxc}^{w} \times (mintr_{ft} + c_j) + maxc^{s} + c_j^{p} \times d_j - c_j^{p} \times mint_s \quad \forall j \in J. \tag{3.25}$$

When $c_j^{p} > \mathrm{maxc}^{w}$, based on inequalities (3.25), the final DBC rule is obtained as:

$$\sum_{i\in I}\sum_{s\in S} \boldsymbol{y_{ijs} a_s} \leq \mathbf{A} \times \boldsymbol{d_j} + \mathbf{B} \times \boldsymbol{c_j} + \mathbf{C} \quad \forall j \in J. \tag{3.26}$$

Here, $\mathrm{A} = \frac{c_j^{p}}{c_j^{p} - \mathrm{maxc}^{w}}$, $\mathrm{B} = -\frac{\mathrm{maxc}^{w}}{c_j^{p} - \mathrm{maxc}^{w}}$,

$$\mathrm{C} = \frac{maxc^{pro} + maxc^{tr} - \mathrm{maxc}^{w} \times mintr_{ft} + maxc^{s} - c_j^{p} \times mint_s}{c_j^{p} - \mathrm{maxc}^{w}}.$$

The DBC rule found the lower limit of the upper boundary for shipment selection, that is the departure time of the selected shipment for job j, should be less than the linear combination of its due date and completion time in the factory. We relax the inequalities (3.21) by enlarging or narrowing the values of the parameters so as to attain the expected improvement of computational efficiency. This approach enhances the restriction for shipments which might be assigned to job j through greatly relating the job's due date information with shipment information.

To illustrate the principle of the proposed valid cuts, an example is displayed below in Fig. 3.2. As is displayed in the following figure, the completion time of job j is 11, and its due date is 21. Firstly, those shipments earlier than Day 11 have been removed represented by shaded area. In this way, the selection area of shipments for job j is from Day 12 to Day 36. Secondly, on the right-hand side, those shipments whose arrival times are far from job j's due date will be removed. Then, the question is how to find the boundary of this removed area. This is critical because it may affect the solution optimality, meanwhile it influences the computational time. In this described example, this boundary may be Day 24, 26 or any other Day after Day 21. The larger the data is, the more the computational time it induced. Similarly, the smaller the data is, the less the computational time it is. But it may cut-off the optimal solution.

So, the contribution of the proposed DBC is to find the lower boundary of shipments selected for each job so as to achieve high computational efficiency without affecting final optimal solutions.

Through the above development procedure, the valid cut is obtained and displayed in inequality (3.26). By this valid cut, the invaluable shipments can be removed from the feasible area and the selection range may be narrowed by almost half in this example. The numerical experiments verified this valid cut DBC worked as expected.

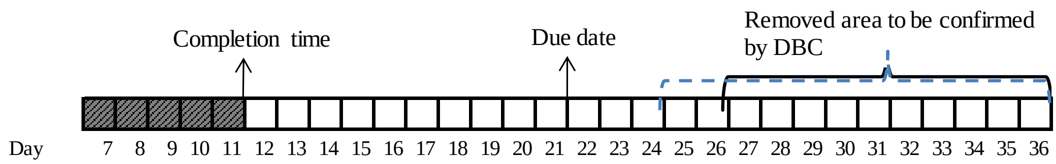

Figure 3.2. Illustration of the due-date based primary cut-off rule.

3.4 Numerical experiments

We firstly conducted numerical experiments to test the performance of the proposed MIPD by MIP and MIP+DBC coded in CPLEX, run on the Intel® Core™ i5-3210M CPU @ 2.50GHz. We tested the problems with 10 jobs composed of different products. Two geographically dispersed factories with two production lines were considered in the manufacturing system. In addition, two terminals were considered in the test. The number of shipments available in Terminal 2 was assumed to be 3 times as many as that in Terminal 1, on average. 3 cases in which 20, 40 and 60 shipments were available in the planning horizon were considered respectively to observe the impacts on the integrated scheduling and system performance of MIPD. Test problems were randomly generated as follows:

a. The unit production cost difference between the factories varied from 0% to 50%.

b. The unit warehouse storage cost $c_j^{w_f}$ was 2% or 3% of the unit production costs required by its nearby factory. The capacity of production in the "expensive" factory was 20% less than that in the “cheaper” factory. The production capacity for each product in the “cheaper” factory is random, from uniform distribution $U(5,10)$. The quantity of each job q_j was randomly generated by $N(75, 5^2)$.

c. The unit penalty cost and the due date of job j are respectively generated by $U(0.4,0.5) * max\left(c_{ij}^{pro}, \forall i \in I\right)$, around 40%~50% of its standard unit production cost, and $N(E(p_{ij}) + E(t_s), 0.01[E(p_{ij}) + E(t_s)]^2)$, the expected time for production and shipping with 10% deviation.

d. The unit transportation cost of job j was $5\% c_{ij}^{pro} tr_{ft}$, i.e., 5% of its production cost multiplied by its travel time.

e. The shipping lead times t_s were randomly generated by $U(10,30)$, and the unit shipping cost of each job was the multiple of $\frac{300}{t_s^2}$, which had negative correlation with its shipping lead time.

f. The unit storage cost per day at DC was 5% of the standard unit production cost for each job.

g. The standard unit production cost of each job was the cost required by the “expensive” factory, which was random from the uniform distribution $U(15,20)$.

3.4.1 Problem generation

To demonstrate the significance of the MIPD, another practical model with shipment schedules consideration is introduced and analyzed in this study.

3.4.2 Multi-factory Separated Production Scheduling Model (MSPS)

In MSPS, the jobs were assigned evenly to each factory according to their production cost and, in this case, production scheduling was independent between these two factories, equivalent to two parallel single-factory integrated production and distribution models. We tested 10 randomly generated data sets for each problem instance. Since we had a total of 4*3 = 12 different instances, we got a total of 120 different problem data sets. For each instance, we calculated the corresponding reduction between the proposed MIPD and MSPS, namely $\frac{Z_S - Z_I}{Z_S} \times 100\%$, where Z_S is the solution of MSPS and Z_I is the solution of MIPD.

3.5 Results of the MIPD vs the MSPS model

Table 3.1 gives the details of the performance of the MIPD model compared with MSPS. It shows that the overall average and maximum cost reductions compared with MSPS are 20.10% and 25.94%, respectively, which demonstrate the new proposed MIPD greatly outperforms MSPS for integrated production scheduling with specific shipment schedules.

Compared with MSPS, the average cost reductions by MIPD under shipment schedules with 20, 40, 60 shipments available are 25.64%, 18.22% and 15.20%, respectively, and the corresponding maximum reductions are 35.69%, 23.80% and 18.34%, respectively. Fig. 3.2 shows the contribution made by the MIPD model decreases as the number of available shipments increases. This result demonstrates that when available shipments are very limited, the significance of integrated production scheduling between factories becomes much stronger. Fig. 3.3 displays an increased trend on the contribution made by MIPD when the production cost difference between two factories becomes large. The production cost difference between the factories is assumed to be 0%, 10%, 30% and 50% in sequence. For each case, the average reduction on the total cost contributed by MIPD is 17.39%, 17.60%, 18.51% and 19.45% respectively. It verifies that the cost difference between factories has positive impacts on the performance of the newly proposed MIPD.

Table 3.2 presents the contributions made by each component cost to the total cost reduction. By comparison, the main contribution comes from the penalty cost, while the inventory cost in the warehouses and DC are in second place. For MSPS, its penalty cost is reduced by 47.26% as a whole. Fig. 3.4 gives the average number of tardy days for each given job under different shipping situations. It shows that the tardy days increase when the shipments available are limited. However, MIPD decreases almost 50% for the tardy days brought about by MSPS on average, and controls the tardiness of each job within one day (Fig. 3.5). Therefore, the improvement of customer service level is achieved by MIPD.

Table 3.1 Performance of the MIPD model compared with MSPS.

$\|J\|$	$\|S\|$	Diff. of c_{ij}^{pro} (%)	Average cost reduction (%)	Max cost reduction (%)
10	20	0	24.53	34.07
		10	24.81	34.88
		30	26.02	36.23
		50	27.21	37.58
	average		25.64	35.69
10	40	0	17.55	22.45
		10	17.69	22.95
		30	18.42	24.22
		50	19.22	25.58
	average		18.22	23.80
10	60	0	14.00	17.44
		10	14.27	17.71
		30	15.64	18.60
		50	16.90	19.62
	average		15.20	18.34
Overall			20.10	25.94

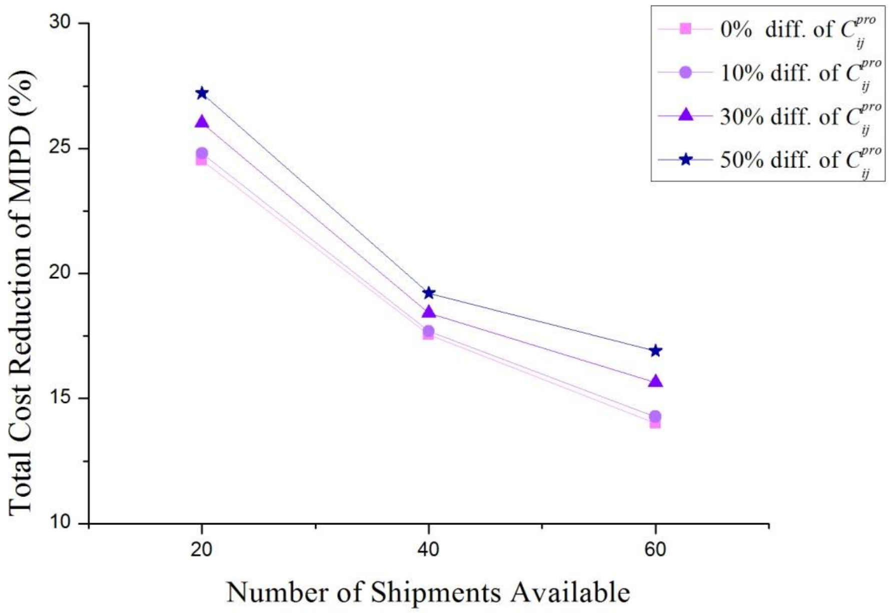

Figure 3.3. Cost reduction of MIPD compared with MSPS in terms of number of shipments available in the planning horizon.

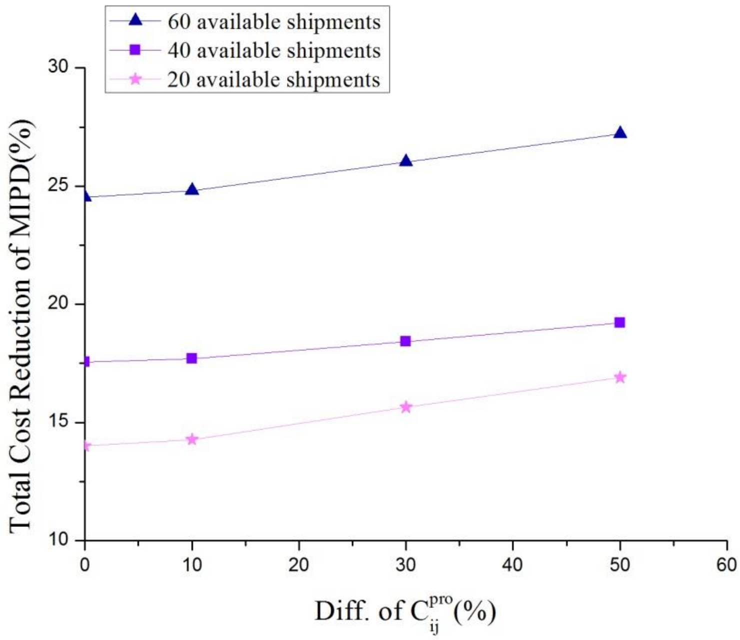

Figure 3.4. Cost reduction of MIPD compared with MSPS in terms of production cost difference between factories.

Table 3.2 Component contribution of MIPD compared with MSPS.

$\lvert J\rvert$	$\lvert S\rvert$	Diff. of c_{ij}^{pro}(%)	Average Reduction (%)					
			Production	Warehouse	Transport	Shipping	DC	Penalty
10	20	0	0.00	22.13	8.32	-13.62	-4.75	53.14
		10	-0.75	23.31	7.46	-13.54	-5.42	53.14
		30	-0.75	19.63	2.72	-13.66	11.84	52.73
		50	-1.46	16.32	4.11	-12.60	-43.09	52.73
10	40	0	0.00	20.56	-3.15	-8.48	8.08	48.59
		10	-0.65	17.88	-3.43	-7.93	8.08	48.50
		30	-1.56	17.80	-4.69	-6.63	32.70	47.12
		50	-2.36	12.56	-5.53	-7.33	26.40	47.33
10	60	0	0.00	25.52	-2.10	-5.29	-79.29	41.05
		10	0.02	18.27	-4.99	-5.60	26.18	41.05
		30	0.43	25.53	-5.37	-5.22	23.11	41.05
		50	1.73	22.85	-6.26	-5.92	16.67	40.70
Overall			-0.45	20.20	-1.08	-8.82	1.71	47.26

Additionally, the inventory costs in the warehouses and DC are reduced by 20.20% and 1.71%. It demonstrates that additionally MIPD performs well in inventory control by decreasing the holding days through the production coordination between factories, as well taking the consideration of the distance-dependent inland transportation lead time.

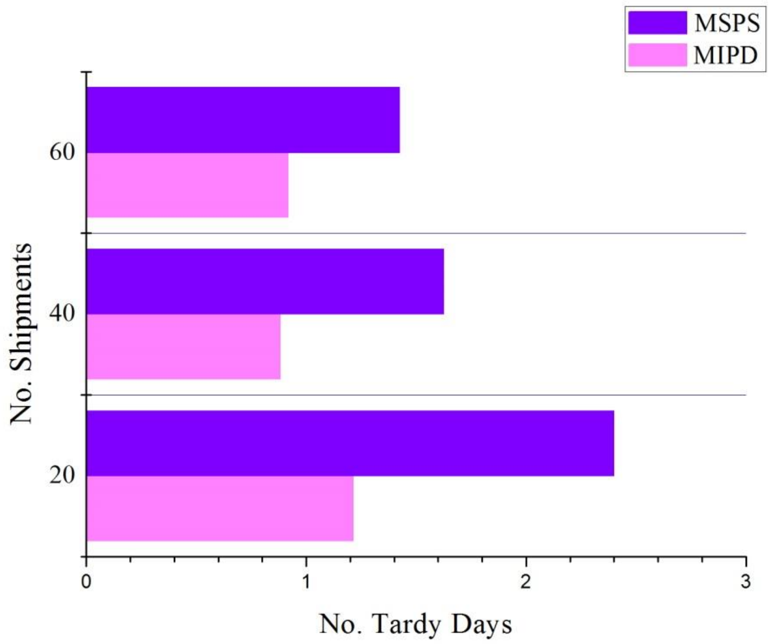

Figure 3.5. Average tardy days per job under different shipment situations.

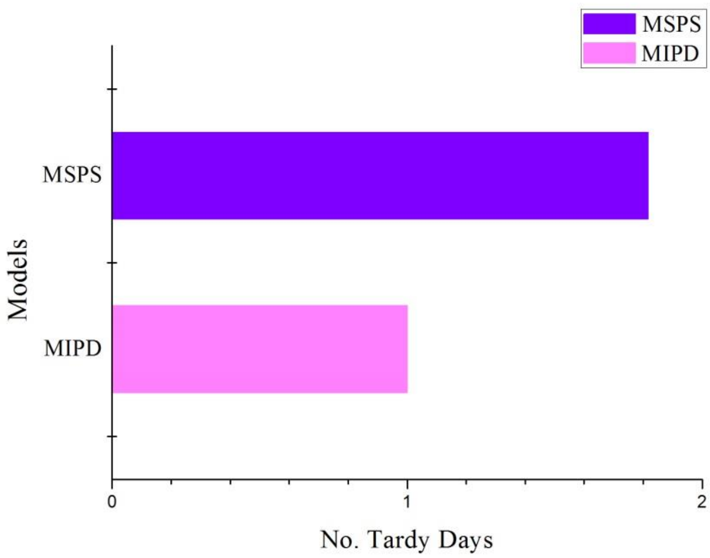

Figure 3.6. Average tardy days per job.

3.6 Results and discussions of MIP with DBC vs MIP

Through the computational results, it can be identified that the MIP with DBC obtain the same optimal solutions as the MIP. Table 3.3 presents the effectiveness of DBC. It demonstrates that the time efficiency of the original exact algorithm is, on average, improved by 80.78% and at maximum by almost 90%, with the assistance of DBC.

Table 3.3 Effectiveness of the DBC rule.

$\lvert S \rvert$	Average CPU time(s)		Reduction (%)		Sol. difference
	Without DBC	With DBC	Average	Maximum	(%)
20	7537	1814	75.93	91.9	0
40	23470	3886	83.44	86.34	0
60	33058	5629	82.97	89.58	0
overall			80.78	89.27	0

3.7 Summary

In this research, we proposed a new model and a new solution method for multi-factory job allocation and production–distribution scheduling problems. In this new model, we considered the variations and limits of maritime transport and their impacts on production and distribution scheduling. The objective was to determine integrated production and inland/maritime transport scheduling in a multi-factory manufacturing system, for the mutual benefit of both the manufacturer and customers. This problem has not been addressed in the existing literature.

The numerical experiments demonstrated that substantial cost savings and delivery efficiency were achieved by the new developed integrated model. In addition, its performance is reliable for the variations in external shipment schedules and production cost difference among factories. The newly proposed due-date based cut-off rule (DBC) achieved 80% improvement for the computational efficiency of the exact algorithm.

Chapter 4 Hybrid 2-level fuzzy guided genetic algorithm for the multi-factory integrated scheduling problem

In Chapter 4, a hybrid genetic algorithm embedded with a new fuzzy logic controller and DBC is introduced. The proposed heuristic approach is aimed at improving the time efficiency and solution quality of large-scale problems. The proposed heuristic approach is composed of two levels. Section 4.1 describes the level 1 with the principles of the fuzzy controllers in the mutation operator in detail. Section 4.2 presents level 2 which is responsible for scheduling and shipment selections combined with a DBC based exhaustive search. The results of numerical experiments are discussed in Section 4.3., and a summary of the proposed heuristic approach was given in Section 4.4.

4.1 Outline of the proposed 2-level hybrid GA

In this algorithm, we decompose the problem into 3 interrelated sub-problems and solve them iteratively, i) Assignment of Jobs to Production Lines, ii) Production Scheduling of Jobs in Production Line, and iii) Shipment Selection. Fig. 4.1 shows the outline of the proposed hybrid 2-Level Fuzzy Guided Genetic Algorithm (H2LFGGA). It consists of 2 interrelated genetic algorithms with an exhaustive heuristic algorithm under DBC application and a fuzzy controller to guide the mutation.

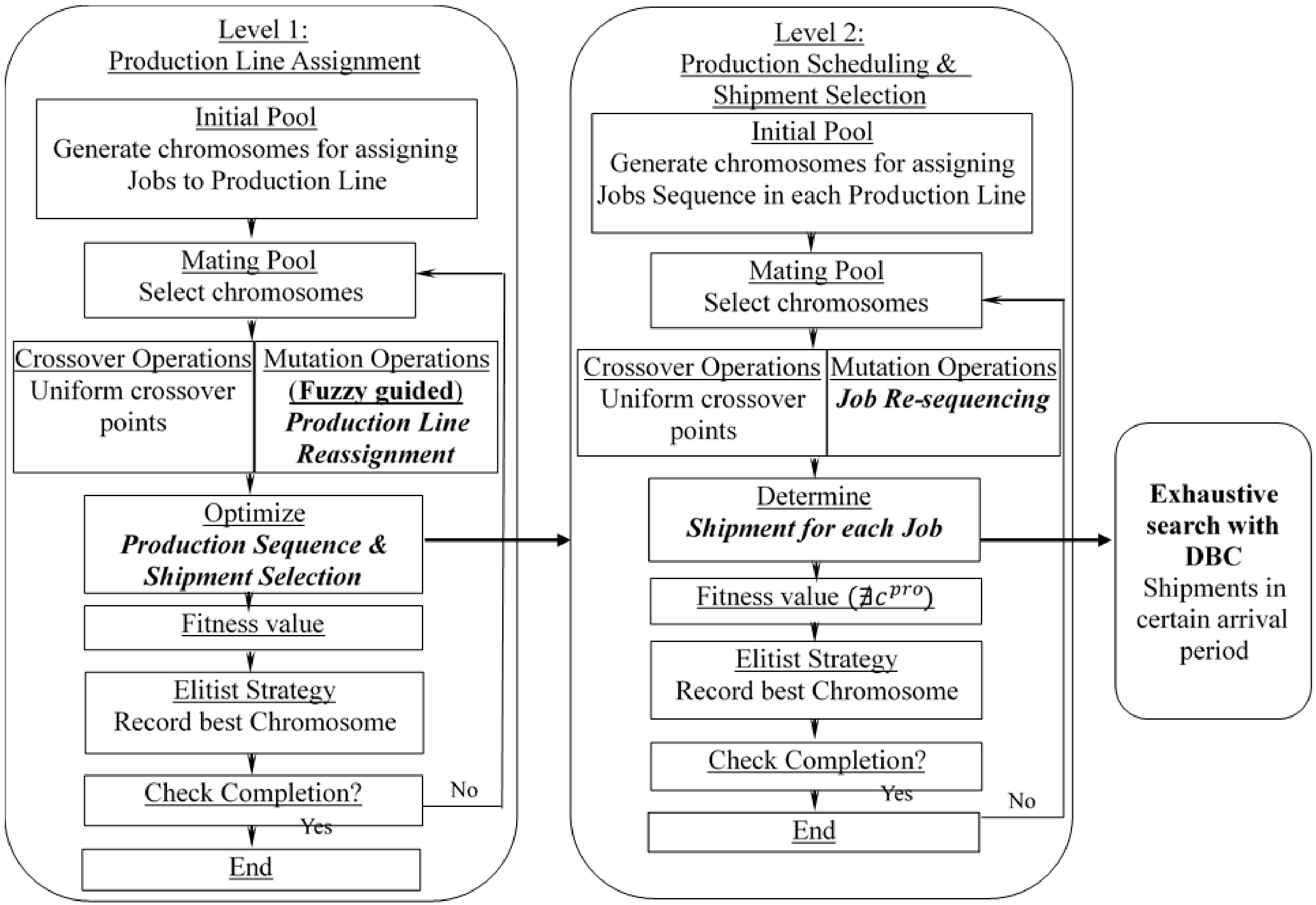

Figure 4.1. Outline of proposed Hybrid 2-Level Genetic Algorithm.

4.2 Level 1 GA

The Level 1 GA optimizes the assignment of jobs to the production lines. The objective in this part is to minimize the total cost of the whole system. This is the highest level of decision making, controlling the global search in this problem, as is hereafter named as Level 1 GA. The fuzzy controller that guides the mutation proposed in level 1 aims to solve the drawbacks of the traditional GA when dealing with multi-factory job allocation problems. Two conditions, the Workload Condition and the Busy Condition, are considered by the fuzzy controller in order to balance the utilization of each production line.

4.2.1 Encoding and decoding of chromosome

In encoding, chromosomes consist of n columns and 2 rows, as an example shown in Fig. 4.2 Each column represents an assignment of a job to a production line. Row 1 represents the job, and Row 2 represents the production line. The production schedule is represented by the production priority, with the highest on the left the lowest on the right. For example, in Fig. 4.2, there are 10 jobs being assigned to 2 production lines. For the decoding, Jobs 8, 2, 7, and 9 will be produced in the order stated in Production line 2. Note that the shipment of each job is not being decided on at this moment and will be determined later by using the exhaustive heuristic with the application of DBC in the Level-2 GA part.

Encoding

Job	3	5	8	1	10	2	4	7	9	6
Production Line	1	1	2	1	1	2	1	2	2	1

Decoding

Job

Production Line 2	8	2	7	9		
Production Line 1	3	5	1	10	4	6

Figure 4.2. Sample encoding and decoding of chromosome in Level 1.

4.2.2 Generation of initial pool

The first chromosome among the population is created according to the heuristic which is trying to equally balance the loading between factories. Jobs are ranked according to the due date from the earliest to the latest and assigned to factory one by one. The rest of chromosomes are generated randomly. For example, assuming that the due date increases along with the job number, then the first chromosome is in the order of 1-2-3-4-5-6-7-8-9-10 as shown in Fig. 4.3 and the rest are randomly scheduled.

Chromosome No.

1	1	2	3	4	5	6	7	8	9	10
	1	2	1	2	1	2	1	2	1	2
2	3	5	8	1	10	2	4	7	9	6
	1	1	2	1	1	2	1	2	2	2
3	5	6	2	4	3	8	7	9	1	10
	1	2	1	2	2	1	2	1	1	2
4	8	7	4	5	2	3	1	6	9	10
	1	1	2	2	1	2	1	2	2	1

Figure 4.3. Sample initial pool for Level 1.

4.2.3 Calculation of fitness value

The objective is to minimize the total cost of the system. It corresponds to the main objective function, as in Eq. (1). Thus, the fitness value of chromosome f_i^{L1} in Level 1 GA is defined as:

$$f_i^{L_1} = 1 - \frac{Z_i}{\sum_{n=N^{L1}} Z_n}$$

where NL1 is the pool size of the Level 1 GA, and Zi is the objective value obtained according to the structure of chromosome *i* after optimization of the production sequence and shipment selection by using the Level-2 GA.

4.2.4 Crossover operations

A uniform crossover approach is adopted here, in which a certain portion of the chromosomes between 2 chromosomes is exchanged. A number of genes are randomly selected depending on a predefined crossover rate cr. A high *cr* favors a global search as the chromosome structure is changed more, while a low rate favors a local search. A low *cr* rate is used throughout the whole evolution in Level 1 because we want to control the chromosome changes at a slow pace as it deals with a global search.

Fig. 4.4 shows an example of a 2-point crossover for Level 1, in which, assuming 2 columns, i.e. 4^{th} and 8^{th}, are randomly selected for crossover. After crossover, the offspring(s) become invalid as duplication of jobs occur (e.g. two Job 5s and two Jobs 8s in Offspring 1, with two Job 1s and two Job 7s in Offspring 2).

Meanwhile, some jobs are missing (e.g. Jobs 1 and 7 in Offspring 1, Jobs 5 and 8 in Offspring 2). For validation, therefore, the duplicated job(s), which is (are) not the one selected for crossover, are changed into the corresponding missing job(s) (i.e. Job 7 is the corresponding job for Job 5, Job 1 is then the corresponding job for Job 8). In addition, to avoid the chromosome structure changing too rapidly, the production line assigned to each missing job (Jobs 1 & 7 for Offspring 1) is the same as that assigned to the job in the Parent stage.

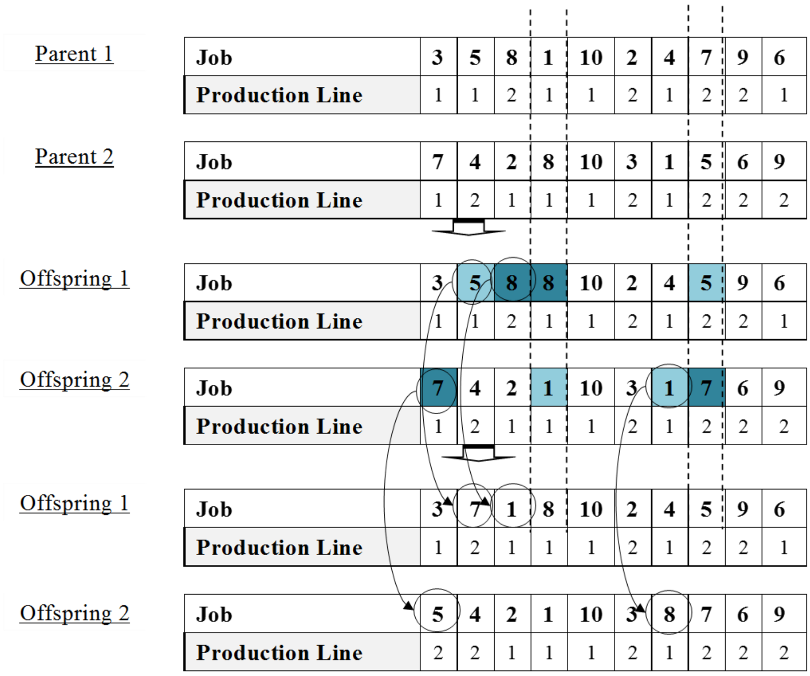

Figure 4.4. Sample crossover operations for Level 1.

4.2.5 Mutation operations: Fuzzy guided approach

Mutation here aims to diversity the chromosomes in the solution pool in terms of Jobs Reallocation to Production Lines. Accordingly, in the classical GA mutation approach, a number of genes could be randomly selected to undergo mutation, i.e. reassigning the randomly selected job(s) from one production line to another randomly selected one(s). However, this approach may have several drawbacks when applied in multi-factory job allocation problems. First of all, the loading condition of the production line during job reallocation has not been considered. For example, if a production line is already very busy, further increasing its workload will definitely result in even higher penalty. Similarly, if the workload of the selected mutation production line is low, further reducing its workload is also meaningless. Such mutations are not wise. Another drawback comes from the due date condition of the jobs. If the jobs being assigned in the same production line have close due dates, it may easily induce a penalty due to tardiness or high storage cost. In this connection, we designed and proposed a fuzzy controller to guide the mutation.

The mutation aims to reallocate jobs to the production lines. Therefore, two production lines will be selected randomly. Then the fuzzy controller will determine the number and direction of job(s) being reallocated due to the workload condition and due date condition. Accordingly, for the fuzzy controller, we need two sets of fuzzy input. First of all, we need to model the difference of workload condition $\overline{WC}$ between the two selected production lines (α and β). $\overline{WC}$ is classified as Less (L), Same (S), and More (M) as in Fig. 6. If the workload of the production line α is 20% less than that of the production line β, then it has less workload. If the workload of α is the same as that of β, then it has the same workload. If the workload of α is 20% more than that of β, then it has more workload, where % difference $= \frac{(\sum_{j=J^\alpha} q_j - \sum_{k=J^\beta} q_k)}{\sum_{k=J^\beta} q_k}$, in which J^α = set of jobs being assigned to production in α, and J^β = set of jobs being assigned to production in β.

Another fuzzy input set is used to model the difference of busy condition $\overline{BC}$ between the two selected production lines in a particular period. $\overline{BC}$ is classified as Less (L), Same (S), and More (M) as in Fig. 4.5. Accordingly, a period $[\pi, \pi + t]$ is randomly selected for comparison, where t is smaller than 1/3 of the total horizon. Then, we calculate the total quantity of jobs with due date falling in that period for the production lines α and β. Similarly, if the total quantity calculated in that period in α is 20% less than that in β, then it is "Less" busy, same as each other is "Same" and, 20% more than the other is "More" busy.

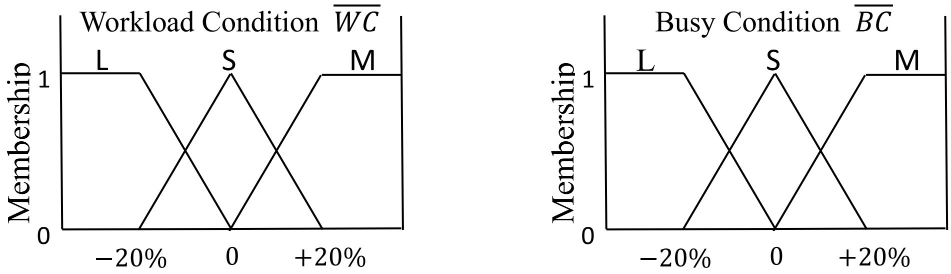

Figure 4.5. Fuzzy input set.

The output set is the number of jobs being released from production line α to β, or taken in from production lines β to α, as shown in Fig. 4.6. They are classified as Few (F), Normal (N), Large (L), and Very Large (VL) numbers of jobs. The rule sets used to construct the fuzzy controller is shown in Fig. 4.7. They are all in the "and" relationship, for example if production line α was less workload and is less busy than that of β in a randomly selected period, then a very large number of jobs will be taken-in from production lines β to α. The commonly used centroid method is used for the influence of each rule on the output.

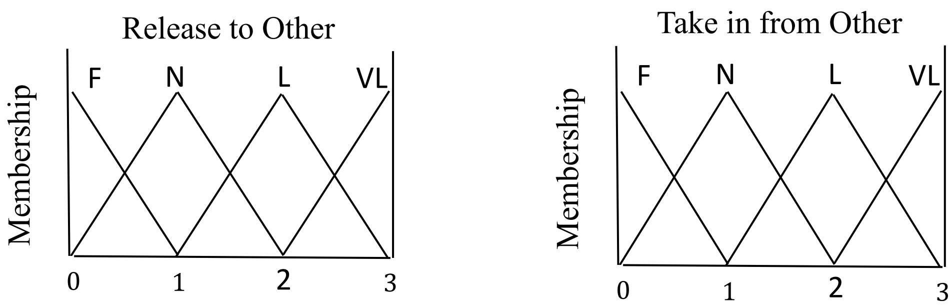

Figure 4.6. Fuzzy output set.

Busy Condition

Workload Condition

	L	S	M
L	TI-VL	TI-N	TI-F
S	TI-F	RT-N	RT-F
M	RT-F	RT-L	RT-VL

Figure 4.7. Rules sets.

4.3 Level 2 GA

Level 2 GA is designed to optimize the production sequence of the chromosome (production lines) generated in Level 1 and shipment selection for each gene (job) by optimizing each chromosome independently. The objective in this part is to minimize the total cost except the production cost of the jobs allocated to the particular production line. As this functions for the local fine tuning of the chromosome in Level 1 GA, hereafter named as Level 2 GA. The exhaustive heuristic algorithm with DBC is devised for level 2, which aims to select the best shipment for each job on the production line, according to its objective, in an efficient way.

4.3.1 Encoding and decoding of chromosome

It is noted that the Level 2 GA aims at optimizing the production sequence of production line *i* of the chromosome generated in level 1 and the shipment selection for each job. Thus in encoding, the length of the chromosome will be equal to the number of jobs being assigned to the production line *i*. Each gene represents one job number, and the production priority is the one with the highest value on the left, as in Level 1 as shown in Fig. 4.8.

Encoding

Job	3	5	1	10	4	6

Decoding

	Job					
Production Line 1	3	5	1	10	4	6

Figure 4.8. Sample encoding and decoding of chromosome in Level 2.

4.3.2 Generation of initial pool

The initial pool is generated based on the chromosomes generated in Level 1 after fuzzy guided mutation. Inside the initial pool, the first chromosome is generated by the earliest due date heuristic. The rest of the chromosomes are generated randomly. For example, if the Level 2 GA is currently optimizing the production scheduling for production line 1 (the Level 1 example in Fig. 4.2), the jobs involved are Jobs 1, 3, 4, 5, 6, and 10 as shown in Fig. 4.8. Assuming the due date increases with the job number, then the first chromosome is in the order of 1-3-4-5-6-10, as shown in Fig. 4.9 and the rest will be randomly scheduled.

	1	1	3	4	5	6	10
Chromosome No.	**2**	3	5	1	10	4	6
	3	10	6	1	5	4	3
	4	4	10	3	1	5	6

Figure 4.9. Sample initial pool for Level 2.

4.3.3 Calculation of fitness value

For Level 2 GA, the objective is to minimize the total costs except the production cost of the jobs allocated to the production line that deviated due to different production sequence, i.e., storage cost in warehouse, transportation cost, shipping cost, storage cost in DC, and penalty cost. We set $Z' = \sum_{j \in J'} q_j (c_j^w + c_j^{tr} + c_j^s + c_j^{DC} h_j^{DC} + c_j^p l_{j)}$, where *J'* is the set of jobs being allocated to the currently optimizing production line. Thus, the fitness value of chromosome f_i^{L2} in Level 2 GA is defined as:

$$f_i^{L2} = 1 - \frac{Z_i'}{\sum_{n=N^{L2}} Z_n'}$$

, where N^{L2} is the pool size of Level 2 GA, and Z_i' is objective value obtained according to the structure of chromosome i.

To select the best shipment for each job, an exhaustive searching approach with the assistance of DBC is applied. After the application of DBC, only a small number of potential shipments are left for selection. Thus, the exhaustive search heuristic is efficient.

4.3.4 Crossover and mutation operations

Fig. 4.10 shows an example of a 2-point crossover for Level 2. The mechanism of the crossover is the same as in Level 1. Assuming 2 columns, i.e. 2th and 4th, are randomly selected for crossover, after crossover, the offspring(s) become invalid as duplication of jobs occur (e.g. two Job 3s and two Jobs 6s in Offspring 1, while two Job 5s and two Job 10s in Offspring 2). Meanwhile, some jobs are missing (e.g. Jobs 5 and 10 in Offspring 1, Jobs 3 and 6 in Offspring 2). For validation, therefore, the duplicated job(s), which is not the one selected for crossover, is changed into the corresponding missing job(s) (i.e. Job 3 is the corresponding job for Job 10, Job 6 is the corresponding job for Job 5). For Mutation, the main idea is to reschedule the production priority of the jobs. Therefore, two genes are randomly selected and swapped (Fig. 4.11), and invalidation does not occur in this operation.

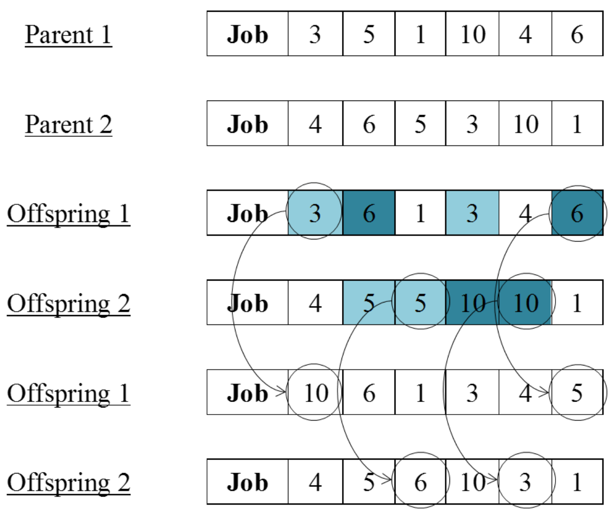

Figure 4.10. Sample crossover operations for Level 2.

Parent	**Job**	10	6	1	3	4	5
Offspring	**Job**	10	6	5	3	4	1

Figure 4.11. Sample mutation operations for Level 2.

4.4 Results and discussions of H2LFGGA *vs* MIP with DBC and classical GA

In this section, the proposed GA is firstly compared with the exact algorithm proposed in Chapter 2 in Section 4.3.1, followed by a discussion of the comparison between the proposed GA and simple GA.

4.4.1 Performance of H2LFGGA vs MIP with DBC

The objective here is to test the performance of the proposed H2LFGGA in terms of solution quality and computational time. We compare the results obtained by the MIP with the DBC above with the proposed H2LFGGA in the 12 different situations used above. The results are summarized in Table 4.1. The results show that the proposed algorithm can obtain results as good as the MIP. This demonstrates that in terms of solution quality, the proposed algorithm is good. However, when comparing the computational time, the proposed algorithm is much better. The time required is only about 1s, 2s, and 2s for the problem size of 10 jobs with 20, 40 and 60 shipments respectively. Thus, in terms of computational time, there is a significant improvement. In addition, it can be seen that although the problems size increased from 20 shipments to 60 shipments, the computational time required by the proposed algorithm does not increase much along with the increased problem computational complexity. This also demonstrates that the adoption of the proposed DBC can successfully reduce the shipment selection range. Therefore, the total computational time does decrease dramatically.

Table 4.1 Testing of solution quality of the proposed H2LFGGA.

$\|J\|$	$\|S\|$	Diff. of c_{ij}^{pro} (%)	MIP with DBC	Time Req.(s)	Proposed GA	Time Req.(s)	Sol. Difference (%)
10	20	0	23357	2237	23357	1	0
		10	22655	1765	22655		0
		30	21042	1650	21042		0
		50	19311	1606	19311		0
10	40	0	23571	3553	23571	2	0
		10	22826	3357	22826		0
		30	21283	4702	21283		0
		50	19653	3934	19653		0
10	60	0	22139	5389	22139	2	0
		10	21251	6425	21251		0
		30	19420	6324	19420		0
		50	17642	4380	17642		0

4.4.2 Performance of H2LFGGA with classical GA

We further test the performance of the proposed H2LFGGA at a larger problem scale. However, since the computational time spent by using MIP with DBC still cannot find solutions for a larger problem scale, even after 24 hours, we compare it with classical GA in this multi-factory production and distribution problem instead. The same problem parameters are used to generate larger problem sizes with 20 jobs and 50 jobs.

First of all, the classical GA is applied to solve the 10 job problems above. The purpose is to have a benchmark for the performance of H2LFGGA. The results indicating the average percentage difference between the solutions obtained by classical GA and H2LFGGA after convergence are summarized in Table 4.2. It additionally presents their corresponding evolution numbers and computational times for convergence for each case.

As for the solution quality, it can be seen that even in the small-scale problem, the classical GA cannot obtain optimal solutions as H2LFGGA does. In addition, when the problem complexity increases along with the number of shipments being increased from 20 to 60, the percentage of the solution value difference gets wider. This further demonstrates the significant of applying the proposed DBC heuristic. In the rest of the large-scale problems, the performance of H2LFGGA clearly outperforms the classical GA. On the other hand, it is shown that the number of evolutions required by H2LFGGA for convergence is far less than that of classical GA. Therefore, H2LFGGA is much more efficient than the classical GA with notable improvement in solution quality for large-scale problems.

Table 4.2 Comparison of classical GA with the proposed H2LFGGA.

$\lvert J \rvert$	$\lvert S \rvert$	Evolution numbers		Time required (s)		Sol. Difference (%)
		H2LFGGA	Classical GA	H2LFGGA	Classical GA	
10	20	10	2500	1	2	2.8
10	40	10	2500	1	2	7.1
10	60	10	10000	1	8	9.7
average						6.5
20	20	50	10000	2	8	5.9
20	40	100	50000	4	40	14.0
20	60	100	50000	4	40	19.1
average						13.0
50	20	200	50000	8	40	24.1
50	40	1000	100000	15	75	31.9
50	60	1000	100000	15	75	44.2
average						33.4

4.5 Summary

In this chapter, a new hybrid meta-heuristic called hybrid 2 level fuzzy guided genetic algorithm, was proposed to solve the multi-factory production and distribution scheduling model proposed in Chapter 3 for practical problem size. The new proposed due-date based cut-off rule was embedded into the new proposed fuzzy guided heuristic approach to further accelerate the computational efficiency. By comparison with the improved efficiency of the exact algorithm in Chapter 3, the new proposed fuzzy guided heuristic approach achieved optimal solutions and better computational efficiency for small-size problems. Moreover, it was identified that, after the application of DBC, it is applicable to practical and large-scale problems with superior solution quality in comparison with the classical genetic algorithm.

Chapter 5 A risk-averse model for integrated multi-factory production scheduling and shipment assignment under liner shipping uncertainty

In this Chapter, a new stochastic model is presented to solve the multi-factory integrated scheduling problem with shipping uncertainty due to maritime transport. A detailed description and formulation for the stochastic problem is presented in Section 5.1. The solution methodology, including the proof of the individual risk cost, was given in Section 5.2. Section 5.3 presents the design of numerical experiments. The results and discussion between the proposed model and the expected method are provided in three aspects in Section 5.4, followed by a summary of the chapter in Section 5.5.

5.1 Problem description and formulation

A stochastic integrated production–distribution scheduling problem in a multi-factory manufacturing system is studied, considering the uncertain shipping lead-times. As illustrated in Fig. 5.1, the factories are located in different regions. In each factory, parallel identical production lines are available to produce multiple products with the same quality. The capacities of the production lines of the factories are different. Therefore, the processing time for each job is different depending on the factory to which it is assigned. The finished jobs are stored in a nearby warehouse for shipping. The transportation time between the factory and a nearby warehouse is negligible compared to the production lead-time.

For distribution, two main transport types, i.e., inland transport and uncertain maritime transport are involved. First, the finished jobs should be transported from the warehouses to the assigned terminals. In this process, transportation time depends on the distance, while transportation cost depends on both the distance and quantity. In the problem considered, multiple terminals are involved that are located at different coastal cities. At each terminal, different shipments to overseas destinations are available with specific expected schedules. Each shipment has a specific freight rate, which has a negative correlation with its shipping lead-time. Moreover, each shipment can carry more than one job, but each job can only be shipped in a single shipment. Partial delivery is not allowed. The timely delivery of each job is particularly vulnerable to the shipping lead-time of the assigned shipment, which represents the time between the departure from one of the domestic ports to the arrival at the destination port. However, in reality, this is often uncertain because of the unexpected waiting and operation time at ports, bad weather, etc. Unlike other studies, mirroring reality, we assume the shipping lead-time of each shipment to be an independent continuous random variable t_s $(\forall\, s \in S)$ with known distributions. Additionally, we assume the following:

(i) Jobs and production lines are given and available at the beginning of the planning horizon.

(ii) The penalty is due to tardiness.

(iii) The cost of the storage in overseas distribution centres (DC) is introduced because of the early arrival of the shipment.

(iv) The time and cost of transportation from the destination port to the overseas

DC are negligible.

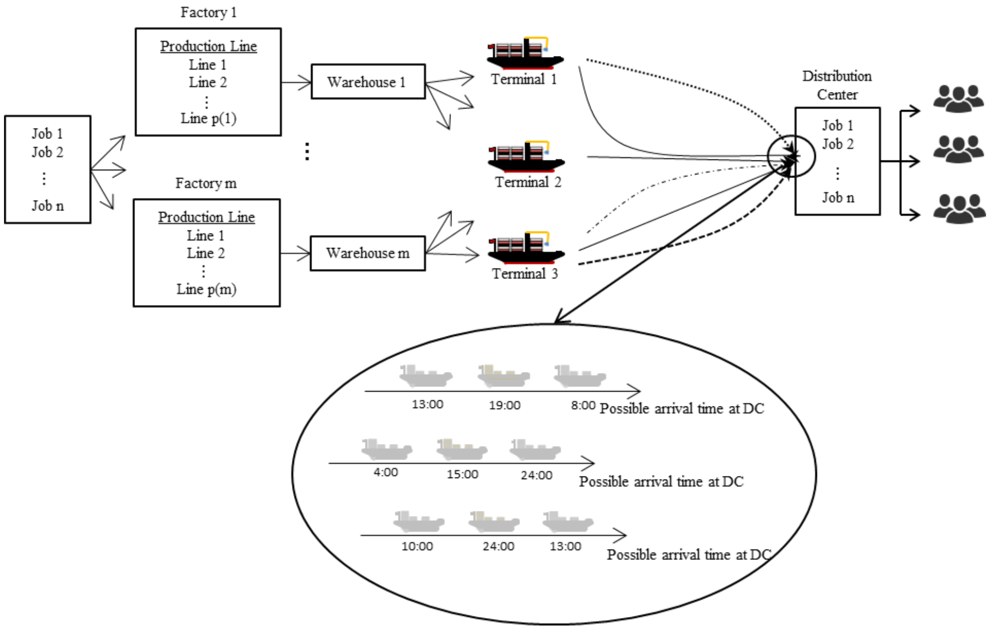

Figure 5.1. Illustration of the production–distribution problem in a multi-factory manufacturing system with uncertain shipping lead-time.

The objective function aims at minimizing the sum of the total operating costs generated in the planning horizon. Six component costs are involved: production cost c_j^{pro}, warehouse storage cost c_j^{w}, inland transportation cost c_j^{tr}, liner shipping cost c_j^{s}, storage cost in the overseas DC $c_j^{DC}E_j^{DC}$ and penalty cost $c_j^{p}T_j$. The objective function is formulated as shown below:

$$\min Z_1 = \sum_{j\in J} q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s} + c_j^{DC}E_j^{DC} + c_j^{p}T_j) \quad (5.1)$$

(i) Production cost

$$c_j^{pro} = \sum_{i\in I}\sum_{k\in J\cup\{o(e)\},k\neq j} c_{ij}^{pro}x_{ijk} \quad (5.2)$$

The unit production cost of job *j* depends on production line *i* to which the job is assigned.

(ii) Warehouse storage cost

$$c_j^w = \sum_{f \in F} c_j^{w_f} h_j^{w_f} \tag{5.3}$$

The unit storage cost of job j in a warehouse w_f nearby the factory depends on factory f that job j is assigned to and the duration for which job j is stored in warehouse w_f. The duration is determined as follows:

$$h_j^{w_f} = \max\left(\sum_{i \in I} \sum_{s \in S} y_{ijs} a_s L_{fi} - \sum_{i \in I} \sum_{s \in S} \sum_{t \in T} y_{ijs} L_{st} L_{fi} tr_{ft} - c_j, 0 \right) \tag{5.4}$$

The duration not only depends on the completion time of production c_j and the available time of the assigned shipment a_s but also depends on its corresponding inland transportation time tr_{ft}.

(iii) Inland transport cost

$$c_j^{tr} = \sum_{f \in F} \sum_{i \in I} \sum_{t \in T} \sum_{s \in S} y_{ijs} L_{st} L_{fi} c_{fjt}^{tr} \tag{5.5}$$

It depends on the distance between the warehouse and the terminal at which the assigned shipment of job j is available.

(iv) Liner shipping cost

$$c_j^s = \sum_{i \in I} \sum_{s \in S} y_{ijs} c_s \tag{5.6}$$

It depends on the unit shipping cost of shipment s to which the job is assigned.

(v) Storage cost in the overseas DC

$$c_j^{DC} E_j^{DC} = c_j^{DC} (d_j - r_j)^+ \tag{5.7}$$

(vi) Penalty cost

$$c_j^p T_j = c_j^p (d_j - r_j)^- \tag{5.8}$$

Here $x^+ = \max(x, 0)$, $x^- = -\min(x, 0)$. In this problem, the early arrival of the job and tardiness are random variables.

Constraints:

(i) Production constraints

Constraints (5.9) – (5.14) control the production sequence on each production line in different factories. All the production lines start producing to maximize the utilization of the facility, and each job can be assigned to only one production line. In addition, each job can have only one predecessor and one successor. $x_{io(s)j}$ and $x_{iko(e)}$ indicate that jobs j and k are the first and last jobs served on production line i.

$$\sum_{i\in I}\sum_{k\in J\cup\{o(e)\},k\neq j} x_{ijk} = 1 \quad \forall\, j \in J \tag{5.9}$$

$$\sum_{i\in I}\sum_{j\in J\cup\{o(s)\},j\neq k} x_{ijk} = 1 \quad \forall\, k \in J \tag{5.10}$$

$$\sum_{j\in J\cup\{o(s)\}}\sum_{n\in J\cup\{o(e)\}}(x_{ijk} - x_{ikn}) = 1 \quad \forall\, k \in J;\ i \in I \tag{5.11}$$

$$\sum_{k\in J\cup\{o(e)\}} x_{io(s)k} = 1 \quad \forall\, i \in I \tag{5.12}$$

$$\sum_{j\in J\cup\{o(s)\}} x_{ijo(e)} = 1 \quad \forall\, i \in I \tag{5.13}$$

$$x_{ijk} + x_{ikj} \leq 1 \quad \forall\, i \in I;\ j \in J; k \in J, j \neq k \tag{5.14}$$

Constraints (5.15) – (5.16) state the relationship of the production starting times between two successive jobs and the calculation of the completion time of each job. Here, N represents a large constant.

$$c_j = s_j + \sum_{i\in I}\sum_{k\in J\cup\{o(e)\},k\neq j} x_{ijk}p_{ij} \quad \forall j \in J \tag{5.15}$$

$$s_k - s_j \geq \sum_{i\in I} x_{ijk}p_{ij} - N\left(1 - \sum_{i\in I} x_{ijk}\right) \quad \forall\, j \in J; k \in J, j \neq k \tag{5.16a}$$

$$s_k - s_j \leq \sum_{i\in I} x_{ijk}p_{ij} + N\left(1 - \sum_{i\in I} x_{ijk}\right) \quad \forall\, j \in J; k \in J, j \neq k \tag{5.16b}$$

(ii) Shipment constraints

Constraint (5.17) limits each job to be assigned to just one shipment.

$$\sum_{i\in I}\sum_{s\in S} y_{ijs} = 1 \quad \forall\, j \in J \tag{5.17}$$

Constraint (5.18) sets the arrival time of each job at the overseas DC.

$$r_j = \sum_{i\in I}\sum_{s\in S} y_{ijs}(a_s + t_s) \quad \forall j \in J \tag{5.18}$$

(iii) Transportation constraints

Constraint (5.19) states that the available time of the assigned shipment cannot be earlier than the production completion time and inland transportation time of the job.

$$\sum_{f\in F}\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s\, L_{if} - \sum_{f\in F}\sum_{i\in I}\sum_{s\in S}\sum_{t\in T} y_{ijs}L_{st}L_{if}tr_{ft} \geq c_j \quad \forall\, j \in J \tag{5.19}$$

(iv) Connection constraints

Constraint (5.20) links the production scheduling with the shipment selection for each job.

$$\sum_{k\in J\cup\{o(e)\}} x_{ijk} - \sum_{t\in T}\sum_{s\in S} y_{ijs}L_{st} = 0 \quad \forall\, i \in I;\ j \in J \tag{5.20}$$

(v) Due date based cut-off rule

Particularly, constraint (5.21) is a heuristic called the due date based cut-off rule. Sun et al. (2015) verified the computational efficiency of the rule without sacrificing the optimality of the exact algorithm. Due to the complexity of the problem, it is included in the modelling as a new constraint to decrease the computational burden.

$$\sum_{i\in I}\sum_{s\in S} \boldsymbol{y_{ijs}a_s} \leq \mathbf{A}_j \times \boldsymbol{d_j} + \mathbf{B}_j \times \boldsymbol{c_j} + \mathbf{C}_j \qquad \forall j \in J \tag{5.21}$$

where

$$A_j = \frac{c_j^p}{c_j^p - \max c^w},\ B_j = -\frac{\max c^w}{c_j^p - \max c^w}, C_j = \frac{\max c^{pro} + \max c^{tr} - \max c^w \times \min tr_{ft} + \max c^s - c_j^p \times \min t_s}{c_j^p - \max c^w}.$$

(vi) Non-negativity constraints

$$x_{ijk},\ y_{ijs} \in \{0,1\};\ s_j,\ c_j \in Z^+;\ r_j,\ c_j^{pro},\ c_j^w,\ c_j^{tr},\ c_j^s,\ E_j^{DC},\ T_j \in R^+. \tag{5.22}$$

In this model, random variables are present in objective function (5.1), constraint (5.18) and constraint (5.21). As constraint (5.18) is included in objective function (5.1), it can be removed by substitution. Additionally, constraint (5.21) is a right-hand-side stochastic constraint. Therefore, we set the joint probabilistic restriction on constraint (5.21) to further relax the cut-off rule.

$$P_r\left(\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s \le \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j + \mathrm{C}_j,\ \ \forall j \in J\right) \ge \beta \tag{5.23}$$

where β is a given confidence/reliability level. As random variable t_{s^*}, where $s^* = arg \min_{s\in S} \mu_s$ is involved only in term C_j, the probabilistic constraint (5.23) can be converted into

$$P_r\left(-\mathrm{C}_j \le -\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s + \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j,\ \ \forall j \in J\right)$$

$$= P_r\left(t_{s^*} \le \frac{-\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s + \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j + C'_j}{\frac{c_j^p}{c_j^p - \max c^w}},\ \ \forall j \in J\right) \ge \beta \tag{5.24}$$

where $C'_j = \frac{\max c^{pro} + \max c^{tr} - \max c^w \times \min tr_{ft} + \max c^s}{c_j^p - \max c^w}$. We set $\mathrm{F}_{t_{s^*}}^{-1}(\cdot)$ as the inverse cumulative distribution function (CDF) of t_{s^*}. Then probabilistic constraint (5.24) is equivalent to

$$\min\left(\frac{-\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s + \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j + C'_j}{\frac{c_j^p}{c_j^p - \max c^w}},\ \ \forall j \in J\right) \ge \mathrm{F}_{t_{s^*}}^{-1}(\beta),$$

which is also equivalent to

$$\frac{-\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s + \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j + C'_j}{\frac{c_j^p}{c_j^p - \max c^w}} \ge \mathrm{F}_{t_{s^*}}^{-1}(\beta) \quad \forall j \in J,$$

namely,

$$\sum_{i\in I}\sum_{s\in S} y_{ijs}a_s \le \mathrm{A}_j \times d_j + \mathrm{B}_j \times c_j + C'_j - \frac{c_j^p}{c_j^p - \max c^w}\mathrm{F}_{t_{s^*}}^{-1}(\beta) \tag{5.25}$$

where

$$A_j = \frac{c_j^p}{c_j^p - \max c^w},\ \ B_j = -\frac{\max c^w}{c_j^p - \max c^w}, C'_j = \frac{\max c^{pro} + \max c^{tr} - \max c^w \times \min tr_{ft} + \max c^s}{c_j^p - \max c^w}.$$

Therefore, Eq. (5.25) is the deterministic equivalent counterpart of the joint probabilistic constraint (5.23).

Hitherto, the uncertainty terms in the problem are present only in objective function (5.1). It is reasonable and feasible to minimize the total operating cost with a given confidence/reliability level to obtain a reliable production–distribution scheduling under uncertainty. According to this concept, the probabilistic constraint is further applied to objective function (5.1) to solve the stochastic production–distribution scheduling problem.

5.2 Solution methodology

In this study, the stochastic multi-factory integrated production and distribution problem with an uncertain shipping lead-time is first modelled into a joint probabilistic constrained integer programming as an approach to measure the reliability of the solutions in terms of total operating cost, which is shown in Subsection 5.2.1. It is then transformed into an approximate linear deterministic equivalent proposed and formulated in Subsection 5.2.2. Fig.5.2 illustrates the procedure for the development of the model.

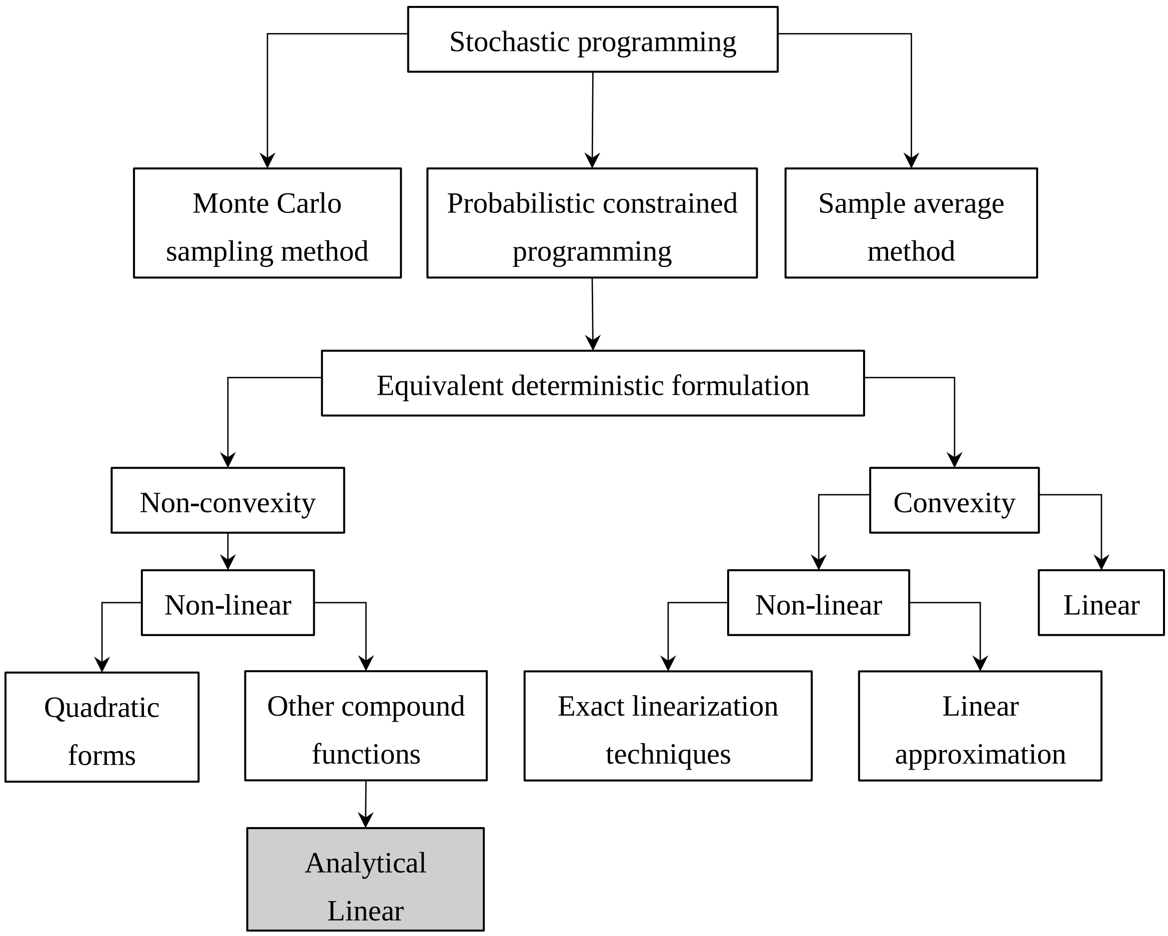

Figure 5.2. Description of model development.

5.2.1 Joint probabilistic constrained integer programming (JPCIP)

We define $M = \{(x_{ijk}, y_{ijs}, \forall\, i \in I\, ; j \in J\, \cup o(s)\, ;\, k \in J\, \cup o(e)\, ; s \in S) \mid (5.9) - (5.17), (5.19), (5.20), (5.22), (5.25)\}$ to be the feasible solutions of the problem modelled in Section 5.1 and use (x, y) to symbolize the element of set M, i.e., $(\mathrm{x}, \mathrm{y}) \in \mathrm{M}$ where *x* symbolizes any feasible production assignments and sequencings, whereas *y* symbolizes any feasible shipment selections of all the jobs. Then the objective function can be expressed as

$$\min Z_2 = f(x, y) \tag{5.26}$$

where

$$f(x,y) = \min(\alpha \left| P_r \left(\sum_{j\in J} q_j (c_j^{pro} + c_j^w + c_j^{tr} + c_j^s + \sum_{i\in I} \sum_{s\in S} y_{ijs} c_j^p \left(t_s + a_s - D_j\right)^+ + \sum_{i\in I} \sum_{s\in S} y_{ijs} c_j^{DC} \left(t_s + a_s - d_j\right)^- \right) \leq \alpha \right) \geq \beta) \quad (5.27)$$

subject to $(x,y) \in M$.

Objective function (5.26) of the JPCIP aims to minimize the total operating cost throughout the system with a probability of at least β. Here, β is a predetermined confidence/reliability level, which usually takes the values 0.9, 0.95 and 0.99. The detailed formulas of each component cost in Eq. (5.27) are the same as shown in (2) – (6). As the probability in (5.27) is continuous and non-decreasing with respect to α, Eq. (5.27) is equivalent to

$$f(x,y) = (\alpha \left| P_r \left(\sum_{j\in J} q_j (c_j^{pro} + c_j^w + c_j^{tr} + c_j^s + \sum_{i\in I} \sum_{s\in S} y_{ijs} c_j^p \left(t_s + a_s - D_j\right)^+ + \sum_{i\in I} \sum_{s\in S} y_{ijs} c_j^{DC} \left(t_s + a_s - d_j\right)^- \right) \leq \alpha \right) = \beta) \quad (5.28)$$

Eq. (5.28) indicates that $f(x, y)$ is the maximum total operating cost for reliability level β, given a feasible production and distribution decision (x, y). Therefore, the decisions that can keep the maximum total operating cost as low as possible under a certain reliability level β need to be determined. The constraints for the JPCIP are almost the same as formulated in section 5.1 except for constraint (5.18), which is removed by substitution, and constraint (5.21), which is replaced by its deterministic equivalent counterpart (5.25) by using the joint probabilistic restriction.

Given a feasible solution $(x,y) \in M$, the expression of probability in Eq. (5.28) becomes

$$P_r\left(\sum_{j\in J} (a_j \eta_{js}^+ + b_j \eta_{js}^-) \leq \alpha'\right) = \beta \quad (5.29)$$

where $a_j = q_j c_j^p, b_j = q_j c_j^{DC}, \alpha' = \alpha - \sum_{j\in J} q_j \left(c_j^{pro} + c_j^w + c_j^{tr} + c_j^s\right), \eta_{js} =$

$t_s + a_s - d_j$. Each component on the left side of the probability (5.29) is a function of t_s, i.e., $f_j(t_s) = a_j\eta_{js}^{+} + b_j\eta_{js}^{-}$. Neither the probability distribution of $f_j(t_s)$ nor the joint probability distribution of $\sum_{j\in J} f_j(t_s)$ can be expressed explicitly. Therefore, α' cannot be transformed into a convex deterministic equivalent of (*x, y*) by Eq. (5.29), i.e., second order conic function, and the convexity cannot be further verified. In order to utilize the convex optimization method and solve for optimality, JPCIP is transformed into an approximate linear deterministic equivalent by considering the reliability of the jobs separately.

5.2.2 Approximate linear deterministic equivalent

In this section, it is shown that the model developed in Subsection 5.2.1 can be transformed into approximate equivalent mixed-integer programming by relaxing the JPCIP into the individual probabilistic constrained integer programming (IPCIP).

When β_j is set as the reliability level of job j, the reliability level of the entire system is $\beta \geq \prod_{j\in J} \beta_j$. A high-reliability level of each job guarantees the reliability of the entire system. In addition, each job belongs to a different customer; thus, it is reasonable to set the reliability level of each job according to the service requirement of its corresponding customer. The solution of the IPCIP is then the upper bound of the JPCIP under a specified reliability level. We define (x_j,y_j) to symbolize any feasible decision for production assignment and sequencing, as well as shipment selection of job *j*. The objective function can be expressed as

$$\min\ Z_3 = \sum_{j\in J} f_j(x_j, y_j) \tag{5.30}$$

where

$$f_j(x_j, y_j) = \min\left(\alpha_j \left| \mathrm{P}_r\left(q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s} + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^{p}(t_s + a_s - d_j)^{+} + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^{DC}(t_s + a_s - d_j)^{-}) \le \alpha_j\right) \ge \beta_j\right.\right) \quad \forall j \in J \tag{5.31}$$

Objective function (5.30) of the IPCIP is aimed at minimizing the sum of the maximum total operating costs of each job under the individual reliability level β_j. Given the feasible solution of job j $(x_j, y_j) \in (x, y) \in M$, we set $\alpha_j' = \alpha_j - q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s})$ $(\forall j \in J)$. Then Eq. (31) can be reformulated into

$$f_j(x_j, y_j) = q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s}) + f_j'(y_j) \tag{5.32}$$

where

$$f_j'(y_j) = \min\left(\alpha_j' \left| \mathrm{P}_r\left(q_j(\sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^{p}(t_s + a_s - d_j)^{+} + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^{DC}(t_s + a_s - d_j)^{-}) \le \alpha_j'\right) \ge \beta_j\right.\right) \tag{5.33}$$

Eq. (5.33) shows the implication of function $f_j'(y_j)(\forall j \in J)$ under a feasible solution, which is the risk cost for the penalty and storage cost in the DC of job j under reliability level β_j.

Therefore, the objective function can be reformulated as

$$\min\ Z_3 = \sum_{j\in J}(q_j(c_j^{pro} + c_j^{w} + c_j^{tr} + c_j^{s}) + f_j'(y_j)) \tag{5.34}$$

subject to $(x, y) \in M$. In this case, the equivalent deterministic counterpart of the IPCIP can be obtained by the following procedures. Before the transformation, let us recall the Principle of Total Probability.

Theorem: Principle of Total Probability –

Let $B_1, B_2, \dots, B_n$ be such that $\bigcup_{i=1}^{n} B_i = \Omega$ and $B_i \cap B_j = \emptyset$ for all $i \neq j$, with $\mathrm{P}_r(B_i) > 0$ for all *i*. Then, for any event *A*,

$$\mathrm{P}_r(A) = \sum_{i=1}^{n} \mathrm{P}_r(A \cap B_i) = \sum_{i=1}^{n} \mathrm{P}_r(A|B_i)\mathrm{P}_r(B_i).$$

As explained in section 5.2.1, Eq. (5.33) is equivalent to

$$f_j'(y_j) = \left(\alpha_j' \middle| \mathrm{P}_r \begin{pmatrix} q_j[\sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^p (t_s + a_s - d_j)^+ \\ + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_j^{DC} (t_s + a_s - d_j)^-] \le \alpha_j' \end{pmatrix} = \beta_j \right) \quad \forall j \in J \tag{5.35}$$

then the probability in Eq. (5.35) can be expressed as

$$\mathrm{P}_r\left(\sum_{i\in I}\sum_{s\in S} y_{ijs}(c_j^p \eta_{js}^+ + c_j^{DC}\eta_{js}^-) \le \frac{\alpha_j'}{q_j}\right) = \beta_j \tag{5.36}$$

where $\eta_{js} = t_s + a_s - d_j$.

According to constraint (5.17), there exists one shipment $s^* \in S$ for $y_{ijs^*} = 1$ and $y_{ijs} = 0$ ($\forall\, s \in S, s \neq s^*$). The expression of Eq. (5.36) becomes

$$\mathrm{P}_r((c_j^p \eta_{js^*}^+ + c_j^{DC}\eta_{js^*}^-) \le \frac{\alpha_{js^*}'}{q_j}) = \beta_j. \tag{5.37}$$

If $\eta_{js^*} \ge 0$, then $c_j^p \eta_{js^*}^+ + c_j^{DC}\eta_{js^*}{}^- = c_j^p \eta_{js^*} \le \frac{\alpha_{js^*}'}{q_j}$, $\eta_{js^*} \le \frac{\alpha_{js^*}'}{c_j^p q_j}$.

If $\eta_{js^*} < 0$, then $c_j^p \eta_{js^*}^+ + c_j^{DC}\eta_{js^*}^- = -c_j^{DC}\eta_{js^*} \le \frac{\alpha_{js^*}'}{q_j}$, $\eta_{js^*} \ge -\frac{\alpha_{js^*}'}{c_j^{DC} q_j}$.

According to the Principle of Total Probability, the left hand side of Eq. (5.37) is

$$\mathrm{P}_r\left((c_j^p \eta_{js^*}^+ + c_j^{DC}\eta_{js^*}^-) \le \frac{\alpha_{js^*}'}{q_j} \right)$$

$$= \mathrm{P}_r\left((c_j^p \eta_{js^*}^+ + c_j^{DC}\eta_{js^*}^-) \le \frac{\alpha_{js^*}'}{q_j} \;\cap\; \eta_{js^*} \ge 0 \right)$$

$$+\mathrm{P}_r\left(\left(c_j^p\eta_{js^*}^+ + c_j^{DC}\eta_{js^*}^-\right) \le \frac{\alpha'_{js^*}}{q_j} \ \cap \ \eta_{js^*} < 0\right)$$

$$= \mathrm{P}_r\left(\max(0, l_{js^*}) \le \ \eta_{js^*} \le \min\left(\frac{\alpha'_{js^*}}{c_j^p q_j}, u_{js^*}\right)\right)$$

$$+\mathrm{P}_r\left(\max(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}) \le \ \eta_{js^*} < \min(0, u_{js^*})\right) \quad (5.38)$$

where (l_{js^*}, u_{js^*}) are the lower and upper bounds of the random variable η_{js^*}, which depends on the probability distribution of t_{s^*}.

Lemma 5.1. For uniform distribution, the corresponding closed form of the individual risk cost α'_{js^*} is:

$\alpha'_{js^*} =$

$$\begin{cases} c_j^{DC} q_j\left[(u_s - l_s)\beta_j - u_s - a_s + d_j\right] & (u_s - l_s)\beta_j > (1 + \frac{c_j^p}{c_j^{DC}})(u_s + a_s - d_j) \\ c_j^p q_j[(u_s - l_s)\beta_j + l_s + a_s - d_j] & (u_s - l_s)\beta_j > -(1 + \frac{c_j^{DC}}{c_j^p})(l_s + a_s - d_j) \\ (u_s - l_s) q_j \beta_j / \left(\frac{1}{c_j^p} + \frac{1}{c_j^{DC}}\right) & otherwise \end{cases}$$

where u_s and l_s are the upper and lower bounds of the stochastic shipping lead-times t_s, i.e., $t_s \sim U(l_s, u_s) (s \in S)$.

Proof:

Let $\eta_{js} = a_s + t_s - d_j$. As $t_s \sim U(l_s, u_s)$, thus the CDF of y_{js} is:

$$\mathrm{F}(\eta_{js}) = \begin{cases} 0 & \eta_{js} \le l_s + a_s - d_j \\ \frac{\eta_{js} - (l_s + a_s - d_j)}{u_s - l_s} & l_s + a_s - d_j < \eta_{js} \le u_s + a_s - d_j \\ 1 & \eta_{js} > u_s + a_s - d_j \end{cases}$$

We have

$$P_r\left(c_j^p q_j \eta_{js}{}^+ + c_j^{DC} q_j \eta_{js}{}^- \le \alpha'_{js^*}\right)$$

$$= P_r\left(c_j^p q_j \eta_{js}{}^+ + c_j^{DC} q_j \eta_{js}{}^- \le \alpha'_{js^*} \cap \ \eta_{js} \ge 0\right)$$

$$+P_r\left(c_j^p q_j \eta_{js}{}^+ + c_j^{DC} q_j \eta_{js}{}^- \le \alpha'_{js^*} \cap \ \eta_{js} < 0\right) \quad (*)$$

Case 1. $l_s + a_s - d_j \geq 0$

$(*) = P_r\left(c_j^p q_j\left(l_s + a_s - d_j\right) \leq c_j^p q_j \eta_{js} \leq \alpha'_{js^*}\right) + 0$

$= P_r(l_s + a_s - d_j \leq \eta_{js} \leq \frac{\alpha'_{js^*}}{c_j^p q_j})$

$= \mathrm{F}\left(\frac{\alpha'_{js^*}}{c_j^p q_j}\right) - 0$

$= \beta_j$

Thus, $\frac{\frac{\alpha'_{js^*}}{c_j^p q_j} - (l_s + a_s - d_j)}{u_s - l_s} = \beta_j$.

$\alpha'_{js^*} = c_j^p q_j[(u_s - l_s)\beta_j + l_s + a_s - d_j]$.

Case 2. $l_s + a_s - d_j < 0$ & $u_s + a_s - d_j \geq 0$

$(*) = P_r\left(0 \leq c_j^p q_j \eta_{js} \leq \alpha'_{js^*} \cap \eta_{js} \leq u_s + a_s - d_j\right) + P_r(-c_j^{DC} q_j \eta_{js} \leq \alpha'_{js^*} \cap$
$l_s + a_s - d_j \leq \eta_{js} < 0)$

$= P_r(0 \leq \eta_{js} \leq \min(\frac{\alpha'_{js^*}}{c_j^p q_j}, u_s + a_s - d_j)) + P_r(\max(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_s + a_s - d_j) \leq$
$\eta_{js} < 0)$

$= P_r(\max(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_s + a_s - d_j) \leq \eta_{js} \leq \min(\frac{\alpha'_{js^*}}{c_j^p q_j}, u_s + a_s - d_j))$

$= \beta_j$

If $u_s + a_s - d_j < \frac{\alpha'_{js^*}}{c_j^p q_j}$ and $l_s + a_s - d_j \leq -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, then $\frac{u_s + a_s - d_j + \frac{\alpha'_{js^*}}{c_j^{DC} q_j}}{u_s - l_s} = \beta_j$.

Therefore,

$\alpha'_{js^*} = c_j^{DC} q_j\left[(u_s - l_s)\beta_j - u_s - a_s + d_j\right]$, under the situation that
$c_j^{DC} q_j\left[(u_s - l_s)\beta_j - u_s - a_s + d_j\right] > c_j^p q_j(u_s + a_s - d_j)$, namely
$(u_s - l_s)\beta_j > (1 + \frac{c_j^p}{c_j^{DC}})(u_s + a_s - d_j)$.

If $u_s + a_s - d_j > \frac{\alpha'_{js^*}}{c_j^p q_j}$ and $l_s + a_s - d_j > -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, then $\frac{\frac{\alpha'_{js^*}}{c_j^p q_j} - (l_s + a_s - d_j)}{u_s - l_s} = \beta_j$.

Therefore,

$\alpha'_{js^*} = c_j^p q_j\left[(u_s - l_s)\beta_j + l_s + a_s - d_j\right]$, under the situation that

$c_j^p q_j\left[(u_s - l_s)\beta_j + l_s + a_s - d_j\right] > -c_j^{DC} q_j\left(l_s + a_s - d_j\right)$, namely

$(u_s - l_s)\beta_j > -(1 + \frac{c_j^{DC}}{c_j^p})(l_s + a_s - d_j)$.

If $u_s + a_s - d_j > \frac{\alpha'_{js^*}}{c_j^p q_j}$ and $l_s + a_s - d_j \leq -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, then $\frac{\alpha'_{js^*}}{c_j^p q_j} + \frac{\alpha'_{js^*}}{c_j^{DC} q_j} = (u_s - l_s)\beta_j$. So, $\alpha'_{js^*} = \frac{(u_s - l_s)\beta_j q_j}{\frac{1}{c_j^p} + \frac{1}{c_j^{DC}}}$ under the situation that $\frac{(u_s - l_s)\beta_j q_j}{\frac{1}{c_j^p} + \frac{1}{c_j^{DC}}} < c_j^p q_j(u_s + a_s - d_j)$ and $\frac{(u_s - l_s)\beta_j q_j}{\frac{1}{c_j^p} + \frac{1}{c_j^{DC}}} \leq -c_j^{DC} q_j(l_s + a_s - d_j)$, namely

$(u_s - l_s)\beta_j < \min((1 + \frac{c_j^p}{c_j^{DC}})(u_s + a_s - d_j), -(1 + \frac{c_j^{DC}}{c_j^p})(l_s + a_s - d_j))$.

Case 3. $u_s + a_s - d_j < 0$

$(*) = 0 + P_r(-c_j^{DC} q_j \eta_{js} \leq \alpha'_{js^*} \cap l_s + a_s - d_j \leq \eta_{js} \leq u_s + a_s - d_j)$

$= P_r(\max(l_s + a_s - d_j, -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}) \leq \eta_{js} \leq u_s + a_s - d_j)$

$= 1 - F(\max(l_s + a_s - d_j, -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}))$

$= \beta_j$

If $-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} > l_s + a_s - d_j$, then $1 - \frac{-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} - (l_s + a_s - d_j)}{u_s - l_s} = \beta_j$. So, $\alpha'_{js^*} = -c_j^{DC} q_j[\left(1 - \beta_j\right)(u_s - l_s) + l_s + a_s - d_j]$.

If $-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \leq l_s + a_s - d_j$, then $1 - 0 = \beta$, in which equality does hold as $\beta_j < 1$. Therefore, the case is impossible to happen. □

Lemma 5.2. For exponential distribution, the individual cost under a given reliability level β_j is as follows

$$\alpha'_{js^*} = \begin{cases} c_j^p q_j[a_s - \frac{1}{\lambda_s}\ln(1-\beta_j) - d_j] & -\frac{\ln(1-\beta_j)}{\lambda_s} > (1+\frac{c_j^{DC}}{c_j^p})(d_j - a_s) \\ c_j^p q_j[a_s - \frac{1}{\lambda_s}\ln(1-p_{js}) - d_j] & otherwise \end{cases}$$

where p_{js} is the root of the equation

$$c_j^p\left[a_s - \frac{1}{\lambda_s}\ln(1-\beta_j) - d_j\right] = c_j^{DC}[d_j - a_s + \frac{1}{\lambda_s}\ln(1-(p_{js}-\beta_j))].$$

, where λ_s is the mean value of the stochastic shipping lead-times t_s, i.e., $t_s \sim Exp(\lambda_s)$.

Proof:

As $t_s \sim Exp(\lambda_s)$, the CDF $\mathrm{F}(t_s) = 1 - e^{-\lambda_s t_s}$.

$$P_r\left(c_j^p q_j(t_s + a_s - d_j)^+ + c_j^{DC} q_j(t_s + a_s - d_j)^- \le \alpha'_{js^*}\right)$$

$$= P_r(c_j^p q_j\left(t_s + a_s - d_j\right)^+ + c_j^{DC} q_j\left(t_s + a_s - d_j\right)^- \le \alpha'_{js^*} \cap t_s + a_s - d_j > 0)$$

$$+ P_r(c_j^p q_j\left(t_s + a_s - d_j\right)^+ + c_j^{DC} q_j\left(t_s + a_s - d_j\right)^- \le \alpha'_{js^*} \cap t_s + a_s - d_j \le 0)$$

$$= P_r\left(c_j^p q_j\left(t_s + a_s - d_j\right) \le \alpha'_{js^*} \cap t_s > d_j - a_s\right)$$

$$+ P_r(-c_j^{DC} q_j\left(t_s + a_s - d_j\right) \le \alpha'_{js^*} \cap 0 < t_s \le d_j - a_s)$$

$$= P_r(d_j - a_s < t_s \le \frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s) + P_r(\max(d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j}, 0) < t_s \le d_j - a_s)$$

$$= P_r(\max(d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j}, 0) \le t_s \le \frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s) \qquad (*)$$

Case 1. If $d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j} > 0$

$$(*) = P_r(d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j} \le t_s \le \frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s)$$

$$= F(\frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s) - F(d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j})$$

$$= (1 - e^{-\lambda_s(\frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s)}) - (1 - e^{-\lambda_s(d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j})})$$

$$= \beta_j$$

Set $P_1 = 1 - e^{-\lambda_s\left(\frac{\alpha'_{js^*}}{c_j^p q_j}+d_j-a_s\right)}$, $P_2 = 1 - e^{-\lambda_s\left(d_j-a_s-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}\right)}$, then

$\alpha'_{js^*} = c_j^p q_j[a_s - \frac{1}{\lambda_s}\ln(1 - P_1) - d_j]$

where p_{js} is the root of the equation

$$\begin{cases} c_j^p\left[a_s - \dfrac{1}{\lambda_s}\ln(1 - P_1) - d_j\right] = c_j^{DC}[d_j + \dfrac{1}{\lambda_s}\ln(1 - P_2) - a_s] \\ P_1 - P_2 = \beta_j \end{cases}$$

Case 2. If $d_j - a_s - \frac{\alpha'_{js^*}}{c_j^{DC} q_j} < 0$

$(*) = F(\frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s) = \beta_j$, thus $1 - e^{-\lambda_s(\frac{\alpha'_{js^*}}{c_j^p q_j}+d_j-a_s)} = \beta_j$. Therefore,

$\alpha'_{js^*} = c_j^p q_j\left[a_s - \frac{1}{\lambda_s}\ln\left(1 - \beta_j\right) - d_j\right]$, under the situation that $c_j^p\left[a_s - \frac{1}{\lambda_s}\ln\left(1 - \beta_j\right) - d_j\right] > c_j^{DC}(d_j - a_s)$,

namely $-\frac{\ln(1-\beta_j)}{\lambda_s} > (1 + \frac{c_j^{DC}}{c_j^p})(d_j - a_s)$. □

Lemma 5.3. For normal distribution, the individual cost under a given reliability level β_j is as follows

$$\alpha'_{js^*} = c_j^p q_j[\mu_s + \sigma_s\Phi^{-1}(p_{js}) + a_s - d_j]$$

where p_{js} is the root of the equation

$c_j^p[\mu_s + \sigma_s\Phi^{-1}(p_{js}) + a_s - d_j] = c_j^{DC}[d_j - a_s - \mu_s - \sigma_s\Phi^{-1}(p_{js} - \beta)]$,

and $\Phi^{-1}(\cdot)$ is the inverse CDF of standard normal distribution, $t_s \sim N(\mu_s, \sigma_s^2)$.

Proof:

$P_r\left(c_j^p q_j(t_s + a_s - d_j)^+ + c_j^{DC} q_j(t_s + a_s - d_j)^- \le \alpha'_{js^*}\right)$

$= P_r(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} + d_j - a_s < t_s \le \frac{\alpha'_{js^*}}{c_j^p q_j} + d_j - a_s)$

$$= \Phi\left(\frac{\frac{\alpha'_{js^*}}{c_j^p q_j}+d_j-a_s-\mu_s}{\sigma_s}\right) - \Phi\left(\frac{-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}+d_j-a_s-\mu_s}{\sigma_s}\right)$$

$= \beta_j$

Set $P_1 = \Phi\left(\frac{\frac{\alpha'_{js^*}}{c_j^p q_j}+d_j-a_s-\mu_s}{\sigma_s}\right)$, $P_2 = \Phi\left(\frac{-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}+d_j-a_s-\mu_s}{\sigma_s}\right)$, thus

$$\alpha'_{js^*} = c_j^p q_j\left[\mu_s + \sigma_s \Phi^{-1}(P_1) + a_s - d_j\right]$$

where P_1 is the root of the equation

$$\begin{cases} c_j^p\left[\mu_s + \sigma_s \Phi^{-1}(P_1) + a_s - d_j\right] = c_j^{DC}\left[d_j - a_s - \mu_s - \sigma_s \Phi^{-1}(P_2)\right] \\ P_1 - P_2 = \beta_j \end{cases} \quad \square$$

Proposition 5.1. The general formula of the individual risk cost under a given reliability level β_j is as follows:

$$\alpha'_{js^*} =$$

$$\begin{cases} c_j^{DC} q_j\left[d_j - a_{s^*} - F^{-1}(1-\beta_j)\right] & c_j^p\left(U_{s^*} + a_{s^*} - d_j\right) \le c_j^{DC}\left(d_j - a_{s^*} - F^{-1}(1-\beta_j)\right) \\ c_j^p q_j\left[F^{-1}(\beta_j) + a_{s^*} - d_j\right] & c_j^p\left[F^{-1}(\beta_j) + a_{s^*} - d_j\right] \ge c_j^{DC}\left(d_j - a_{s^*} - L_{s^*}\right) \\ c_j^p q_j\left[F^{-1}(P_{js^*}) + a_{s^*} - d_j\right] & otherwise \end{cases}$$

where P_{js^*} is the root of

$$\begin{cases} c_j^P\left[F^{-1}(P_{js^*}) + a_{s^*} - d_j\right] = c_j^{DC}\left[d_j - a_{s^*} - F^{-1}(P'_{js^*})\right] \\ P_{js^*} - P'_{js^*} = \beta_j \end{cases}$$

Here, $F^{-1}(\cdot)$ represents the inverse CDF of the shipping lead-time t_{s^*}, and (L_{s^*}, U_{s^*}) are its lower and upper bounds.

Proof: *For the case that* $0 < u_{js^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j}$ and $l_{js^*} > 0$, Eq. (5.38) becomes

$$\mathrm{P}_r\left(l_{js^*} \le \eta_{js^*} \le u_{js^*}\right) + \mathrm{P}_r\left(l_{js^*} \le \eta_{js^*} < 0\right) > 1$$

which is impossible, so $l_{js^*} \le 0$. Thus Eq. (5.38) is converted into

$$\mathrm{P}_r\left(0 \le \eta_{js^*} \le u_{js^*}\right) + \mathrm{P}_r\left(\max\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}\right) \le \eta_{js^*} < 0\right)$$

$$= \mathrm{P}_r\left(\max\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}\right) \le \eta_{js^*} < u_{js^*}\right) \tag{5.39}$$

If $l_{js^*} < -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, Eq. (5.39) becomes

$$\mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \leq \eta_{js^*} < u_{js^*}\right) = \mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} + d_j - a_{s^*} \leq t_{s^*} < U_{s^*}\right) = \beta_j \quad (5.40)$$

Then, $\mathrm{P}_r\left(t_{s^*} < -\frac{\alpha'_{js^*}}{c_j^{DC} q_j} + d_j - a_{s^*}\right) = 1 - \beta_j$, $-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} + d_j - a_{s^*} = F^{-1}(1 - \beta_j)$.

So, in this case, $\alpha'_{js^*} = c_j^{DC} q_j\left[d_j - a_{s^*} - F^{-1}(1 - \beta_j)\right]$.

If $l_{js^*} \geq -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, Eq. (5.39) is

$\mathrm{P}_r\left(l_{js^*} \leq \eta_{js^*} \leq u_{js^*}\right) = 1 \neq \beta_j$.

For the case where $u_{js^*} \leq 0$, we have $l_{js^*} < u_{js^*} \leq 0$. Thus, Eq. (5.38) becomes

$$\mathrm{P}_r\left(0 \leq \eta_{js^*} \leq u_{js^*}\right) + \mathrm{P}_r\left(\max\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}\right) \leq \eta_{js^*} < u_{js^*}\right)$$

$$= 0 + \mathrm{P}_r\left(\max\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}\right) \leq \eta_{js^*} < u_{js^*}\right) \quad (5.41)$$

As $-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} > l_{js^*}$ must be hold, so Eq. (5.41) turns into $\mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \leq \eta_{js^*} < u_{js^*}\right) = \beta_j$, the same as Eq. (5.40). The above procedure indicates that when $u_{js^*} = U_{s^*} + a_{s^*} - d_j \leq \frac{c_j^{DC}}{c_j^{p}}\left(d_j - a_{s^*} - F^{-1}(1 - \beta_j)\right)$, $\alpha'_{js^*} = c_j^{DC} q_j\left[d_j - a_{s^*} - F^{-1}(1 - \beta_j)\right]$. In this case, $l_{js^*} = L_{s^*} + a_{s^*} - d_j < F^{-1}(1 - \beta_j) + a_{s^*} - d_j$ must be hold.

For the case where $u_{js^*} = U_{s^*} + a_{s^*} - d_j > \frac{\alpha'_{js^*}}{c_j^{p} q_j}$, Eq. (38) is converted into

$$\mathrm{P}_r\left(\max\left(0, l_{js^*}\right) \leq \eta_{js^*} \leq \frac{\alpha'_{js^*}}{c_j^{p} q_j}\right) + \mathrm{P}_r\left(\max(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j}, l_{js^*}) \leq \eta_{js^*} < 0\right) = \beta_j \quad (5.42)$$

If $l_{js^*} = L_{s^*} + a_{s^*} - d_j \geq -\frac{\alpha'_{js^*}}{c_j^{DC} q_j}$, Eq. (42) becomes

$$\mathrm{P}_r\left(\max\left(0, l_{js^*}\right) \leq \eta_{js^*} \leq \frac{\alpha'_{js^*}}{c_j^{p} q_j}\right) + \mathrm{P}_r\left(l_{js^*} \leq \eta_{js^*} < 0\right)$$

$$= \mathrm{P}_r\left(l_{js^*} \le \eta_{js^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j}\right) = \mathrm{P}_r\left(L_{s^*} \le t_{s^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j} - a_{s^*} + d_j\right) = \beta_j \qquad (5.43)$$

So, $\alpha'_{js^*} = c_j^p q_j\left[F^{-1}(\beta_j) + a_{s^*} - d_j\right]$, which indicates that $c_j^p\left[F^{-1}(\beta_j) + a_{s^*} - d_j\right] \ge c_j^{DC}(d_j - a_{s^*} - L_{s^*})$.

If $l_{js^*} = L_{s^*} + a_{s^*} - d_j < -\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \le 0$, Eq. (5.42) becomes

$$\mathrm{P}_r\left(0 \le \eta_{js^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j}\right) + \mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \le \eta_{js^*} < 0\right)$$

$$= \mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} \le \eta_{js^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j}\right) = \mathrm{P}_r\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} - a_{s^*} + d_j \le t_{s^*} \le \frac{\alpha'_{js^*}}{c_j^p q_j} - a_{s^*} + d_j\right)$$

$$= \mathrm{F}\left(\frac{\alpha'_{js^*}}{c_j^p q_j} - a_{s^*} + d_j\right) - \mathrm{F}\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} - a_{s^*} + d_j\right) = \beta_j \qquad (5.44)$$

Set $P_{js^*} = \mathrm{F}\left(\frac{\alpha'_{js^*}}{c_j^p q_j} - a_{s^*} + d_j\right)$ and $P'_{js^*} = \mathrm{F}\left(-\frac{\alpha'_{js^*}}{c_j^{DC} q_j} - a_{s^*} + d_j\right)$,

$\alpha'_{js^*} = c_j^p q_j\left[F^{-1}(P_{js^*}) + a_{s^*} - d_j\right] = c_j^{DC} q_j[d_j - a_{s^*} - F^{-1}(P'_{js^*})]$, for the case that $c_j^p\left[F^{-1}(\beta_j) + a_{s^*} - d_j\right] < c_j^{DC}(d_j - a_{s^*} - L_{s^*})$. Due to Eq. (5.44), P_{js^*} is the root of

$$\begin{cases} c_j^p\left[F^{-1}(P_{js^*}) + a_{s^*} - d_j\right] = -c_j^{DC}\left[F^{-1}(P'_{js^*}) + a_{s^*} - d_j\right] \\ P_{js^*} - P'_{js^*} = \beta_j. \end{cases}$$

In the above case, $u_{js^*} = U_{s^*} + a_{s^*} - d_j > F^{-1}(\beta_j) + a_{s^*} - d_j$ must hold. □

Proposition 5.1 verified that the individual risk cost can be found under once the probability distribution is given and this closed form is applicable to any distribution satisfying the basic probability distribution properties. Given the probability distribution, the value of P_{js^*} can be calculated numerically and is determined by the selected shipment and its responsible job. Because $s^* \in S$ is any feasible shipment selection for job j, the expression of $f'_j(y_j)$ is

$f'_j(y_j) = \alpha'_j = \sum_{i \in I} \sum_{s \in S} y_{ijs} \alpha'_{js}$, $\forall\, j \in J$.

Eventually, the IPCIP is formulated into

$$\min\ Z_4 = \sum_{j\in J} q_j\Big(\sum_{i\in I}\sum_{k\in J\cup\{o(e)\},k\neq j} c_{ij}^{pro} x_{ijk} + \sum_{f\in F} c_j^{w_f} \max\Big(\sum_{i\in I}\sum_{s\in S} y_{ijs} a_s L_{fi} + \sum_{i\in I}\sum_{s\in S}\sum_{t\in T} y_{ijs} L_{st} L_{fi} tr_{ft} - c_j, 0\Big) + \sum_{f\in F}\sum_{i\in I}\sum_{t\in T}\sum_{s\in S} y_{ijs} L_{st} L_{fi} c_{fjt}^{tr} + \sum_{i\in I}\sum_{s\in S} y_{ijs} c_s\Big) + \sum_{i\in I}\sum_{s\in S} y_{ijs} \alpha'_{js} \tag{5.45}$$

where,

$$\alpha'_{js} = \begin{cases} c_j^{DC} q_j\left[d_j - a_s - F^{-1}(1-\beta_j)\right] & c_j^p(U_s + a_s - d_j) \le c_j^{DC}(d_j - a_s - F^{-1}(1-\beta_j)) \\ c_j^p q_j\left[F^{-1}(\beta_j) + a_s - d_j\right] & c_j^p\left[F^{-1}(\beta_j) + a_s - d_j\right] \ge c_j^{DC}(d_j - a_s - L_s) \\ c_j^p q_j\left[F^{-1}(P_{js}) + a_s - d_j\right] & otherwise, \end{cases}$$

where P_{js} is the root of

$$\begin{cases} c_j^p\left[F^{-1}(P_{js}) + a_s - d_j\right] = c_j^{DC}\left[d_j - a_s - F^{-1}(P'_{js})\right] \\ P_{js} - P'_{js} = \beta_j. \end{cases}$$

subject to (5.9) - (5.17), (5.19), (5.20), (5.22) and (5.25).

It thus indicates that the IPCIP can be equivalent to mixed-integer programming and is applicable to any continuous probability distribution.

5.2.3 Managerial insights

Remark 5.1. The inverse cumulative distribution function $F^{-1}(\cdot)$ is an increasing function of the standard deviation of the random variable t_s ($\forall s \in S$). Given the reliability level and the mean of the shipping lead-time, a deviation in the shipping lead-time directly determines the varying ranges of the risk cost of each job according to the formula in Proposition 5.1. This is illustrated in Fig. 5.3 and Fig. 5.4.

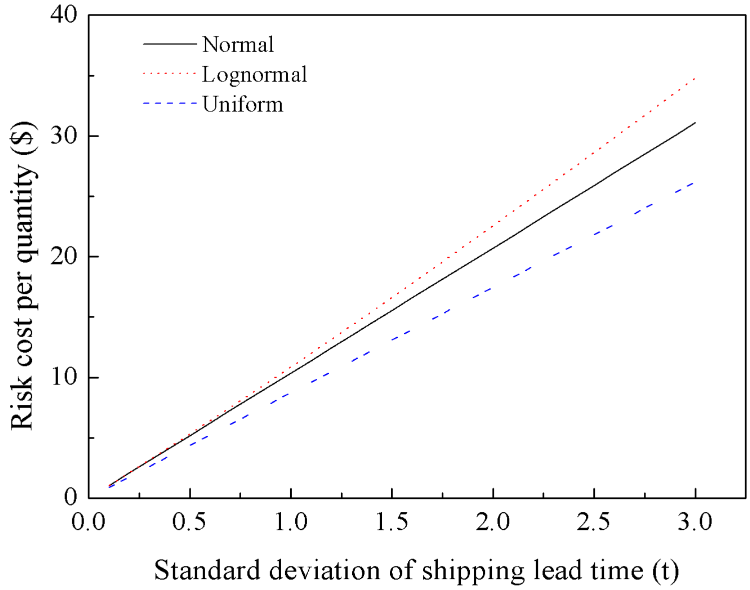

Figure 5.3. Illustration of the quantitative relationship between shipping deviation and unit risk cost (β_j= 0.95, c_j^p= 6.3, c_j^{DC}= 0.8, d_j = 30, a_s= 20, μ_s= 10).

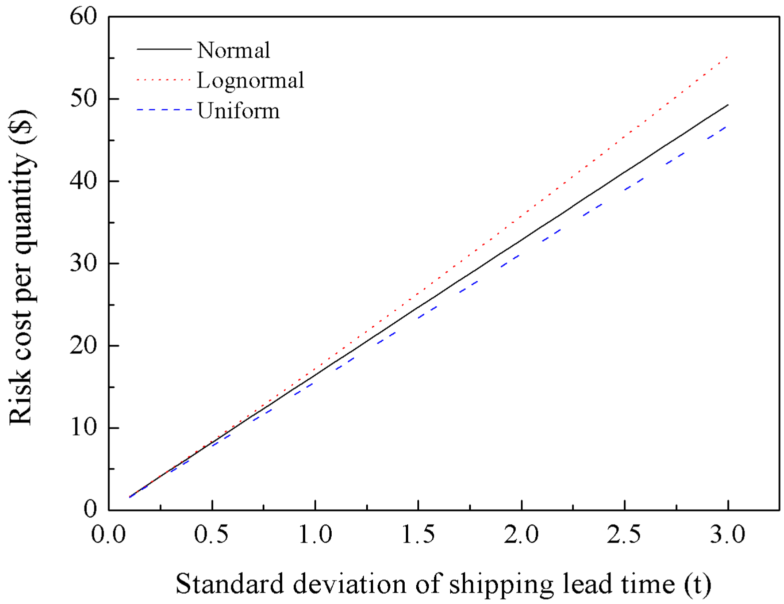

Figure 5.4. Illustration of the quantitative relationship between shipping deviation and unit risk cost (β_j= 0.95, c_j^p= 10, c_j^{DC}= 1, d_j = 30, a_s= 20, μ_s= 10).

Remark 5.2. For the risk-averse case, when the deviation of the shipment cannot be predicted, the shipment with an earlier departure time can cut down the risk cost, which requires the production scheduling to be much more adaptive so as to make the completion time early enough.

Corollary 5.1. For any case, a negative impact of the shipping lead-time uncertainty on the risk cost cannot be avoided. For the risk-averse case, the smaller the deviation of the selected shipment is, the lower the risk cost can be. Except for the extreme situation of $c_j^p(U_s + a_s - d_j) \leq c_j^{DC}(d_j - a_s - F^{-1}(1 - \beta_j))$, the decrease is significant and equals $[F_{\sigma+\Delta\sigma}^{-1}(\beta) - F_{\sigma}^{-1}(\beta)]c_j^p q_j$ ($\beta \geq \beta_j, j \in J$).

Corollary 5.2. Except for the external factors, a high penalty level of job j amplifies the negative impact of the shipping lead-time uncertainty on the risk cost of the job by $\Delta c_j^p q_j F^{-1}(\beta)$ ($\beta \geq \beta_j$).

Corollary 5.3. An additional risk cost of job j is introduced because of the possible storage cost in the DC under reliability level β_j when the cost ratio is $\frac{c_j^{DC}}{c_j^p} > \frac{[F^{-1}(\beta_j)+a_s-d_j]}{(d_j-a_s-L_s)}$. The additional risk cost depends on β_j, which is equal to $c_j^p q_j[F^{-1}(P_{js}) - F^{-1}(\beta_j)]$.

This is an intuitive result as a low storage cost brings about a lower impact on the operating cost, and a high penalty cost dominates the risk cost. However, the effect of a high storage cost on the risk cost cannot be negligible under a high-reliability level. This lemma formally formulates these intuitions by the cost ratio of the DC storage cost and penalty cost. It also implies that the selection of shipments with earlier departure times and short lead-times cannot always be risk-averse decisions.

5.3 Numerical experiments

This section is divided into two subsections. The method of problem generation for numerical experiments is presented firstly. Then, the method for comparison between stochastic model and deterministic model is described in Subsection 5.3.2.

5.3.1 Problem generation

In this section, we evaluate the performance of the proposed IPCIP from three distinct aspects. To test the effectiveness of the IPCIP, the shipping lead-time is assumed to follow a normal distribution. We coded this mixed-integer programming in the IBM ILOG CPLEX Optimization Studio 12.5 and executed it on Intel® Core™ i7-4700MQ CPU @ 2.40GHz. Small-size problems are generated with 10 jobs at two geographically dispersed factories that have two production lines each. It is assumed that the unit production costs are the same in these two factories. Three shipping market situations are considered here, i.e., peak season, normal and off-season to observe their impact on the performance of the proposed model. The situation is reflected by the number of shipments available in the shipping market during the planning horizon, i.e., 20, 40 and 60 shipments. Two terminals are considered in the assumed maritime transport network, and the number of shipments available in Terminal 1 is 2–3 times of that in Terminal 2. The input data are randomly generated as follows.

Table 5.1 Data generation

Input data	Description
Unit production cost (c_{ij}^{pro})	U(15,20)
Unit warehouse storage cost ($c_j^{w_f}$)	$2\% - 3\% c_j^{pro}$
Production capacity in the middle land factory	U(5,10)
Production capacity in the coastal factory	80%U(5,10)
Quantity (q_j)	N(75, 5^2)
Due date (d_j)	$N(E(p_{ij}) + E(\mu_s), 0.01[E(p_{ij}) + E(\mu_s)]^2)$
Unit penalty cost (c_j^p)	$20\% - 100\% c_j^{pro}$
Expected shipping lead time (μ_s)	U(10,30)
Standard deviation of shipping lead time (σ_s)	$\frac{\mu_s}{10}, \frac{\mu_s}{9}, \frac{\mu_s}{8}, \frac{\mu_s}{7}, \frac{\mu_s}{6}$
Unit inland transportation cost (c_{fjt}^{tr})	$5\% c_j^{pro} tr_{ft}$
Unit liner shipping cost (c_s)	$\frac{300}{\mu_s^2}$
Unit storage cost at DC (c_j^{DC})	$5\% c_j^{pro}$

5.3.2 Demonstration of the significance of the proposed model

To demonstrate the significance of the proposed model, the traditional deterministic method of the proposed model, which is called the deterministic multi-factory integrated production and distribution model (DMIPD), is used for comparison in this research. In DMIPD, the multiple factories are treated as an integrated manufacturing system. The production and distribution scheduling among the factories are related and affect each other. In terms of the shipments, the uncertainty of the shipping lead-time is represented by its expected value.

We test the performance of the proposed IPCIP from three distinct aspects: shipping market situation, uncertainty level and penalty level. All the optimal solutions of the IPCIP are obtained at an individual reliability level $\beta_j = 0.95$ $(\forall j \in J)$. For each instance of the problem, 10 data sets are randomly generated for the tests. Because we have (3*5) + (2*3*2) = 27 different instances, we obtain 270 different problem data sets. For each instance, we calculate the estimated reliability level by Monte Carlo sampling for both the proposed IPCIP and DMIPD and the corresponding improvement in the reliability level, namely ($\widetilde{P_r^c}(\alpha) - \widetilde{P_r^d}(\alpha)$), where α is the given budget level. The estimated probability $\widetilde{P}_r(\alpha) = \frac{1}{N}\sum_{i=1}^{N} 1_{(0,\infty)}(\alpha - Z_i)$ where $1_{(0,\infty)}(t) = \begin{cases} 1 \; if \; t > 0 \\ 0 \; if \; t \leq 0 \end{cases}$, Z_i is the total operating cost of the *i*th sample. Here, N = 1,000,000.

5.4 Results and discussion of the proposed IPCIP vs DMIPD

In the section, the comparison between the proposed stochastic model and the traditional expected model was carried considering three aspects. Subsection 5.4.1 demonstrates the comparison under different shipping market situations. Subsections 5.4.2 and 5.4.3 demonstrate the comparison results in terms of different uncertainty levels and penalty levels.

5.4.1 Performance of IPCIP vs DMIPD in terms of shipping market situations

Fig. 5.5 shows the estimated average probabilities at which the total operating cost is within certain budget levels, which are obtained by the optimal solutions of the IPCIP and the DMIPD in terms of different shipping market situations. Here, we assume that the number of shipments available in the market represents different shipping market situations. Table 5.2 presents the corresponding data of Fig. 5.5 in detail. The *i*th line of Table 5.2 indicates the estimated probabilities at which the total operating cost is no more than (1+0.05(i-1)) times the expected optimal value Z by the corresponding to the solutions of the IPCIP and DMIPD, i.e., $\widetilde{P_r^c}([1+0.05(i-1)]Z)$ and $\widetilde{P_r^d}([1+0.05(i-1)]Z)$ under three different shipping market situations. Firstly, the first line of Table 5.2 shows that irrespective of the model, the probability of realizing the expected optimal value Z is less than 3% under any situation. It is verified that if uncertainty exists, the expected optimal value obtained by the traditional deterministic method is fake, which is too low to be realized. Secondly, as we increase the budget level, the reliability level of the entire production–distribution system is improved. With the use of the IPCIP, the reliability level is increased faster than with the DMIPD for any shipment availability situation in the planning horizon. When the budget level increases by 35% of the expected optimal operating cost, the reliability level of the entire system can be improved from 2.3% to 83.9%, 1.9% to 75.6% and 0.6% to 65.5% for the situations of 20, 40 and 60 shipments being available in the market, respectively. Compared with the DMIPD, the corresponding improved percentages achieved by the IPCIP are 9%, 17.9% and 23.9%. It is demonstrated that the results obtained by the traditional deterministic method are unreliable for the situation with many shipments being available.

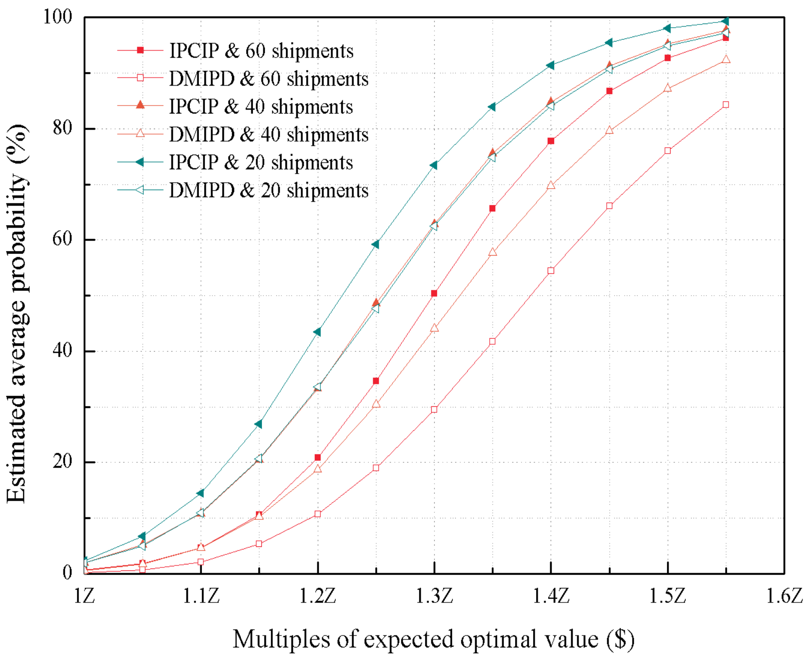

Figure 5.5. Estimated reliability level achieved by DMIPD and IPCIP given the budget levels.

Table 5.2 Performance of the IPCIP and DMIPD within the given budget levels under different shipment situations.

No. of available shipments								
60			40			20		
Multiples of expected optimal values ($)	Estimated probability (%)		Multiples of expected optimal values ($)	Estimated probability (%)		Multiples of expected optimal values ($)	Estimated probability (%)	
	new	exp.		new	exp.		new	exp.
Z	0.6	0.2	1Z	1.9	0.5	1Z	2.3	1.9
1.05Z	1.9	0.7	1.05Z	5.2	1.7	1.05Z	6.7	5.0
1.1Z	4.7	2.1	1.1Z	10.8	4.6	1.1Z	14.4	10.9
1.15Z	10.6	5.3	1.15Z	20.4	10.2	1.15Z	26.9	20.7
1.2Z	20.8	10.7	1.2Z	33.4	18.8	1.2Z	43.5	33.6
1.25Z	34.6	18.9	1.25Z	48.6	30.4	1.25Z	59.2	47.7
1.3Z	50.3	29.5	1.3Z	62.8	44.1	1.3Z	73.5	62.5
1.35Z	65.6	41.7	1.35Z	75.6	57.7	1.35Z	83.9	74.9
1.4Z	77.8	54.4	1.4Z	84.8	69.8	1.4Z	91.4	84.1
1.45Z	86.8	66.1	1.45Z	91.2	79.7	1.45Z	95.5	90.7
1.5Z	92.7	76.1	1.5Z	95.3	87.2	1.5Z	98.1	94.9
1.55Z	96.3	84.3	1.55Z	97.7	92.4	1.55Z	99.3	97.2

Fig. 5.6 presents the estimated improved percentages achieved by the IPCIP. It

shows that the average improved percentage first increases along with the budget level and later decreases and approaches 0. The reason is that the corresponding probabilities of both the IPCIP and the DMIPD approach 1 when the budget level is continuously extended to a large value. It is observed that when the available shipments are 20, 40 and 60, the corresponding maximum improvements made by the IPCIP are, on average, 11.5%, 18.7% and 23.9%. It demonstrates that with the increase in the number of available shipments, the performance of the IPCIP becomes much more significant with respect to the improvement in the reliability of the production–distribution system. Figs. 5.7 and 5.9 and Figs. 5.8 and 5.10 illustrate in detail the optimal production–distribution scheduling obtained by the DMIPD and the IPCIP, respectively, for the cases of 20 and 60 shipments available in the market. The shaded boxes in Fig. 5.8 and Fig. 5.10 show the adjusted scheduling for both the production and distribution parts after applying the IPCIP. It is demonstrated that when many shipments are available in the market, the new model can make the production scheduling adaptive for better shipment selections with small deviated lead-times or early departure times to decrease the negative impact of the shipping uncertainty.

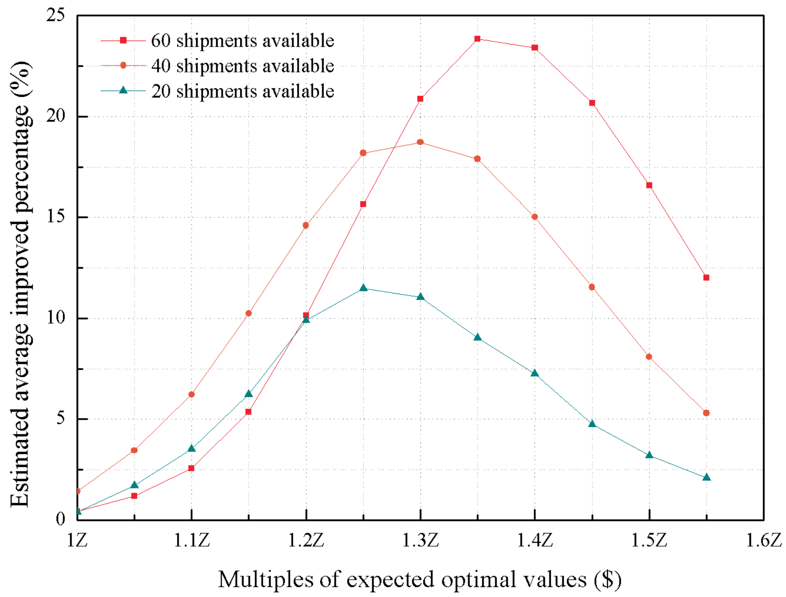

Figure 5.6. Estimated improved percentages by IPCIP given the budget levels under different shipment available situations.

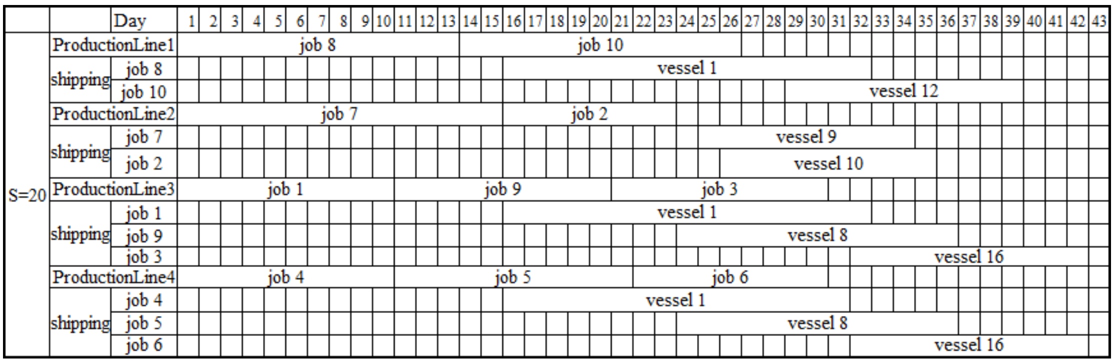

Figure 5.7. Illustration of the detailed optimal solution for a scheduling problem with 10 jobs and 20 shipment selections by the DMIPD.

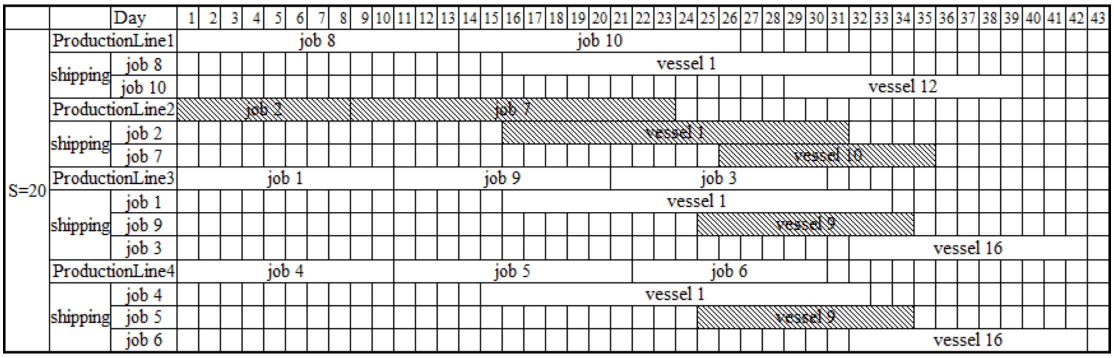

Figure 5.8. Illustration of the detailed optimal solution for a scheduling problem with 10 jobs and 20 shipment selections by the IPCIP.

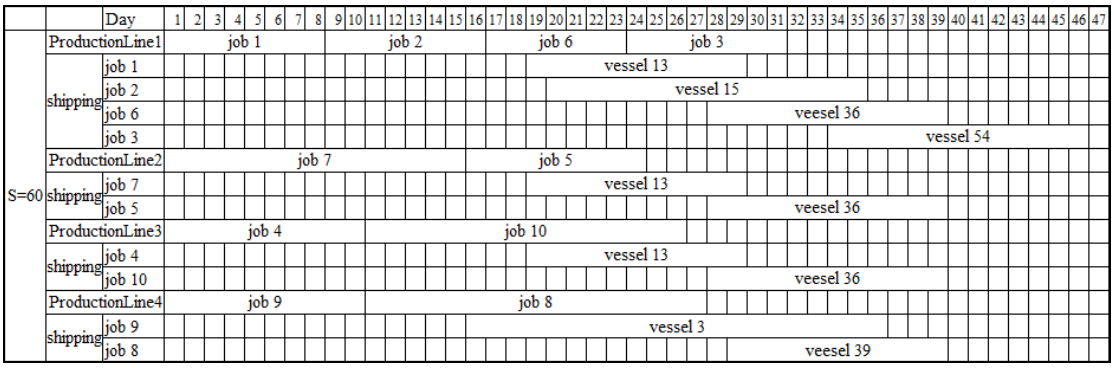

Figure 5.9. Illustration of the detailed optimal solution for a scheduling problem with 10 jobs and 60 shipment selections by the DMIPD.

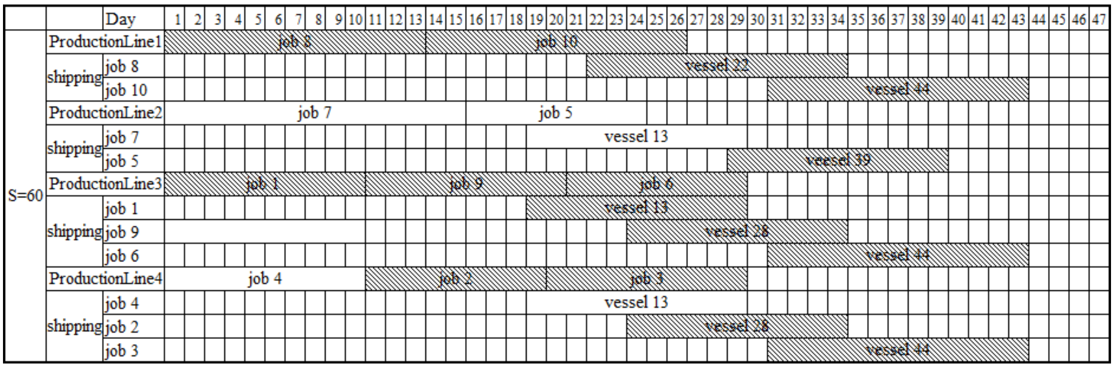

Figure 5.10. Illustration of the detailed optimal solution for a scheduling problem with 10 jobs and 60 shipment selections by the IPCIP.

5.4.2 Performance of IPCIP vs DMIPD in terms of uncertainty level

Tables 5.3, 5.4 and 5.5 reflect the influence of different uncertainty levels on the performance of the IPCIP and DMIPD under three different shipping market situations, respectively. The ith line of Table 5.3 (5.4, 5.5) indicates the estimated reliability levels of the corresponding solutions of the IPCIP and DMIPD under a certain budget level $[1 + 0.05(i - 1)]Z$, i.e., $\widetilde{P_r^c}([1 + 0.05(i - 1)]Z)$ and $\widetilde{P_r^d}([1 + 0.05(i - 1)]Z)$ for different uncertainty levels. The uncertainty level is measured by the standard deviation of the random shipping lead-time t_s, which is varied within $[\frac{\mu_s}{10}, \frac{\mu_s}{6}]$. Large (small) standard deviations correspond to high (low) uncertainty levels. Firstly, it is shown that the solutions obtained from the DMIPD are extremely unreliable when the uncertainty level increases, which is consistent with the analytical results of Proposition 5.1. Given a budget level of 135% of the expected optimal value Z, when the standard deviation of the shipping lead-time increases from $\frac{\mu_s}{10}$ to $\frac{\mu_s}{6}$ ($\forall$ s ∈ S), the reliability levels of the DMIPD solutions decrease from 99.2% to 74.9%, 96.5% to 57.7% and 90.5% to 41.7% for 20, 40 and 60 available shipments, respectively. However, under the IPCIP, the reliability levels corresponding to a high uncertainty level (i.e., $\sigma_s = \frac{\mu_s}{6}$, $\forall$ s ∈ S) are 83.9%, 75.6% and 65.6%, respectively. Secondly, even for a low uncertainty level, the reliability levels of the DMIPD solutions are not satisfactory. When the standard deviation is $\frac{\mu_s}{10}$ and the budget is increased by 25%, its reliability level only reached 65.6%, whereas the corresponding reliability level of the IPCIP solutions is 83%.

Table 5.3. Performance of the IPCIP and DMIPD in terms of different uncertainty levels under the case of a large number of shipments available.

Multiples of expected optimal value ($)	Standard deviation σ_S									
	$\mu_S/6$		$\mu_S/7$		$\mu_S/8$		$\mu_S/9$		$\mu_S/10$	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
Z	0.6	0.2	1.0	0.3	1.5	0.6	1.9	0.8	2.3	1.2
1.05Z	1.9	0.7	3.0	1.4	4.1	2.2	5.4	3.3	6.7	4.6
1.1Z	4.7	2.1	7.5	4.0	10.5	6.4	14.3	9.5	18.2	13.0
1.15Z	10.6	5.3	16.4	9.4	23.0	14.7	31.5	20.8	38.2	27.8
1.2Z	20.8	10.7	30.8	18.3	41.2	27.2	53.8	37.0	63.7	46.6
1.25Z	34.6	18.9	48.6	30.5	61.5	42.9	74.1	54.8	83.0	65.6
1.3Z	50.3	29.5	66.2	44.7	79.5	59.0	88.3	71.0	94.0	80.7
1.35Z	65.6	41.7	80.4	59.0	89.6	73.2	95.6	83.7	98.2	90.5
1.4Z	77.8	54.4	89.7	71.7	95.6	84.0	98.6	91.6	99.5	95.9
1.45Z	86.8	66.1	95.1	81.8	98.4	91.2	99.6	96.2	99.9	98.5
1.5Z	92.7	76.1	98.0	89.1	99.5	95.6	99.9	98.4	100.0	99.5
1.55Z	96.3	84.3	99.2	93.8	99.9	97.9	100.0	99.4	100.0	99.9

Table 5.4 Performance of the IPCIP and DMIPD in terms of different uncertainty levels under the case of a medium number of shipments available.

Multiples of expected optimal value ($)	Standard deviation σ_S									
	$\mu_S/6$		$\mu_S/7$		$\mu_S/8$		$\mu_S/9$		$\mu_S/10$	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
Z	1.9	0.5	2.7	0.9	2.9	1.3	3.4	1.8	3.2	2.3
1.05Z	5.2	1.7	6.8	3.0	8.6	4.5	10.5	6.2	10.9	8.1
1.1Z	10.8	4.6	15.1	7.8	19.5	11.6	24.0	16.1	28.7	21.0
1.15Z	20.4	10.2	29.0	16.7	37.0	23.9	43.9	32.5	52.3	40.7
1.2Z	33.4	18.8	46.5	29.5	56.1	40.8	65.6	52.4	75.0	62.8
1.25Z	48.6	30.4	62.3	44.9	73.2	58.8	81.7	70.7	89.7	80.2
1.3Z	62.8	44.1	76.6	60.6	85.9	74.2	91.8	84.3	96.7	91.0
1.35Z	75.6	57.7	86.9	74.1	93.4	85.6	96.9	92.7	99.1	96.5
1.4Z	84.8	69.8	93.4	84.2	97.3	92.6	98.9	96.9	99.8	98.8
1.45Z	91.2	79.7	96.9	91.1	99.0	96.6	99.7	98.8	100.0	99.6
1.5Z	95.3	87.2	98.7	95.3	99.7	98.5	99.9	99.6	100.0	99.9
1.55Z	97.7	92.4	99.5	97.7	99.9	99.4	100.0	99.9	100.0	100.0

The corresponding improvement curves of the reliability level of the system achieved by the IPCIP are presented in Figs. 5.11, 5.12 and 5.13. Firstly, it is shown that for any shipping market situation, overall, the improved percentages increase with an increase in the standard deviation of the shipping lead-time σ_s ($s \in S$). When the standard deviation σ_s ($s \in S$) increases from $\frac{\mu_s}{10}$ to $\frac{\mu_s}{6}$, the maximum improved percentages increase from 5.2% to 11.5%, 12.2% to 18.7% and 17.4% to 23.9% for the cases of the 20, 40 and 60 available shipments, respectively. The following is the analysis of covariance (ANCOVA), which is conducted to check whether the uncertainty level is related to the shipping market situation towards the performance of the proposed IPCIP.

Table 5.5 Performance of the IPCIP and DMIPD in terms of different uncertainty levels under the case of a small number of shipments available

Multiples of expected optimal value ($)	Standard deviation σ_s									
	$\mu_s/6$		$\mu_s/7$		$\mu_s/8$		$\mu_s/9$		$\mu_s/10$	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
Z	2.3	1.9	3.1	2.6	3.9	3.5	4.3	4.0	5.8	5.0
1.05Z	6.7	5.0	9.0	7.2	12.0	10.0	15.3	12.3	18.7	15.8
1.1Z	14.4	10.9	21.4	16.1	27.4	22.4	35.2	28.6	40.6	36.0
1.15Z	26.9	20.7	38.0	29.9	47.8	40.1	58.9	50.6	65.3	60.1
1.2Z	43.5	33.6	55.1	46.9	67.6	59.4	78.6	70.4	84.0	79.8
1.25Z	59.2	47.7	73.9	63.4	83.4	75.7	91.4	85.2	94.7	91.3
1.3Z	73.5	62.5	85.1	77.5	92.2	87.4	97.1	93.8	98.5	96.8
1.35Z	83.9	74.9	92.8	87.2	96.9	94.2	99.2	97.7	99.7	99.2
1.4Z	91.4	84.1	97.0	93.5	99.1	97.6	99.8	99.2	99.9	99.8
1.45Z	95.5	90.7	98.8	96.9	99.7	99.1	100.0	99.8	100.0	99.9
1.5Z	98.1	94.9	99.5	98.6	99.9	99.7	100.0	100.0	100.0	100.0
1.55Z	99.3	97.2	99.9	99.5	100.0	99.9	100.0	100.0	100.0	100.0

Table 4.6 gives the test results for the relation between the uncertainty level and the number of shipments available in the market. When the p-value equals 0.082 > 0.05, there is no significant relation between these two factors. ANCOVA shows that both these factors have significant effects on the performance of the IPCIP. By regression analysis, as presented in Table 4.7, given the budget and penalty levels, we obtain the linear relationship $P_{improvement} = \beta_0 + \beta_1 A + \beta_2 B$ with

$R^2 = 0.947$, where $P_{improvement}$ represents the improved percentage obtained from the IPCIP compared with the DMIPD, and A and B represent the shipping market situation and uncertainty level, respectively. $\beta_0, \beta_1, \beta_2$ are the constants related to the given budget as well as the penalty levels.

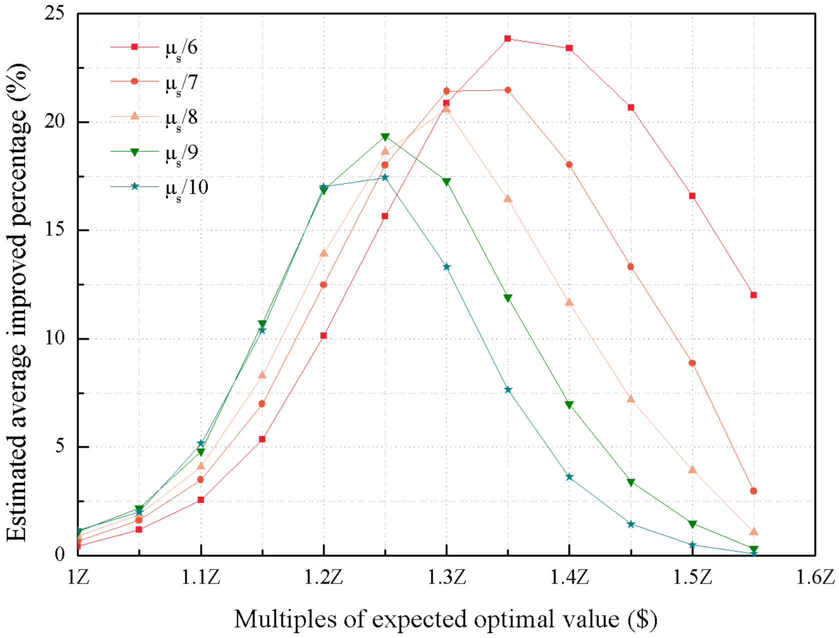

Figure 5.11. Estimated improved percentages by the IPCIP under different uncertainty levels with a large number of shipments available.

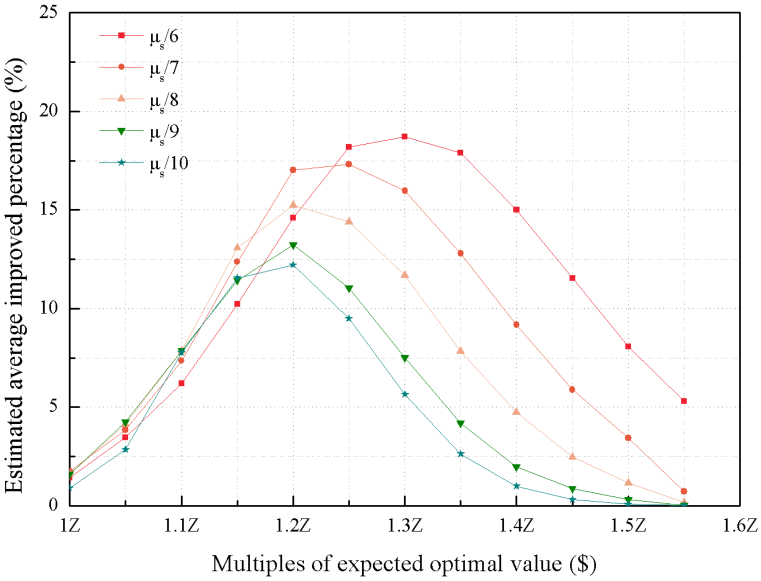

Figure 5.12. Estimated improved percentages by the IPCIP under different uncertainty levels with a medium number of shipments available.

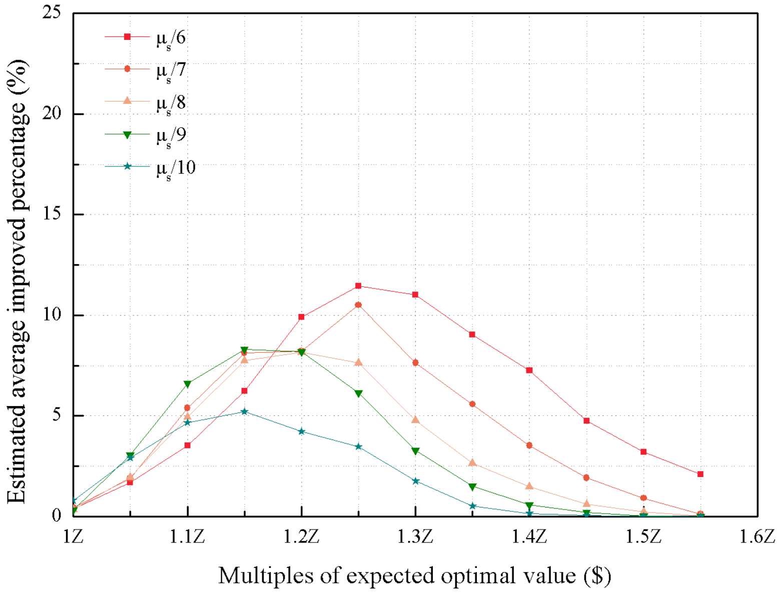

Figure 5.13. Estimated improved percentages by the IPCIP under different uncertainty levels with a small number of shipments available.

Therefore, it is demonstrated that the performance of the IPCIP has a positive correlation with the uncertainty level for any shipping market situation. However, the impact of the uncertainty level on the performance of the IPCIP is independent of the shipping market situation. It indicates that even under the case of limited shipments being available, if high uncertainty is predictable, the new model can guarantee a relative improvement in the reliability of the system to a certain extent.

Table 5.6 Test for the interaction effect between the uncertainty level and the number of shipments available in the market on the performance of the IPCIP.

	F	Sig.
shipment size*uncertainty level	3.349	0.082
shipment size	8.700	0.008
penalty level	86.690	0.000

Table 5.7 Regression analysis for the performance of the IPCIP in terms of the uncertainty level and the number of shipments available in the market.

	Coef.	Std.err.	Sig.
(constant)	-20.255	2.649	0.000
shipment size	6.500	0.534	0.000
uncertainty level	149.837	18.468	0.000
F	106.977		0.000
R^2	0.947		

5.4.3 Performance of IPCIP vs DMIPD in terms of penalty level

Figs. 5.14–5.19 show the estimated improved percentages obtained from the IPCIP in terms of different penalty levels given the different shipping market situations and uncertainty levels. The corresponding data are shown in Tables 5.8–5.10. The penalty level of each job is denoted by the ratio of its unit penalty cost to the unit production cost (i.e., $\frac{c_j^p}{c_j^{pro}}$) and is set to be 20%, 50% and 100%.

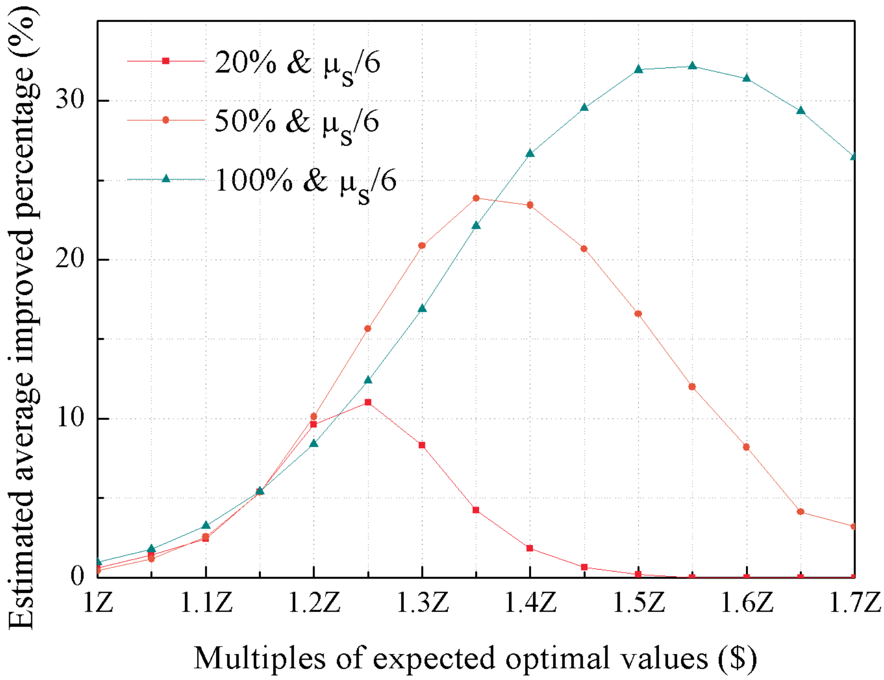

Figure 5.14. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a large number of available shipments and a high uncertainty level.

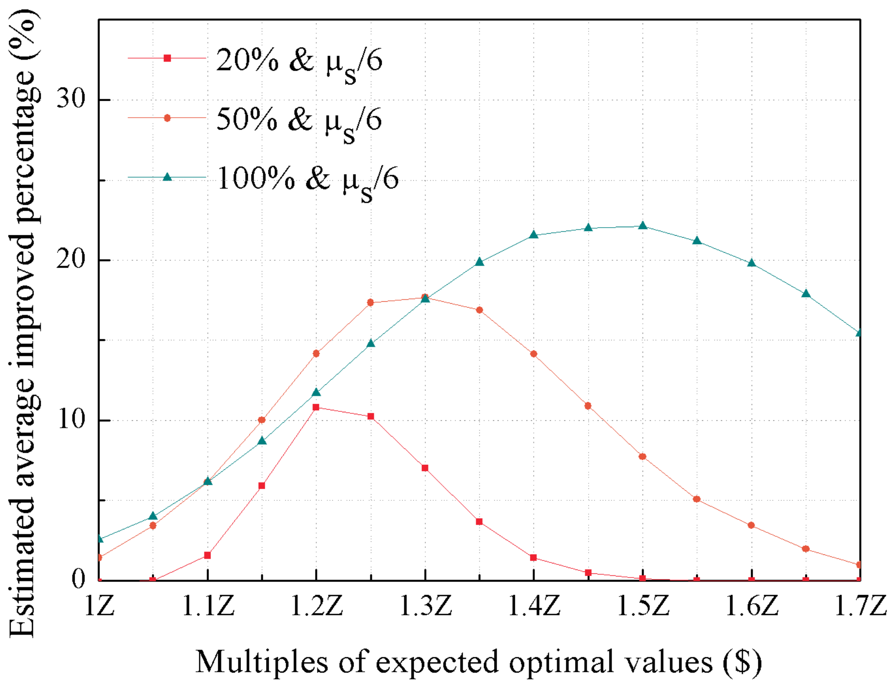

Figure 5.15. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a medium number of available shipments and a high uncertainty level.

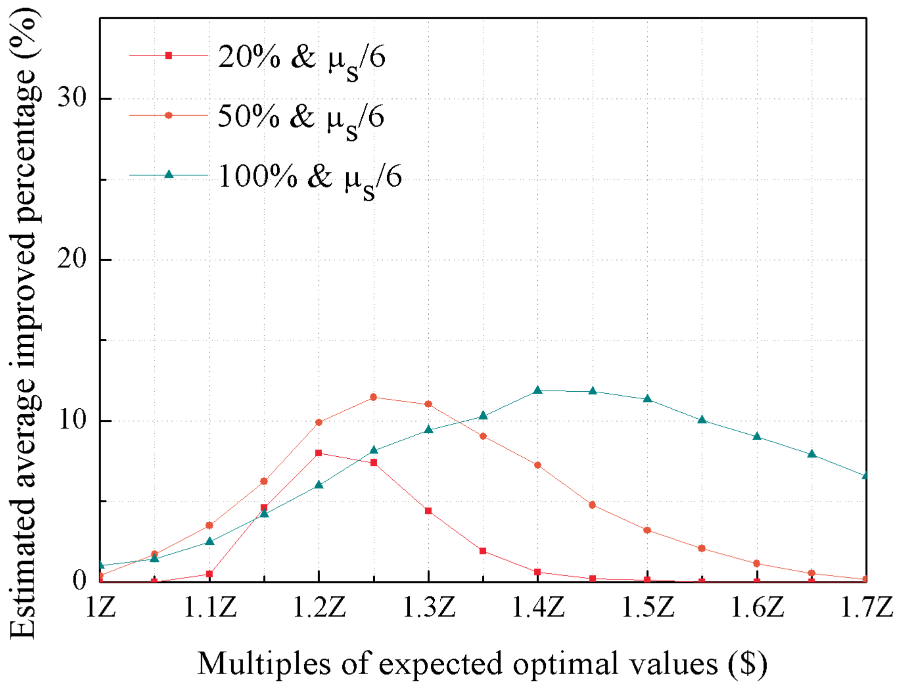

Figure 5.16. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a small number of available shipments and a high uncertainty level.

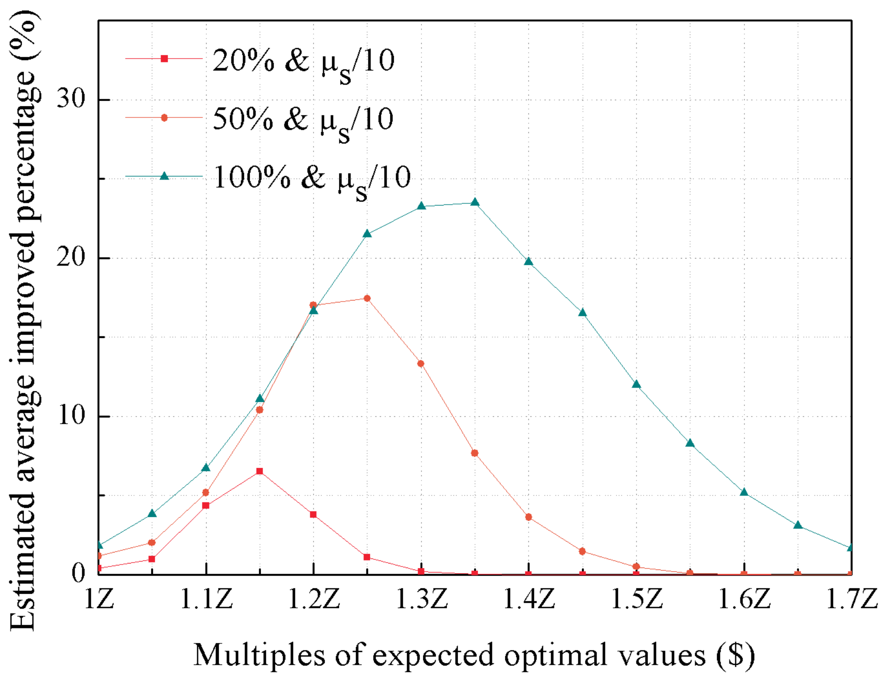

Figure 5.17. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a large number of available shipments and a low uncertainty level.

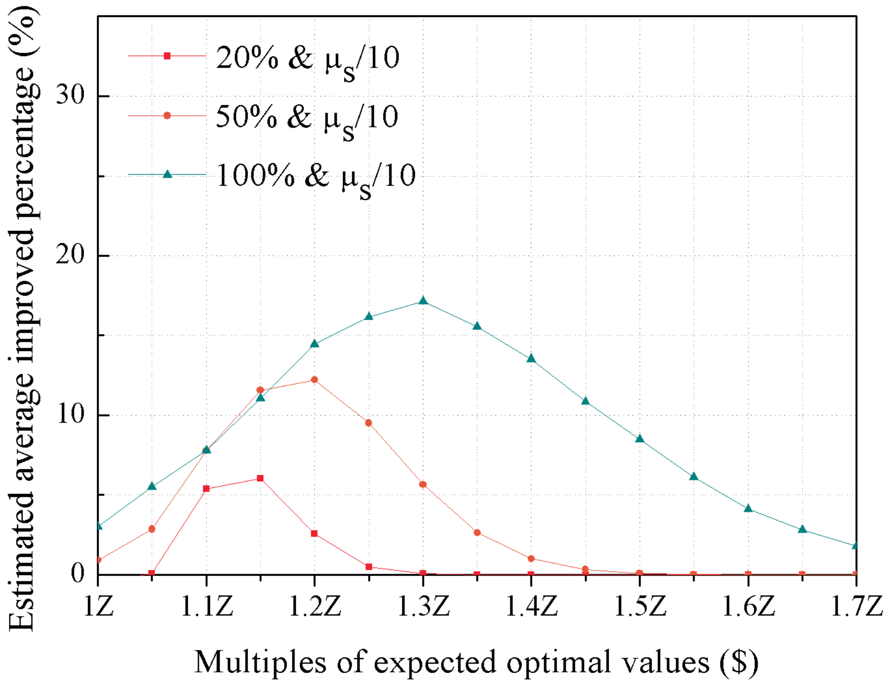

Figure 5.18. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a medium number of shipments available and low uncertainty level.

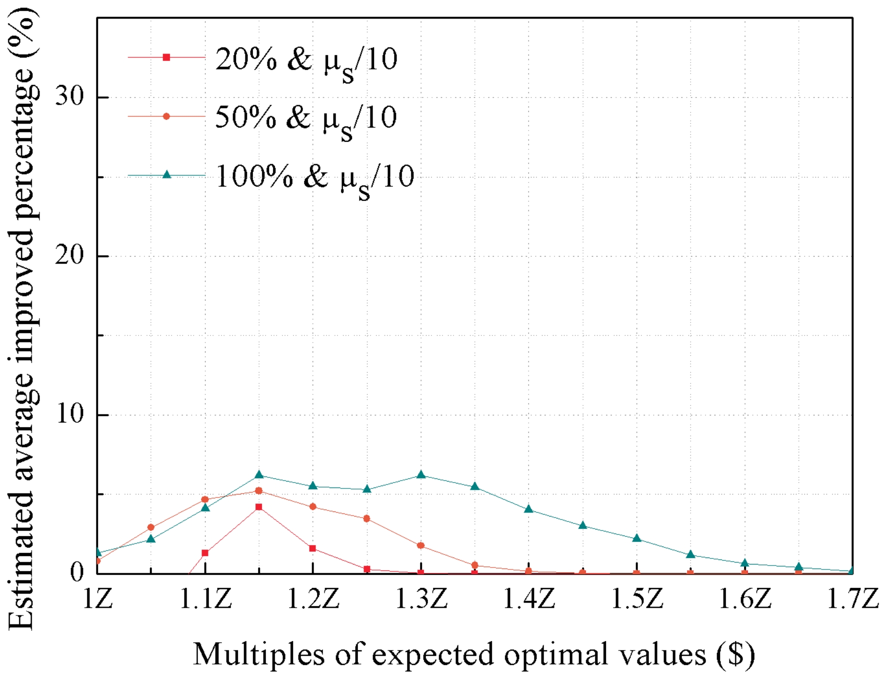

Figure 5.19. Estimated average improved percentages by the IPCIP in terms of different penalty levels under the case of a small number of available shipments and a low uncertainty level.

Firstly, as shown in Figs. 5.14–5.19, the improved percentage has an increasing trend with the penalty level for any shipping market situation and uncertainty level. Secondly, given the case of 60 available shipments and a high uncertainty level (i.e., $\sigma_s = \frac{\mu_s}{6}$, $\forall$ s $\in$ S) (see Fig. 5.14), the maximum improved percentages are 11%, 23.9% and 32.2% for the cases of 20%, 50% and 100% penalty levels, respectively. Under the low uncertainty situation (see Fig. 5.17), the corresponding improved percentages are 6.5%, 17.4% and 23.5%. Comparatively, under a high uncertainty level, both the mean and variance of the improved percentages are larger. Thirdly, as presented in Figs. 5.14, 5.15 and 5.16 (5.17, 5.18 and 5.19), when the penalty is low (i.e., 20% of the production cost), the impact of the number of available shipments on the performance of the IPCIP is not significant. The maximum improvements are 8%, 10.8% and 11% (4.2%, 6.1% and 6.5%). However, when the penalty is increased to 100% of the production cost, the impact of the number of available shipments on the performance of the IPCIP becomes significant where the maximum improved percentage is increased from 11.9% to 32.2% (6.2% to 20.4%). The impact of the penalty level on the performance of the IPCIP has a great correlation with the shipping market situation. Therefore, regression analysis is conducted to identify the correlation between the penalty level (C) and the shipping market situation (A), as well as that between the penalty level (C) and the uncertainty level (B).

Table 5.8 Performance of the IPCIP and DMIPD in terms of different penalty levels under the case of a large number of shipments available.

Multiples of expected optimal value ($)	$\sigma_s = \mu_s/6$						$\sigma_s = \mu_s/10$					
	20%		50%		100%		20%		50%		100%	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
Z	1.3	0.5	0.7	0.2	1.1	0.2	4.2	3.7	2.8	1.4	2.8	1.0
1.05Z	4.4	2.6	2.1	0.8	2.2	0.4	13.6	13.4	7.2	5.3	6.5	2.7
1.1Z	10.9	8.5	5.1	2.3	4.2	1.0	39.7	37.6	19.1	14.4	12.7	6.0
1.15Z	26.3	21.2	11.6	5.7	7.4	1.9	77.2	71.2	40.0	29.7	22.8	11.7
1.2Z	51.6	41.5	22.5	11.4	11.8	3.4	95.7	91.5	66.6	48.9	36.6	20.0
1.25Z	76.3	64.3	37.2	20.1	18.3	5.9	99.6	98.2	85.8	67.8	51.7	30.2
1.3Z	91.2	82.2	53.7	31.1	26.1	9.3	100	99.7	96.0	82.6	65.5	42.3
1.35Z	97.5	92.7	69.2	43.7	35.7	13.5	100	100	99.0	91.8	78.1	54.6
1.4Z	99.4	97.4	81.0	56.8	45.6	18.9	100	100	99.8	96.6	86.1	66.3
1.45Z	99.9	99.1	89.3	68.5	54.8	25.3	100	100	100	98.7	92.6	76.1
1.5Z	100	99.7	94.3	78.4	64.2	32.3	100	100	100	99.6	96.0	84.0
1.55Z	100	100	97.4	86.0	71.9	39.8	100	100	100	99.9	98.0	89.7
1.6Z	100	100	98.8	91.6	78.8	47.4	100	100	100	100	98.9	93.8
1.65Z	100	100	99.5	96.5	84.4	55.1	100	100	100	100	99.4	96.3
1.7Z	100	100	99.8	97.2	88.6	62.2	100	100	100	100	99.6	98.0

Table 5.11 shows the test results for the correlation between any two of these three factors. The p-values corresponding to the correlations between A and B, B and C and A and C are 0.326, 0.020 and 0.000, respectively. It is identified that an interaction effect exists between the shipping market situation (A) and penalty level (C), as well as between the uncertainty level (B) and penalty level (C). No obvious interaction effect exists between the shipment market situation (A) and uncertainty level (B), which is consistent with the results in section 5.4.2. By regression analysis (see Table 5.12), we obtain the relationship $P_{IPCIP} - P_{DMIPD} = \beta_0' + C * (\beta_1' A + \beta_2' B)$ with $R^2 = 0.848$ where $P_{IPCIP(DMIPD)}$ represents the reliability level achieved by the IPCIP (DMIPD) given a certain budget level, and β_0', β_1', β_2' are the coefficients related to the budget level.

Table 5.9 Performance of the IPCIP and DMIPD in terms of different penalty levels under the case of a medium number of shipments available.

Multiples of expected optimal value ($)	$\sigma_s = \mu_s/6$						$\sigma_s = \mu_s/10$					
	20%		50%		100%		20%		50%		100%	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
Z	0.2	0.3	1.9	0.5	3.4	0.8	1.2	1.6	3.2	2.3	6.0	3.0
1.05Z	2.2	2.2	5.2	1.7	5.7	1.7	13.2	13.1	10.9	8.1	12.0	6.5
1.1Z	11.4	9.8	10.8	4.6	9.3	3.2	49.8	44.4	28.7	21.0	20.2	12.5
1.15Z	32.3	26.4	20.4	10.2	14.3	5.6	84.5	78.5	52.3	40.7	32.3	21.3
1.2Z	60.0	49.2	33.4	18.8	20.5	8.8	97.5	94.9	75.0	62.8	46.6	32.2
1.25Z	81.2	71.0	48.6	30.4	27.9	13.2	99.8	99.3	89.7	80.2	61.0	44.8
1.3Z	93.1	86.1	62.8	44.1	36.4	18.9	100	99.9	96.7	91.0	73.7	56.6
1.35Z	98.0	94.4	75.6	57.7	45.3	25.4	100	100	99.1	96.5	83.4	67.9
1.4Z	99.5	98.1	84.8	69.8	54.1	32.6	100	100	99.8	98.8	90.1	76.6
1.45Z	99.9	99.4	91.2	79.7	62.2	40.3	100	100	100	99.6	94.7	83.8
1.5Z	100	99.9	95.3	87.2	70.2	48.1	100	100	100	99.9	97.4	88.9
1.55Z	100	100	97.7	92.4	76.8	55.7	100	100	100	100	98.7	92.6
1.6Z	100	100	98.9	95.5	82.4	62.6	100	100	100	100	99.4	95.3
1.65Z	100	100	99.6	97.6	87.0	69.1	100	100	100	100	99.8	97.0
1.7Z	100	100	99.8	98.8	90.3	74.9	100	100	100	100	99.9	98.1

The results demonstrate that the individual analytical relationship between the reliability level and the deviation of the selected shipment, as well as the penalty level of the job, formulated in Proposition 5.1, is suitable for the entire system. Irrespective of the situation of the shipping market, when the shipping lead-time deviation is large, a high penalty coefficient will further amplify the negative impact of the shipping uncertainty on the reliability of the entire system. However, the proposed IPCIP can well compensate the low reliability of the risk cost caused by the amplification effect between the penalty level and shipping uncertainty, especially in the peak season of the shipping market.

Table 5.10 Performance of the IPCIP and DMIPD in terms of different penalty levels under the case of a small number of shipments available.

Multiples of expected optimal value ($)	$\sigma_s = \mu_s/6$						$\sigma_s = \mu_s/10$					
	20%		50%		100%		20%		50%		100%	
	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)	new (%)	exp. (%)
1Z	1.8	1.8	2.3	1.9	3.7	2.7	4.0	5.2	5.8	5.0	6.8	5.5
1.05Z	7.1	7.1	6.7	5.0	6.0	4.5	23.2	26.2	18.7	15.8	13.3	11.1
1.1Z	21.3	20.8	14.4	10.9	9.8	7.4	64.6	63.3	40.6	36.0	23.7	19.5
1.15Z	47.5	42.9	26.9	20.7	15.5	11.3	93.4	89.2	65.3	60.1	37.5	31.3
1.2Z	74.4	66.4	43.5	33.6	22.5	16.5	99.5	97.9	84.0	79.8	52.4	46.9
1.25Z	91.3	83.9	59.2	47.7	31.3	23.1	100	99.7	94.7	91.3	66.2	60.9
1.3Z	97.7	93.4	73.5	62.5	40.3	30.9	100	100	98.5	96.8	79.3	73.0
1.35Z	99.5	97.6	83.9	74.9	49.6	39.3	100	100	99.7	99.2	88.2	82.7
1.4Z	99.9	99.3	91.4	84.1	60.0	48.1	100	100	99.9	99.8	93.6	89.6
1.45Z	100	99.8	95.5	90.7	68.2	56.4	100	100	100	99.9	96.9	93.9
1.5Z	100	99.9	98.1	94.9	75.9	64.6	100	100	100	100.0	98.7	96.5
1.55Z	100	100	99.3	97.2	81.9	71.8	100	100	100	100.0	99.4	98.2
1.6Z	100	100	99.8	98.7	86.9	77.9	100	100	100	100	99.8	99.1
1.65Z	100	100	100	99.5	90.9	83.0	100	100	100	100	99.9	99.5
1.7Z	100	100	100	99.9	93.8	87.2	100	100	100	100	100	99.8

Table 5.11 Test for the interaction effect between any two of the three factors on the performance of the IPCIP.

	F	Sig.
shipment size*penalty level	7.104	0.000
shipment size*uncertainty level	1.170	0.326
uncertainty level* penalty level	3.857	0.020

Table 5.12 Regression analysis for the performance of the IPCIP in terms of the three factors.

	Coef.	Std.err.	Sig.
(constant)	-0.027	0.568	0.963
shipment size*penalty level	3.605	0.545	0.000
uncertainty level*penalty level	42.173	10.076	0.000
F	117.112		0.000
R^2	0.848		

5.5 Summary

In global supply chains, the uncertainty due to shipping problems leads to risk costs for the shippers, i.e., manufacturers, which influences the overall profitability and service level of the shippers. In this study, we focus on the impacts of the liner shipping lead-time uncertainty on the multi-factory production−distribution scheduling from the perspective of the manufacturers. Instead of applying the expected value in the objective function, the probabilistic constrained technique is applied to quantify the total operating cost including the risk cost under a specific reliability level. The decision should be made in terms of three aspects: the job assignment among the factories, production scheduling in each factory, as well as the selection of the shipment for each job. The objective function is to minimize the total operating cost under an overall reliability level. As jobs belong to different customers, the reliability level of each job guarantees the reliability of the entire system. Thus, the JPCIP is reformulated into the IPCIP by considering the reliability level of each job separately. In this way, equivalent deterministic mixed-integer programming is formulated to assess the necessity for considering the shipping randomness and its impact on the multi-factory production–distribution scheduling and the total operating costs.

Based on probability theory, the analytical quantitative relationship of the individual risk cost in terms of the probabilistic and schedule information of the selected shipment under a specified reliability level is determined. For any case, a negative impact of the shipping lead-time uncertainty cannot be avoided. Therefore, adaptive production scheduling is highly required to avoid high-risk shipment selections, especially in the shipping market peak season. Additionally, a high penalty level will amplify the negative impact of the shipping uncertainty. However, when the storage cost reaches a particular point, additional risk cost will be introduced. Therefore, the pure buffer method cannot always be a good risk-averse solution.

The numerical experiments and statistical analyses are carried out to verify the effectiveness of the proposed optimization method IPCIP as well as the suitability of the proposed relationship for the entire system. It was demonstrated that when a large number of shipments are available in the market, the new model can make the production scheduling adaptive to the better shipment selections with small deviated lead-times or early departure times so as to decrease the negative impact of the shipping uncertainty. In addition, the degree of impact of the uncertainty level on the performance of the proposed model is not affected by the shipping market situation, which indicates that once high uncertainty exists, the new model can guarantee relative improvement on the reliability level of the system even under the case of limited shipments being available. Moreover, the proposed model is highly recommended for the case when the penalty level is high, as it enables compensation for the low reliability on the risk cost brought about by the amplification effect between the penalty level and the shipping uncertainty, especially in the peak season of the shipping market.

Chapter 6 Overall conclusions and future studies

In this chapter, the proposed models and methodologies are discussed firstly. The results obtained are then analysed for implication and managerial insights. Finally, the limitations of the studies and future work are discussed.

6.1 Overall conclusions

As the main support in the global trade, the reliability of container liner shipping dominates the reliability level of the whole supply chain. However, the high risk coming from the expensive storage and penalty costs brought about by the unreliability of container liner shipping is usually undertaken by the shippers, i.e., manufacturers. Moreover, the decisions cannot change once the products depart from the ports, thus the shipment assignment with distinct available times and long liner shipping lead-times brings many more challenges for make-to-order manufacturers. More reliable production scheduling and shipment assignment is essential to coordinate the limits and uncertainties coming from container liner shipping. However, in the existing literature, researchers focused on studies under a single-factory manufacturing environment, and the impact of the dominated transport mode, i.e., maritime transport, on the production and distribution for detailed scheduling level has not been addressed. Therefore, the corresponding research gaps were filled in this research study period, and the main contribution are summarized as follows:

1. A new integrated model which can simultaneously determine the bi-

assignment of each job among factories and machines, job scheduling on each machine as well as shipment assignment of each job was proposed to solve the practical production and distribution problems faced by the make-to-order approach under a deterministic background. Pure mathematical programming was formulated for this problem with consideration of two types of transportation, i.e., in-land distance and quantity dependent multi-destination transport and shipping schedule based maritime transport. The objective was to minimize total operating cost including production, earliness due to waiting for delivery at warehouses, in-land transport, liner shipping, earliness and tardiness of delivery.

2. Due to the complexity and strong NP-hardness, even for small-scale problems, it cannot be solved in acceptable times. Thus, based on the proposed objective function, a valid inequality called the due-date based cut-off rule (DBC) was developed to accelerate the computational time of the enumerated branch and bound method, and thus optimal solutions were obtained in a reasonable time.

3. In order to make the model applicable, a novel hybrid 2-level genetic algorithm that is guided by fuzzy controllers was proposed. Level 1 is responsible for production line assignment. Two fuzzy controllers based on the workload condition and busy condition on each production line were developed for the mutation operator in level 1. Level 2 is responsible for job scheduling and shipment assignment. A greedy search with DBC was used for the shipment assignment for each job. It was verified that the proposed hybrid fuzzy guided GA can get optimal solutions for small-scale problems and superior solutions for large-scale problems compared with simple GA in terms

of both computational time and solution quality.

4. Based on the proposed deterministic model, a new stochastic model for the detailed production and distribution scheduling problem for a parallel-structured multi-factory manufacturing system was proposed with further consideration of liner shipping uncertainty. Thus, a new objective function which makes a trade-off between deterministic cost and risk cost was proposed to obtain more reliable production and distribution scheduling solutions.

5. A deterministic equivalent counterpart for the risk cost of each job was formulated in terms of the non-monotonic loss function composed of both earliness and tardiness penalties. The proposed formulation was a general form for the individual risk cost, which was applicable for arbitrary continuous probability distributions.

Based on the proposed models, methodologies, and formulations, useful implication and managerial insights were obtained according to the results obtained by numerical experiments. The following summarises the main results and managerial insights:

1. Under the deterministic problem background, the integrated model outperformed the separated multi-factory scheduling model in terms of total operating cost, especially for cases when the number of shipments available in the market is limited and the production cost difference among factories

become large. The main contribution came from the reduction of earliness penalties caused by the holding cost at the warehouse in waiting for delivery and early arrival at the overseas destination, as well as the tardiness penalties due to late delivery. It verified that coordination among different factories with distinct production capacities was highly important to realize overall benefits. Timely delivery can be achieved by close linkage between production and distribution, which can be attained only after sufficient coordination among the factories.

2. Under the stochastic problem background, the numerical experiments verified that as long as uncertainty exists, the expected optimal cost obtained by the expected method was fake, being too low to be achieved. The proposed stochastic model was verified to be remarkably significant under the case of many shipments being available in the market. In addition, once high uncertainty is predicable, the proposed model can guarantee relative improvement in the reliability level of the system, even for the case of limited shipments being available. Moreover, the proposed model enabled compensation on the amplification effect between the penalty level and the shipping uncertainty, especially in the peak season. The results verified that, for any case, a negative impact of the shipping lead-time uncertainty cannot be avoided. Therefore, adaptive production scheduling is greatly required to avoid high-risk shipment selections, especially in the shipping market peak season. When high storage cost is involved, additional risk costs will be introduced. Thus, the pure buffer method cannot always be a good risk-averse solution in terms of total costs.

6.2 Limitations and future work

In order to study the complicated integrated production and distribution scheduling problem, some assumptions related to both production network and maritime transport have been simplified for the current stage studies. The studies can be extended to more practical problems, as in the following suggestions:

1. In the current study discussed in Chapter 5, a stochastic production and distribution scheduling problem was modelled with the objective of minimizing the total costs without random variables and the sum of individual risk cost of each job under a given reliability level. The risk cost was considered at the individual order level. However, multiple jobs can be assigned to the same shipment, which corresponds to a joint risk cost of jobs shipped together. The formulation of the joint risk cost will be different from the individual risk cost mathematically, which made the modelling a more general form. The relationship for jobs shipped together as well as the relationship among the jobs and their assigned shipment can be further studied.

2. In the current stage study, it was assumed that multiple jobs belonging to different customers can be shipped by one shipment and discharged at the same destination port. In reality, due to the characteristics of maritime transport, a vessel has its own routing and multiple stops are involved in its voyage. Each stop corresponds to one port of call. The jobs ordered by different customers via one shipment can be discharged at different destination ports. In that case, vessel routing instead of direct shipping is involved. The shipping lead-time is then divided into several shipping lead-

times in which the follow-up shipping lead time depends on its precedent. The shipping lead-times are not independent any more. Variant variance of the shipments undertaken by the same vessel may be taken into consideration.

3. For production part, perfect reliability in terms of the multi-factory production network was assumed. However, there is no perfect manufacturing system in reality and correction maintenance for an uncertain machine breakdown is inevitable. In that case, the decisions to be made maybe divided into two stages. The decision made in the second stage, i.e., shipment selection, depends on the state and decision made in the first stage, i.e., the job allocation and scheduling.

4. Due to the high uncertainty brought about by maritime transport, the traditional pricing method without consideration of uncertainty is not reasonable. In the existing literature, the integrated scheduling problems involving pricing and due date assignment were considered under a deterministic background. When uncertainty exists, the pricing method is supposed to be modified with consideration of risk costs. In that case, reliability is a factor affecting the pricing in a positive way.

References

Adulyasak, Y. and Jaillet, P. (2016). Models and Algorithms for Stochastic and Robust Vehicle Routing with Deadlines. Transportation Science 50(2): 608-626.

Agnetis, A., Aloulou, M. A. and Fu, L. L. (2014). Coordination of production and interstage batch delivery with outsourced distribution. European Journal of Operational Research 238(1): 130-142.

Agnetis, A., Aloulou, M. A. and Fu, L.-L. (2016). Production and interplant batch delivery scheduling: Dominance and cooperation. International Journal of Production Economics 182: 38-49.

Al-Khamis, T. and M’Hallah, R. (2011). "A two-stage stochastic programming model for the parallel machine scheduling problem with machine capacity." Computers & Operations Research 38(12): 1747-1759.

Armstrong, R., Gao, S. and Lei, L. (2008). A zero-inventory production and distribution problem with a fixed customer sequence. Annals of Operations Research 159(1): 395-414.

Assarzadegan, P. and Rasti-Barzoki, M. (2016). Minimizing sum of the due date assignment costs, maximum tardiness and distribution costs in a supply chain 个 scheduling problem. Applied Soft Computing 47: 343-356.

Averbakh, I. and Xue, Z. (2007). On-line supply chain scheduling problems with preemption. European Journal of Operational Research 181(1): 500-504.

Azadian, F., Murat, A. and Chinnam, R. B. (2015). Integrated production and logistics planning: Contract manufacturing and choice of air/surface transportation. European Journal of Operational Research 247(1): 113-123.

Behnamian, J. (2013). Decomposition based hybrid VNS–TS algorithm for distributed parallel factories scheduling with virtual corporation. Computers & Operations Research.

Behnamian, J., and Ghomi, S. F. (2014). A survey of multi-factory scheduling. Journal of Intelligent Manufacturing, 1-19.

Behnamian, J. (2017). Matheuristic for the decentralized factories scheduling problem. Applied Mathematical Modelling 47: 668-684.

Behnamian, J. and Fatemi Ghomi, S. M. T. (2013). The heterogeneous multi-factory production network scheduling with adaptive communication policy and parallel machine. Information Sciences 219: 181-196.

Bentaha, M. L., Battaïa, O., Dolgui, A. and Hu, S. J. (2015). Second order conic approximation for disassembly line design with joint probabilistic constraints. European Journal of Operational Research 247(3): 957-967.

Bilsel, R. U. and Ravindran, A. (2011). A multiobjective chance constrained programming model for supplier selection under uncertainty. Transportation Research Part B: Methodological 45(8): 1284-1300.

Bilgen, B., and Çelebi, Y. (2013). Integrated production scheduling and distribution planning in dairy supply chain by hybrid modelling. Annals of Operations Research, 211(1), 55-82.

Borodin, V., Dolgui, A., Hnaien, F. and Labadie, N. (2016). Component replenishment planning for a single-level assembly system under random lead times: A chance constrained programming approach. International Journal of Production Economics 181: 79-86.

Cai, X. and Tu, F. (1996). Scheduling jobs with random processing times on a single machine subject to stochastic breakdowns to minimize early‐tardy penalties. Naval Research Logistics 43(8): 1127-1146.

Cai, X. and Zhou, S. (1999). Stochastic Scheduling on Parallel Machines Subject to

Random Breakdowns to Minimize Expected Costs for Earliness and Tardy Jobs. Operations Research 47(3): 422-437.

Cao, C., Gu, X. and Xin, Z. (2010). Stochastic chance constrained mixed-integer nonlinear programming models and the solution approaches for refinery short-term crude oil scheduling problem. Applied Mathematical Modelling 34(11): 3231-3243.

Chan, F. T. S., Chung, S. H., and Chan, P. L. Y. (2005a). An adaptive genetic algorithm with dominated genes for distributed scheduling problems. Expert Systems with Applications, 29(2), 364-371.

Chan, F. T. S., Chung, S. H.., and Wadhwa, S. (2005b). A hybrid genetic algorithm for production and distribution. Omega, 33(4), 345-355.

Chan, F. T. S., Chung, S. H., and Chan, P. L. Y. (2006). Application of genetic algorithms with dominant genes in a distributed scheduling problem in flexible manufacturing systems. International Journal of Production Research, 44(3), 523-543.

Chan, F. T. S., Chung, S. H., Chan, L. Y., Finke, G. and Tiwari, M. K. (2006). Solving distributed FMS scheduling problems subject to maintenance: Genetic algorithms approach. Robotics and Computer-Integrated Manufacturing 22(5): 493-504.

Chan, F. T. S., Prakash, A., Ma, H. L. and Wong, C. S. (2013). A hybrid Tabu sample-sort simulated annealing approach for solving distributed scheduling problem. International Journal of Production Research 51(9): 2602-2619.

Chang, C. S., Chao, X., Pinedo, M. and Weber, R. (1992). On the optimality of LEPT and cμ rules for machines in parallel. Journal of Applied Probability 29(3): 667-681.

Chang, H. C. and Liu, T. K. (2015). Optimisation of distributed manufacturing flexible job shop scheduling by using hybrid genetic algorithms. Journal of Intelligent

Manufacturing.

Chang, Y. C. and Lee, C. Y. (2004). Machine scheduling with job delivery coordination. European Journal of Operational Research 158(2): 470-487.

Chang, Y. C., Li, V. C. and Chiang, C. J. (2014). An ant colony optimization heuristic for an integrated production and distribution scheduling problem. Engineering Optimization 46(4): 503-520.

Chen, B. and Lee, C. Y. (2008). Logistics scheduling with batching and transportation. European Journal of Operational Research 189(3): 871-876.

Chen, J., Huang, G. Q., Luo, H. and Wang, J. (2015). Synchronisation of production scheduling and shipment in an assembly flowshop. International Journal of Production Research 53(9): 2787-2802.

Chen, Z. L. (1996). Scheduling and common due date assignment with earliness-tardiness penalties and batch delivery costs. European Journal of Operational Research 93(1): 49-60.

Chen, Z. L., and Vairaktarakis, G. L. (2005). Integrated scheduling of production and distribution operations. Management Science, 51(4), 614-628.

Chen, Z. L., and Pundoor, G. (2006). Order assignment and scheduling in a supply chain. Operations Research, 54(3), 555-572.

Chen, Z. L., and Pundoor, G. (2009). Integrated order scheduling and packing. Production and Operations Management, 18(6), 672-692.

Chen, L., Yang, J., and Guo, Z. (2015, June). A heuristic algorithm for integrated production and transportation scheduling with multiple transportation modes. In Service Systems and Service Management (ICSSSM), 2015 12th International Conference on (pp. 1-6). IEEE.

Cheng, B. Y., Leung, J. Y. T. and Li, K. (2015). Integrated scheduling of production and distribution to minimize total cost using an improved ant colony optimization method. Computers & Industrial Engineering 83: 217-225.

Cheng, B. Y., Leung, J. Y. T. and Li, K. (2017). Integrated scheduling on a batch machine to minimize production, inventory and distribution costs. European Journal of Operational Research 258(1): 104-112.

Cheng, B., Li, K. and Hu, X. (2015). Approximation algorithms for two-stage supply chain scheduling of production and distribution. International Journal of Systems Science: Operations & Logistics 2(2): 78-89.

Cheng, B. Y., Leung, J. Y. T., Li, K. and Yang, S. L. (2015). Single batch machine scheduling with deliveries. Naval Research Logistics 62(6): 470-482.

Cheng, T. C. E. and Chen, Z. L. (1994). Parallel-Machine Scheduling Problems with Earliness and Tardiness Penalties. Journal of the Operational Research Society 45(6): 685-695.

Chung, S. H., Chan, F. T. S., and Chan, H. K. (2009a). A modified genetic algorithm approach for scheduling of perfect maintenance in distributed production scheduling. Engineering Applications of Artificial Intelligence, 22(7), 1005-1014.

Chung, S. H., Lau, H. C., Ho, G. T., and Ip, W. H. (2009b). Optimization of system reliability in multi-factory production networks by maintenance approach. Expert Systems with Applications, 36(6), 10188-10196.

Chung, S. H., Lau, H. C. W., Choy, K. L., Ho, G. T. S., and Tse, Y. K. (2010). Application of genetic approach for advanced planning in multi-factory environment. International Journal of Production Economics, 127(2), 300-308.

Condotta, A., Knust, S., Meier, D. and Shakhlevich, N. V. (2013). Tabu search and lower bounds for a combined production–transportation problem. Computers & Operations Research 40(3): 886-900.

Danese, P., and Bortolotti, T. (2014). Supply chain integration patterns and operational performance: a plant-level survey-based analysis. International Journal of

Production Research, 52(23), 7062-7083.

De Giovanni, L., and Pezzella, F. (2010). An improved genetic algorithm for the distributed and flexible job-shop scheduling problem. European journal of operational research, 200(2), 395-408.

Devapriya, P., Ferrell, W. and Geismar, N. (2017). Integrated production and distribution scheduling with a perishable product. European Journal of Operational Research 259(3): 906-916.

Drewry, 2015. Carrier Performance Insight - March 2015, Drewry Shipping Consultants, London

Drewry, 2016. Carrier Performance Insight - March 2015, Drewry Shipping Consultants, London

Du, J., and Leung, J. Y. T. (1990). Minimizing total tardiness on one machine is NP-hard. Mathematics of operations research, 15(3), 483-495.

Emmons, H. and Pinedo, M. (1990). Scheduling stochastic jobs with due dates on parallel machines. European Journal of Operational Research 47(1): 49-55.

Erdirik-Dogan, M. and Grossmann, I. E. (2008). Simultaneous planning and scheduling of single-stage multi-product continuous plants with parallel lines. Computers & Chemical Engineering 32(11): 2664-2683.

Fu, L.-L., Aloulou, M. A. and Triki, C. (2017). Integrated production scheduling and vehicle routing problem with job splitting and delivery time windows. International Journal of Production Research: 1-16.

Gao, S., Qi, L. and Lei, L. (2015). Integrated batch production and distribution scheduling with limited vehicle capacity. International Journal of Production Economics 160: 13-25.

Garcia, J. M. and Lozano, S. (2005). Production and delivery scheduling problem with time windows. Computers & Industrial Engineering 48(4): 733-742.

Geismar, H. N., Laporte, G., Lei, L. and Sriskandarajah, C. (2008). The Integrated Production and Transportation Scheduling Problem for a Product with a Short Lifespan. INFORMS Journal on Computing 20(1): 21-33.

Gen, M., and Syarif, A. (2005). Hybrid genetic algorithm for multi-time period production/distribution planning. Computers & Industrial Engineering, 48(4), 799-809.

Gharbi, A. and Haouari, M. (2002). Minimizing makespan on parallel machines subject to release dates and delivery times. Journal of Scheduling 5(4): 329-355.

Giovanni, P., Kjetil, F. and W., W. S. (2016). Uncertainty in Fleet Renewal: A Case from Maritime Transportation. Transportation Science 50(2): 390-407.

Gittins, J. C. (1979). Bandit processes and dynamic allocation indices. Journal of the Royal Statistical Society. Series B (Methodological): 148-177.

Glazebrook, K. D. (1984). Scheduling stochastic jobs on a single machine subject to breakdowns. Naval Research Logistics Quarterly 31(2): 251-264.

Gong, H., Tang, L. and Leung, J. Y. T. (2016). Parallel machine scheduling with batch deliveries to minimize total flow time and delivery cost. Naval Research Logistics 63(6): 492-502.

Graham, R. L. (1966). Bounds for Certain Multiprocessing Anomalies. Bell System Technical Journal 45(9): 1563-1581.

Guo, Z., Shi, L., Chen, L. and Liang, Y. (2017). A harmony search-based memetic optimization model for integrated production and transportation scheduling in MTO manufacturing. Omega 66: 327-343.

Guo, Z., Zhang, D., Leung, S. Y. S. and Shi, L. (2016). A bi-level evolutionary optimization approach for integrated production and transportation scheduling. Applied Soft Computing 42: 215-228.

H'Mida, F. and Lopez, P. (2013). Multi-site scheduling under production and transportation constraints. International Journal of Computer Integrated Manufacturing 26(3): 252-266.

Hajiaghaei-Keshteli, M. and Aminnayeri, M. (2014). Solving the integrated scheduling of production and rail transportation problem by Keshtel algorithm. Applied Soft Computing 25: 184-203.

Hall, N. G., Lesaoana, M., and Potts, C. N. (2001). Scheduling with fixed delivery dates. Operations Research, 49(1), 134-144.

Hall, L. A. and Shmoys, D. B. (1992). Jackson's Rule for Single-Machine Scheduling: Making a Good Heuristic Better. Mathematics of Operations Research 17(1): 22-35.

Hall, N. G., and Posner, M. E. (1991). Earliness-tardiness scheduling problems, I: weighted deviation of completion times about a common due date. Operations Research, 39(5), 836-846.

Hall, N. G. and Potts, C. N. (2003). Supply Chain Scheduling: Batching and Delivery. Operations Research 51(4): 566-584.

Hall, N. G. and Potts, C. N. (2005). The Coordination of Scheduling and Batch Deliveries. Annals of Operations Research 135(1): 41-64.

Heydari, J. (2014). Lead time variation control using reliable shipment equipment: An incentive scheme for supply chain coordination. Transportation Research Part E: Logistics and Transportation Review 63: 44-58.

Hoogeveen, J. A. and Vestjens, A. P. A. (2000). A Best Possible Deterministic On-Line Algorithm for Minimizing Maximum Delivery Time on a Single Machine. SIAM Journal on Discrete Mathematics 13(1): 56-63.

Hooker, J. N. (2005). A Hybrid Method for the Planning and Scheduling. Constraints 10(4): 385-401.

Hung, Y. F. and Hsiao, J. Y. (2013). Inventory rationing decision models during replenishment lead time. International Journal of Production Economics 144(1): 290-300.

Huo, Y., Leung, J. Y. T. and Wang, X. (2010). Integrated production and delivery scheduling with disjoint windows. Discrete Applied Mathematics 158(8): 921-931.

Hwang, H.-C., Lee, K. and Chang, S. Y. (2005). The effect of machine availability on the worst-case performance of LPT. Discrete Applied Mathematics 148(1): 49-61.

Nasiri, G. R., Zolfaghari, R., and Davoudpour, H. (2014). An integrated supply chain production–distribution planning with stochastic demands. Computers & Industrial Engineering, 77, 35-45.

Jackson, J. R. (1955). Scheduling a production line to minimize maximum tardiness. California Univ Los Angeles Numerical Analysis Research.

Jia, C. (2001). Stochastic single machine scheduling with an exponentially distributed due date. Operations Research Letters 28(5): 199-203.

Jia, H. Z., Nee, A. Y., Fuh, J. Y., and Zhang, Y. F. (2003). A modified genetic algorithm for distributed scheduling problems. Journal of Intelligent Manufacturing, 14(3-4), 351-362.

Jia, H. Z., Fuh, J. Y. H., Nee, A. Y. C. and Zhang, Y. F. (2007). Integration of genetic algorithm and Gantt chart for job shop scheduling in distributed manufacturing systems. Computers & Industrial Engineering 53(2): 313-320.

Joo, C. M. and Kim, B. S. (2017). Rule-based meta-heuristics for integrated scheduling of unrelated parallel machines, batches, and heterogeneous delivery trucks. Applied Soft Computing 53: 457-476.

Karaoğlan, İ. and Kesen, S. E. (2017). The coordinated production and transportation scheduling problem with a time-sensitive product: a branch-and-cut algorithm. International Journal of Production Research 55(2): 536-557.

Karimi, N. and Davoudpour, H. (2015). A branch and bound method for solving multi-factory supply chain scheduling with batch delivery. Expert Systems with Applications 42(1): 238-245.

Kawaguchi, T. and Kyan, S. (1986). Worst Case Bound of an LRF Schedule for the Mean Weighted Flow-Time Problem. SIAM Journal on Computing 15(4): 1119-1111.

Kergosien, Y., Gendreau, M. and Billaut, J. C. (2017). A Benders decomposition-based heuristic for a production and outbound distribution scheduling problem with strict delivery constraints. European Journal of Operational Research 262(1): 287-298.

Kerkhove, L. P. and Vanhoucke, M. (2014). Scheduling of unrelated parallel machines with limited server availability on multiple production locations: a case study in knitted fabrics. International Journal of Production Research 52(9): 2630-2653.

Kim, E. S. and Oron, D. (2013). Multi-location production and delivery with job selection. Computers & Operations Research 40(5): 1461-1466.

Koç, U., Toptal, A. and Sabuncuoglu, I. (2017). Coordination of inbound and outbound transportation schedules with the production schedule. Computers & Industrial Engineering 103: 178-192.

Kouvelis, P. and Li, J. (2012). Contingency Strategies in Managing Supply Systems with Uncertain Lead-Times. Production and Operations Management 21(1): 161-176.

Kouvelis, P. and Tang, S. Y. (2012). On Optimal Expediting Policy for Supply Systems with Uncertain Lead-Times. Production and Operations Management 21(2): 309-330.

Lawler, E. L. and Wood, D. E. (1966). Branch-and-Bound Methods: A Survey. Operations Research 14(4): 699-719.

Lawler, E. L. (1977). A pseudopolynomial time algorithm for sequencing jobs to minimize total tardiness. Annals of Discrete Mathematics, 1, 331-342.

Lawler, E. L., Lenstra, J. K., Kan, A. H. R., and Shmoys, D. B. (1993). Sequencing and scheduling: Algorithms and complexity. Handbooks in operations research and management science, 4, 445-522.

Lee, C. Y., Lee, H. L. and Zhang, J. (2015). The impact of slow ocean steaming on delivery reliability and fuel consumption. Transportation Research Part E: Logistics and Transportation Review 76: 176-190.

Lee, C. Y. and Chen, Z. L. (2001). Machine scheduling with transportation considerations. Journal of Scheduling 4(1): 3-24.

Lee, J., Kim, B. I., Johnson, A. L. and Lee, K. (2014). The nuclear medicine production and delivery problem. European Journal of Operational Research 236(2): 461-472.

Lee, K., Leung, J. Y. T. and Pinedo, M. L. (2011). Scheduling jobs with equal processing times subject to machine eligibility constraints. Journal of Scheduling 14(1): 27-38.

Lei, L., Liu, S., Ruszczynski, A., and Park, S. (2006). On the integrated production, inventory, and distribution routing problem. IIE Transactions, 38(11), 955-970.

Leung, J. Y. T. and Chen, Z. L. (2013). Integrated production and distribution with fixed delivery departure dates. Operations Research Letters 41(3): 290-293.

Leung, J. Y. T. and Li, C. L. (2008). Scheduling with processing set restrictions: A survey. International Journal of Production Economics 116(2): 251-262.

Leung, J. Y. T. and Pinedo, M. (2003). Minimizing Total Completion Time on Parallel Machines with Deadline Constraints. SIAM Journal on Computing 32(5): 1370-1388.

Li, C. L. (2006). Scheduling unit-length jobs with machine eligibility restrictions. European Journal of Operational Research 174(2): 1325-1328.

Li, C. L. and Ou, J. (2005). Machine scheduling with pickup and delivery. Naval Research Logistics 52(7): 617-630.

Li, C. L. and Ou, J. (2007). Coordinated scheduling of customer orders with decentralized machine locations. IIE Transactions 39(9): 899-909.

Li, C. L., Vairaktarakis, G. and Lee, C. Y. (2005). Machine scheduling with deliveries to multiple customer locations. European Journal of Operational Research 164(1): 39-51.

Li, K., Ganesan, V. K. and Sivakumar, A. I. (2006). Scheduling of single stage assembly with air transportation in a consumer electronic supply chain. Computers & Industrial Engineering 51(2): 264-278.

Li, K., Jia, Z. H. and Leung, J. Y. T. (2015). Integrated production and delivery on parallel batching machines. European Journal of Operational Research 247(3): 755-763.

Li, K., Zhou, C., Leung, J. Y. T. and Ma, Y. (2016). Integrated production and delivery with single machine and multiple vehicles. Expert Systems with Applications 57: 12-20.

Li, K. P., Ganesan, V. K. and Sivakumar, A. I. (2005). Synchronized scheduling of assembly and multi-destination air-transportation in a consumer electronics supply chain. International Journal of Production Research 43(13): 2671-2685.

Li, C., Qi, X. and Song, D. (2015). Real-time schedule recovery in liner shipping service with regular uncertainties and disruption events. Transportation Research Part B: Methodological 93: 762–788.

Li, Z. and Li, Z. (2015). Optimal robust optimization approximation for chance constrained optimization problem. Computers & Chemical Engineering 74: 89-99.

Lin, Y. and Li, W. (2004). Parallel machine scheduling of machine-dependent jobs with unit-length. European Journal of Operational Research 156(1): 261-266.

Liu, P. and Lu, X. (2016). Integrated production and job delivery scheduling with an availability constraint. International Journal of Production Economics 176: 1-6.

Liu, T. K., Chen, Y. P. and Chou, J. H. (2014). Solving Distributed and Flexible Job-Shop Scheduling Problems for a Real-World Fastener Manufacturer. IEEE Access 2: 1598-1606.

Liu, Z. and Cheng, T. C. E. (2002). Scheduling with job release dates, delivery times and preemption penalties. Information Processing Letters 82(2): 107-111.

Lin, S. W., Ying, K. C., and Huang, C. Y. (2013). Minimising makespan in distributed permutation flowshops using a modified iterated greedy algorithm. International Journal of Production Research, 51(16), 5029-5038.

Low, C., Chang, C. M., Li, R. K., and Huang, C. L. (2014). Coordination of production scheduling and delivery problems with heterogeneous fleet.International Journal of Production Economics, 153, 139-148.

Ma, H. L., Chan, F. T., and Chung, S. H. (2013). Minimising earliness and tardiness by integrating production scheduling with shipping information.International Journal of Production Research, 51(8), 2253-2267.

Masoud, S. A. and Mason, S. J. (2016). Integrated cost optimization in a two-stage, automotive supply chain. Computers & Operations Research 67: 1-11.

Mensendiek, A., Gupta, J. N. D. and Herrmann, J. (2015). Scheduling identical parallel machines with fixed delivery dates to minimize total tardiness. European Journal of Operational Research 243(2): 514-522.

Mínguez, R., Conejo, A. J. and García-Bertrand, R. (2011). Reliability and decomposition techniques to solve certain class of stochastic programming problems. Reliability Engineering & System Safety 96(2): 314-323.

M'Hallah, R., and Al-Khamis, T. (2012). Minimising total weighted earliness and tardiness on parallel machines using a hybrid heuristic. International Journal of Production Research, 50(10), 2639-2664.

Moon, C., Kim, J. and Hur, S. (2002). Integrated process planning and scheduling with minimizing total tardiness in multi-plants supply chain. Computers & Industrial Engineering 43(1): 331-349.

Moon, C., Lee, Y. H., Jeong, C. S. and Yun, Y. (2008). Integrated process planning and scheduling in a supply chain. Computers & Industrial Engineering 54(4): 1048-1061.

Moon, C. and Seo, Y. (2005). Evolutionary algorithm for advanced process planning and scheduling in a multi-plant. Computers & Industrial Engineering 48(2): 311-325.

Notteboom, E. T. (2006). The Time Factor in Liner Shipping Services. Maritime Economics & Logistics 8(1): 19-39.

Naderi, B. and Azab, A. (2014). Modeling and heuristics for scheduling of distributed job shops. Expert Systems with Applications 41(17): 7754-7763.

Naderi, B., and Ruiz, R. (2014). A scatter search algorithm for the distributed permutation flowshop scheduling problem. European Journal of Operational Research.

Pinedo, M. (1983). Stochastic scheduling with release dates and due dates. Operations Research, 31(3), 559-572.

Pinedo, M. and Rammouz, E. (1988). A Note on Stochastic Scheduling on a Single Machine Subject to Breakdown and Repair. Probability in the Engineering and Informational Sciences 2(1): 41-49.

Pinedo, M. and Weiss, G. (1979). Scheduling of stochastic tasks on two parallel processors. Naval Research Logistics Quarterly 26(3): 527-535.

Potts, C. N. (1980). Technical Note—Analysis of a Heuristic for One Machine Sequencing with Release Dates and Delivery Times. Operations Research 28(6): 1436-1441.

Pundoor, G. and Chen, Z. L. (2005). Scheduling a production–distribution system to optimize the tradeoff between delivery tardiness and distribution cost. Naval Research Logistics 52(6): 571-589.

Pundoor, G. and Chen, Z. L. (2009). Joint cyclic production and delivery scheduling in a two-stage supply chain. International Journal of Production Economics 119(1): 55-74.

Qi, X. and Song, D.-P. (2012). Minimizing fuel emissions by optimizing vessel schedules in liner shipping with uncertain port times. Transportation Research Part E: Logistics and Transportation Review 48(4): 863-880.

Radhakrishnan, S. and Ventura, J. A. (2000). Simulated annealing for parallel machine scheduling with earliness-tardiness penalties and sequence-dependent set-up times. International Journal of Production Research 38(10): 2233-2252.

Rasti-Barzoki, M. and Hejazi, S. R. (2013). Minimizing the weighted number of tardy jobs with due date assignment and capacity-constrained deliveries for multiple customers in supply chains. European Journal of Operational Research 228(2): 345-357.

Rasti-Barzoki, M. and Hejazi, S. R. (2015). Pseudo-polynomial dynamic programming for an integrated due date assignment, resource allocation, production, and distribution scheduling model in supply chain scheduling. Applied Mathematical Modelling 39(12): 3280-3289.

Rawls, C. G. and Turnquist, M. A. (2010). Pre-positioning of emergency supplies for disaster response. Transportation Research Part B: Methodological 44(4): 521-534.

Ruifeng, C., and Subramaniam, V. (2011). Performance evaluation for tandem multi-factory supply chains: an approximate solution. International Journal of Production Research, 49(11), 3285-3305.

Safaei, A. S., Moattar Husseini, S. M., Z. Farahani, R., Jolai, F., and Ghodsypour, S. H. (2010). Integrated multi-site production-distribution planning in supply chain by hybrid modelling. International Journal of Production Research, 48(14), 4043-4069.

Sawik, T. (2016). Integrated supply, production and distribution scheduling under disruption risks. Omega 62: 131-144.

Seo, D. K., Klein, C. M. and Jang, W. (2005). Single machine stochastic scheduling to minimize the expected number of tardy jobs using mathematical programming models. Computers & Industrial Engineering 48(2): 153-161.

Shen, S. (2014). Using integer programming for balancing return and risk in problems with individual chance constraints. Computers & Operations Research 49: 59-70.

Shim, S. O. (2009). Generating subproblems in branch and bound algorithms for parallel machines scheduling problem. Computers & Industrial Engineering 57(3): 1150-1153.

Sidney, J. B., and Steiner, G. (1986). Optimal sequencing by modular decomposition: Polynomial algorithms. Operations Research, 34(4), 606-612.

Sivrikaya-Şerifoğlu, F. and Ulusoy, G. (1999). "Parallel machine scheduling with earliness and tardiness penalties." Computers & Operations Research 26(8): 773-787.

Song, D., Li, D. and Drake, P. (2015). Multi-objective optimization for planning liner shipping service with uncertain port times. Transportation Research Part E: Logistics and Transportation Review 84: 1-22.

Soroush, H. M. (1999). Sequencing and due-date determination in the stochastic single machine problem with earliness and tardiness costs. European Journal of Operational Research 113(2): 450-468.

Soroush, H. M. (2007). Minimizing the weighted number of early and tardy jobs in a stochastic single machine scheduling problem. European Journal of Operational Research 181(1): 266-287.

Soroush, H. M. and Fredendall, L. D. (1994). The stochastic single machine scheduling problem with earliness and tardiness costs. European Journal of Operational Research 77(2): 287-302.

Stecke, K. E. and Zhao, X. (2007). Production and Transportation Integration for a Make-to-Order Manufacturing Company with a Commit-to-Delivery Business Mode. Manufacturing & Service Operations Management 9(2): 206-224.

Steiner, G. and Zhang, R. (2009). Approximation algorithms for minimizing the total weighted number of late jobs with late deliveries in two-level supply chains. Journal of Scheduling 12(6): 565.

Sun, W., Huang, G. H., Lv, Y. and Li, G. (2013). Inexact joint-probabilistic chance-constrained programming with left-hand-side randomness: An application to solid waste management. European Journal of Operational Research 228(1): 217-225.

Timpe, C. H., and Kallrath, J. (2000). Optimal planning in large multi-site production networks. European Journal of Operational Research, 126(2), 422-435.

Thomas, D. J., and Griffin, P. M. (1996). Coordinated supply chain management. European Journal of Operational Research, 94(1), 1-15.

Thoney, K. A., Hodgson, T. J., King, R. E., Taner, M. R., and Wilson, A. D. (2002). Satisfying due-dates in large multi-factory supply chains. IIE Transactions, 34(9), 803-811.

Toptal, A., Koc, U., and Sabuncuoglu, I. (2013). A joint production and transportation planning problem with heterogeneous vehicles. Journal of the Operational Research Society, 65(2), 180-196.

Tang, L., Gong, H., Liu, J. and Li, F. (2014). "Bicriteria scheduling on a single batching machine with job transportation and deterioration considerations." Naval Research Logistics (NRL) 61(4): 269-285.

Terrazas-Moreno, S. and Grossmann, I. E. (2011). "A multiscale decomposition method for the optimal planning and scheduling of multi-site continuous multiproduct plants." Chemical Engineering Science 66(19): 4307-4318.

Ullrich, C. A. (2013). Integrated machine scheduling and vehicle routing with time windows. European Journal of Operational Research, 227(1), 152-165.

Ulusoy, G., Sivrikaya-Şerifoğlu, F., and Bilge, Ü. (1997). A genetic algorithm approach to the simultaneous scheduling of machines and automated guided vehicles. Computers & Operations Research, 24(4), 335-351.

Varthanan, P. A., Murugan, N., and Kumar, G. M. (2013). An AHP based heuristic DPSO algorithm for generating multi criteria production–distribution plan. Journal of Manufacturing Systems, 32(4), 632-647.

Ventura, J. A. and Kim, D. (2003). Parallel machine scheduling with earliness–tardiness penalties and additional resource constraints. Computers & Operations Research 30(13): 1945-1958.

Vepsalainen, A. P. J. and Morton, T. E. (1987). Priority Rules for Job Shops with Weighted Tardiness Costs. Management Science 33(8): 1035-1047.

Viergutz, C., and Knust, S. (2014). Integrated production and distribution scheduling with lifespan constraints. Annals of Operations Research, 213(1), 293-318.

Wang, S. and Meng, Q. (2012). Liner ship route schedule design with sea contingency time and port time uncertainty. Transportation Research Part B: Methodological 46(5): 615-633.

Wang, G. and Cheng, T. C. E. (2000). Parallel machine scheduling with batch delivery costs. International Journal of Production Economics 68(2): 177-183.

Wang, H. and Lee, C. Y. (2005). Production and transport logistics scheduling with two transport mode choices. Naval Research Logistics (NRL) 52(8): 796-809.

Wang, Q., Batta, R. and J. Szczerba, R. (2005). Sequencing the processing of incoming mail to match an outbound truck delivery schedule. Computers & Operations

Research 32(7): 1777-1791.

Wang, T., Meng, Q., Wang, S. and Tan, Z. (2013). Risk management in liner ship fleet deployment: A joint chance constrained programming model. Transportation Research Part E: Logistics and Transportation Review 60: 1-12.

Wang, X. and Cheng, T. C. E. (2007). Machine scheduling with an availability constraint and job delivery coordination. Naval Research Logistics (NRL) 54(1): 11-20.

Weber, R. R. (1982). Scheduling jobs by stochastic processing requirements on parallel machines to minimize makespan or flowtime. Journal of Applied Probability 19(1): 167-182.

Webster, S. T. (1996). A general lower bound for the makespan problem. European Journal of Operational Research 89(3): 516-524.

Weiss, G. (1992). Turnpike Optimality of Smith's Rule in Parallel Machines Stochastic Scheduling. Mathematics of Operations Research 17(2): 255-270.

Woeginger, G. J. (1994). heuristics for parallel machine scheduling with delivery times. Acta Informatica 31(6): 503-512.

Xiong, F., Xing, K., Wang, F., Lei, H., and Han, L. (2014). Minimizing the total completion time in a distributed two stage assembly system with setup times. Computers & Operations Research, 47, 92-105.

Xiong, F., and Xing, K. (2014). Meta-heuristics for the distributed two-stage assembly scheduling problem with bi-criteria of makespan and mean completion time. International Journal of Production Research, 52(9), 2743-2766.

Xu, X., Cui, W., Lin, J. and Qian, Y. (2013). "Robust makespan minimisation in identical parallel machine scheduling problem with interval data." International Journal of Production Research 51(12): 3532-3548.

Yazdani, M., Gohari, S. and Naderi, B. (2015). Multi-factory parallel machine problems: Improved mathematical models and artificial bee colony algorithm. Computers & Industrial Engineering 81: 36-45.

Zegordi, S. H., Abadi, I. N. K. and Nia, M. A. B. (2010). A novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain. Computers & Industrial Engineering 58(3): 373-381.

Zhong, W., Dósa, G. and Tan, Z. (2007). On the machine scheduling problem with job delivery coordination. European Journal of Operational Research 182(3): 1057-1072.

Ziaee, M. (2014). A heuristic algorithm for the distributed and flexible job-shop scheduling problem. The Journal of Supercomputing, 67(1), 69-83.

Zhang, G., Shang, J. and Li, W. (2011). Collaborative production planning of supply chain under price and demand uncertainty. European Journal of Operational Research 215(3): 590-603.

Zhang, Z., Zheng, L., Li, N., Wang, W., Zhong, S., and Hu, K. (2012). Minimizing mean weighted tardiness in unrelated parallel machine scheduling with reinforcement learning. Computers & Operations Research, 39(7), 1315-1324.