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Intelligent Production Control Decision-Making for Apparel Manufacturing Process

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

August 2007

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TO MY PARENTS AND MY WIFE

For their constant love, support and encouragement

Abstract

As a traditional labor-intensive industry with low-level automation, the production control decision-making process of today's apparel industry mainly rests on the experience and subjective assessment of shop floor management or simple computation. Facing the increasingly fierce competition and fast changing customer demand, apparel enterprises have stringent demands for lowering production costs and shortening the production lead time by using systematic and effective methods of production control and decision-making. The purpose of this research is to develop intelligent algorithm-based methodologies for the production control decision-making process of apparel manufacture.

An effective framework for production control decision-making in an apparel manufacturing company was developed through integrating three types of apparel production control problems, namely order scheduling at the factory level, apparel assembly line (AAL) scheduling at the shop floor level, and AAL balancing at the assembly line level. On the basis of genetic algorithms (GA), these three types of problems were formulated mathematically and solved by effective methodologies.

The order scheduling problem at the factory level considered multiple uncertainties in real apparel production, including uncertain processing time, uncertain arrival time and uncertain production orders. The uncertain time was described as continuous or discrete random variable. Based on the uncertain processing time of production processes, uncertain beginning time and completion time were determined by using the probability theory. A genetic optimization model with the variable length of sub-chromosomes was developed to generate the order scheduling solution.

A bi-level genetic optimization model was proposed to solve the AAL scheduling problem with two orders. It comprised two genetic optimization processes on different levels, where the second-level GA (GA-2) was nested in the first-level GA (GA-1). GA-1 generated the optimal operation assignment of each order while GA-2 determined the optimal beginning time of each order based on the operation assignment from GA-1. In GA-1, a novel chromosome representation was proposed to deal with the flexible operation assignment in PBS.

For the AAL balancing problem at the assembly line level, work-sharing, workstation revisiting and variable operative efficiencies were considered. A GA-based optimization model was developed to solve this problem. In this proposed model, a bi-level multi-parent GA (BiMGA) was developed to generate the optimal operation assignment to sewing workstations and the task proportions of the shared operation being processed in different workstations, and a heuristic operation routing rule was presented to route the shared operation of each garment to an appropriate workstation based on the results of BiMGA. The learning curve theory was used to describe the change of operative efficiency.

Based on the production data from the real-life PBS, experiments were conducted to evaluate the performance of the proposed methodologies. The experimental results demonstrate the effectiveness of the proposed methodologies for the production control decision-making process of apparel manufacture.

Acknowledgements

I would like to express my sincere thanks to my chief supervisor, Dr. W.K. Wong, for his constructive guidance, advice and encouragement during this research. His enthusiastic attitude towards research will always motivate me in future endeavors. I also thank my co-supervisors, Dr. S.Y.S. Leung, Prof. J.T. Fan and Dr. S.F. Chan, for their guidance and many helpful suggestions in this research. This thesis would not have been possible without their unwavering support and belief in me.

I would like to thank Innovation and Technology Commission of the Government of the Hong Kong SAR and Genexy Company Limited for the financial support in this research. Special thanks are given to Mr. Maurice Wong from Genexy Company Limited for providing industrial data for the validation of the proposed methodologies.

I extend my thanks to my colleagues, Aihua Dong, Xianhui Zeng, Zhenlong Zhang, Tao Liu, and all others for their helps and making my stay in PolyU most memorable.

Finally, I am forever indebted to my wife Min Li, my parents Saifan Guo and Guanyu Wang. It is their love and patience that make me strive to be better and achieve more than I ever could alone.

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A_i, time of production order P_i arriving at the factory

ACT_i, actual cycle time of order P_i

AM_i, set of sewing workstations processing order P_i

B, smoothness performance of the production flow of the assembly system

BO_{ij}, actual beginning (starting) time of sewing operation O_{ij}

BP_{ij}, beginning time of apparel production process R_{ij}

C_i, completion time of order P_i

CL_i, actual completion time for order P_i in the sewing assembly line

CO_{ij}, completion time of sewing operation O_{ij}

CP_{ij}, completion time of process R_{ij}

D_i, desired due date of order P_i

DCT_i, desired cycle time of order P_i which is the desired time interval of consecutive jobs entering the assembly line

DL_i, desired due date of order P_i in the sewing assembly line which is pre-determined by the production manager

EM_{ijkl}, operator's efficiency to process operation O_{ij} on sewing machine M_{kl}

IT, total idle time of all workstations in each cycle

L_{kl}, l th assembly line of shop floor S_k

m, number of production orders

M_{kl}, l th machine of the k th sewing machine type

MAT_{kl}, average assembly time of each product on machine M_{kl}

n, number of orders in the rth scheduling status

N_i, number of workstations processing order P_i

o_i, number of operations of order P_i

O_{ij}, jth sewing operation of order P_i

OS_i, order size of order P_i

P_i, ith apparel production order

PB_i, balance index of order P_i

$PR(O_{ij})$, set of the preceding operations of operation O_{ij}

PTO_{ij}, average processing time of operation O_{ij}

PTP_{ijkl}, processing time of R_{ij} on assembly line L_{kl}

Q, total earliness/tardiness penalties of all orders

R_{ij}, jth production process of order P_i

S_k, kth shop floor

SAL_{ij}, set of assembly lines which can perform process R_{ij}

SB_r, balance index of the rth scheduling status

SO_{kl}, set of operations which can be processed on machine M_{kl}

$SP(R_{ij'})$, set of the preceding processes of process $R_{ij'}$

SPT_r, processing time of the rth scheduling status

SL, total satisfactory level which is used to evaluate the grade of the due dates of all orders being met

SM_{ij}, set of workstations which can handle operation O_{ij}

ST_{ij}, standard processing time of operation O_{ij}

TT, expected value of total throughput time of all orders

TTO_{ij}, transportation time between workstations processing operations O_{ij} and its next operation

TTP_{ij}, transportation time between assembly lines processing process R_{ij} and its following process

U_{ij}, setup time of operation O_{ij}, which is the time to change the setting on the machine

X_{ijkl}, indicates if process R_{ij} is assigned to assembly line L_{kl} (if so, X_{ijkl} is equal to 1, otherwise it is equal to 0)

Y_{ijkl}, indicates if sewing operation O_{ij} is assigned to machine M_{kl} (if so, Y_{ijkl} is equal to 1, otherwise Y_{ijkl} is 0)

Z, indicates the degree how the actual cycle time is close to desired cycle time

α_i, tardiness weight (the penalty cost per time unit of the delay) of order P_i

β_i, earliness weight of order P_i, the storage cost per time unit if order P_i is completed earlier than DL_i

λ_i, denotes if the tardiness of order P_i is greater than 0 (if so, λ_i is equal to 1, otherwise it is equal to 0)

η_{ijkl}, weight of efficiency penalty of operation O_{ij} being assigned to machine M_{kl}

ρ_{ijkl}, task proportion (weight) of operation O_{ij} being performed on machine M_{kl}

ω_i, penalty weight for order P_i when its actual cycle time is less than its desired cycle time

ξ_i, penalty weight for order P_i when its actual cycle time is greater than its desired cycle time

δ_i, indicates that if the actual cycle time ACT_i is less than the desired cycle time DCT_i, δ_i is equal to 1, otherwise it is equal to 0

Chapter 1

Introduction

1.1 Background

1.1.1 Today's Apparel Manufacturing

Today's apparel manufacturing is characterized by short product life cycles, volatile and unpredictable customer demands, tremendous product varieties, and long supply processes (Sen 2007). In face of the increasingly fierce competition and fast changing customer demands, today's apparel enterprises must keep on looking for ways to produce various types of products in shorter lead time with less production costs and higher production quality.

To meet the fierce global market competition, various manufacturing strategies have been introduced and employed in apparel manufacturing (Sullivan and Kang 1999; Bruce et al. 2004), including quick response manufacturing, lean manufacturing and agile manufacturing. Whichever manufacturing strategy is employed, the performance of apparel manufacturing relies greatly on the effectiveness of production control in the factory.

Computer management systems have been adopted to monitor the production status of the shop floor in real-world production of some apparel enterprises, including management information system (MIS) and enterprise resource planning (ERP) system. These systems use computers to manage the resources of enterprises, but they have limited capacity in making an effective production decision. The production data in these systems are obtained usually on a daily basis but the real-time production data and the operative efficiencies of sewing operators cannot be obtained. Owing to the absence of real-time production data, these systems cannot reflect the real-time production status on the shop floor and the assembly line.

Despite advances in manufacturing strategies and computer management systems, apparel manufacturing remains labor-intensive and has few automation capabilities. An entire apparel production undergoes generally multiple production processes such as cutting, embroidering, silk-screen, fusing, sewing, finishing, and packaging. The performance of apparel manufacturing is determined by the performances of these production processes. In real-world production, sewing is the dominant process. According to different garment styles, the sewing process of each order can include several to even more than one hundred manual sewing operations. The apparel production system, which is also called the sewing system, actually concentrates on the production of sewing operations, which directs work flow and generates finished garments and is an integration of material handling, sewing operation, personnel and equipment.

The apparel production system consists of workstations with different types of sewing machines and each workstation is a physical location that accommodates a sewing operator and a sewing machine. Each type of sewing machine can include multiple machines. Nowadays, the adopted apparel production system usually includes the progressive bundle system (PBS), the unit production system (UPS), and the modular system (Sen 2007).

PBS is a push system in which bundles of work are moved from workstations to workstations and is well suited to piecework compensation because operators are normally assigned large quantities of work to do in a given time period. Each operator can only operate one machine at any time. Each bundle consists of garment parts or garment components needed for the completion of some specific operations. For example, a bundle for pocket setting might include a shirt front and pockets to be attached. The bundle size may range from one part to tens of parts. Each operator receives a bundle of unfinished garments and then performs one or more operations on each garment in the bundle. The completed bundle is then placed in a buffer with other bundles that have been completed to that point where the bundles in the buffer are ready for the next operator in the sequence. Large quantities of work in progress are often a characteristic feature of this type of production system. This may lead to long throughput time, poor quality concealed by bundles, large inventory, and difficulties in controlling the inventory. Moreover, large quantities of work in progress make it difficult to track specific orders.

Unlike PBS in which a batch of garment components (bundle) is transported from workstations to workstations, the UPS has an automated hanger to transport one garment component from workstations to workstations. UPS is an apparel production system which responds to competitive pressure from customer demands and increasing global competition. Though it basically adopts the characteristics of a PBS with assembly lines, individual piece rate compensation and increased supervisors' monitoring capabilities, UPS is an efficient technique of mass production but not a suitable system for apparel production that has many style variations (Bailey 1993).

The modular system is a contained, manageable work unit that includes an empowered work team with multiple skills, equipment, and work to be executed. Each unit is called a module. Modular units can be used to perform all the operations for a garment or a certain portion of the assembly operations, depending on the organization of modules and assembly operations. Modules operate as mini-factories with teams, usually five to fifteen people, responsible for group goals and self-management. The modular system is recommended for any company whose strategy focus is on meeting customers' wants and needs. The product would be one with frequent style changes. Bailey (1993) has suggested that being highly typical in apparel manufacturing also hinders the cooperative teamwork approach of the modular system.

Though both UPS and modular system are adopted by an increasing number of apparel manufacturers, PBS is still the dominant apparel production system in use (Bailey 1993; Gu 1999; Sen 2007). PBS allows flexible operation assignment. One operation can be assigned to multiple workstations and multiple operations can also be assigned to one general-purposed machine. Work-sharing and workstation revisiting are the usual assembly phenomena in PBS. Work-sharing means that one operation (task) is assigned to multiple workstations for processing. Workstation revisiting occurs when the semi-finished product (uncompleted product) revisits the workstation for another operation being processed after the product has been processed by other workstations. In other words, the workstation performs two or more operations which are not proximate. Moreover, in PBS, two or more production orders can be produced in any intermixed sequence or separately in batches, which are the features of the mixed-model assembly line and the multi-model assembly line respectively (Guo et al. 2006). Obviously, PBS is one type of flexible assembly line having the characteristics of both the mixed-model assembly line and the multi-model assembly line. The investigation into PBS has greater academic and practical significance comparing with other apparel production systems. In this research, the investigated apparel assembly line (AAL) denotes the assembly line of PBS.

Though effective production control is very important and helpful in improving production and management performances and lowering production costs of factories, as a traditional labor-intensive industry with low-level automation, production control of today's apparel industry still depends mainly on the experience of supervisors and managers and simple computation. To tackle the ever increasing global competition, the apparel industry has stringent demands for lowering production costs and reducing the lead time by using effective and efficient methods of production control and decision-making. This research investigates production control in apparel manufacturing factories and it emphasizes production control decision-making of PBS.

1.1.2 Production Control and Decision-Making

Production control is an important area of research for both academicians and industrialists. It concerns ensuring that the production department meets its objectives (Bolton 1994) so that competitive delivery dates can be offered for products, customers' orders can be delivered on time, effective use is made of all the plants and manpower, and there is not too high a build-up of stock or too much work in progress. A generic architecture for production control decision-making is shown in Figure 1-1. In some real-world production environment, production data, including the information of production orders, quantities of various workstations and assembly lines, and the operative efficiency of operators, are collected from the assembly lines by various types of methods, including manual recording and barcode scanning. Based on the collected production data, the production manager makes production decisions to achieve various production objectives. In many factories, it is impossible to make timely and efficient production control decisions without real-time and accurate production data.

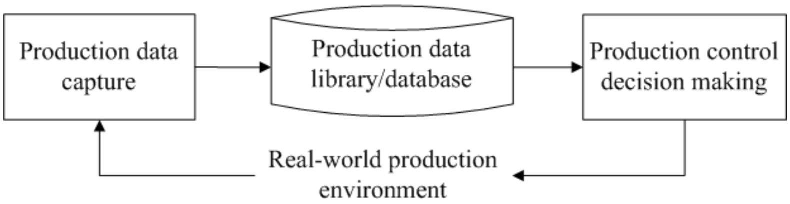


Figure 1-1: A generic architecture for production control decision-making

Production control decision-making involves mainly two types of problems: production scheduling and assembly line balancing (ALB). Production scheduling is the allocation of available production resources over the production time of products while optimizing one or more objectives without violating restrictions imposed on the production system. The ALB problem is to assign a set of tasks or operations to a set of workstations so that the workload in each workstation is balanced and measures of performance are optimized.

In practice, some simple methods or rules are used in production control decision-making. For example, the practical assembly line balancing depends mainly on the precedence diagram-based manual method and the trial-and-error method (Bhattacharjee and Sahu 1987).

The literature on the area of production control is sizable (Doumeingts et al. 1978; Cruycke 1979; Doumeingts and Roubellat 1979; Sinha and Hollier 1984; Por et al. 1990; Meybodi 1995; Wang et al. 1995; Chan and Chan 2004; Becker and Scholl 2006). Based on different research issues, various production control problems have been investigated. Production scheduling involves mainly shop scheduling problems (Ramasesh 1990; Cheng et al. 1996; Linn and Zhang 1999) and flexible manufacturing system (FMS) scheduling (Gupta et al. 1991; Kim et al. 1998; Ben Abdallah et al. 2002; Chan and Chan 2004). Assembly line balancing involves simple ALB problems (Baybars 1986; Ghosh and Gagnon 1989; Scholl and Becker 2006) and generalized ALB problems (Becker and Scholl 2006). However, production control for flexible assembly lines, the uncertainties and variable operative efficiency on production control have received little attention so far. The consideration for flexibility, uncertainty, and variability increases the complexity of the corresponding production control problems. In the existing literature, investigation of production control is usually confined to assembly lines or shop floors. It has not been considered at a higher level from the viewpoint of factory managers or production planners, that is, to consider production control among multiple shop floors or assembly lines at the factory level.

A wide range of techniques such as simulation-based techniques (Guley and Stinson 1980; Ramasesh 1990; Chan et al. 2002), classical optimization techniques (Park and Kim 2000; Tozkapan et al. 2003), and intelligent optimization algorithms (Metaxiotis and Psarras 2003; Ying and Liao 2003; Ross and Corne 2005) have been considered as candidates for the construction of a production control decision-making model. However, none of the algorithms is universally applicable to any production control problems without adjustment or modification. The existing algorithms are not applicable to the production control problem of flexible assembly lines considering various production realities, such as work-sharing, workstation revisiting and production uncertainties.

1.1.3 Production Control Decision-Making in Apparel Manufacturing

To date, the research on production control decision-making in apparel manufacturing has received relatively little attention. Few papers have been published to investigate AAL balancing problems (Betts and Mahmoud 1992; Chan et al. 1998; Wong et al. 2006) and production scheduling problems (Chen et al. 1992; Bowers and Agarwal 1993; Tomastik et al. 1996; Mok et al. 2007) from different aspects.

These existing studies aimed at creating a simplified model of the real-life production control problem on different assembly lines or shop floors. For example, Vojdani (1997) and Mok et al (2007) considered flowshops scheduling for the cutting process; Betts and Mahmoud (1992), Chan et al (1998), and Wong et al. (2006) considered the ALB problem in different apparel production systems. Yet these studies are far different from the industrial practice because many significant factors in practical production situations have not been considered, such as flexible operation assignment, variable operative efficiency and uncertain processing time. Thus, the corresponding research results are limited and cannot be employed in practical production control.

In fact, production control decision-making for today's apparel manufacturing mainly relies on the experience of managers or supervisors. However, these decisions tend to be subjective, late, inconsistent and even inaccurate owing to the complexity of problems.

1.2 Problem Statement

Without intelligent planning, control and integration of the production system, no business can be competitive in today's global marketplace (Sipper and Bulfin 1997). On the basis of intelligent algorithms, this research investigates production control decision-making methodology for real-world apparel production, which will be implemented by offering solutions to the following three types of production control problems, which occur at three different management levels, including the factory level, the shop floor level and the assembly line level.

(1) Order scheduling problem: The scheduling of production orders among different shop floors and assembly lines will be investigated at the factory level, while taking into account multiple uncertainties, including uncertain processing time, uncertain arrival time and uncertain production orders, aiming at determining when and where each apparel production process of each order would be executed. The objectives are to maximize the total satisfactory level of all orders and minimize their total throughput time.

(2) AAL scheduling problem: The AAL scheduling problem will be investigated at the shop floor level considering flexible operation assignment and order preemption. The objectives are to minimize the total earliness/tardiness (E/T) penalty costs and maximize the smoothness of the sewing production flow, which can be implemented by deciding when to start the production of each order and how to assign sewing operations of each order to sewing machines.

(3) AAL balancing problem: The AAL balancing problem with work-sharing and workstation revisiting will be investigated at the assembly line level. The two objectives are to meet the desired cycle time of each apparel production order and minimize the total idle time of the sewing assembly line. The variable operative efficiency and its effects on ALB balancing results are also investigated.

1.3 Objectives

The primary objective of this research is to develop an intelligent algorithm-based methodology to deal with production control decision-making for apparel manufacturing closer to reality. Based on the three types of production control problems at different management levels, an effective and integrated framework for production control decision-making will be developed in the apparel factory with assembly lines of PBS, in which the following objectives will be reached.

(1) To identify and formulate the production control problems in apparel manufacturing mathematically, including the order scheduling problem at the factory level, the AAL balancing problem at the shop floor level and the AAL scheduling problem at the assembly line level.

(2) To investigate and develop an intelligent algorithm-based methodology for solving the order scheduling, which is effective to tackle various uncertainties in real-world production, such as uncertain processing time, uncertain arrival time, and uncertain orders.

(3) To investigate and develop an intelligent algorithm-based methodology to deal with the AAL scheduling and balancing problems, in which the flexible operation assignment, work-sharing, workstation revisiting and variable operative efficiency in PBS will be considered.

1.4 Methodology

This research implements effective production control decision-making for apparel manufacturing by solving three production control problems at three different management levels. To solve the three production control problems, different methodologies were developed on the basis of genetic algorithm (GA), and are described as follows:

(1) The probability theory and GA were combined to solve the order scheduling problem at the factory level. The probability distribution functions were used to describe the investigated uncertainties. Uncertain beginning time and completion time of production processes were derived firstly by using the probability theory. A genetic optimization model with the variable length of sub-chromosomes was then developed to derive the order scheduling solution to optimize the objectives.

(2) A bi-level genetic optimization model (BiGA) was developed to solve the AAL scheduling problem at the shop floor level. In this algorithm, the first level is to assign sewing operations to sewing machines while the second level is to decide on the beginning time of processing each apparel production order. To tackle the flexible operation assignment, assigning one operation to multiple machines and multiple operations to one machine, a new chromosome representation was presented. Corresponding to the proposed representation, a heuristic initialization process and modified genetic operators were also proposed.

(3) A GA-based optimization model was developed to tackle the AAL balancing problem on the assembly line, which involved two parts. A bi-level multi-parent GA

(BiMGA) was developed to determine the operation assignment to sewing workstations and the task proportions of each shared operation being processed in different workstations. A heuristic operation routing rule was then presented to route the shared operation of each garment to an appropriate workstation when it should be processed. To consider variable operative efficiency, learning curves were used to describe the change of operative efficiency of sewing operators over the accumulated operating time.

1.5 Significance of this Research

Using intelligent algorithms to make the production control decisions for apparel manufacturing, this research is significant in the following aspects:

(1) The first significant contribution of this research is to broaden the investigation and enrich our understanding on apparel production control decision-making from the perspectives of both academic research and industrial practice.

(2) The MIS or ERP systems in apparel enterprises, which place great emphasis on monitoring the production flow from the viewpoint of the factory or enterprise, fail to deal with production control on the shop floor or the assembly line. In addition, little research on apparel production control has been done. The development of this research will help fill this gap in both academia and industry.

(3) The development of this research will help enrich the methodologies of production

control decision-making for apparel manufacturing. The proposed methodologies can also be used in dealing with the production control problems of other similar manufacturing industries. For example, the methodologies of AAL balancing can be extended to the balancing problem of the mixed-model assembly line or the multi-model assembly line.

(4) The development of this research is helpful in improving the capability of production control decision-making for apparel and other manufacturing processes with multi-stage manufacturing processes. The proposed methodologies can generate systematic, consistent and optimal (or near-optimal) solutions to the production control decision-making process for production management to avoid the reliance on the subjective, inconsistent and ad-hoc assessment.

1.6 Structure of this Thesis

The aim of this research is to develop intelligent production control decision-making (IPCDM) methodologies for apparel manufacturing processes. The subsequent chapters will detail the research work, and they are summarized as follows:

Chapter 2 provides a comprehensive literature review on the existing research of production control decision-making in apparel and other manufacturing industries, including various production control problems, techniques for production control decision-making and variable operative efficiencies.

Chapter 3 identifies some major research challenges of making effective production control decisions for general and apparel manufacturing processes. On the basis of these challenges, a solution mechanism was proposed and an IPCDM model was set up to deal with production control decision-making for apparel manufacturing processes. The model involved three different production control problems in three stages of real apparel production. Since the intelligence of decision-making was generated by a GA in this research, GA is reviewed in the chapter and developed to deal with the flexible operation assignment in PBS.

Chapters 4 to 6 investigate respectively three different production control problems in three stages of real-world apparel production, namely the order scheduling problem at the factory level, the AAL scheduling problem at the shop floor level and the AAL balancing problem at the assembly line level. The mathematical models and the GA-based methodologies for these problems are presented. By using industrial data from real-world apparel factories, a number of experiments were conducted to validate the effectiveness of the proposed methodologies.

Finally, Chapter 7 summarizes the findings and limitations of this research. Further research directions are also suggested.

Chapter 2

Literature Review

As an important and necessary process in production, production control and its decision-making have drawn much attention in both academia and industry. This chapter is to review existing achievements of the general industry and the apparel industry in the field of production control. In section 2.1, research topics of production control are reviewed. Algorithms and techniques used in production control decision-making are reviewed in section 2.2. Previous research in apparel production control and variable operative efficiency are reviewed respectively in sections 2.3 and 2.4. Lastly, conclusions are drawn from the previous research in section 2.5.

2.1 Production Control

The production control problem has been considered under the framework of a production planning and control system, which is presented and employed to meet various manufacturing strategies. Pandey et al. (1995) presented a scheme for an integrated production planning and control system. Wang et al. (1996) proposed an experimental push/pull production planning and control system to combine the philosophy of just in time (JIT) with manufacturing resource planning (MRP-II) by means of the E/T production planning method, push/pull control strategy and the 'suggestions for improvement of production line' function module. Karacapilidis and Pappis (1996) employed an interactive model method to build up the production planning and control system in the textile industry.

Lima et al. (2006) adopted the multi-agent technique to construct a distributed production planning and control system, which can be dynamically adaptable to local and distributed utilization of production resources and materials.

Some production control systems have also been introduced, such as Kanban system (Sugimori et al. 1977; Huang and Kusiak 1996; Song and Takahashi 1996; Takahashi 2003), CONWIP system (Spearman et al. 1990; Ip et al. 2002; Takahashi and Nakamura 2002; Framinan et al. 2003), materials requirement planning (MRP) system (Grand and Cook 1983; Rushinek and Rushinek 1989; Nakagiri and Kuriyama 1996; Huang et al. 1998), and MRP-II system (Wight 1984; Kessler 1991; Turbide 1995).

However, these studies placed much emphasis on providing a framework or mechanism for implementing production control and could not generate effective and efficient production control decision-making.

In the existing literature, production control decision-making is usually investigated in two aspects, including production scheduling and assembly line balancing.

2.1.1 Production Scheduling

Production scheduling problems arise whenever a common set of resources – labor, material, and equipment – must be used to make various products during the same period of time. These problems focus mostly on scheduling for various production systems, such as shop scheduling, FMS scheduling, and assembly line scheduling.

Regarding the shop scheduling problem, investigations have been done extensively in different shop types, including single machine shops (Chakravarthy 1986; Abdulrazaq et al. 1990; Biskup 1999; Al-Turki et al. 2001; Yen and Wan 2003; Crauwels et al. 2005), parallel machine shops (Darel and Karni 1980; Cheng and Sin 1990; Chen 1996; Mokotoff 2001; Mosheiov 2001; Peng and Liu 2004; Tan and He 2007), flow shops (Gupta 1971; Park et al. 1984; Liao et al. 1995; Hejazi and Saghafian 2005; Gupta and Stafford 2006; Koulamas and Kyparisis 2007), job shops (Holloway and Nelson 1974; Kiran and Smith 1984; Ramasesh 1990; Kuroda and Wang 1996; Ponnambalam et al. 2000; Coello et al. 2003; Zhang and Gong 2006) and open-shops (Gonzalez and Sahni 1976; Adiri and Aizikowitz 1989; deWerra et al. 1996; Drobouchevitch and Strusevich 2001; Puente et al. 2003; Senthilkumar and Shahabudeen 2006). The details of these research can be found in some comprehensive review papers (Blazewicz et al. 1996; Jain and Meeran 1999; Linn and Zhang 1999; Mokotoff 2001; Yen and Wan 2003; Hejazi and Saghafian 2005).

FMS has received increasing attention in the last 20 years and has emerged in the last decade as one of the important keys to organizational success (Chan and Chan 2004). This system is defined as a group of workstations connected together by a material handling system producing or assembling a number of different component types under the central control of a computer (Okeefe and Kasirajan 1992). It is designed to combine the efficiency of an assembly line and the flexibility of a job shop to best suit the batch production of mid-volume and mid-variety of products (Sarin and Chen 1987). FMS scheduling has been extensively investigated over the last two decades and it continues to attract interest from both academia and industry and much literature has been published (Stecke and Solgerg 1981; Gupta et al. 1989; Gupta, Evans et al. 1991; Rachamadugu and Stecke 1994; Priore et al. 2001).

The literature involves and considers various scheduling practices in shop and FMS production, such as learning effects (Cheng and Wang 2000; Mosheiov 2001; Koulamas and Kyparisis 2007), variable processing time (Lin 2001; Cheng et al. 2004; Peng and Liu 2004; Zhang and Gong 2006), bottleneck machines (Drobouchevitch and Strusevich 1999; Drobouchevitch and Strusevich 2001), production uncertainties (Chen and Chen 2003; Sung and Vlach 2003; Sharafali et al. 2004; Xu and Gu 2005; Szmerekovsky 2007), preemptive scheduling (Baker et al. 1983; Brucker et al. 1999; Chan and Chan 2001; Azizoglu 2003; Liaw 2005; Lushchakova 2006), and deadlock avoidance (Ben Abdallah et al. 2002; ElMekkawy and ElMaraghy 2003). However, because shop and FMS productions are designed for small-scale and medium-scale production tasks respectively, the studies on these topics cannot deal with the scheduling of large-scale production tasks of multiple orders with different due dates and production processes or operations.

Assembly lines are adopted extensively for medium-scale and large-scale productions in numerous industries. However, scheduling of the assembly line has received little attention so far. Kaufman (1974) developed an almost optimal algorithm to solve the assembly line scheduling problem in the area of multiprocessor scheduling. Some researchers aimed at scheduling mixed-model assembly lines by using different techniques (Vargas et al. 1992; Celano et al. 1999; Caridi and Sianesi 2000; Zhang et al. 2000; Sawik 2002; Yu et al. 2006). Piramuthu et al. (1994) discussed the scheduling of a flexible assembly line in a circuit board assembly plant which used the surface mount technology for inserting electronic components. Kyparisis and Koulamas (2002) addressed the assembly line scheduling problem with concurrent operations per station and each concurrent operation was performed by a set of identical parallel machines. The existing literature is very limited and many issues about assembly line scheduling have not been investigated so far. For example, flexible operation assignment in PBS has not been considered. The existing research mainly focuses on scheduling problems, which do not allow current orders to be preempted on the assembly line. However, if rush orders exist, order preemptions can play an important role in meeting customers' delivery dates. Flexible operation assignment and rush orders have to be considered in apparel production control because they are usual practices in the make-to-order apparel production environment.

The production scheduling problem has also been investigated from other perspectives. Ashby and Uzsoy (1995) presented a set of scheduling heuristics to tackle order release, group scheduling and order sequencing for a make-to-order manufacturing facility organized into group technology cells. Based on a single-machine production system, Charnsirisakskul et al. (2004) proposed a mechanism for coordinating order selection, lead-time and scheduling decisions, and discussed under what conditions lead time flexibility is most useful for increasing the manufacturer's profits. Axsater (2005) discussed the order release problem in a multi-stage assembly network by an approximate decomposition technique. These studies only focused on determining the starting time for different production processes of orders. Where the process should be produced has not been considered. Leung et al. (2005) investigated the order scheduling problem in an environment with dedicated resources in parallel and presented two heuristic algorithms to solve it. Chen and Pundoor (2006) considered the order assignment and scheduling at the supply chain level, which focused on assigning orders to different factories and exploring a schedule for processing the assigned orders in each factory. However, multiple shop floors and multiple assembly lines are set up in most factories. The order scheduling problem at the factory level, which schedules the production process of each order to the appropriate assembly line, has not been reported so far.

Various objective criteria have also been presented in the literature of scheduling. Hart et al. (2005) classified the most frequent objective criteria into two categories, including objectives based on complete time and objectives based on due-date. The former involves seeking the minimization of maximum complete time (Caprihan and Wadhwa 1997), mean flow time (Kravchenko and Werner 2001), total complete time (Leung and Pinedo 2003), and maximum flow time (Ambuhl and Mastrolilli 2005); whilst the latter minimizes some quality measures such as mean tardiness (Ho and Chang 1991), maximum tardiness (Guinet and Solomon 1996), maximum earliness (Mandel and Mosheiov 2001) and maximum lateness (Lin and Jeng 2004). With the increasing awareness of the JIT production philosophy, the scheduling objective considering E/T penalty cost has attracted more attention in recent years

(Gordon et al. 2002; Lauff and Werner 2004). However, most of these studies with the E/T cost objective focused on either single machine problems or parallel machine problems with a common due date, and few studies discussed multi-machine scheduling and order scheduling problems with E/T penalties or with different due dates. Moreover, the scheduling problem with a single objective is far away industrial practice and cannot satisfy real-life production demand. For example, the workload of each workstation or operator can be quite different if the scheduling objective is to minimize the E/T costs only, especially when due dates are not tight. Thus, it is necessary to investigate the scheduling problem with multi-objective consideration.

2.1.2 Assembly Line Balancing

The assembly line is designed to produce large volumes of one product, and it divides complex tasks into small, easy-to-learn segments that can be repeated over and over. The development of the first real example of assembly lines is credited to Henry Ford who developed such a line in 1913. The assembly line has since been employed extensively.

The first analytical statement of the ALB problem was formulated by Salveson (1955). Since then, the topic of line balancing has been of great interest to academics. Some comprehensive review articles were published (Baybars 1986; Ghosh and Gagnon 1989; Erel and Sarin 1998; Amen 2000; Becker and Scholl 2006; Scholl and Becker 2006). In the literature, the research of the ALB problem is usually classified into four categories: single model deterministic (SMD), single model stochastic (SMS), multi/mixed model deterministic

(MMD), and multi/mixed model stochastic (MMS). The SMD version of the ALB problem assumes dedicated, single-model assembly lines where the task time is known deterministically and efficiency criterion is optimized. On the basis of SMD, the concept of task-time variability is introduced for the SMS problem which is more realistic for manual assembly lines, where the operating time of each worker is seldom constant. The MMD version assumes the deterministic task time, but introduces the concept of producing multiple products on a single assembly line. Multi-model lines involve multiple products separately in batches, whereas mixed-model lines assemble multiple similar products simultaneously. The MMS version is the most complex ALB problem, which considers multiple products and stochastic task-time.

On a highly automated assembly line, it is usual that the efficiency of processing a certain task is deterministic; but on some flexible assembly lines with manual tasks, the operative efficiency of each task is seldom constant. The existing literature mainly focuses on the ALB problem with the deterministic task time (Helgeson and Birnie 1961; Anderson and Ferris 1994; Klein and Scholl 1996; Gokcen and Agpak 2006; Kilincci and Bayhan 2006; Wong, Mok et al. 2006; Bautista and Pereira 2007; Guo et al. 2007), and only a relative minority considers the variable task time which is distributed according to a specified probability distribution function. Moodie and Young (1965) assumed that the task time is an independent normal variable. Most of the later studies with the variable task time consideration followed their assumption (Kottas and Lau 1973; Reeve and Thomas 1973; Kottas and Lau 1981; Suresh and Sahu 1994; Guerriero and Miltenburg 2003; Gamberini et al. 2006). There are also some researchers assuming other distributions (Arcus 1966; Sphicus and Silverman 1976; Nkasu and Leung 1995). In these studies, however, the change of the task time is stochastic and cannot reflect the operator's efficiency increase caused by repetitive and cumulative operations. In recent years, Cohen et al. (2006) have discussed the learning effects on ALB by allocating work to stations of an assembly line and showed that in the presence of learning, to achieve an optimal objective requires imbalanced allocation of work to stations. The study assumes that all operators have the identical learning rate despite the fact that the learning rate of each operator is probably different in a real-life production environment. The learning effects on various production environments should also be investigated further.

Most of the existing ALB literature is about modeling and solving the simple ALB problem which has restricting assumptions with respect to the real-world assembly lines (Ghosh and Gagnon 1989; Becker and Scholl 2006; Scholl and Becker 2006). In recent years, some researchers have intensified their efforts to identify, formulate and solve more realistic ALB problems, the so-called generalized ALB problems, which consider practical production characteristics (Becker and Scholl 2006) such as parallel stations, machine breakdown, operator absenteeism, U-shaped line layout and mixed-model assembly. Mcclain et al. (1992) pointed out that work-sharing can improve the efficiency of the assembly line. Some ways of work-sharing on the assembly line were suggested, such as bucket brigade (Bartholdi and Eisenstein 1996), D-skill chaining (Hopp et al. 2004), and craft (Hopp and Van Oyen 2004). However, work-sharing has received little attention in the existing ALB literature.

Furthermore, the ALB problem with workstation revisiting consideration has not been reported so far.

A number of technical and economic objective criteria have been introduced in the ALB literature. Technical objectives are the traditional dominant choices, which include minimizing the following: the number of workstations for a given cycle number (Johnson 1983; Gokcen et al. 2005), the cycle time for a given number of workstations (Kao 1976; Klein and Scholl 1996), the total idle time along the line (Thomopoulos 1970), the balance delay (Macaskil 1972), the probability that one or more stations exceed the cycle time (Okamura and Yamashina 1979) and the maximal deviation of a station time of any model from the average station time per unit (Decker 1993). However, since the mid-1970s, economic objective criteria have drawn increasing attention, including minimizing the following: combined cost of labor, workstations and product incompleteness (Silverman and Carter 1986), the labor cost per unit (Pinto et al. 1978), the inventory, set-up and idle-time costs (Chakravarty and Shtub 1985), and the expected total cost which is the sum of labor cost and the cost arising from incomplete tasks (Shin 1990). Various ALB problems with multiple objectives were also investigated (Malakooti and Kumar 1996; Ponnambalam et al. 2000; Pastor et al. 2002; Simaria and Vilarinho 2004).

Though the ALB problem with various production objectives has been studied extensively, the mathematical models of the ALB problems for different assembly systems and production tasks are different. Formulating and solving the ALB problem closer to reality is the goal researchers have been pursuing. The existing ALB research focuses only on assigning tasks or operations to workstations, and does not consider the release time and the due date of each order. The consideration on the two factors is very important to meet the due dates when multiple orders are processed on the assembly line.

2.2 Techniques for Production Control Decision-Making

Both the balancing problem and the scheduling problem are optimization problems. A wide range of techniques have been investigated as candidates for the construction of these problems' optimal decision-making models, including simulation-based techniques, priority-rule-based techniques, classical optimization techniques and intelligent optimization techniques.

2.2.1 Simulation-Based Techniques

Simulation is defined as "a powerful tool for the analysis of new system designs, retrofits to existing systems and proposed changes to operating rules" (Carson 2003). In production and manufacturing industries, computer simulation has been adopted and emerged as an advanced, sophisticated and flexible management analysis tool which is able to take into account the complexities and dynamic changes within the production environment. Many researchers used simulation-based approaches to make production control decisions (Eilon and Hodgson 1967; Rogers and Gordon 1993; Hollocks 1995; Chong et al. 2003; Chan and Chan 2004).

Several researchers (Harmonosky and Robohn 1991; Harmonosky 1995) reviewed the use of simulation in scheduling. Recently, Chong et al. (2003) introduced a simulation-based real-time scheduling mechanism comprising off-line simulation evaluation and on-line reactive scheduling for dynamic discrete manufacturing.

Using the simulation-based approach to make production control decisions has two main advantages. First, it can model the effects of various factors as situation changes, which are difficult to be tackled by an analytic method (Stecke and Solgerg 1981). Second, it can provide the user with the opportunity of performing exploratory tests upon the schedules being produced (Baker and Dzielinski 1960).

The accuracy of a simulation process is limited by the judgment and the skills of the programmers (Gershwin et al. 1986). Various simulation software systems (Alan 2007) have been developed, such as Extend, OpEMCSS, AnyLogic and ProModel. Of these systems, ProModel offers a simulation environment to model manufacturing systems ranging from small job shops and machining cells to large assembly lines, FMSs, and supply chain systems. It is a Windows-based environment with intuitive graphical interfaces and object-oriented modeling constructs, eliminating the need for programming. It combines the flexibility of a general-purpose simulation language with the convenience of data-driven simulators (Harrell and Price 2002) and has obtained successful applications in many industries (ProModel Corporation 2007).

In summary, the simulation-based techniques depend mainly on the trial-and-error method to generate an appropriate production decision under a specific experimental setting. It is difficult for these techniques to be generalized beyond the specific experimental setting employed. Therefore, the simulation-based technique has little contribution to the methodology of production control decision-making.

2.2.2 Priority-Rule-Based Techniques

Priority rules are also called heuristic rules, or dispatching rules in production control literature, which are probably the most frequently applied heuristics for solving the production control problems in practice (Ghosh and Gagnon 1989; Blazewicz et al. 1996). The priority rules can be implemented in real time because they do not require much computer (CPU) time.

In production scheduling, priority rules are used for selecting the job to be processed on a particular machine. A number of priority rules have been introduced (Haupt 1989; Hunsucker and Shah 1992; Weiss 1995; Blazewicz et al. 1996; Sellers 1996; Neumann and Schneider 1999; Weng and Ren 2006) and comprehensive reviews on these rules are also available (Haupt 1989; Blazewicz et al. 1996; Sellers 1996). The most popular priority rules include shortest processing time, shortest operation time, earliest due date, first come first served and critical ratio rules.

In ALB, the operations are ranked firstly according to certain criteria or priority rules, and then assigned to appropriate workstations (Kilbridge and Wester 1961; Kottas and Lau

1973; Amen 2000; Scholl and Becker 2006). Amen (2000) divided the priority rules into methods using one problem-oriented priority rule and methods using several problem-oriented priority rules. The former includes the maximal task time (Tonge 1965), the maximal positional weight (Helgeson and Birnie 1961) and the maximal number of immediate followers (Tonge 1965). The latter includes the heuristic method of Steffen (Steffen 1977), heuristic method of Heizmann (Heizmann 1981), and heuristic method “wage rate” of Rosenberg/Ziegler (Rosenberg and Ziegler 1992).

Though the priority-rule-based techniques are easy to understand and implement, they have not been proven to be within any range of optimal or even evolving towards an optimal solution for complex production control problems. That is, the performances of the priority-rule-based techniques are unpredictable for apparel production control problems in real-world PBS.

2.2.3 Classical Optimization Techniques

The classical optimization technique uses an appropriate mathematical description of the production control problem that is optimized through the application of an optimization algorithm. In general, there are four classical optimization approaches used in solving the scheduling/balancing problem. The first one is the integer programming method (Foster and Ryan 1976; Graves and Lamar 1983; Pan 1997; Sawik 2004). The second is the branch and bound method (Siegel 1974; Conterno et al. 1991; Klein and Scholl 1996; Balasubramanian and Grossmann 2002; Tozkapan et al. 2003; Crauwels et al. 2005) which provides limited enumeration of possible schedules allowing the method to be applied to more serious problems than complete enumeration. The third is dynamic programming (Roman 1971; Ibraki and Nakamura 1994; Lorigeon et al. 2002; Choi et al. 2004), which is also an enumeration technique used to search for an optimal solution among the possible solutions. And the fourth is the relaxation method (Narahari and Srigopal 1996; Zhang et al. 2000; Hwang and Chang 2003; Tang and Xuan 2006) which allows a near-optimal solution to be reached with less computation.

Many researchers have investigated the complexity of the scheduling/balancing problem from different aspects. It is well known that even a very simple version of the scheduling problem is NP-hard (NP stands for non-deterministic polynomial time) and belongs to the most intractable problems (Stoop and Wiers 1996; Shakhlevich et al. 2000; Lauff and Werner 2004). For example, for job-shop scheduling, if the number of machines is two and the number of operations per job is also restricted to two, then the problem is computationally easy. Yet as long as either three operations per job or more than two machines is allowed, the problem is NP-hard. Similarly, whenever the number of jobs is more than two, the problem is also NP-hard. Undoubtedly, real-world examples of job-shop scheduling problems are more sizeable than these problems. Moreover, Gutjahr and Nemhauser (1964) pointed out that the ALB problem also falls into the NP-hard class of combinatorial optimization problems. Leung et al. (2005) showed that the order scheduling problem in an environment with dedicated resources, when more than two parallel machines and minimizing total completion times are considered, is strongly NP-hard. Therefore, it is very difficult for these classical techniques to make an optimal decision for the production control problem because their computational time is usually much longer than that the practical applications can afford.

2.2.4 Intelligent Optimization Techniques

In recent years, some intelligent optimization techniques have become popular and they have been used extensively in production control, such as tabu search (Barnes and Chambers 1995; Tucci and Rinaldi 1999; Al-Turki, Fedjki et al. 2001; Liaw 2003; Liu et al. 2005), simulated annealing methods (Vanlaarhoven et al. 1992; Ponnambalam et al. 1999), expert systems (Vargas et al. 1992; Oh 1997; Metaxiotis et al. 2002), artificial neural network (Willems and Rooda 1994; Jain and Meeran 1998; Chen and Huang 2001; Feng et al. 2003; Metaxiotis and Psarras 2003), ant colony optimization (T'kindt et al. 2002; Ying and Liao 2003; Boryczka 2004; Sun and Sun 2005), genetic programming (Hart et al. 2005), artificial immune system (Coello et al. 2003; Hart et al. 2005), and GA (Park and Park 1995; Cheng et al. 1996; Cheng et al. 1999; Jain et al. 2000; Chaudhry and Luo 2005; Liu et al. 2006).

Tabu search (Glover 1989; Glover 1990) is a mathematical optimization method which belongs to the class of local search techniques and enhances the performance of a local search method by using memory structures. Simulated annealing (Kirkpatrick et al. 1983) is a generic probabilistic meta-algorithm for the global optimization problem, which simulates the annealing process in metallurgy involving heating and controlled cooling of a material to increase the size of its crystals and reduce their defects. The expert system (Ignizio 1991), also known as the knowledge-based system, is a computer program that contains subject-specific knowledge, and knowledge and analytical skills of one or more human experts. The artificial neural network (Gurney 1997) is composed of an interconnected group of artificial neurons and is an information processing paradigm inspired by the way biological nervous systems do. The ant colony optimization algorithm (Dorigo et al. 1996) is a probabilistic technique for solving computational problems and it can be used to find good paths through graphs. It is inspired by the behaviour of ants in finding paths from colony to food. The genetic programming (Koza 1992) is an evolutionary algorithm-based methodology inspired by biological evolution to find computer programs that perform a user-defined task. The artificial immune system (Farmer et al. 1986) is a type of optimization algorithm inspired by the principles and processes of the vertebrate immune system, which typically exploits the immune system's characteristics of learning and memory to solve a problem. GA (Holland 1975) is a global search heuristic which is inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (also called recombination). Among these algorithms, GA is the most commonly used (Cheng et al. 1999; Chaudhry and Luo 2005).

GA was first introduced by Holland (1975). The theory of GA has since been enriched and enhanced continuously. The first step in constructing GA is to define an appropriate genetic representation. On the basis of different problem types investigated, different representation types exist, including binary representation, real-coded representation, integer representation, and order-based representation. Representations in production control generally belong to the order-based representation. Cheng et al. (1996) divided these representations into two categories: direct and indirect. The former includes job-based representation, operation-based representation, job-pair relation based representation, and completion-time based representation; the latter includes preference-list based representation, priority-rule based representation, disjunctive-graph based representation and machine-based representation. However, the existing representations cannot be used to represent both the processing of multiple operations on one machine and the processing of one operation on multiple machines simultaneously. These processing forms are the usual operation assignment in PBS. Crossover is a genetic operator that combines (mates) two chromosomes (parents) to produce a new chromosome (offspring). The idea behind crossover is that a new chromosome may be better than both of its parents if it takes the best characteristics from them. A large range of crossover operators have been proposed (Poon and Carter 1995). The most common ones observed in GA and used in production control are uniform-order crossover (Zhang et al. 2001) and job-based order crossover (Ono et al. 1996). The uniform-order crossover has the merit of preserving the position of some genes and the relative ordering of the rest. This may be helpful in trying to bring good building blocks together, but it depends on the nature of the problem being solved. The job-based order crossover preserves the order of each job on all machines whilst creating children, taking into account dependencies amongst machines. Some researchers concluded that using multi-parent crossover does increase the performance of GA with binary or real-coded representation (Eiben et al. 1994; Tsutsui and Ghosh 1998). However, GA with multi-parent crossover has not been fully developed to handle the production control problem. Mutation is an important part of the genetic search process, which helps to prevent the population from stagnating at any local optima. Mutation occurs during evolution according to a user-definable mutation probability. Many mutation operators have been developed (Ferreira 2002), such as swap mutation, inversion mutation and displacement mutation.

2.3 Previous Research in Apparel Production Control

Several studies in production control for apparel manufacturing processes have been published on the basis of scheduling and balancing.

Chen et al. (1992) solved a production scheduling problem in the make-to-order apparel industry based on time-phased operative efficiency and the simulated annealing technique, but the complexity of the algorithm was very high and the computation time was very long. Bowers and Agarwal (1993) proposed a 3-tiered hierarchical production planning and scheduling framework to formally link long-term, short-term, and daily planning tasks, in which the daily production scheduling problem was modeled as a traveling salesman problem, but they did not discuss the concrete operation assignment and order scheduling. Tomastik et al. (1996) developed a low-order integer programming model which integrated scheduling with resource allocation for an apparel FMS. The model was solved using a modified Lagrangian relaxation method, but the method was not appropriate for scheduling assembly lines. Fozzard et al. (1996) constructed a simulation framework of PBS, incorporating operator performance variations and learning effects, machine failure and repair, operator absenteeism, quality failure and knowledge-based supervisory control. Yet the paper did not report how to implement the simulation framework. Khan (1999) used a spreadsheet to construct a garment production simulation model to minimize the average daily production cost through the investigation of various man-machine combinations. Using ordinal optimization ideas, Lee et al. (2000) discussed the production scheduling of an apparel manufacturing system characterized by the co-existence of the traditional assembly line and the flexible assembly line. Some researchers also discussed the flowshop scheduling problem for fabric-cutting processes (Vojdani 1997; Wong et al. 2001; Mok et al. 2007).

Solinger (1988) suggested an easily applicable procedure to balance an apparel production system by firstly ensuring enough number of operators in each operation and then adding enough work-in-process inventories to each operation to smooth the production. Betts and Mahmoud (1992) introduced a branch and bound method to solve the AAL balancing problem by processing a single product and allowing varying skills of operators. Chan et al. (1998) used GA to solve the ALB problem in which the number of operations equaled the number of operators and each operator processed an operation. Yet in real-world apparel production, the number of operations is usually not equal to the number of operators. Wong et al. (2006) also developed a GA to balance an assembly line of UPS and investigated the impact of different levels of skill inventories on the assembly makespan. In this research, the number of operations is less than the number of workstations and each operation can be assigned to multiple operators, but this research cannot deal with a situation in which multiple operations are assigned to one operator.

The existing studies on apparel production control are based on simplified problem models. Many important realistic factors have not been considered, such as uncertainty, flexible operation assignment and learning effects. Research on scheduling and balancing of PBS closer to reality is desired.

2.4 Change of Operative Efficiency

As a labor-intensive industry, the performance of the sewing assembly line depends on the operator's operative efficiency to a great extent. However, little research has discussed the operative efficiency of sewing operators. Racine et al. (1992) identified 16 operation-related and 3 operator-related factors for the formulation of 3 efficiency prediction models: (1) the time-phased efficiency of a new employee (the training model), (2) the time-phased efficiency of an operator being switched to a new operation from another operation (the switching model), and (3) the time-phased efficiency of an operator restarting an operation (the forgetting model). However, these models were based on a great amount of historical data and their effectiveness has not been validated. It is also very difficult to determine the influences and weights of the 19 factors. Therefore, this model cannot be used to describe and predict operative efficiency in real-world production management.

In real-life production, the operative efficiency of an operator increases when he/she does a task repetitively owing to the learning phenomenon. The earliest attempt to scientifically analyze the learning phenomenon focused on human subjects' behavior at the end of the 19th century (Thorndike 1898; Thurstone 1919). Since then, a great deal of literature has been published and the studies showed that the time required for executing a specific operation decreased with the cumulative experience. The learning curve theory describes the changing trend of efficiency for processing a unit as the cumulative number of produced units increases. It can be used to predict the performance of an individual (or a group of individuals).

Learning curves can also be called experience curves (Lloyd 1979), start-up curves (Ballof 1970), progress functions (Glover 1966), improvement curves (Steedman 1970), or learning by doing (Argote and Epple 1990). The literature related to this research is very extensive. Many leaning curve models were developed and several comprehensive surveys were also published (Yelle 1983; Badiru 1992). The most popular model is the power function learning curve introduced by Wright (1936), which is also called the 80% rule. The major problem of this curve is that its asymptote is zero. In order to conquer this problem, many models (Glover 1966; Hitchings 1972) with positive asymptotes have been developed. Hackett (1983) compared some models and concluded that the time-constant model (Bevis 1970; Hitchings 1972) was a good choice for general use because it could fill a wide range of observed data.

2.5 Summary

From the above literature review, the following conclusions can be drawn:

(1) Though the production control decision-making problem has been studied extensively, none of the existing methodologies is applicable to the implementation of production control decision-making of the manufacturing factory on the whole.

(2) Previous studies on production control decision-making, especially for apparel manufacturing, are limited when considering various situations closer to realistic production, such as uncertain processing time, uncertain orders. Effective methodologies are desired to cope with the production control problems closer to reality.

(3) Some particular characteristics of apparel manufacturing, such as flexible operation assignment, workstation revisiting, work-sharing, order preemption and variable operative efficiency, have not been investigated in the existing apparel production control literature. Corresponding methodologies are desired to generate optimal decision-making of production control with the consideration of the above factors.

(4) Order scheduling among different assembly lines at the factory level has not been considered. It is an unavoidable decision-making problem in apparel manufacturing because the apparel factory is characterized by multiple production processes and multiple assembly lines.

In summary, previous studies on both production control and its decision-making, especially for apparel manufacturing processes are very limited, and leave much room for further research exploration. This research will investigate the apparel production control problems closer to reality, in which various realistic situations are considered, such as uncertain processing time, uncertain arrival time, uncertain orders and flexible operation assignment method. Effective methodologies based on GA will also be developed to solve these problems. Undoubtedly, this research will enrich greatly the study on production control and decision-making.

Chapter 3

Research Challenges and Solution Mechanisms

Chapter 2 presents a detailed review on the up-to-date achievements in the field of production control and decision-making. However, so far the literature on production control decision-making, especially for the apparel manufacturing process, has been very limited and it made little impact on industrial practice despite the widely accepted fact that effective production control decision-making is helpful in improving the performances of production control and management.

This chapter investigates the research challenges that hinder the development of production control decision-making methodologies and formulates an effective and efficient solution mechanism. GA is introduced in this chapter, which is adopted as the basis of the methodologies to apparel production control decision-making.

3.1 Research Challenges to Production Control Decision-Making for Apparel Manufacturing Process

For several decades, quite a few studies have been dedicated to exploring effective methodologies for production control decision-making for apparel and other manufacturing processes. These studies available are only applicable to some simplified production situations and have little impact on industrial practice because of the various research difficulties. These difficulties are regarded as challenges of this research, which can be classified into two categories: common to most manufacturing industries and special to the apparel industry.

3.1.1 Common Phenomena to Production Control Decision-Making in Manufacturing Industry

The following common phenomena are faced by most manufacturing industries and should be considered in the production control decision-making process.

1) Complexity of Production Control Decision-Making

Since most production control problems belong to the class of NP-hard problems, it implies that it is very difficult to get optimal production control decision-making within short computation time even for problems of reasonable size. For example, when considering an ALB problem with 20 operations and 20 workstations, even if we assume that each workstation can only process one operation and each operation can be processed at one workstation, there are still $20! = 2.43 \cdot 10^{18}$ possible operation assignments. If these assumptions are relaxed, the solution space will be much larger. It is very difficult to obtain an optimal solution from such a huge solution space.

2) Uncertain and Unpredictable Phenomena in Production Processes

Uncertain and unpredictable phenomena usually occur in real production, such as uncertain production orders, uncertain processing time, unpredictable operator absenteeism and machine breakdown.

If uncertain factors are considered, greater complexity has to be faced. For instance, there are three orders and each has two possible arriving time, there exist 8 possible production circumstances to be considered. That is, the solution space is 8 times larger than that of a deterministic problem.

Production resources on the shop floor are dynamic and they undergo rapid changes. New operators and machines can be added to the assembly line to expand production capabilities, while those that are no longer required can be removed. Therefore, it is possible that the previous production control method becomes infeasible after changes occur.

How to deal with uncertain and unpredictable phenomena becomes an important challenge of effective production control decision-making.

3) Absence of Integrated Communication Structure

In a factory with multiple production processes and shop floors (or assembly lines), production control decisions in real-life production are made by different production managers and supervisors independently. For instance, the factory manager deals with order scheduling at the factory level and the line supervisor is in charge of assembly line balancing. However, when communication between the production managers and supervisors is not direct, they may not know the full details of the available production tasks or resources. The consequent decision-making can be inaccurate and the solution is far from optimal. The existing research usually focuses on one part of production control of the whole factory, such as shop scheduling, assembly line scheduling or balancing. It is necessary to construct an effective mechanism for dealing with the production control problems of a factory. How to implement this mechanism is a difficult problem.

3.1.2 Phenomena of Production Control Decision-Making in Apparel Industry

Apparel manufacturing, especially PBS, has some distinct characteristics, such as low automation level, large product and process varieties and flexible operation assignment. These distinct industry characteristics bring new difficulties to implement effective production control decision-making.

1) Absence of Real-Time and Accurate Production Data

Today's apparel manufacturing, especially PBS, is still characterized by its low automation level and time-consuming manual operation. The production data in the apparel production system are collected manually. For instance, sewing operators write down the completed tasks on a data sheet during production and then these data are entered into spreadsheets manually by computer operators. This data collection process is tedious and time-consuming. The data are never real-time and their accuracy could be questionable. Owing to the absence of an effective data capture system, it is impossible to obtain real-time and accurate production data from sewing assembly lines, which are the premise of effective and efficient production control decision-making.

2) Multiple Products and Multiple Processes

Due to the trend of diversity in customer demands, today's apparel industry has a multi-product and small-batch production trend. PBS is an effective assembly form to accommodate this trend because it has the characteristics of both multi-model and mixed-model assembly lines. In addition, each order includes multiple production processes and production processes of each order can be different. For example, processes of order 1 include cutting, sewing and finishing while processes of order 2 include cutting, embroidering, sewing and finishing. That is, the number of production tasks on each shop floor can be quite different.

The existence of multiple varieties and multiple production processes brings the following additional difficulties to production control decision-making.

(1) The large quantity of different garment products increases the difficulty of production control decision-making. It is extremely difficult, if not impossible, for the production management to manually schedule and balance production of every product.

(2) One factory usually includes multiple shop floors and assembly lines, it is very difficult to schedule and balance production among different shop floors and assembly lines.

3) Flexible Operation Assignment

In PBS, flexible operation assignment is adopted. One sewing operation can be assigned to multiple workstations and one workstation can process multiple operations. This operation assignment method increases greatly the complexity of production control decision-making. The solution space will be enlarged explosively with the increase of the flexible degree of operation assignment. Suppose that we assign three sewing operations to three sewing workstations. If each operation can only be assigned to one workstation, there will be 6 (P_3^3 =3!) different operation assignment methods. If the flexible operation assignment is allowed, the number of possible operation assignment methods is 186 ($C_6^2 C_4^2 + 3 \cdot (C_4^2 P_3^3 - P_3^3) + P_3^3$), which is much greater than 6. For problems with more operations and workstations, the enlargement of solution space will become much greater.

4) Work-Sharing on Apparel Assembly Line

When the processing of one sewing operation is shared on multiple workstations, that is, this operation is assigned to multiple workstations, it presents another difficulty to determine the task proportions of the operation being processed in different workstations. The line supervisors usually route the shared operation of a garment to a workstation based on their subjective estimations and ad-hoc assessments. Due to the absence of real-time and accurate production information, and the limitations of the line supervisor's competence, these estimations are usually not optimal or inaccurate.

5) Variable Operative Efficiencies

Since PBS is characterized by manual sewing operations, the operative efficiency of sewing operators is never constant in real-life production. The variable operative efficiency leads to fluctuation in the actual cycle time and increases the complexity of production control.

Moreover, on a balanced assembly line, the change of operative efficiency can also lead to the change of the status of the balanced line.

In real-life production, starvation and blockage are two usual phenomena in a workstation. Starvation arises when a workstation must wait for the product to arrive from its preceding station, while blockage occurs when a workstation finishes processing the product but cannot pass it to the next workstation. A workstation that is working slower than its successor causes the successor to be starved. On the other hand, an enhanced learning of that workstation decreases the time to produce a product when it becomes faster than its successor station. Obviously, the variety of operative efficiency can lead to the change of status of the workstation. For instance, there are two workstations M_{11} and M_{12}, and M_{11} is the preceding station. If the processing of M_{11} is faster than M_{12}, M_{12} is blocked. Yet due to the effects of learning, the processing of M_{12} becomes faster than M_{11}, then M_{12} will be starved.

Because the efficiency change of each operator is different, it is impossible to find an optimal balancing method to keep the assembly line balanced constantly. A feasible method is to consider the whole production process and to find a global optimal balancing solution. The more garment quantity to be processed, the more complex the process of seeking an optimal solution.

3.2 Solution Mechanisms

Though great challenges and complexities exist in dealing with production control decision-making for apparel manufacturing processes, the apparel industry has insistent demands for overcoming them. This section presents an effective solution mechanism to deal with these challenges.

3.2.1 System Architecture of Intelligent Production Control Decision-Making

The accuracy and real-time capacity of production data are the premises of implementing effective production control decision-making. In recent years, as the application of radio frequency identification technology (RFID) has become economically feasible, some RFID-based data capture systems have been developed to obtain real-time and accurate production data and their effectiveness has been proved by various industrial applications and practices (Epicdata Inc 2007; MSC Limited 2007).

Figure 3-1 shows the architecture of an IPCDM system for apparel manufacturing, which integrates an RFID-based data capture system with an IPCDM model. As shown in Figure 3-1, the RFID-based data capture system collects various real-time job processing records and production data from the AAL. It is composed of RFID tags, RFID terminals, switches and data capture servers. In each sewing workstation, an RFID terminal is installed, which can collect the job processing records by reading RFID tags attached to each bundle of work in progress. The terminal can also display the historical job records to the sewing operator. The terminals of each AAL are integrated into a network by the switch. The switch is a device that channels incoming data from any of the multiple input ports to the specified output port that will take the data toward its intended destination, which is connected with a data capture server. The data communication uses the TCP/IP protocol.

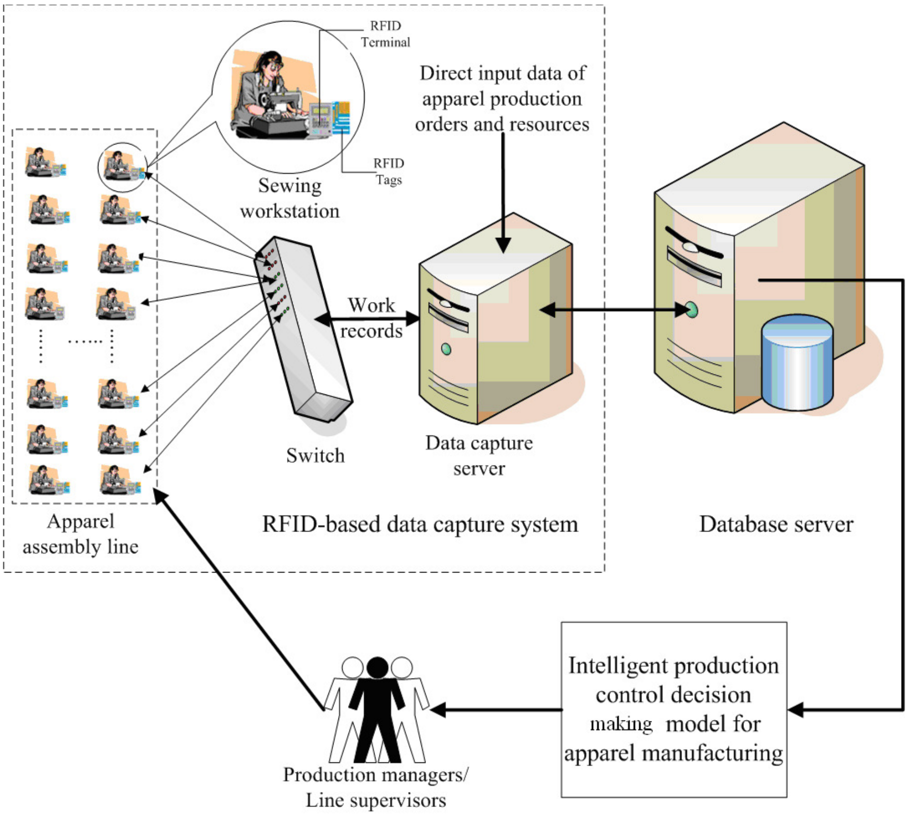


Figure 3-1: System architecture of intelligent production control decision-making for apparel manufacturing

The data capture server collects production data based on two ways and saves them in a database. Firstly, the given data of apparel production orders, sewing workstations, and sewing operators are input directly by the computer operator. Secondly, during the production process, each sewing operator reads the RFID tag attached to each bundle of work-in-progress garment components using the RFID terminal after finishing a sewing operation. The job records from RFID terminals are transmitted by Ethernet. On the other hand, the data capture server also reads production information in the database and displays them on RFID terminals. On the basis of the real-time production data stored in a database using MySQL, MS SQL Server, or Oracle according to the different requirements of data processing, the IPCDM model generates effective solutions for production control in apparel manufacturing. The recommended solutions will be implemented by the production managers or line supervisors through scheduling or assigning production orders and sewing operations on a real-time basis.

3.2.2 Intelligent Production Control Decision-Making Model

In the system architecture shown in Figure 3-1, the kernel is the IPCDM model, which is presented in this sub-section.

In real-world apparel manufacturing, after an order is ready for production in the factory, its production control is implemented according to the following three stages.

(1) The first stage happens at the factory level. If a production order waits to be produced, production manager should assign appropriate shop floors or assembly lines to execute this order according to the existing and possible production tasks, their due dates and the production capacity of each shop floor or assembly line.

(2) The second stage happens at the shop floor level. Once a shop floor or assembly line is assigned to process the order, the shop manager will determine when the order will be started according to its due date and the production capacity of the shop floor or assembly line.

(3) The third stage happens at the assembly line level. After the production has begun on the assembly line, the line supervisor will be in charge of production control. The supervisor aims at balancing the workload of each workstation and improving the line efficiency so as to meet the desired due date and other production criteria.

The production control problem described in stage 1 corresponds to order scheduling at the factory level. Since this research mainly focuses on the production control of PBS, the production control in stages 2 and 3 correspond respectively to AAL scheduling and AAL balancing, as described in section 1.2.

On the basis of the above description, an IPCDM model for apparel manufacturing process is proposed and its architecture is shown in Figure 3-2. As shown in this figure, the production data database is the basis of the model. The production data in the database involve a variety of information, such as information of production managers, operators, shop floors, assembly lines, various sewing machines and production orders, working records of each sewing operator, and operating time of each operator to complete each sewing operation.

In the proposed model, the production control decision-making for apparel manufacturing processes is done according to the following procedures.

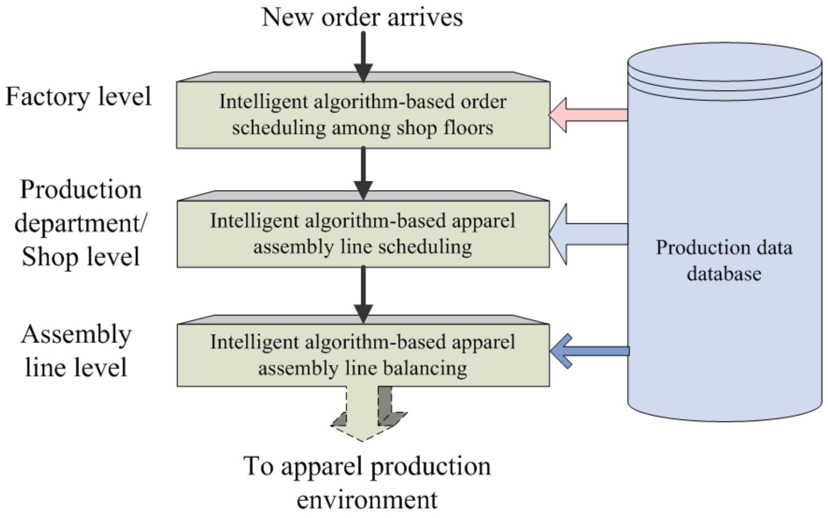


Figure 3-2: Architecture of intelligent production control decision-making model for apparel manufacturing processes

(1) After a new production order is confirmed, the order scheduling problem at the factory level arises. Necessary inputs from the database should be provided to solve this problem, including the due dates of existing and uncertain orders, processing time of production processes of each order, the order size, the number of shop floors, and the number of assembly lines on each shop floor. The investigation into order scheduling problem generates an optimal assignment which assigns production processes of each order to different assembly lines.

(2) The AAL scheduling problem arises after the production order arrives at the apparel assembly line. The inputs from the database include the due date of each order, the number of various types of sewing machines on the assembly line and the operative efficiency of sewing operators on different machines. The investigation into this problem generates the optimized order release time on the assembly line.

(3) The AAL balancing problem arises after the production starts on the assembly line. The inputs from the database include the cycle time of each order, the number of various types of sewing machines on the sewing assembly line, the operative efficiency of operators on different machines, and so on. The investigation into the balancing problem generates optimized operation assignment and a routing solution.

The above tasks are to be investigated in detail in chapters 4, 5 and 6.

The three addressed problems belong to the type of NP-hard combinatorial optimization problem, due to the intractable nature and huge solution space of these problems, heuristic and global optimization algorithms are required to seek optimal production control solutions. The GA is a good choice and will be adopted in this research owing to its capacity of global optimization as well as widely accepted and effective applications in solving various combinatorial optimization problems.

Moreover, in the above three problems mentioned, important realistic factors, such as production uncertainties, flexible operation assignment, work-sharing and variable operative efficiency, will be considered in the proposed model. In this research, flexible operation assignment, work-sharing and workstation revisiting will be implemented by the proposed genetic optimization processes with a novel chromosome representation. Production uncertainties will be tackled using the probability theory. The uncertain processing time is described as a continuous random variable while uncertain production orders and their arrival time are described as discrete random variables. On the basis of the stochastic processing time, the stochastic beginning time and completion time of processes are derived using the probability theory. The variability of operative efficiency in PBS will be defined and described using the learning curve theory. While an operator processes an identical operation repetitively, his/her operative efficiency increases with the increase of accumulated operating time according to the operator's learning curve. Moreover, this research assumes the production data collected by RFID-based data capture system are all real-time and accurate, and does not consider the data inaccuracy caused by human factors.

3.3 Genetic Algorithm (GA)

GA is adopted as the basis of proposed methodologies in this research. Several novel genetic representations and operators will be proposed and discussed based on various characteristics of addressed problems in this research. A brief introduction of GA and the reason for selecting it are presented in this section.

3.3.1 Introduction of GA

GA was pioneered by John Holland (1975) over the course of the 1960s and 1970s, which is an adaptive heuristic search algorithm premised on the ideas of natural selection and evolution. The basic concept of GA is to simulate processes in a natural system necessary for evolution, specifically those that follow the principle of "survival of the fittest" first presented by Charles Darwin.

In general, GA is implemented according to the following procedures.

Initialization: Generate an initial population of chromosomes randomly. Each chromosome represents a feasible solution to the problem on the basis of a certain representation.

Fitness Evaluation: Evaluate the fitness of each chromosome in the population by using the fitness function.

Generation of New Population: Create a new population by repeating the following steps until a new population is complete.

Elitism: Select the best chromosome or chromosomes to be carried over to the next generation. This procedure can be omitted.

Selection: Select two parent chromosomes from the current population according to a selection rule.

Crossover: With a certain crossover probability, the crossover operation is performed to generate child chromosomes (new offspring). If no crossover is performed, child chromosomes are the exact copies of the parents.

Mutation: With a certain mutation probability, child chromosomes mutate according to a mutation rule.

Acceptance: Place the new chromosomes in a new population.

Replacement: Use the newly generated population to replace the parental population.

Test: If the termination criterion is satisfied, stop this procedure and return the best solution; otherwise, go to step 2 to start a new iteration.

In the above procedure, each iteration is called a generation. The new population is supposed to inherit the excellent genes from previous generations so that the average quality of solutions is better than before.

In order to solve an optimization problem, the following processes and operations need to be determined on the basis of the above GA procedure.

Representation: It determines how to create a chromosome. A chromosome is composed of a list of genes. A good representation is crucial because it significantly affects all the subsequent steps of the GA.

Fitness function: It reflects the fitness of each chromosome and is relevant to the objective function to be optimized. Given a particular chromosome, the value of fitness function represents its probability of survival. The greater the fitness of a chromosome , the greater the probability of survival.

Selection: It determines how to select parents for the genetic operators.

Genetic operations: How to perform two genetic operations (crossover and mutation) has to be determined. Both genetic operations are random processes with the pre-specified probability. The typical probabilities of crossover and mutation operations are between 0.6 and 1.0 and between 0.0012 and 0.03 respectively.

3.3.2 Reasons for the Selection of GA

The addressed production control decision-making problems in this research are extremely intractable owing to their NP-hard nature. Their solution spaces are huge and they increase exponentially with the increase in the size of the problem. In considering various factors closer to the reality of apparel production, such as uncertainty, flexible operation assignment and work-sharing, the solution spaces of the addressed problems enlarge further. It is difficult for classical optimization techniques to obtain optimal, even acceptable, production decisions.

GA is an adaptive random search technique, which can solve problems deemed difficult for classical optimization techniques. The major advantage of GA is that it is independent of the particular problem being analyzed. The only requirement is a fitness function indicating system performance. This function can be nonlinear, non-differentiable, or discontinuous. GA only requires that system performance can be evaluated for any set of the decision variables. GA can also handle arbitrary kinds of constraints and objectives. All such things can be handled as weighted components of the fitness function, making it easy to adapt the GA optimizer to the particular requirements of a wide range of objectives. GA can also provide many other useful and efficient solutions, when (1) the search space is large, complex or poorly understood; (2) the domain knowledge is scarce or the expert knowledge is difficult to encode and narrow the search space; (3) no mathematical analysis is available; and (4) traditional search methods fail. Undoubtedly, the production control decision-making problem matches the above conditions and GA is a feasible method for the addressed problems.

Owing to the above characteristics and advantages, GA has been studied and used widely in solving various optimization problems in scientific and engineering fields, including numerical optimization (Cui and Zeng 2005), combinatorial optimization (Larranaga et al. 1999; Chaudhry and Luo 2005), automatic programming (Suzuki and Saito 2006), and machine and robot learning (Harpham et al. 2004; Yamamoto et al. 2006). Not only does GA provide an alternative method to solve problems, it consistently outperforms the traditional methods in most of the problems.

Some researchers compared the optimization performances of GA with various techniques on the basis of different applications. Reeves (1995) compared the performance of GA with the performances of the naive neighbourhood search technique and the proven simulated annealing algorithm. His work demonstrated that GA was better for solving the more serious problems in flow shop sequencing. Fleury and Gourgand (1998) compared the performance of GA, simulated annealing and heuristic methods against the one-machine and flowshop scheduling problems and concluded that GA was better than other heuristic methods. Li (1998) demonstrated the robustness of a search technique based on GA against a number of conventional techniques over a spectrum of power dispatch problems. His research verified that the more complex a problem is, the more benefit one can obtain from a GA. Sakawa and Kubota (2000) proposed a GA to solve the multi-objective job shop scheduling problem with fuzzy processing time and fuzzy due dates. Their studies also showed that GA was superior to other techniques. Based on two lateral canal scheduling problems, Wardlaw and Bhaktikul (2004) compared the optimization results of GA with those of linear and integer programming, and concluded that GA was more robust and efficient in solving lateral canal scheduling problems. Freschi and Repetto (2006) compared the performances of artificial immune system and GA to detect the global maximum with multimodal functions and concluded that GA was faster to converge at the global optimum. These applications and analyses show the extensive applicability and effectiveness of GA.

There still exists much room for further investigation although GA has been applied extensively. For example, the existing genetic representation cannot deal with flexible operation assignment in PBS; it is also worth investigating whether GA with multi-parent crossover is effective in solving production control decision-making problems.

GA is therefore an appropriate technique to handle the addressed production control decision-making problems.

3.4 Summary

This chapter presents the challenges of making effective production control decisions for apparel manufacturing processes. To meet the identified research challenges, a solution mechanism was developed to integrate the production control of the three stages of real production by using an IPCDM model. As one of the most important parts in this proposed solution mechanism, the GA is introduced briefly and the reasons for using it in this research are also discussed in detail in this chapter.

Chapter 4

Order Scheduling at Factory Level with Multiple Uncertainties

Following the solution mechanism presented in Chapter 3, three production control problems at the three levels of apparel manufacturing are to be investigated. To assign the production process of an apparel production order to different assembly lines is the first production control problem in real-world apparel production processes. This chapter investigates the order scheduling problem with multiple uncertainties, including uncertain processing time, uncertain arrival time and uncertain orders. Firstly, a detailed problem formulation for the order scheduling problem is presented. Uncertain beginning time and completion time of production processes were derived by using the probability theory. Next, a GA, in which the representation with variable lengths of sub-chromosomes is presented, was developed to seek an optimal order scheduling solution. Experiments were also conducted to validate the effectiveness of the proposed methodology using the real production data from PBS.

4.1 Problem Formulation

In apparel manufacturing, cutting, sewing and finishing are the three key value-added production processes to produce garments. Other production processes such as fusing, embroidering and silk-screening may also be involved in some apparel factories. Figure 4-1 illustrates the flow of the production process in a typical apparel manufacturing factory.

Different types of production processes should be performed on different types of shop floors. Each type of shop floor has one or more assembly lines. According to the predetermined production flow, each production process involved in different orders must be completed on an assembly line on a corresponding shop floor. The purpose of order scheduling at the factory level is to schedule the processes of each apparel production order to appropriate assembly lines so that the due date of each production order is satisfied and the total throughput time of all orders is minimized. For the sake of simplicity, it is assumed that each production process can only be assigned to one assembly line for processing and the production of each process cannot be preempted in this research.

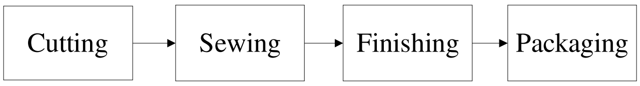


Figure 4-1: Flow of the production process in a typical apparel manufacturing factory

In this research, P_i represents the i th apparel production order, m denotes the number of orders, R_{ij} denotes the j th production process of the order P_i, S_k denotes the shop floors of the k th type, L_{kl} represents the l th assembly line on shop floor S_k, X_{ijkl} indicates whether process R_{ij} is assigned to assembly line L_{kl} (If so, X_{ijkl} is equal to 1; otherwise, it is equal to 0). BP_{ij} is the beginning (starting) time of process R_{ij}, and CP_{ij} is the completion time of process R_{ij}.

The real-life apparel manufacturing environment has many peculiar characteristics. Apparel production processes are characterized by manual operation, and thus the processing time of production process is inevitably uncertain. The arrival time of an apparel production order, the time that the order is ready for production, may also be uncertain because it is affected by the transportation and production processes of materials. In addition, a production order can never be executed if the customer changes the contract or even cancels the order. Apparel manufacturing is also subject to some other constraints. The constraints for the order scheduling problem at the factory level are as follows:

(1) Arrival constraint: Order P_i cannot be executed before this order is ready for production, i.e.

$$A_i \leq BP_{i1} \tag{4-1}$$

where A_i is the arrival time of order P_i, BP_{i1} is the beginning (starting) time of process R_{i1}. A_i is described as a discrete random variable in this research.

(2) Allocation constraint: Production process R_{ij} can only be processed on the corresponding shop floor which can process it, i.e.,

$$\sum_{kl, L_{kl} \notin SAL_{ij}} X_{ijkl} = 0 \tag{4-2}$$

where SAL_{ij} denotes a set of assembly lines which can perform process R_{ij}.

Each production process must be performed, i.e.,

$$\sum_{kl} X_{ijkl} \geq 1 \tag{4-3}$$

(3) Process precedence constraint: For one apparel production order, one process cannot start before its preceding processes are completed and materials for this order are transported to the corresponding assembly line, i.e,

$$CP_{ij} + TTP_{ij} \leq BP_{ij'}, \quad R_{ij} \in SP(R_{ij'}) \tag{4-4}$$

where TTP_{ij} is the transportation time between assembly lines processing process R_{ij} and its following process $R_{ij'}$, $SP(R_{ij'})$ denotes a set of processes prior to process $R_{ij'}$.

(4) Processing time constraint: Process R_{ij} must be assigned processing time, i.e.,

$$CP_{ij} = BP_{ij} + PTP_{ijkl} \tag{4-5}$$

where PTP_{ijkl} denotes the processing time of R_{ij} on assembly line L_{kl}. In this research, PTP_{ijkl} is a random variable whose probability density function is defined as

$$f(PTP_{ijkl}) = \begin{cases} k_1 \cdot PTP_{ijkl} + b_1 & t_L < PTP_{ijkl} \leq t_L + \tau / 2 \\ -k_1 \cdot PTP_{ijkl} + b_2 & t_L + \tau / 2 < PTP_{ijkl} \leq t_L + \tau \\ 0 & otherwise \end{cases} \tag{4-6}$$

A graph of $f(PTP_{ijkl})$ is shown in Figure 4-2, in which the values of t_L, τ, p_L and p_U are predetermined constants. The four constants can decide uniquely the proposed probability distribution of processing time and the vector form (t_L, τ, p_L, p_U) can thus be used to represent the probability density function of this type. Based on the given vector, the values of k_1, b_1 and b_2 in equation (4-6) can be obtained easily.

Since the total probability in the sample space is 1, the following relationship exists,

$$(p_L + p_U) \cdot \tau = 2 \tag{4-7}$$

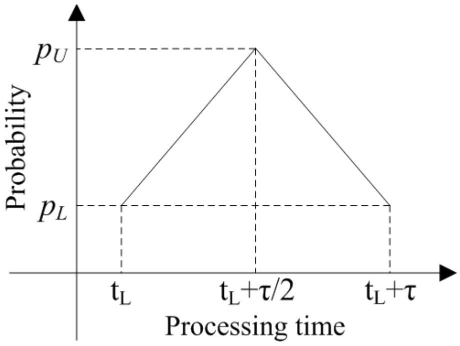


Figure 4-2: Probability distribution of processing time

Because the arrival time of order P_i and the processing time of its production processes can be uncertain, the above constraints (1)-(4) are required to be satisfied for each possible realization to model the uncertainties accurately.

In the make-to-order apparel factory, one of the most important production objectives is to meet the desired due dates of production orders. Since the processing time of production processes is uncertain probabilistically, the completion time of each production order is also uncertain. It is difficult to evaluate directly if the desired due dates are met. In this research, the total satisfactory level $SL(\cdot)$ is presented to evaluate the level (grade) of all orders to meet their due dates. It is defined as the function of BP_{i1} and X_{ijkl}, and is expressed as follows:

$$SL(BP_{i1}, X_{ijkl}) = \frac{1}{m}\sum_{i=1}^{m}\int_0^{\infty} f(C_i) \cdot s(C_i) d(C_i) \tag{4-8}$$

where $f(C_i)$ is the probability density function of the actual completion time C_i of order P_i. $s(C_i)$ describes the relationship of C_i with its satisfactory level, which is defined as follows:

$$s(C_i)=\begin{cases} k_3 \cdot C_i + b_3 & t_L < C_i \le D_i \\ k_4 \cdot C_i + b_4 & D_i < C_i \le t_U \\ 0 & otherwise \end{cases} \tag{4-9}$$

where D_i denotes the desired due date of order P_i in the factory, which is usually predetermined by the customer. A graph of $s(C_i)$ is shown in Figure 4-3. The values of k_3, k_4, b_3 and b_4 can be obtained based on the given three coordinates in this figure. These coordinate values are determined by the decision maker. When C_i is closer to its due date, its satisfactory level is higher. Moreover, the decrease of the satisfactory level is faster when $C_i > D_i$ than when $C_i < D_i$. This is because tardiness penalties generated by the former are greater than earliness penalties generated by the latter.

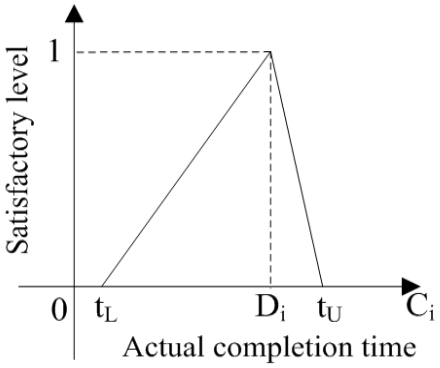


Figure 4-3: Relationship between C_i and its satisfactory level

The primary objective of the addressed problem is to maximize the total satisfactory level $SL(\cdot)$, which is expressed as

$$Obj1: \max SL(BP_{i1}, X_{ijkl})$$

with

$$SL(BP_{i1}, X_{ijkl}) = \frac{1}{m}\sum_{i=1}^{m}\int_{0}^{\infty} f(C_i) \cdot s(C_i) d(C_i) \tag{4-10}$$

Based on the optimized total satisfactory level, the secondary objective of the addressed problem is to minimize the expected value of total throughput time TT of all orders, which is expressed as follows:

$$Obj2: \min TT(BP_{i1,} X_{ijkl})$$

with

$$TT(BP_{i1,} X_{ijkl}) = E(\sum_{i=1}^{m}(C_i - BP_{i1})) \tag{4-11}$$

where $C_i - BP_{i1}$ is the throughput time of order P_i which is a random variable. $E(\cdot)$ denotes the expected value of a random variable.

4.2 Uncertain Completion and Beginning Time

Since the processing time of the apparel production process is uncertain, its completion time and its next production process's beginning time are also uncertain. The uncertain time can be formulated and computed as shown in the following sections.

4.2.1 Completion Time of the Production Process

The completion time CP_{ij} of process R_{ij} is determined by its beginning time BP_{ij} and processing time PTP_{ijkl}. Since the beginning time and the processing time are independent, the probability density function $f(CP_{ij})$ of CP_{ij} is equal to the convolution of probability density functions of its beginning time and processing time according to the theory of probability.

$$f(CP_{ij}) = f(BP_{ij}) * f(PTP_{ijkl}) = \int_{-\infty}^{+\infty} f(CP_{ij} - BP_{ij}) \cdot f(BP_{ij}) d(BP_{ij}) \qquad (4\text{-}12)$$

4.2.2 Beginning Time of the Next Production Process

Since both the processing time and the completion time of process R_{ij} are uncertain, the beginning time of $R_{i,j+1}$, which is the next production process of R_{ij}, is also uncertain.

Consider a production situation: production processes R_{12} and R_{22} are assigned orderly to assembly line L_{21} for processing, and the probability density functions of the completion time of R_{12} and R_{21} are determined by vectors (t_{L1}, τ_1, p_{L1}, p_{U1}) and vectors (t_{L2}, τ_2, p_{L2}, p_{U2}) respectively, which are shown in Figure 4-4 (Assume $t_{L1} \le t_{L2}$). R_{22} is the process subsequent to R_{21}. Obviously, process R_{22} cannot begin until processes R_{12} and R_{21} are both completed.

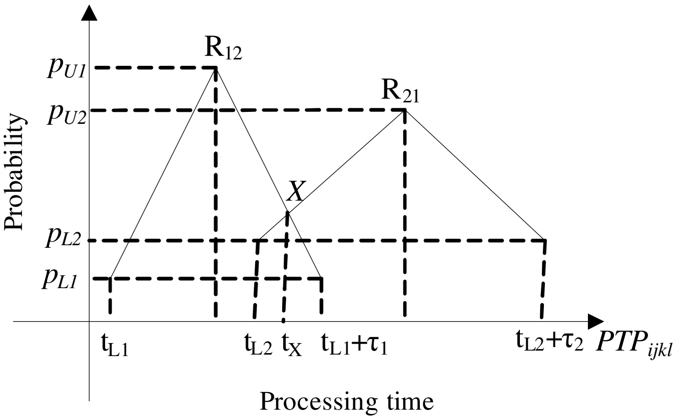


Figure 4-4: Probability distributions of the processing time of processes R_{12} and R_{21}

The probability density function of the beginning time BP_{22} of R_{22} (the next production process of R_{21}) is computed as follows:

If $t_{L1}+\tau_1 \le t_{L2}$, BP_{22} is determined solely by the completion time CP_{21} of R_{21} and has the same probability density function as CP_{21}.

If $t_{L1}+\tau_1 > t_{L2} \ge t_{L1}$, BP_{22} is determined jointly by the completion time of both R_{12} and R_{21}, the beginning time BP_{22} will be located between t_{L2} and $t_{L2}+\tau_2$, and its cumulative probability distribution function $F(BP_{22})$ in several different intervals is as follows:

$$F(BP_{22})=\begin{cases} P_{21}^1 - P_{21}^1 \cdot P_{12}^3 & t_{L2} \le BP_{22} < t_X \\ P_{21}^2 + P_{21}^1 \cdot P_{12}^3 & t_X \le BP_{22} < t_{L1}+\tau_1 \\ P_{21}^3 & t_{L1}+\tau_1 \le BP_{22} < t_{L2}+\tau_2 \end{cases} \tag{4-13}$$

where $P_{21}^1, P_{21}^2, P_{21}^3$ is the cumulative probability distributions of the completion time CP_{21} of R_{21} in (t_{L2}, t_X), $(t_X, t_{L1}+\tau_1)$ and $(t_{L1}+\tau_1, t_{L2}+\tau_2)$ respectively, and P_{12}^3 is the cumulative probability distribution of the completion time C_{12} of R_{12} in $(t_X, t_{L1}+\tau_1)$.

The probability density function $f(BP_{22})$ of BP_{22} is

$$f(BP_{22})=\begin{cases} g(BP_{22}) - g(BP_{22}) \cdot h(BP_{22}) & t_{L2} \le BP_{22} < t_X \\ g(BP_{22}) + g(BP_{22}) \cdot h(BP_{22}) & t_X \le BP_{22} < t_{L1}+\tau_1 \\ g(BP_{22}) & t_{L1}+\tau_1 \le BP_{22} < t_{L2}+\tau_2 \end{cases} \tag{4-14}$$

where $g(\cdot)$ is the probability density function of the completion time of R_{21} and $h(\cdot)$ is the probability density function of the completion time of R_{12}.

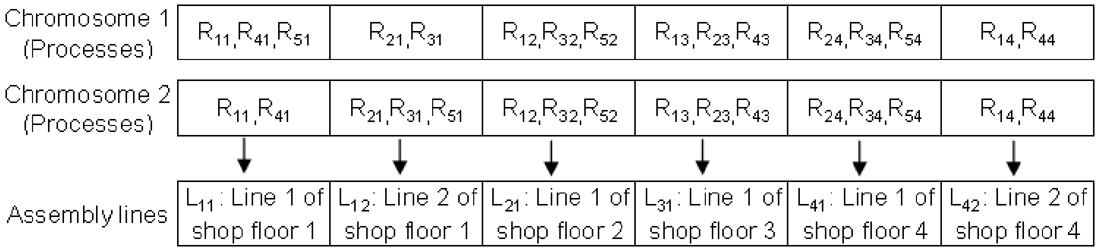
4.3 Genetic Optimization Model for the Order Scheduling Problem

The number of the possible solutions of the addressed order scheduling problem grows exponentially with the number of assembly lines, orders and processes. This section describes in detail how a genetic optimization model is developed to generate an optimized solution of the addressed problem.

4.3.1 Representation

The first step in constructing GA is to define an appropriate genetic representation (coding). To tackle the order scheduling problem, a process order-based representation with variable lengths of sub-chromosomes is developed. Each chromosome is composed of sub-chromosomes. Each sub-chromosome represents an assembly line and the value of each gene in the sub-chromosome represents a process which the corresponding assembly line performs. If one sub-chromosome comprises multiple genes, it indicates that the corresponding assembly line performs multiple processes according to the gene sequence in the sub-chromosome. Because the number of production processes performed on the assembly line could be different, the length of the sub-chromosome, i.e, the number of genes in the sub-chromosome, is variable.

Figure 4-5 shows two examples of this representation which describe the assignment of 16 apparel production processes from 5 orders to 6 assembly lines from 4 shop floors. As shown in Figure 4-5, each chromosome includes 6 sub-chromosomes which are identified by grids. In the two examples, the lengths of the sub-chromosomes corresponding to assembly line 1 of shop floor 1 are different, which are 3 and 2 respectively. Based on each chromosome, we could obtain the process assignment for different assembly lines and the processing sequence of these processes. For example, according to the first sub-chromosome of chromosome 1, three processes, R_{11}, R_{41} and then R_{51}, will be performed orderly in the assembly line 1 of shop floor 1.



Chromosome 1 (Processes)	R_{11},R_{41},R_{51}	R_{21},R_{31}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	R_{24},R_{34},R_{54}	R_{14},R_{44}
Chromosome 2 (Processes)	R_{11},R_{41}	R_{21},R_{31},R_{51}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	R_{24},R_{34},R_{54}	R_{14},R_{44}
Assembly lines	L_{11}: Line 1 of shop floor 1	L_{12}: Line 2 of shop floor 1	L_{21}: Line 1 of shop floor 2	L_{31}: Line 1 of shop floor 3	L_{41}: Line 1 of shop floor 4	L_{42}: Line 2 of shop floor 4

Figure 4-5: Examples of the chromosome representation

4.3.2 Initialization

GA operates on a population of chromosomes. Anderson and Ferris (1994) have mentioned that the performance of the GA scheme is not so good from the pre-selected starting population as it is from a random start. In this research, each chromosome is randomly initialized by assigning the processes of all orders to the assembly lines which can handle it. The initialization process can be described as follows:

Step 1. Initialize parameters: set index $i = 1$, population $POP = \{\phi\}$, and initialize population size $Psize$.

Step 2. Randomly generate a chromosome CHR_i, $POP = POP \cup CHR_i$.

Step 3. Set $i = i + 1$. Stop if $i > Psize$, otherwise go to step 2.

The procedure for generating a chromosome randomly is as follows:

Step 1. Initialize parameters: the number of assembly lines on shop floor S_k is LQ_k, the number of shop floors in the factory is SQ, and shop floor index k is equal to 1.

Step 2. Divide the processes of all orders randomly, which need to be performed on shop floor S_k, into LQ_k set of processes. Each set of processes forms a sub-chromosome.

Step 3. Place the generated sub-chromosomes in the corresponding positions of the chromosome in turn.

Step 4. Set $k = k + 1$. Stop if $k > SQ$, otherwise go to step 2.

4.3.3 Fitness and Selection

Fitness function is defined as the fitness of each chromosome to determine which chromosome can reproduce and survive in the next generation. Different problems produce different fitness functions. In this research, objective functions (4-10) and (4-11) can be combined as below:

$$OBJ1(BP_{i1}, X_{ijkl}) = \max(\gamma \cdot \frac{SL(BP_{i1}, X_{ijkl})}{TT(BP_{i1}, X_{ijkl})}) \tag{4-15}$$

where γ denotes the objective weight used to adjust the weighted relationship between the satisfactory level objective and the throughput time objective, and it can be determined according to the policy of the factory and the experience of the production decision maker.

The fitness function $ft1$ can thus be defined as

$$ft1 = \gamma \cdot \frac{SL(BP_{i1}, X_{ijkl})}{TT(BP_{i1}, X_{ijkl})} \tag{4-16}$$

The tournament selection (Goldberg et al. 1989) is commonly utilized because it is simple to implement and can provide good solutions. In this research, this selection scheme is used and its procedure can be described as follows:

Step 1. Set a tournament size $k \geq 2$.

Step 2. Generate a random permutation of the chromosomes in the current population.

Step 3. Compare the fitness values of the first k chromosomes listed in the permutation and copy the best ones into the next generation. Discard the strings compared.

Step 4. If the permutation is exhausted, generate another permutation.

Step 5. Repeat steps 3 and 4 until no more selections are required for the next generation.

The scheme can control population diversity and selective pressure by adjusting the tournament size k. Larger values of k will increase the selective pressure while decreasing the population diversity.

4.3.4 Genetic Operators

Genetic operators are used to combine existing solutions with others and to generate the diversity of population. The former can be implemented by a crossover operator, and the latter can be implemented by a mutation operator.

In addressing the order scheduling problem, each process must be performed on the assembly lines of the corresponding type. Thus, the genes of a chromosome with different types of processes should be independent and the genetic operations can only be done among genes with the same type of assembly line. For the sub-chromosomes of each shop floor type, the genetic operators are implemented respectively.

1) Crossover

The crossover operation is a random process with the probability of crossover, which breeds a pair of child chromosomes from a pair of parental chromosomes. Uniform-order crossover (Davis 1991) is commonly utilized because it has the advantage of preserving the position of some genes and the relative ordering of the rest. It is adopted in the genetic process for the addressed order scheduling problem. Its procedure is listed as follows:

Step 1. Create a bit string of the same length as the chromosomes.

Step 2. Copy the genes from parent 1 wherever the bit code is ‘1’ and fill them in the corresponding positions in child 1. (Now child 1 is filled in wherever the bit code is “1” and its gaps remain wherever the bit code is “0”.)

Step 3. Select the genes from parent 1 wherever the bit code is ‘0’.

Step 4. Permute the genes so that they appear in the same order as they appear in parent 2.

Step 5. Fill the permuted genes orderly in the gaps in child 1.

Step 6. Carry out a similar procedure according to steps 2-5 to make child 2.

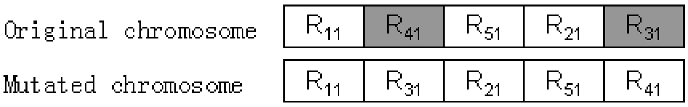
Figure 4-6 shows an example of the uniform-order crossover operator.

Parent 1	R_{11}	R_{41}	R_{51}	R_{21}	R_{31}
Parent 2	R_{21}	R_{31}	R_{11}	R_{41}	R_{51}
Random bit string	1	0	0	1	0
Child 1	R_{11}	R_{31}	R_{41}	R_{21}	R_{51}
Child 2	R_{41}	R_{31}	R_{11}	R_{21}	R_{51}

Figure 4-6: Example of a uniform-order crossover operator

2) Mutation

The mutation operation is used to transform chromosomes by means of changing some genes randomly. It is important to form a successful global optimization since it diversifies the search direction and prevents a population prematurely converging at a local minimum. In this chapter, the inversion mutation operator (Holland 1975) is adopted, which is implemented by simply inverting the genes between two randomly selected genes of a chromosome. Figure 4-7 shows an example of this mutation operator.



Original chromosome	R_{11}	R_{41}	R_{51}	R_{21}	R_{31}
Mutated chromosome	R_{11}	R_{31}	R_{21}	R_{51}	R_{41}

Figure 4-7: Example of an inversion mutation operator

4.3.5 Termination Criterion

GA is controlled by a specified number of generations and by using a diversity measure to stop the algorithm. The diversity is defined by the standard deviation of the fitness values of all chromosomes of a population in a certain generation. The standard deviation should be less then a certain value which corresponds to the allowed lowest diversity of a population. If either of these two termination criteria is satisfied, the mechanism of GA will be terminated. For example, the specified maximal number of generations is 100 and the lowest allowed standard deviation value is 0.2. Once the standard deviation is less than 0.2, whichever generation GA is running in, it will be terminated.

In this research, the termination criterion will also be used in other genetic procedures described in other chapters.

4.4 Experimental Results and Discussion

To evaluate the performance of the proposed algorithm for the order scheduling problem, a series of experiments were conducted. The experimental data were collected from a make-to-order apparel manufacturing factory producing outerwear and sportswear. This section highlights three of these experiments in detail. Each example includes several cases. In each case, the order scheduling result generated by the proposed method is compared with that of the practical method from industrial practice. In industrial practice, all random variables are replaced by their means and the subsequent deterministic problems are solved usually by using precedence diagrams and trial-and-error methods (Bhattacharjee and Sahu 1987).

The investigated apparel manufacturing factory comprises 7 shop floors, which are numbered 1 to 7 and perform cutting, embroidering, silk-screen, fusing, sewing, finishing, and packaging processes respectively. Each shop floor is composed of one or two assembly lines. Each apparel production order includes part or all of these production processes and each production process can only be performed on the assembly line(s) on a corresponding shop floor. For each production process, its process number is identical to the shop floor number. For instance, cutting and sewing processes are numbered 1 and 5 respectively. The cutting and sewing processes of order 1 are denoted as R_{11}, and R_{15} respectively. Processes of each production order should be performed based on the specified processing sequence. The process with smaller process number should be done earlier.

In these experiments, it is assumed that there is no work in progress on each assembly line and the uncertain processing time obeys the probability distribution presented in section 4.1 with $\tau = 2$, p_L equals 0.25 and p_U equals 0.75. The transportation time between different assembly lines is also negligible because it is much less than the processing time on assembly lines.

4.4.1 Experiment 1: Order Scheduling with Uncertain Processing Time

In this experiment, 3 different cases were involved, which are described in detail as follows:

Case 1: 5 production orders were scheduled, in which 5 different types of production processes were processed on 5 shop floors.

Case 2: 5 production orders were scheduled, in which 7 different types of production processes were processed on 7 shop floors.

Case 3: 7 production orders were scheduled on 7 types of shop floors.

In the above cases, the processing time of processes on shop floor 5 was stochastic. The relevant data for these cases are shown in Tables 4-1, 4-2 and 4-3 respectively. In these tables, the first column (Order No.) shows the order number, the column of 'Arrival time' shows the arrival time of each order, the column of 'Due time' shows the due time of each order, and other columns show the mean of the processing time of production process on the corresponding assembly line. For example, value 4 in the second column and the row of 'Order 1' represents that the average processing time of process R_{11}, the first process of order 1, is 4 units of time on assembly line 1 of shop floor 1. In this research, each time unit represents one working day. In the investigated factory, shop floors 1 and 5 are both composed of two assembly lines and each of other shop floors comprises only one assembly line.

Table 4-1: Data for case 1 of experiment 1

Order No.	Processing time of process in the corresponding assembly line							Arrival time	Due time
	Shop floor 1		Line 1 of shop floor 2	Line 1 of shop floor 3	Shop floor 5		Line 1 of shop floor 7		
	Line 1	Line 2			Line 1	Line 2			
Order 1	4	6	2.5	2	5	5.5	2	0	17
Order 2	3	4.5	/	4	4	4.5	1.5	0	18.5
Order 3	6	7	3	/	5.5	6.5	2.5	2	27
Order 4	5	5.5	/	3	5	6	2	4	24
Order 5	5.5	7	4	/	6	6.5	2	8	31

Table 4-2: Data for case 2 of experiment 1

Order No.	Processing time of process in the corresponding assembly line									Arrival time	Due time
	Shop floor 1		Line 1 of shop floor 2	Line 1 of shop floor 3	Line 1 of shop floor 4	Shop floor 5		Line 1 of shop floor 6	Line 1 of shop floor 7		
	Line 1	Line 2				Line 1	Line 2				
Order 1	3	2.5	2.5	1.5	/	5.5	5.5	1	0.5	0	14
Order 2	4	3	/	4	1.5	4	4.5	1.5	1	0	20
Order 3	5.5	5	4.5	/	/	6	6.5	1	1.5	0	24
Order 4	6	5.5	/	3	2	5	6	1.5	1.5	5	28
Order 5	2	1.5	/	/	/	2.5	3	0.5	1	8	24

Table 4-3: Data for case 3 of experiment 1

Order No.	Processing time of process in the corresponding assembly line									Arrival time	Due time
	Shop floor 1		Line 1 of shop floor 2	Line 1 of shop floor 3	Line 1 of shop floor 4	Shop floor 5		Line 1 of shop floor 6	Line 1 of shop floor 7		
	Line 1	Line 2				Line 1	Line 2				
Order 1	3.5	4	4	3.5	/	5	5	1.5	1	0	24
Order 2	5	4.5	/	4	1.5	4	4.5	1.5	1	0	18
Order 3	4	4.5	4.5	/	/	6.5	6	1	1.5	0	26
Order 4	5.5	5	/	2	3	5.5	6	2	1.5	7	35
Order 5	2	2	1.5	/	2	2.5	2	0.5	1	10	27
Order 6	4.5	4.5	/	/	/	2.5	2.5	1	1	16	33
Order 7	3	3.5	/	3	/	3	2	1	1.5	20	32

The order scheduling solutions for the cases of this experiment are shown in Experiment 1 of Figure 4-8. Based on the order scheduling solutions and the processing time of each process, the Gantt chart of processes being performed on different assembly lines was obtained. Figure 4-9 shows the Gantt charts for case 1 of experiment 1 based on the solutions generated by the proposed method and the practical method. For other cases in this chapter, the Gantt charts can be found in Appendix.

The order scheduling results of the three cases are shown in Tables 4-4, 4-5 and 4-6. Consider the order scheduling results of case 1 shown in Table 4-4. According to the results of the proposed method, the mean of the completion time of each order was equal or very close to the desired due time and the total satisfactory level of all orders was 99.02%

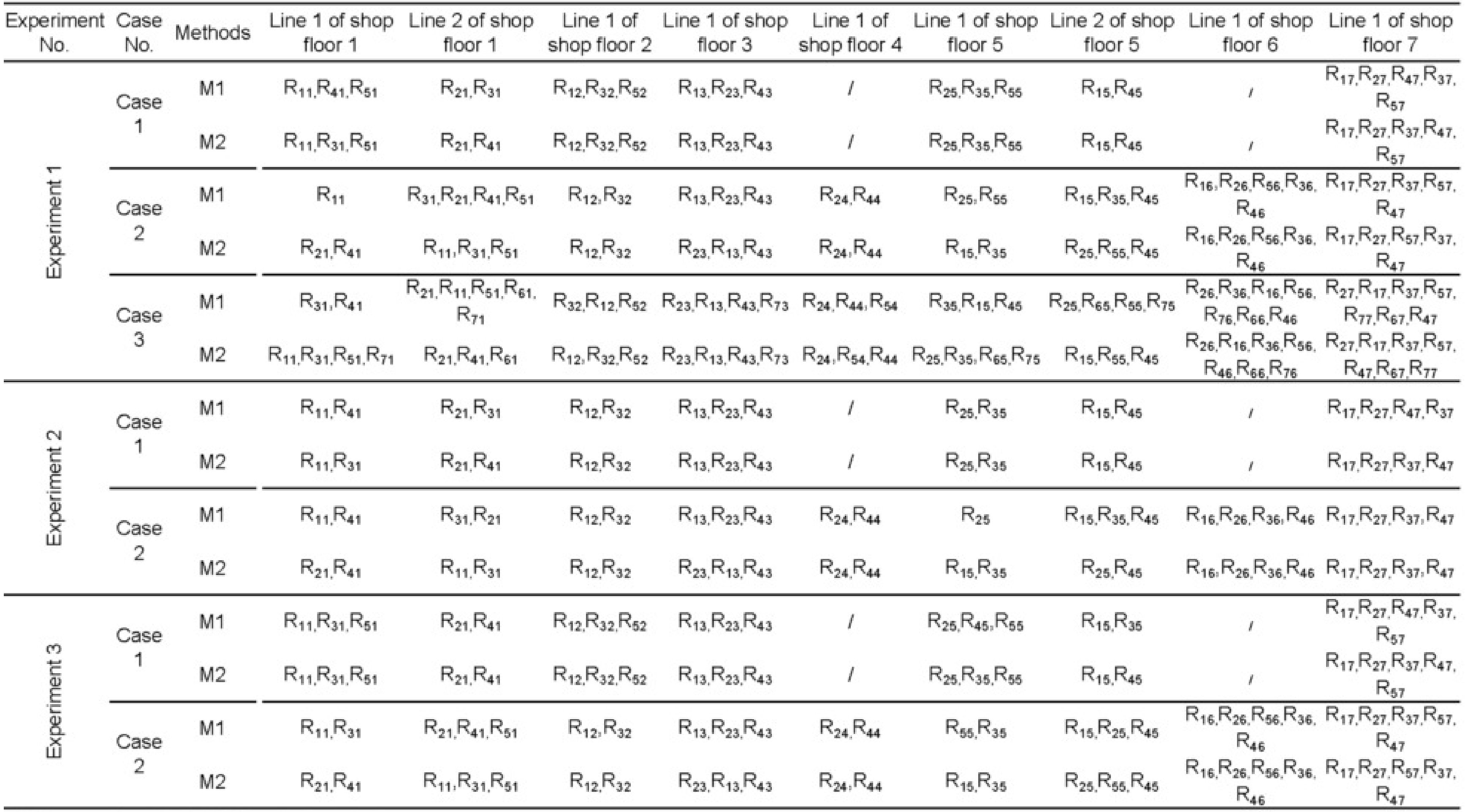
$(\frac{1}{5}(99.00\% + 99.01\% + 99.00\% + 99.09\% + 99.00\%))$. The total satisfactory level of the practical method was 5.1% less than that of the proposed method because the completion time of order 4 had about 2.5 time units of tardiness and its satisfactory level was only 75%. The total throughput time generated by the proposed method was 96.07 $(16 + 18.07 + 21.5 + 19.5 + 21)$ and the one generated by the practical method was 96.5. Obviously, the performance of the proposed method is better than that of the practical method in this case.

Table 4-4: Order scheduling results for case 1 of experiment 1

		Order 1	Order 2	Order 3	Order 4	Order 5
Proposed method	Mean of completion time	16	18.07	26	23.5	30
	Satisfaction level	99.00%	99.01%	99.00%	99.09%	99.00%
	Throughput time	16	18.07	21.5	19.5	21
Practical method	Mean of completion time	16	18	24.5	26.5	30
	Satisfaction level	99.00%	99.09%	97.50%	75.00%	99.00%
	Throughput time	16	18	20.5	22	20

Table 4-5: Order scheduling results for case 2 of experiment 1

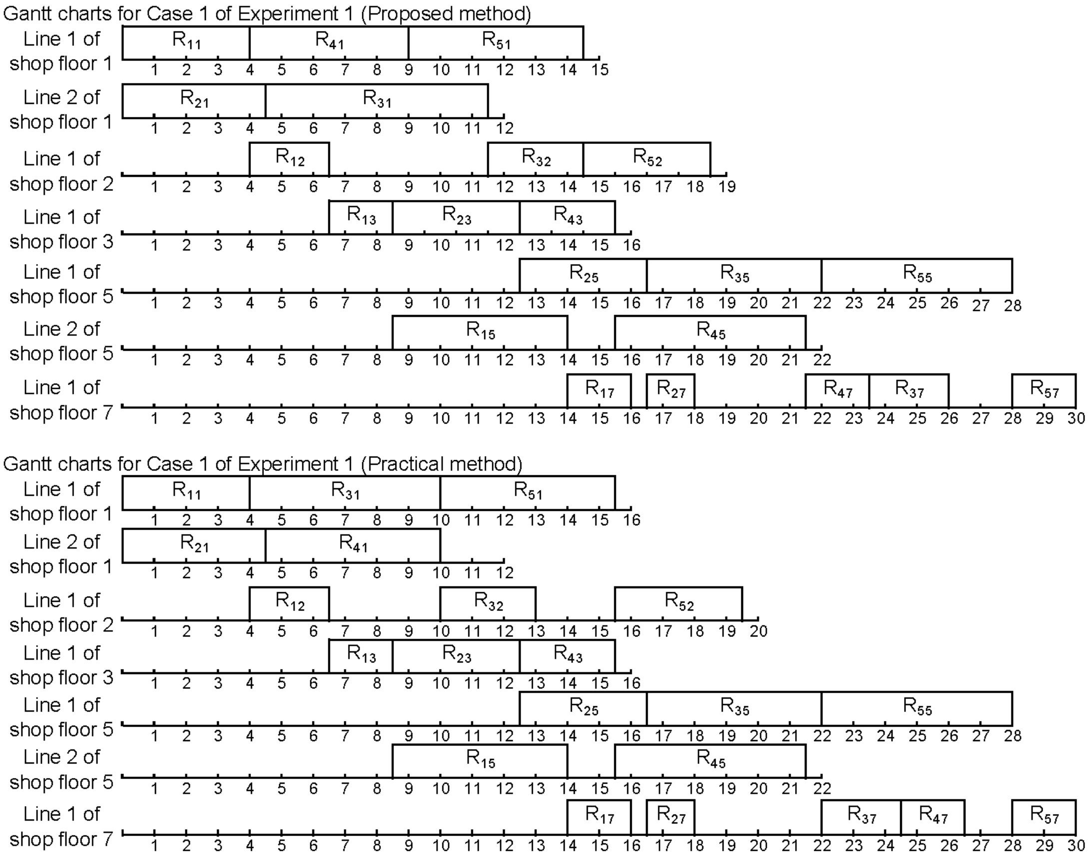
		Order 1	Order 2	Order 3	Order 4	Order 5
Proposed method	Mean of completion time	14	20	23	28	24
	Satisfaction level	97.80%	99.00%	99.00%	99.00%	99.00%
	Throughput time	14	15	23	20	10.5
Practical method	Mean of completion time	16.5	18.5	23.5	26	19.5
	Satisfaction level	75%	97.50%	99.09%	97.00%	94.50%
	Throughput time	16.5	18.5	21	21	11.5



Experiment No.	Case No.	Methods	Line 1 of shop floor 1	Line 2 of shop floor 1	Line 1 of shop floor 2	Line 1 of shop floor 3	Line 1 of shop floor 4	Line 1 of shop floor 5	Line 2 of shop floor 5	Line 1 of shop floor 6	Line 1 of shop floor 7
Experiment 1	Case 1	M1	R_{11},R_{41},R_{51}	R_{21},R_{31}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	/	R_{25},R_{35},R_{55}	R_{15},R_{45}	/	$R_{17},R_{27},R_{47},R_{37},R_{57}$
		M2	R_{11},R_{31},R_{51}	R_{21},R_{41}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	/	R_{25},R_{35},R_{55}	R_{15},R_{45}	/	$R_{17},R_{27},R_{37},R_{47},R_{57}$
	Case 2	M1	R_{11}	$R_{31},R_{21},R_{41},R_{51}$	R_{12},R_{32}	R_{13},R_{23},R_{43}	R_{24},R_{44}	R_{25},R_{55}	R_{15},R_{35},R_{45}	$R_{16},R_{26},R_{56},R_{36},R_{46}$	$R_{17},R_{27},R_{37},R_{57},R_{47}$
		M2	R_{21},R_{41}	R_{11},R_{31},R_{51}	R_{12},R_{32}	R_{23},R_{13},R_{43}	R_{24},R_{44}	R_{15},R_{35}	R_{25},R_{55},R_{45}	$R_{16},R_{26},R_{56},R_{36},R_{46}$	$R_{17},R_{27},R_{57},R_{37},R_{47}$
	Case 3	M1	R_{31},R_{41}	$R_{21},R_{11},R_{51},R_{61},R_{71}$	R_{32},R_{12},R_{52}	$R_{23},R_{13},R_{43},R_{73}$	R_{24},R_{44},R_{54}	R_{35},R_{15},R_{45}	$R_{25},R_{65},R_{55},R_{75}$	$R_{26},R_{36},R_{16},R_{56},R_{76},R_{66},R_{46}$	$R_{27},R_{17},R_{37},R_{57},R_{77},R_{67},R_{47}$
		M2	$R_{11},R_{31},R_{51},R_{71}$	R_{21},R_{41},R_{61}	R_{12},R_{32},R_{52}	$R_{23},R_{13},R_{43},R_{73}$	R_{24},R_{54},R_{44}	$R_{25},R_{35},R_{65},R_{75}$	R_{15},R_{55},R_{45}	$R_{26},R_{16},R_{36},R_{56},R_{46},R_{66},R_{76}$	$R_{27},R_{17},R_{37},R_{57},R_{47},R_{67},R_{77}$
Experiment 2	Case 1	M1	R_{11},R_{41}	R_{21},R_{31}	R_{12},R_{32}	R_{13},R_{23},R_{43}	/	R_{25},R_{35}	R_{15},R_{45}	/	$R_{17},R_{27},R_{47},R_{37}$
		M2	R_{11},R_{31}	R_{21},R_{41}	R_{12},R_{32}	R_{13},R_{23},R_{43}	/	R_{25},R_{35}	R_{15},R_{45}	/	$R_{17},R_{27},R_{37},R_{47}$
	Case 2	M1	R_{11},R_{41}	R_{31},R_{21}	R_{12},R_{32}	R_{13},R_{23},R_{43}	R_{24},R_{44}	R_{25}	R_{15},R_{35},R_{45}	$R_{16},R_{26},R_{36},R_{46}$	$R_{17},R_{27},R_{37},R_{47}$
		M2	R_{21},R_{41}	R_{11},R_{31}	R_{12},R_{32}	R_{23},R_{13},R_{43}	R_{24},R_{44}	R_{15},R_{35}	R_{25},R_{45}	$R_{16},R_{26},R_{36},R_{46}$	$R_{17},R_{27},R_{37},R_{47}$
Experiment 3	Case 1	M1	R_{11},R_{31},R_{51}	R_{21},R_{41}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	/	R_{25},R_{45},R_{55}	R_{15},R_{35}	/	$R_{17},R_{27},R_{47},R_{37},R_{57}$
		M2	R_{11},R_{31},R_{51}	R_{21},R_{41}	R_{12},R_{32},R_{52}	R_{13},R_{23},R_{43}	/	R_{25},R_{35},R_{55}	R_{15},R_{45}	/	$R_{17},R_{27},R_{37},R_{47},R_{57}$
	Case 2	M1	R_{11},R_{31}	R_{21},R_{41},R_{51}	R_{12},R_{32}	R_{13},R_{23},R_{43}	R_{24},R_{44}	R_{55},R_{35}	R_{15},R_{25},R_{45}	$R_{16},R_{26},R_{56},R_{36},R_{46}$	$R_{17},R_{27},R_{37},R_{57},R_{47}$
		M2	R_{21},R_{41}	R_{11},R_{31},R_{51}	R_{12},R_{32}	R_{23},R_{13},R_{43}	R_{24},R_{44}	R_{15},R_{35}	R_{25},R_{55},R_{45}	$R_{16},R_{26},R_{56},R_{36},R_{46}$	$R_{17},R_{27},R_{57},R_{37},R_{47}$

M1-Proposed method, M2-Practical method

Figure 4-8: Order scheduling solutions for all cases of 3 experiments


Gantt charts for Case 1 of Experiment 1 (Proposed method)

Gantt charts for Case 1 of Experiment 1 (Practical method)

Figure 4-9: Gantt charts for case 1 of experiment 1

Table 4-6: Order scheduling results for case 3 of experiment 1

		Order 1	Order 2	Order 3	Order 4	Order 5	Order 6	Order 7
Proposed method	Mean of completion time	23.5	17	25	34.58	26.57	32.57	31.5
	Satisfaction level	99.09%	99.00%	99.00%	99.58%	99.57%	99.57	99.09%
	Throughput time	19	17	25	27.58	16.57	16.57	11
Practical method	Mean of completion time	19.5	16.5	22.5	28.5	23.5	29.5	31.5
	Satisfaction level	78.66%	98.50%	96.50%	93.50%	96.50%	96.50%	99.09%
	Throughput time	19.5	16.5	19	21.5	13.5	13.5	11.5

As shown in Tables 4-5 and 4-6, the satisfactory levels of order 1 in cases 2 and 3 were both less than 79% in the practical method while the satisfactory levels of all orders in the proposed method were greater than 97.80%. In terms of the total throughput time, the proposed method outperformed the practical method in case 2. Regarding the total throughput time in case 3, the result of the proposed method was slightly inferior to that of the practical method. This is because the proposed method generated the scheduling result from the viewpoint of the global optimization.

The above three cases demonstrate that the proposed method can obtain better optimization performance than the practical method from industrial practice.

4.4.2 Experiment 2: Order Scheduling with Uncertain Order

In the two cases of this experiment, some existing orders and an uncertain production order were scheduled. The data for cases 1 and 2 were similar to cases 1 and 2 of experiment 1 except that order 5 was uncertain. In cases 1 and 2 of experiment 1, order 5 arrived at time 8 (the 8th day). In this experiment, however, order 5 might come at time 8 with the probability of 0.3, or it might not come at all. That is, two different production events might occur in each case. If order 5 arrived, 5 orders would be scheduled; otherwise, only 4 orders were scheduled.

In the proposed method, two possibilities of each case were scheduled. Based on the proposed method, the order scheduling results of the two cases are shown in the rows of ‘Proposed method’ in Tables 4-7 and 4-8 respectively on condition that order 5 does not come. In each case, the total satisfactory level was equal to the probability expectation of the satisfactory levels under different possibilities. Take case 1 as an example. If order 5 came, the total satisfactory level of 5 orders would be 99.02%. If it did not come, the total satisfactory level of 4 orders would be 99.03%. Therefore, the total satisfactory level of case 1 was $99.02\% \cdot 0.3 + 99.03\% \cdot 0.7 = 99.027\%$. Similarly, the total satisfactory level of case 2 was obtained and was 98.575%, and the total throughput times of cases 1 and 2 were 81.37 and 76.34 respectively.

Table 4-7: Order scheduling results for case 1 of experiment 2

		Order 1	Order 2	Order 3	Order 4
Proposed method	Mean of completion time	16	18.07	26	23.5
	Satisfaction level	99.00%	99.01%	99.00%	99.09%
	Throughput time	16	18.07	21.5	19.5
Practical method	Mean of completion time	16	18	24.5	26.5
	Satisfaction level	99.00%	99.09%	97.50%	75.00%
	Throughput time	16	18	20.5	22

Table 4-8: Order scheduling results for case 2 of experiment 2

		Order 1	Order 2	Order 3	Order 4
Proposed method	Mean of completion time	14	20	21.7	28
	Satisfaction level	97.80%	99.00%	97.70%	99.00%
	Throughput time	14	15	21.7	23
Practical method	Mean of completion time	16.5	18.5	23.5	25
	Satisfaction level	75.00%	97.50%	99.09%	96.00%
	Throughput time	16.5	18.5	21	20

In the practical method, the uncertain order, order 5, was treated as ‘never arriving’. The order scheduling considered only 4 orders and the scheduling results of the two cases are shown in the rows of ‘Practical method’ of Tables 4-7 and 4-8 respectively. The total satisfactory levels of cases 1 and 2 were 92.65% and 91.90% respectively. The total throughput times of the two cases were 82.5 and 80.1 respectively, which were inferior to the results obtained from the proposed method.

Following the above discussion of this experiment, it can be concluded that the order scheduling results generated by the proposed method are better than those generated by the practical method.

4.4.3 Experiment 3: Order Scheduling with Uncertain Arrival Time

In this experiment, the arrival time of some orders was uncertain. The data for cases 1 and 2 were also similar to cases 1 and 2 of experiment 1 except that the two orders had uncertain arrival time. In case 1, the arrival time of order 4 was random: either time 4 with the probability of 0.2 or time 5 with the probability of 0.8. In case 2, the arrival time for order 3 was random: either time 0 with the probability of 0.3 or time 3 with the probability of 0.7.

In the proposed method, the uncertain arrival time was considered according to all the possible arrival times. The above two cases both had two possible circumstances. For each case, the scheduling results of one possible circumstance have been presented in experiment 1. The scheduling results of other possible circumstances are shown in the rows of 'Proposed method' in Tables 4-9 and 4-10. Take case 1 as an example. The total satisfactory level was 99.02% if the arrival time of order 4 was time 4, and the total satisfactory level was 98.92% if its arrival time was time 5. Consequently, the total satisfactory level of case 1 was 98.94%. Similarly, the total satisfactory level of case 2 could be obtained, which was 98.64%.

In the practical method, the uncertain arrival time of the order was replaced by its mean. That is, the arrival time of order 4 in case 1 was considered as 4.8 and the arrival time of order 3 in case 2 was considered as 2.1. Their scheduling results are shown in the rows of ‘Practical method’ in Tables 4-9 and 4-10. The total satisfactory levels of the two cases were 93.92% and 95% respectively. These results are also worse than those generated by the proposed method.

Table 4-9: Order scheduling results for case 1 of experiment 3

		Order 1	Order 2	Order 3	Order 4	Order 5
Proposed method	Mean of completion time	16	18.07	26	23.5	29.5
	Satisfaction level	99.00%	99.01%	99.00%	99.09%	98.50%
	Throughput time	16	18.07	22	15.5	19.5
Practical method	Mean of completion time	16	18	24.5	26.5	30
	Satisfaction level	99.00%	99.09%	97.50%	75.00%	99.00%
	Throughput time	16	18	20.5	18.5	20

Table 4-10: Order scheduling results for case 2 of experiment 3

		Order 1	Order 2	Order 3	Order 4	Order 5
Proposed method	Mean of completion time	14	19.5	23	26.07	24
	Satisfaction level	99.00%	99.09%	99.00%	98.07%	97.80%
	Throughput time	14	19.5	20	21.07	13.5
Practical method	Mean of completion time	16.5	18.5	23.5	26	19.5
	Satisfaction level	85%	98.50%	99.09%	98.00%	95.50%
	Throughput time	16.5	18.5	20.5	21	11.5

In the above experiments, the order scheduling performance generated by the proposed method outperformed that of the practical method because the former met the production objectives better. The optimized results in this chapter were obtained based on the following parameter setting: the population size and the maximum numbers of the generation of the proposed genetic optimization model were 100 and 50 respectively; the tournament size was 2; the probabilities of crossover and mutation were 0.6 and 0.01 respectively; the objective weight γ was 1; and the proportional parameters k_3 and k_4 in equation (4-9) were 0.01 and 0.1 respectively.

4.5 Summary

This chapter investigates a multi-objective order scheduling problem at the factory level, where uncertainties are described as continuous or discrete random variables. The objectives considered are to maximize the total satisfactory level of all orders and minimize the total throughput time, both of which are particularly helpful in meeting the due dates of orders and reducing the work in progress on each shop floor.

Based on the uncertain processing time of a particular production process, its uncertain completion time and its next process's beginning time are derived by using the probability theory. The genetic optimization model with a novel process order-based representation was developed to explore an optimal order scheduling solution. Experiments were conducted to validate the effectiveness of the proposed algorithm. The experimental results from the proposed algorithm are substantially better than the results from the industrial practice. It shows that the proposed algorithm is superior to the practical method in respect of order scheduling at the factory level.

Chapter 5

Apparel Assembly Line Scheduling at Shop Floor Level with Flexible Operation Assignment

Chapter 4 discusses the order scheduling problem at the factory level. Based on the optimized order scheduling results, the apparel production process is assigned to the appropriate assembly line for processing. The production manager of the factory sets the due date of each production order in PBS based on its contract delivery date and the order scheduling results at the factory level. The sewing production is desired to be completed before the specified due date in PBS.

To determine the beginning time of each production order on the AAL for meeting the due date in PBS, the AAL scheduling problem arises at the shop floor level of real-life apparel production in which flexible operation assignment and order preemption are investigated in this chapter. Firstly, the mathematical model of the problem is constructed with the objectives of minimizing the weighted sum of tardiness and earliness penalties, and balancing the production flow of the AAL. Secondly, a bi-level genetic optimization model (BiGA) is developed to solve the scheduling problem. Experimental results to validate the performance of the proposed BiGA are then presented. Lastly, the summary of this chapter is presented.

5.1 Problem Formulation

In this research, O_{ij} denotes the j th sewing operation of order P_i, M_{kl} represents the l th machine of the k th sewing machine type, BO_{ij} denotes the actual beginning time of operation O_{ij}, and Y_{ijkl} indicates if operation O_{ij} is assigned to machine M_{kl} (if so, Y_{ijkl} is equal to 1, otherwise Y_{ijkl} is 0).

5.1.1 Objective Function

For the scheduling of real-life AAL of PBS, the whole scheduling process comprises one or multiple scheduling statuses, each of which represents an operation assignment status of the assembly system. For instance, the production of orders P_i and P_j is performed on a same AAL. A possible production sequence is shown in Figure 5-1, in which orders P_i and P_j are processed separately and orderly. In this research, an unchanged operation assignment on the AAL is defined as a scheduling status. The operation assignment of orders P_i and P_j is assumed to be unchanged during their production. Figure 5-1 involves two scheduling statuses of orders P_i and P_j. The aim of AAL scheduling is to decide how to generate and implement these scheduling statuses, that is, to determine appropriate production beginning time BO_{i1} of the first operation of order P_i and generate optimal operation assignment Y_{ijkl} of operation O_{ij} in different scheduling statuses.

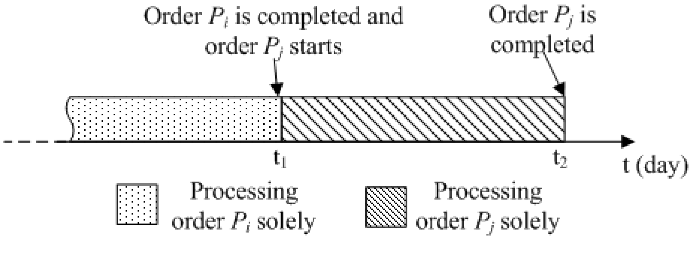


Figure 5-1: A production sequence of two orders on the AAL

The objective of the addressed scheduling problem in this research is twofold. The first one aims at minimizing the weighted sum of E/T penalties while the other is to balance the production flow of the sewing assembly system. The objective of minimizing the total E/T penalties can be described as follows:

$$\min_{\{BO_{i1}\},\{Y_{ijkl}\}} Q(BO_{i1}, Y_{ijkl})$$

with

$$Q(BO_{i1}, Y_{ijkl}) = \sum_{i=1}^{m} (\alpha_i \cdot (CL_i - DL_i) \cdot \lambda_i + \beta_i \cdot (DL_i - CL_i) \cdot (1 - \lambda_i)) \tag{5-1}$$

where α_i is the tardiness weight (the penalty cost per time unit of delay) of order P_i and β_i is the earliness weight of order P_i (the storage cost per time unit if order P_i is completed earlier than the due date in PBS), DL_i denotes the desired due date of order P_i on AAL, CL_i is the actual completion time of order P_i on AAL, and λ_i denotes that if the tardiness of order P_i is greater than 0, λ_i is equal to 1; otherwise, it is equal to 0.

As another objective of this research is to maximize the balance performance of the AAL, a balance index denoted as $B(\cdot)$ is devised so as to indicate the smoothness of the production flow of the assembly system, which is also the function of BO_{i1} and Y_{ijkl}. The second objective is expressed as follows:

$$\max_{\{BO_{i1}\},\{Y_{ijkl}\}} B(BO_{i1}, Y_{ijkl}) \tag{5-2}$$

with

$$B(BO_{i1}, Y_{ijkl}) = \frac{\sum_r (SPT_r \cdot SB_r)}{\sum_r SPT_r} \tag{5-3}$$

where SPT_r is the processing time of the rth scheduling status, and SB_r is the balance index of the rth scheduling status, which is computed by the following equations:

$$SB_r = \sum_i PB_i / n \tag{5-4}$$

$$PB_i = \frac{\sum_l PTO_{ij}}{o_i \cdot \max(PTO_{ij})} \tag{5-5}$$

where $n\,(n \geq 1)$ is the number of orders in the rth scheduling status, PB_i is the balance index of order P_i, o_i is the number of operations of order P_i, and PTO_{ij} is the average processing time of operation O_{ij} on AAL.

5.1.2 Constraints

The constraints for AAL investigated in this research are detailed mathematically as follows:

(1) Allocation constraint: operation O_{ij} can only be operated in the workstations which can handle it, i.e.,

$$\sum_{kl, M_{kl} \notin SM_{ij}} Y_{ijkl} = 0 \tag{5-6}$$

where SM_{ij} is the set of workstations which can handle operation O_{ij}.

Each operation must be processed, i.e.,

$$\sum_{kl} Y_{ijkl} \geq 1 \tag{5-7}$$

(2) Operation precedence constraint: the operation precedence constraint states that an operation cannot be started before its preceding operation is completed and it is transported to the corresponding machine, i.e.,

$$CO_{ij} + TTO_{ij} \leq BO_{ij'}, \quad O_{ij} \in PR(O_{ij'}) \tag{5-8}$$

where CO_{ij} is the completion time of operation O_{ij}, TTO_{ij} is the transportation time between workstations processing operations O_{ij} and $O_{ij'}$, and $PR(O_{ij'})$ is the set of the preceding operations of operation $O_{ij'}$.

3) Processing time requirement: operation O_{ij} must be assigned processing time and setup time. This research assumes that an operation cannot be interrupted once it is started. It is reasonable because the processing time of each sewing operation is very short. Thus, the following relationship exists:

$$CO_{ij} = BO_{ij} + U_{ij} + PTO_{ij} \tag{5-9}$$

where PTO_{ij} denotes the processing time of operation O_{ij}, and U_{ij} indicates the setup time of the workstation for processing operation O_{ij}, which is the time to change the setting on the sewing machine.

In real-world AAL scheduling, the shop floor managers cannot know the production details in PBS in advance and they usually estimate the production of sewing operations on average. In considering AAL scheduling, expressions (5-8) and (5-9) are used to describe the time relationship between sewing operations on the basis of these operations' average processing time. TTO_{ij}, U_{ij} and PTO_{ij} use their own averages. For the same operation of different garments, these values are unchanged. The average of PTO_{ij}, $\overline{PTO_{ij}}$, is equal to the average time of operation O_{ij} of one garment being processed on all assigned machines simultaneously. It is determined by the quantity and efficiencies of the sewing operators processing this operation, and the number of sewing operations the operator processed. It can be computed approximatively by the following expression

$$\overline{PTO_{ij}} = \frac{ST_{ij}}{\sum_{kl} Y_{ijkl} EM_{ijkl} \eta_{ijkl}} \tag{5-10}$$

where ST_{ij} represents the standard processing time (standard time, ST) of operation O_{ij} which is the time to complete operation O_{ij} of one garment with 100% operative efficiency, EM_{ijkl} is the operative efficiency to process operation O_{ij} on machine M_{kl} (the efficiency of different machines or operators could be different). The time of processing operation O_{ij} on machine M_{kl} is equal to ST_{ij} / EM_{ijkl}, η_{ijkl} is the weight of efficiency penalty. Obviously, if only operation O_{ij} is processed on machine M_{kl}, η_{ijkl} is equal to 1; if multiple operations are processed on machine M_{kl}, η_{ijkl} is less than 1 because only a certain portion of the working time of machine M_{kl} will be put on operation O_{ij}. If machine M_{kl} processes nl operations, it is assumed that the weights of efficiency penalty η_{ijkl} of these operations are equal to $1/nl$ in AAL scheduling. This assumption is reasonable because AAL scheduling mainly investigates if the due dates of orders can be met and it has relatively little concern about the operating task of each workstation.

5.2 Bi-Level Genetic Optimization Model for AAL Scheduling

If a sewing machine is assigned to process different sewing operations frequently on real-life AAL, more additional setup time will be needed and the efficiency of the sewing operator will decrease and fluctuate inevitably. On the basis of switching operations as infrequently as possible on each machine, the AAL scheduling problem with two orders (i.e., 2-order scheduling problem) at the shop floor level is optimized in this chapter.

5.2.1 Structure of Bi-Level Genetic Optimization Model

As two apparel production orders are scheduled, there are five possible scheduling modes shown in Figure 5-2 based on different production tasks and delivery dates. In modes (a), (b) and (d), two orders can be processed simultaneously while each order must be processed separately in modes (c) and (e). Actually, mode (d) can be considered as a particular instance of modes (a) and (b) while mode (e) can be taken as a particular instance of mode (c). In these modes, 3 different scheduling statuses are involved, including the status of processing order P_i solely, the status of processing order P_j solely, and the status of processing both orders P_i and P_j simultaneously. In scheduling mode (c), order preemption occur and it is necessary when order P_j is a rush one.

To solve the addressed problem described in section 5.1, it is of utmost important to select appropriate scheduling modes as well as the operation assignment and the beginning time of each order. In this section, the BiGA is presented, which comprises two genetic optimization processes at different levels, where the second-level GA (GA-2) is nested in the first-level GA (GA-1). GA-1 generates the optimal operation assignment in 3 different scheduling statuses of the 2-order scheduling problem, where GA-2 determines the optimal beginning time of each scheduling status on the basis of the operation assignment from GA-1.

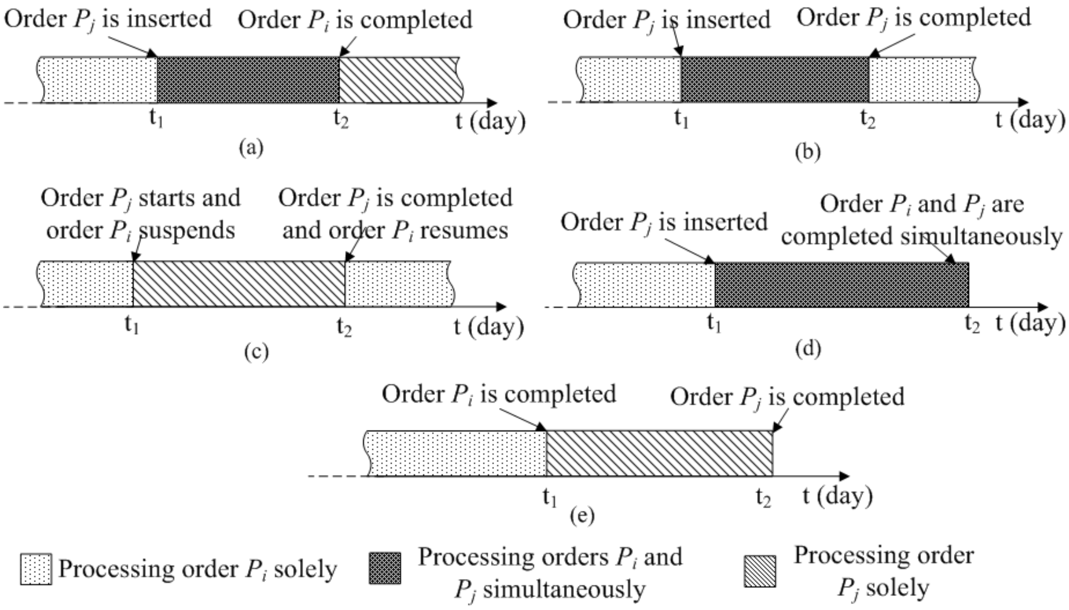


Figure 5-2: Scheduling modes of processing two orders on the AAL

The steps involved in the algorithm are illustrated in Figure 5-3. In considering scheduling modes (a), (b) and (d) of the 2-order scheduling problem at the shop floor level, GA-2 is to determine the beginning time of the scheduling status processing two orders simultaneously based on the operation assignment of GA-1. However, the scheduling modes (c) and (e) are to determine the beginning time of the scheduling status of order P_i solely. Whichever mode is considered, to determine the beginning time of order P_i is a simple unary first-order function optimization problem, which is easy to be optimized by a real-coded GA.

In GA-1 and GA-2, the selection operation and the termination criterion are also the same as those in the GA for the order scheduling problem described in Chapter 4. Other procedures are described in the following sections.

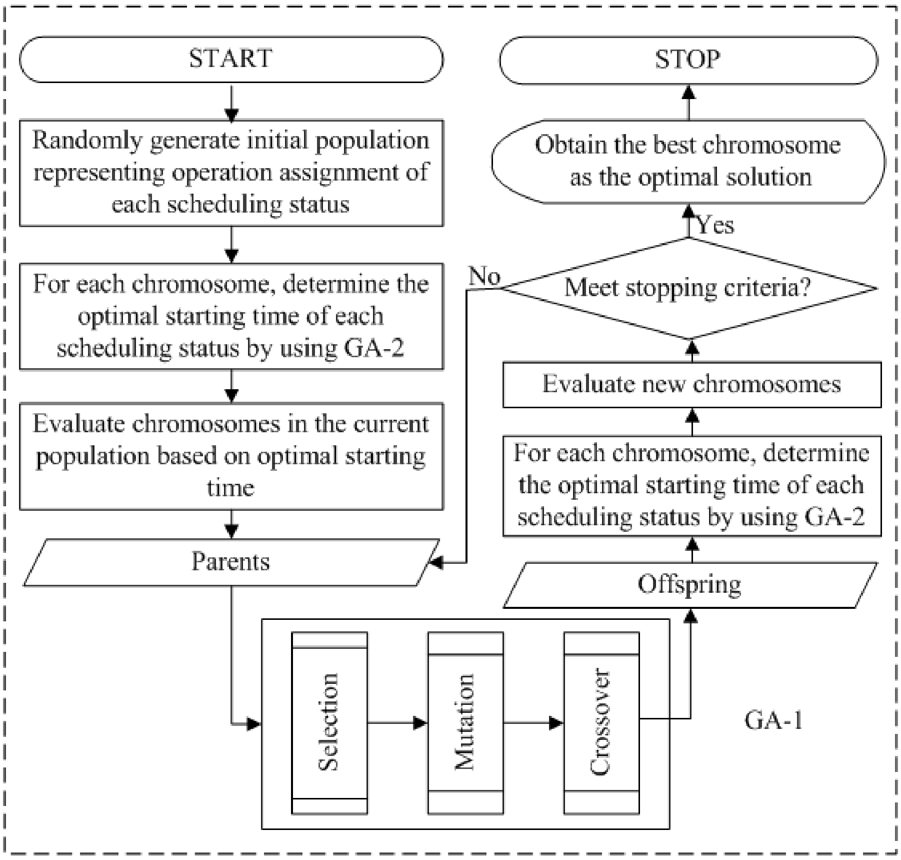


Figure 5-3: Bi-level genetic optimization model

5.2.2 Representation

In GA-1, to tackle flexible operation assignment in PBS, a novel chromosome representation is developed. Each chromosome is a sequence of genes and its length is equal to the number of machines to which operations can be assigned. In a chromosome, each gene represents a machine and the value of each gene represents the operation number(s) of one or more operations which the corresponding machine processes. If the number of the machine type is $t\,(t \geq 1)$, the genes in each chromosome will be divided into t parts in turn. Each part represents one type of machine. Each operation can only be assigned to the machines which can handle it. Figure 5-4 shows an example of this representation which considers a problem with 6 operations to be assigned to 12 sewing machines. These machines are divided into two types, the lockstitch type including machines 1 through 7, and the overlock type including machines 8 through 12. Operations 1, 2, 3 and 4 must be processed on lockstitch sewing machines, while operations 5 and 6 must be operated on overlock machines. A feasible solution, represented in an array of length 12, could be [1 2 3 (3,4) 4 2 1 5 6 (5,6) 5 6]. Based on this solution, machine 4 processes operations 3 and 4 while machine 10 processes operations 5 and 6 at the same time. Furthermore, some operations are assigned to more than one machine. For example, operation 1 is assigned to machines 1 and 7, and operation 3 is assigned to machines 3 and 4.

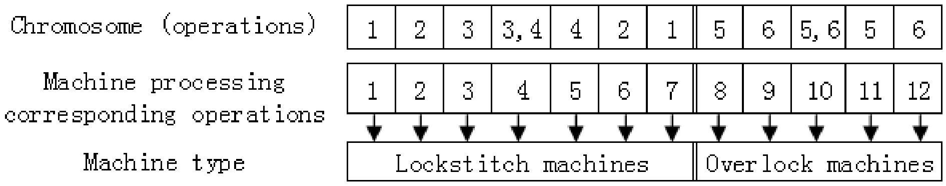


Figure 5-4: Sample of the chromosome representation

The above representation describes the operation assignment of a scheduling status. In GA-1, the operation assignments of 3 different scheduling statuses are optimized separately and independently.

In GA-2, the real-coded chromosome comprises one gene. The value of the gene is the beginning time of order P_j (i.e., the beginning time of the second scheduling status in each scheduling mode).

5.2.3 Initialization

In GA-1, each chromosome is randomly initialized by assigning all operations of a scheduling status to the machines which can handle it. The initialization process can thus be described as follows:

Step 1. Initialize parameters: index $i = 1$, a population size $Psize$, population $POP = \{\phi\}$ and a maximum quantity mxQ of machines to which an operation can be assigned.

Step 2. Randomly generate a string chromosome CHR_i, $POP = POP \cup CHR_i$.

Step 3. Set $i = i + 1$. Stop if $i > Psize$, otherwise go to step 2.

The process for randomly generating a chromosome is detailed as follows:

Step 1. Set index j =1. For each operation, let PRO =1, where PRO represents the probability that an operation is selected to be processed.

Step 2. Generate randomly an integer k between 1 and the number of operations which can be processed on machine j.

Step 3. Randomly select k operation(s) which can be processed on this machine. The operation with greater PRO will be selected with a greater probability. If $PRO = 0$, the operation cannot be selected.

Step 4. Assign the selected operation(s) to machine j. For each selected operation, let $PRO = PRO - \frac{1}{mxQ}$.

Step 5. Set $j = j + 1$. If $j > h$, go to step 6; otherwise go to step 2.

Step 6. Stop if all operations are assigned, otherwise go to step 1.

In GA-2, the initial population is generated by initializing randomly the beginning time of each scheduling status within the due date in PBS.

5.2.4 Fitness

In tackling the addressed AAL scheduling problem, two objective functions should be optimized. For the second objective, ideally, the maximal balance index of an assembly system is 100%. Balance index less than 100% implies extra production cost, i.e. imbalance penalty. The imbalance penalty is set as κ when the balance index decreases by 1%. Consequently, the two objectives can be combined as $OBJ2(BO_{i1},Y_{ijkl})$, which minimizes the summation of earliness and tardiness as well as imbalance penalties as follows,

$$OBJ2(BO_{i1},Y_{ijkl}) = Q(BO_{i1},Y_{ijkl}) + \kappa \cdot (1 - B(BO_{i1},Y_{ijkl})) \tag{5-11}$$

The fitness function $ft2$ of GA-1 and GA-2 can thus be defined as

$$ft2 = \frac{10}{OBJ2(BO_{i1},Y_{ijkl})+1} = \frac{10}{Q(BO_{i1},Y_{ijkl}) + \kappa \cdot (1 - B(BO_{i1},Y_{ijkl}))+1} \tag{5-12}$$

5.2.5 Crossover

In GA-1, in accord with the proposed chromosome representation, a modified crossover operator similar to the uniform-order crossover is developed and described as below:

Step 1. Create a bit string randomly with the same length as the chromosomes.

Step 2. Copy the genes from parent 1 wherever the bit code is ‘1’ and fill them in the corresponding positions in child 1. (Positions in child 1 are filled in wherever the bit code is “1” and positions are left blank wherever the bit code is “0”.)

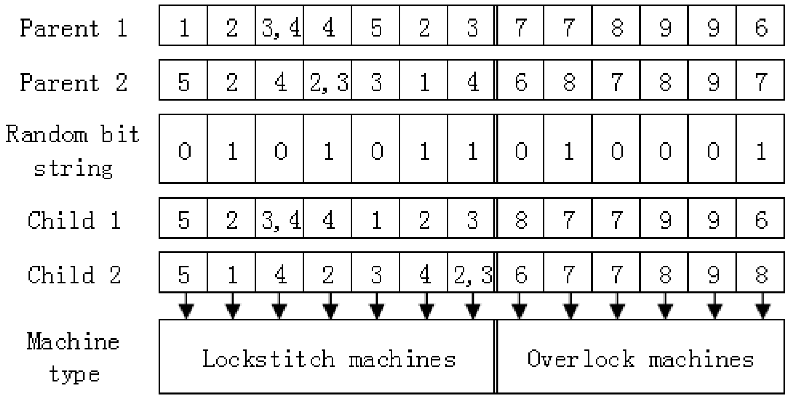
Step 3. Select the genes from parent 1 wherever the bit code is ‘0’.

Step 4. Permute these genes so that they follow the same order of genes appearing in parent 2. For the gene with two or more operations, its first operation is used for permuting the positions of genes of child 1 following the order of genes of parent 2. If the number of genes in the list is more than the number of corresponding genes with same operation(s) in parent 2, then the sequence of genes in parent 2 will be duplicated and appended to its end.

Step 5. Fill these permuted genes orderly in the gaps in child 1.

Step 6. Carry out a similar process to make child 2 according to steps 2-6.

Each sewing operation must be processed on machines of a certain type. Thus, the genes of different machine types in a chromosome should be independent and the crossover and mutation operations could only be performed among genes with the same machine type. Therefore, for the genes of each machine type, the genetic operations are performed separately. Figure 5-5 shows an example of the modified uniform-order crossover operation considering the two types of machines.



Parent 1	1	2	3, 4	4	5	2	3	7	7	8	9	9	6
Parent 2	5	2	4	2, 3	3	1	4	6	8	7	8	9	7
Random bit string	0	1	0	1	0	1	1	0	1	0	0	0	1
Child 1	5	2	3, 4	4	1	2	3	8	7	7	9	9	6
Child 2	5	1	4	2	3	4	2, 3	6	7	7	8	9	8
Machine type	Lockstitch machines							Overlock machines					

Figure 5-5: Sample of the modified uniform-order crossover operator

In GA-2, the BLX-α crossover operator (Eshelman and Schaffer 1993) is used. Herrera et al (1996) compared some real-coded crossover operators and concluded that the BLX-α crossover operator was the best one. This operator uniformly picks values that lie between two points that contain two parents, but may extend equally on either side determined by a user-specified GA-parameter α (See Figure 5-6). For instance, BLX-0.3 picks parameter values from points that lie on an interval that extends $0.3I$ on either side of the interval I between the parents.

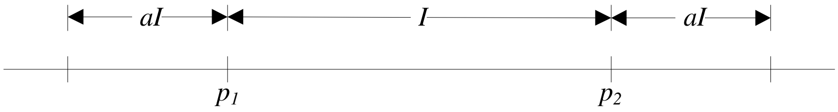


Figure 5-6: BLX-α crossover

5.2.6 Mutation

In GA-1, to correspond with the proposed representation, a modified mutation operation similar to the inversion mutation operator (Holland 1975) was developed. This operation inverts firstly the genes between two randomly selected genes of a chromosome with a predetermined probability of mutation. According to the suitable probability (between 0.6 and 1), the gene with two or more operations is then divided and the separated operations recombines with its proximate gene. Figure 5-7 shows an example of a mutation operator.

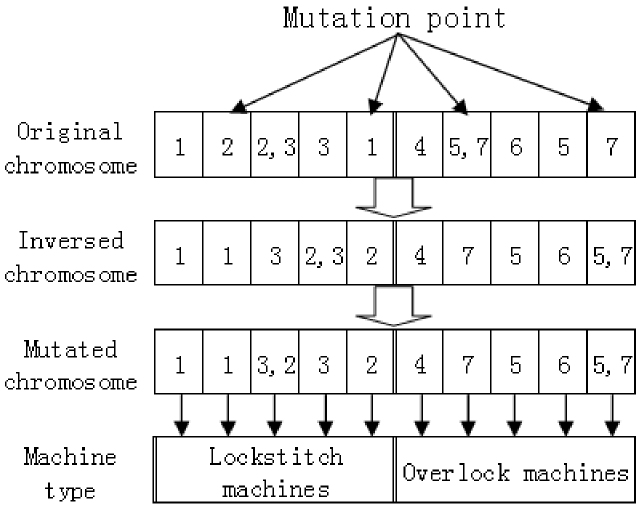


Figure 5-7: Sample of the modified inversion mutation operator

Herrera (1998) compared three commonly used mutation operators for a real-coded GA, including random mutation (Michalewicz 1992), real number creep (Davis 1991) and non-uniform mutation (Michalewicz 1992), and concluded that the non-uniform mutation operator outperformed the other two. In GA-2, the non-uniform mutation operator is used and its procedures are described as follows:

If $s_v^t = \langle v_1, v_2, \cdots, v_h \rangle$ is a chromosome (t is the generation number) and gene v_k is selected for this mutation, the result is vector $s_v^{t+1} = \langle v_1, \cdots, v_k^{'}, \cdots, v_h \rangle$, where

$$v_k^{'} = \begin{cases} v_k + \Delta(t, UB - v_k) & \textit{if a random digit is } 0, \\ v_k - \Delta(t, v_k - LB) & \textit{if a random digit is } 1 \end{cases} \tag{5-13}$$

and LB and UB are lower and upper domain bounds of variable v_k. Function $\Delta(t, y)$ returns a value in the range $[0, y]$. The probability of $\Delta(t, y)$ being close to 0 increases as t increases. This property causes this locally at later stages, thus increasing the probability of generating a new number closer to its successor than a random choice. The following function is used:

$$\Delta(t, y) = y \cdot (1 - (rnd)^{(1 - \frac{t}{t\_\max})^q}) \tag{5-14}$$

where rnd is a random number from [0,1], $t\_\max$ is the maximal generation number, and q is a system parameter determining the degree of dependency on the iteration number (In this research q is equal to 5).

5.3 Experimental Results and Discussion

A series of experiments were conducted to evaluate the performance of the proposed BiGA for the AAL scheduling problem. Two experiments are presented in this section. In experiment 1, the same scheduling tasks were scheduled in two different cases. Each workstation could process only one sewing operation in case 1 while each workstation could process a maximum of two sewing operations simultaneously in case 2. In experiment 2, three production problems with different due dates were scheduled. In real-world PBS, garment components are processed and transported in bundles which are composed of certain number of garment components being tied by strings. An operative assistant is responsible for transporting the garment components between workstations. Compared with the total operating time of one bundle of garment components, the transportation time and the setup time are thus negligible in the decision-making process. Moreover, the AAL used for modeling was empty initially in this research. In other words, there was no work in progress in each workstation. All production orders, materials and sewing workstations were ready for processing from time zero. There was no shortage of materials, machine breakdown and absence of operators in the assembly environment.

5.3.1 Experiment 1

In this experiment, two apparel production orders were scheduled over a planning horizon of 20 units (days) of time. Each time unit (day) had 8 working hours. The data for each order is shown in Table 5-1. The columns describe, respectively, the order number, order size (quantity of products in the order), due date, tardiness weight, earliness weight and operation number of each order, the required sewing machine type and standard processing time to perform the operation. These two orders were different in terms of order sizes, due dates and penalty weights. Order 1 comprised 7 sewing operations which should be processed from operations 1 to 7 continuously. Order 2 involved 5 sewing operations which should be processed continuously, namely operations 8, 9, 10, 11 and 12. The two orders were scheduled on an AAL with 7 lockstitch sewing machines and 7 overlock machines. Operations 2, 3, 4, 7, 10 and 12 must be processed on lockstitch sewing machines while other operations must be processed on overlock machines. On the AAL, the operative efficiency of sewing operator in each sewing workstation depends on the type of machine, the skill level and the recent performances of the operator. Table 5-2 demonstrates a detailed efficiency inventory of each workstation for the operations of the two orders. The efficiency was set as 0 if the operator could not process the corresponding operation. The processing time of operation O_{ij} on machine M_{kl} was equal to the standard processing time of this operation divided by the relevant operator's efficiency on machine M_{kl}.

Table 5-1: Data for orders of experiment 1

Order No.	Order size	Due date	Tardi-ness weight	Earli-ness weight	Operation No.	Machine type required	Standard time
1	2000	15	5000	100	1	O	308
					2	L	310
					3	L	150
					4	L	160
					5	O	280
					6	O	320
					7	L	270
2	2000	20	3000	100	8	O	218
					9	O	156
					10	L	280
					11	O	120
					12	L	200

Machine type 'O' denotes overlock machine, 'L' denotes lockstitch sewing machine

Table 5-2: Operative efficiency in workstations of experiment 1

Machine type	Work-station No.	Operation No. of order 1							Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10	11	12
Lockstitch sewing machine	1	0	100%	95%	90%	0	0	100%	0	0	100%	0	95%
	2	0	75%	70%	70%	0	0	75%	0	0	80%	0	70%
	3	0	80%	80%	85%	0	0	80%	0	0	60%	0	85%
	4	0	70%	65%	60%	0	0	70%	0	0	75%	0	65%
	5	0	85%	75%	80%	0	0	85%	0	0	95%	0	80%
	6	0	90%	85%	90%	0	0	90%	0	0	90%	0	95%
	7	0	95%	100%	100%	0	0	95%	0	0	85%	0	100%
Overlock machine	8	90%	0	0	0	95%	95%	0	90%	95%	0	95%	0
	9	80%	0	0	0	80%	70%	0	85%	90%	0	70%	0
	10	60%	0	0	0	70%	65%	0	70%	70%	0	80%	0
	11	75%	0	0	0	70%	80%	0	80%	85%	0	70%	0
	12	100%	0	0	0	100%	90%	0	90%	90%	0	85%	0
	13	95%	0	0	0	100%	90%	0	100%	85%	0	100%	0
	14	90%	0	0	0	85%	100%	0	95%	100%	0	90%	0

On the AAL, one sewing workstation can process one or more operations. If only one operation is processed repetitively, it is helpful to improve the efficiency of this operator processing the operation owing to learning effects. However, if the number of workstations is less than the number of operations which have not been assigned, some workstations have to be assigned with more than one operation. It is helpful to improve the flexibility and balance performance of PBS if some workstations process multiple operations with different processing time. This experiment considers the scheduling problem according to whether each workstation can process only one or more operations in the three scheduling statuses explained in section 5.2 in the following sub-sections.

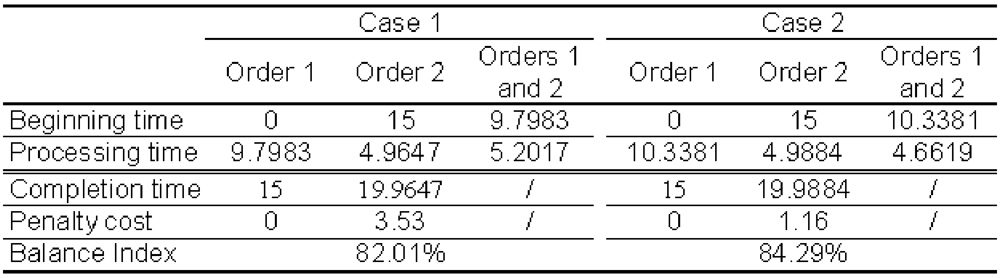
1) Case 1. In this case, each workstation processed only one operation in each scheduling status. Under this condition, the optimized operation assignments and order scheduling generated by the proposed GA are shown respectively in case 1 of Tables 5-3 and 5-4. In Table 5-3, the number in the second row represents the workstation number, and each row of the cases describes the optimized operation assignment of the corresponding order(s) which is (are) processed on the AAL. For example, the first row of case 1 of Table 5-3 describes the operation assignment of order 1 being processed solely on the AAL. In Table 5-4, the result rows describe the beginning time to process the order(s) of each scheduling status, the processing time for the order(s) of each scheduling status, the completion time of each order, the penalty cost of each order and the balance index of the AAL of each schedule.

Table 5-3: Optimized operation assignment for experiment 1

Case	Processed	Workstation No.													
No.	Orders	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Order 1	2	4	7	4	7	3	2	6	5	5	5	6	1	1
	Order 2	10	10	12	10	12	12	10	8	8	11	8	9	9	11
	Orders 1 & 2	4	3	12	10	2	12	7	1	11	11	8	9	6	5
2	Order 1	2	4,7	2,4	3,4	3	7	2,7	1,5	6	1	1,5	5,6	1,6	5,6
	Order 2	10	10,12	10,12	10,12	10,12	10,12	10,12	9,11	8	9	8,11	8	9	8,11
	Orders 1 & 2	10	7	3,7	3,12	4,12	4	2	8	5,8	5	6,9	9,11	1,6	11

In terms of the optimized operation assignment results, some operations were performed only in one workstation while some operations were performed in multiple workstations. For example, for the assignment result of order 1 being processed solely, operation 3 was processed only in workstation 6 while operation 2 was processed in workstations 1 and 7. Case 1 of Table 5-4 shows that the assembly system processed order 1 solely from beginning time 0 with processing time 9.7983 units. Then orders 1 and 2 were processed simultaneously with 4.9647 time units, and finally order 2 was processed solely until time 19.9647. The completion time of order 1 and order 2 were 15 and 19.9647 respectively. Based on this schedule, order 1 could be completed on time, and the earliness penalty of order 2 was 3.53. The balance index of this schedule was 82.01%.

Table 5-4: Results of optimized scheduling of experiment 1



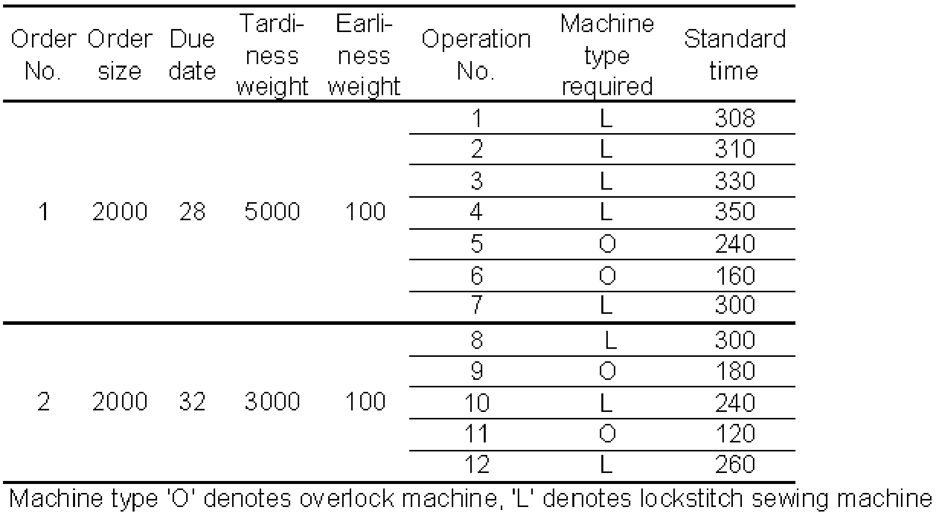
	Case 1			Case 2		
	Order 1	Order 2	Orders 1 and 2	Order 1	Order 2	Orders 1 and 2
Beginning time	0	15	9.7983	0	15	10.3381
Processing time	9.7983	4.9647	5.2017	10.3381	4.9884	4.6619
Completion time	15	19.9647	/	15	19.9884	/
Penalty cost	0	3.53	/	0	1.16	/
Balance Index		82.01%			84.29%	

2) Case 2. In this case, each workstation could process a maximum of two operations in each scheduling status. Case 2 of Table 5-3 shows the optimized operation assignments of all workstations processing a maximum of two operations. The optimized order scheduling was given in case 2 of Table 5-4. According to this result, the assembly system processed order 1 solely from time 0 with processing time 10.3381 units, then orders 1 and 2 were processed simultaneously with 4.6619 time units. Afterwards, order 2 was processed solely with processing time 4.9884 units. Since order 1 was accomplished punctually, there was no penalty. Order 2 was completed by 0.0116 time units in advance and its earliness penalty was only 1.16. The balance index of this schedule was 84.29%. This value is better than that of the optimized schedule in case 1 because the imbalance grade of the assembly system is probably weakened when some workstations processed two operations.

5.3.2 Experiment 2

Three apparel production tasks were scheduled over a planning horizon of 32 units of time in this experiment. The details of each order are given in Table 5-5. The sewing operations of orders 1 and 2 were from operations 1 to 7, and operations 8 to 12 respectively. In the experiment, the assembly system comprised 8 workstations of lockstitch sewing machines and 2 workstations of overlock machines. Operations 5, 6, 9 and 11 must be processed on overlock machines while other operations must be processed on lockstitch sewing machines. The detailed efficiency inventory of each workstation for the two orders is given in Table 5-6.

Table 5-5. Data for orders of experiment 2



Order No.	Order size	Due date	Tardiness weight	Earliness weight	Operation No.	Machine type required	Standard time
1	2000	28	5000	100	1	L	308
					2	L	310
					3	L	330
					4	L	350
					5	O	240
					6	O	160
					7	L	300
2	2000	32	3000	100	8	L	300
					9	O	180
					10	L	240
					11	O	120
					12	L	260

Machine type 'O' denotes overlock machine, 'L' denotes lockstitch sewing machine

Table 5-6. Operative efficiency in workstations of experiment 2

Machine type	Work-station No.	Operation No. of order 1							Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10	11	12
Lockstitch sewing machine	1	90%	100%	95%	90%	0	0	100%	90%	0	100%	0	95%
	2	70%	75%	70%	70%	0	0	75%	80%	0	80%	0	70%
	3	80%	80%	80%	85%	0	0	80%	80%	0	75%	0	85%
	4	70%	70%	65%	60%	0	0	70%	70%	0	75%	0	65%
	5	80%	85%	75%	80%	0	0	85%	90%	0	95%	0	80%
	6	90%	90%	85%	90%	0	0	90%	90%	0	90%	0	95%
	7	95%	95%	100%	100%	0	0	95%	90%	0	85%	0	100%
	8	80%	75%	75%	75%	0	0	80%	85%	0	75%	0	80%
Overlock machine	9	0	0	0	0	100%	90%	0	0	85%	0	90%	0
	10	0	0	0	0	70%	80%	0	0	85%	0	75%	0

In terms of different due dates, different scheduling solutions are required to meet the production objectives. In this experiment, three different production tasks were simulated by setting different due dates. These tasks are described as 3 cases as follows:

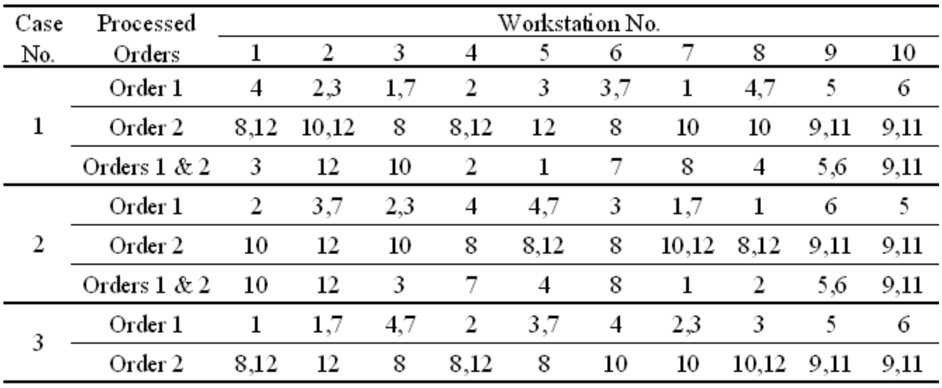
Case 1: The due dates of orders 1 and 2 were 28 and 32 respectively.

Case 2: The due dates of orders 1 and 2 were 32 and 28 respectively.

Case 3: The due dates of orders 1 and 2 were 32 and 20 respectively.

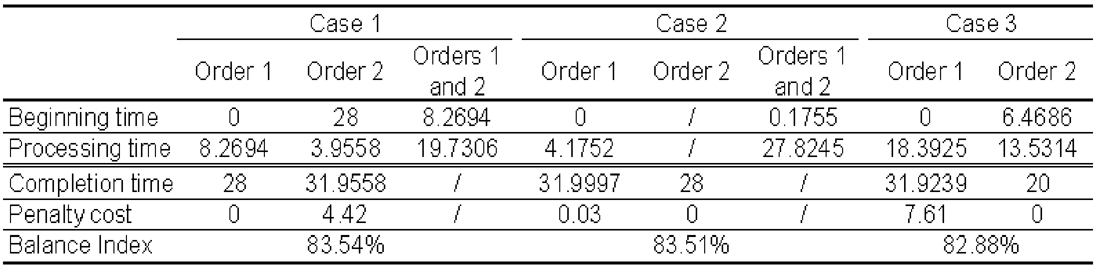
The optimized operation assignment and order scheduling of the three cases generated by the proposed genetic optimization model are shown in Tables 5-7 and 5-8 respectively. Although the production quantity and expected total production time of orders 1 and 2 in the three cases were the same, their scheduling solutions were different because of the differences of due dates. In case 1, the assembly system processed order 1 solely from time 0 with processing time 8.2694 units, then orders 1 and 2 were processed simultaneously with 19.7306 time units, and finally order 2 was processed solely. However, in case 2, order 2 was not processed solely. In case 3, orders 1 and 2 were not processed simultaneously because of the limited production capacity of the assembly system. Order 2 could not be accomplished on schedule when two orders were processed simultaneously and thus they had to be processed separately. That is, order 2 was a rush order. Order preemption occurred when the production of order 1 was interrupted. The optimized schedules of cases 1, 2 and 3 represent scheduling modes (a), (b) and (c) respectively.

Table 5-7: Optimized operation assignment of experiment 2



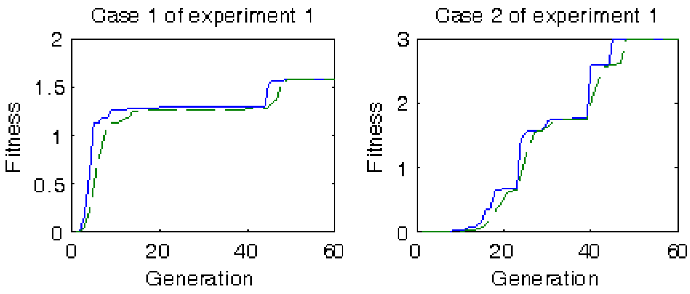
Case No.	Processed Orders	Workstation No.									
		1	2	3	4	5	6	7	8	9	10
1	Order 1	4	2,3	1,7	2	3	3,7	1	4,7	5	6
	Order 2	8,12	10,12	8	8,12	12	8	10	10	9,11	9,11
	Orders 1 & 2	3	12	10	2	1	7	8	4	5,6	9,11
2	Order 1	2	3,7	2,3	4	4,7	3	1,7	1	6	5
	Order 2	10	12	10	8	8,12	8	10,12	8,12	9,11	9,11
	Orders 1 & 2	10	12	3	7	4	8	1	2	5,6	9,11
3	Order 1	1	1,7	4,7	2	3,7	4	2,3	3	5	6
	Order 2	8,12	12	8	8,12	8	10	10	10,12	9,11	9,11

Table 5-8: Results of optimized scheduling of experiment 2

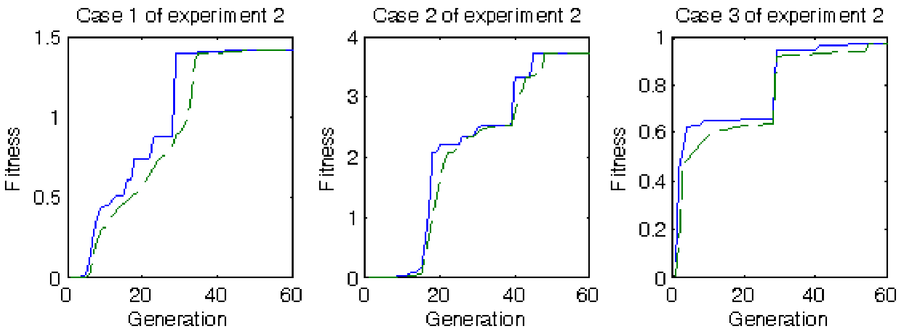


	Case 1			Case 2			Case 3	
	Order 1	Order 2	Orders 1 and 2	Order 1	Order 2	Orders 1 and 2	Order 1	Order 2
Beginning time	0	28	8.2694	0	/	0.1755	0	6.4686
Processing time	8.2694	3.9558	19.7306	4.1752	/	27.8245	18.3925	13.5314
Completion time	28	31.9558	/	31.9997	28	/	31.9239	20
Penalty cost	0	4.42	/	0.03	0	/	7.61	0
Balance Index	83.54%			83.51%			82.88%	

In this section, the results of the first experiment show that the proposed algorithm can schedule not only the processing of one operation on multiple machines but also that of multiple operations on one machine. The second experiment demonstrates the capability of the proposed algorithm for scheduling real production problems with different production tasks on the AAL. These experiments covered all scheduling modes of two orders being processed on an AAL. The penalty cost of each case was very low and negligible because each production task could be scheduled effectively and earliness or tardiness of each order was equal or very close to zero. These results show that the BiGA proposed in section 5.2 can solve the 2-order scheduling problem on the AAL effectively.



(a). Experiment 1



(b). Experiment 2

Figure 5-8: Trends of chromosome fitness
solid line: maximum fitness; dashdotted line: mean fitness.

In the optimization processes of these experiments, the evolutionary trajectories of fitness over generations are shown in Figure 5-8 where the solid line represents the maximum fitness and the dashdotted line represents the mean fitness. The optimized results in this section were obtained based on the following settings: the population sizes of GA-1 and GA-2 were 200 and 30 respectively; the maximum numbers of generations of GA-1 and GA-2 were 60 and 20 respectively; the imbalance penalty κ was 10 and the tournament size was 3. In order to reduce the computation time of the optimization process, probabilities of crossover and mutation were adjusted according to the fitness values of the population based on the method developed by Syswerda (1991).

5.4 Summary

This chapter investigates the AAL scheduling problem with the objectives of minimizing the total E/T penalty costs and maximizing the smoothness of the sewing production flow. These objectives are very useful in helping shop floors of PBS to meet the due dates, decrease the inventories and improve the efficiency of the assembly system by optimizing the utilization of limited resources.

Due to the intractable nature of the addressed scheduling problem, the heuristic global optimization process BiGA was developed to tackle it by determining when to start the production of each order and how to assign operations of each order to machines. Experiments were conducted to evaluate the performance of the BiGA. Experimental results demonstrate that the algorithm can solve the AAL scheduling problem with two orders effectively. In a real-life mid- to high-volume production environment, as there are often not more than two production orders processed simultaneously on an AAL, the proposed optimization algorithm can be widely applied.

In the AAL scheduling described in this chapter, the processing time of each sewing operation was computed on average according to the accumulated efficiency of all assigned workstations processing it simultaneously. The proposed scheduling model considered the average balance performance of PBS. Although the model is feasible to solve the scheduling problem at the shop floor level, the differences in the idle time between different operations of each garment and between same operations of different garments were not considered.

This chapter makes an assumption: if machine M_{kl} processes nl operations, the weights of efficiency penalty η_{ijkl} of these operations are the same and equal to $1/nl$. In other words, this chapter assumes that each sewing workstation (operator) spends the same working time on the assigned production tasks. However, in real-world PBS, it is probable that the processing time on different tasks is quite different so as to balance the AAL. The next chapter will thus present the AAL balancing problem considering the difference in the processing time of the same sewing operation and the difference of assigned task proportions being processed in different workstations.

Chapter 6

Apparel Assembly Line Balancing with Work-Sharing and Workstation Revisiting

The AAL scheduling problem discussed in Chapter 5 places great emphasis on investigating whether the due date of each order can be met by determining the beginning time of each apparel production order. Once the production of an order is started in PBS, the AAL balancing problem arises at the assembly line level. In the production process of PBS, work-sharing and workstation revisiting are allowed, and the operative efficiency of a sewing operator is variable due to the effects of various factors, such as learning factor, psychological and physical factors.

This chapter investigates the AAL balancing problem with work-sharing and workstation revisiting. Firstly, a mathematical model of the problem is presented with the objectives of meeting the desired cycle time of each order and minimizing the total idle time of all workstations in each production cycle. A GA-based optimization model, comprising a BiMGA (bi-level multi-parent GA) and a heuristic routing rule, is then developed to tackle the addressed problem. Next, experiments and discussions without the consideration of learning effects are presented to evaluate the effectiveness of the proposed optimization model. This chapter also discusses AAL balancing with learning effects and presents the experimental results with the consideration of learning effects.

6.1 Problem Formulation

In this research, the symbol ρ_{ijkl} ($0 \le \rho_{ijkl} \le 1$) denotes the task proportion (weight) of sewing operation O_{ij} being performed on machine M_{kl}, that is, the ρ_{ijkl} time of the total tasks of operation O_{ij} is processed on machine M_{kl}. On average, for operation O_{ij} of each garment, the task of $\rho_{ijkl} ST_{ij}$ should be processed on machine M_{kl}. If operation O_{ij} is only processed on machine M_{kl}, ρ_{ijkl} =1; and if operation O_{ij} is not processed on machine M_{kl}, ρ_{ijkl} =0. For each operation O_{ij}, $\sum_{kl} \rho_{ijkl} = 1$. The average assembly time MAT_{kl} of each garment on machine M_{kl} can be expressed as

$$MAT_{kl} = \sum_{ij,O_{ij} \in SO_{kl}} \frac{\rho_{ijkl} ST_{ij}}{EM_{ijkl}} \tag{6-1}$$

where SO_{kl} denotes the set of sewing operations which can be processed on machine M_{kl}.

6.1.1 Objective Function

The aim of AAL balancing is to generate the optimal operation assignment and the routing Y_{ijkl} of each operation O_{ij}. In this research, the objective of the AAL balancing problem is twofold. The first one is to satisfy the desired cycle time of each apparel production order, while the second one aims at minimizing the total idle time of all workstations in each production cycle. A production cycle is the process for completing a production run of a garment in an AAL. In the real-life apparel sewing process, the desired cycle time is the desired time processing the sewing process of each garment from start to finish. The objective of satisfying the desired cycle time can be described as

$$\min_{\{Y_{ijkl}\}} Z(Y_{ijkl})$$

with

$$Z(Y_{ijkl}) = \sum_{i=1}^{m}[\omega_i \delta_i (DCT_i - ACT_i) + \xi_i (1-\delta_i)(ACT_i - DCT_i)] \tag{6-2}$$

where DCT_i represents the desired cycle time of order P_i, ACT_i represents the actual cycle time of order P_i, ω_i denotes the penalty weight for order P_i when its actual cycle time is less than its desired cycle time, ξ_i denotes the penalty weight for order P_i when its actual cycle time is greater than its desired cycle time, and δ_i indicates that if the actual cycle time ACT_i is less than the desired cycle time DCT_i, δ_i is equal to 1; otherwise, it is equal to 0. $Z(Y_{ijkl})$ is used to measure the degree of how close the actual cycle time is to the desired cycle time. The smaller the value of $Z(Y_{ijkl})$, the better the actual cycle time satisfies the desired cycle time. The delivery date is delayed and the tardiness penalty is generated if the actual cycle time is more than the desired cycle time, whereas the storage cost arises and the earliness penalty is generated if the actual cycle time is less than the desired one.

The second objective of the AAL balancing problem is to minimize the total idle time IT of all workstations in each production cycle, which can be expressed as follows:

$$\min_{\{Y_{ijkl}\}} IT(Y_{ijkl}),$$

with

$$IT(Y_{ijkl}) = \sum_{i=1}^{m}(ACT_i \cdot N_i - \sum_{kl, M_{kl} \in AM_i} MAT_{kl}) \tag{6-3}$$

where AM_i denotes a set of workstations processing order P_i, and N_i denotes the number of workstations processing order P_i.

6.1.2 Constraints

A feasible solution to the AAL balancing problem must satisfy three basic types of constraints, including allocation constraint, operation precedence constraint and processing time requirement constraint. The mathematical expressions of these constraints are the same as the expressions of the corresponding constraints described in section 5.1.3, including expressions (5-6) to (5-9).

An ideal AAL balancing implies that no idle time exists between the sewing operations of each garment and each workstation. The production of each sewing operation is considered on the basis of each garment in AAL balancing. Therefore, expressions (5-8) and (5-9) are used to describe the time relationship between the sewing operations based on each garment in AAL balancing. For operation O_{ij} of one garment, its processing time PTO_{ij} is determined by the efficiency EM_{ijkl} of the sewing operator processing this operation and the assigned machine. Due to the effects of learning or other factors, the efficiency EM_{ijkl} can be different for different garments. PTO_{ij} is computed according to the following equation:

$$PTO_{ij} = \frac{ST_{ij}}{EM_{ijkl}} \tag{6-4}$$

6.2 GA-Based Optimization Model for AAL Balancing

In order to solve the addressed AAL balancing problem, a GA-based optimization model is presented in this section. In this model, a BiMGA is used to deal with the flexible operation assignment on the AAL, which involves assigning sewing operations to different workstations and determining the task proportions of the shared operation to be processed in different workstations. Then a heuristic operation routing process (operation routing rule) is used to route the shared sewing operation of each garment to an appropriate workstation. These two processes are described in detail in the following sections.

6.2.1 Bi-Level Multi-Parent GA

The flexible operation assignment in the AAL balancing problem can be considered as a two-stage optimization problem where the first stage is to assign operations to workstations and the second one is to determine the task proportions of each operation assigned to different workstations. Since the solution to the second-stage sub-problem depends on the solution to the first-stage sub-problem, the complexity of the process generating the optimal solution increases greatly. The BiMGA is thus proposed to solve the two-stage AAL optimization problem.

The structure of BiMGA is very similar to that of BiGA described in section 5.2. Unlike BiGA, the multi-parent crossovers are adopted in the two genetic optimization processes of BiMGA. As shown in Figure 6-1, the second-level multi-parent GA (MGA-2) is nested in the first-level multi-parent GA (MGA-1). MGA-1 generates the optimal operation assignment to workstations using the representation described in section 5.2.2. Based on each chromosome of MGA-1, MGA-2 determines the task proportions (weights) of each sewing operation which is assigned to different workstations. If an operation is assigned to multiple workstations, the weights on these workstations will be optimized. To seek these optimal weights is a first order multivariate function optimization problem, which can be optimized by a real-coded genetic optimization process.

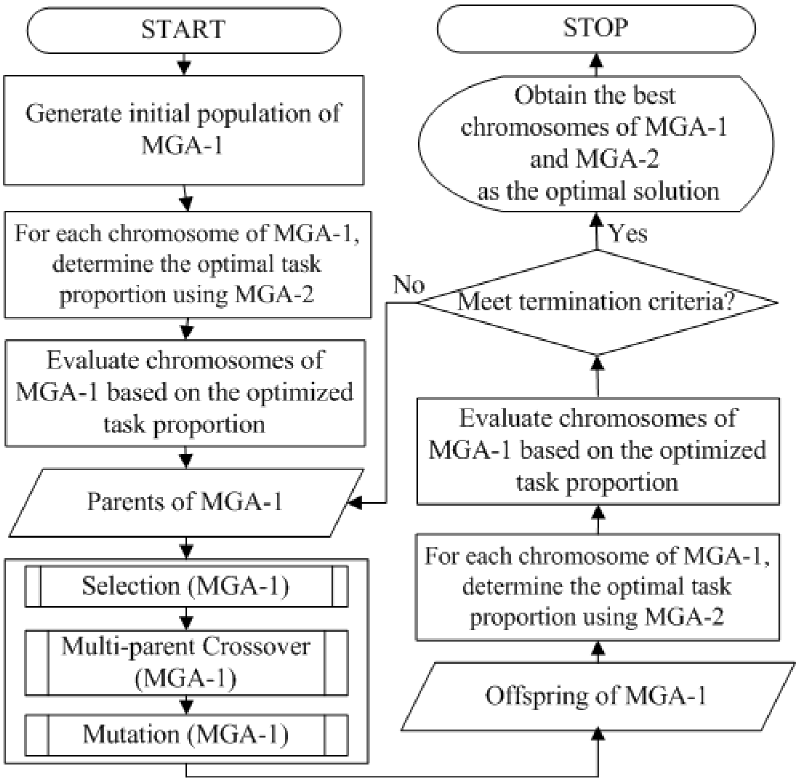


Figure 6-1: Bi-level multi-parent GA

1) MGA-1

The procedures for MGA-1 of BiMGA are the same as GA-1 of BiGA described in section 5.2 except the crossover operation and the fitness function.

(1) Multi-Parent Crossover

In this chapter, a multi-parent crossover developed by Eiben et al. (1994), the fitness based scanning crossover, is modified to suit the proposed order-based representation, which is described as below.

Step 1. Let sp_1, sp_2, …, sp_d be the selected parents with LH genes.

Step 2. Initialize parameters: position markers $i_1 = \cdots = i_d = 1$, i.e., the position markers are all initialized to the first position in each of the parents; the gene position in the child chromosome $k = 1$.

Step 3. Choose a gene from the d genes in the marked positions of the parents, which is based on the rule that the probability of the parental gene being chosen is proportional to the fitness values of the parent. For instance, for a maximization problem where parent sp_i has a fitness of $ft(i)$, the probability $PR(i)$ of choosing the gene from parent sp_i can be:

$$PR(i) = \frac{ft(i)}{\sum ft(i)} \qquad (6\text{-}5)$$

Step 4. Put the chosen gene in the k th position of the child chromosome.

Step 5. Update position markers $i_1, \cdots, i_d$. For each parent, if the gene in the current position is the same as the chosen gene, increase its marker until it denotes a value which has not yet been added to the child chromosome or equals LH.

Update $k = k + 1$.

Step 6. Repeat steps 3, 4 and 5 until the gene position k is greater than LH.

Step 7. Stop if each operation in the parent is assigned to machines, else go to step 2.

Figure 6-2 shows an example of how the proposed crossover mechanism works, in which the fitness of Parents 1 to 3 are 0.90, 0.45 and 0.45 respectively. The marked positions in parents are indicated by shaded grids.

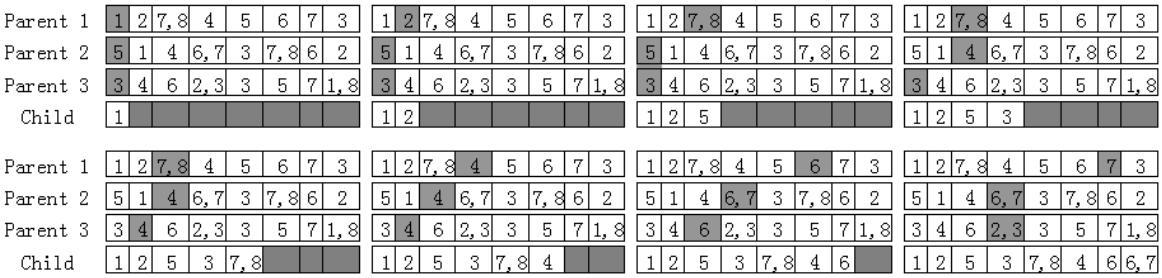


Figure 6-2: Example of a modified fitness-based scanning crossover operator

(2) Fitness Function

For the addressed AAL balancing problem, two objective functions described in section 6.1.1 are optimized, which can be combined as the following equation,

$$OBJ3(Y_{ijkl}) = w_Z \cdot Z(Y_{ijkl}) + w_{IT} \cdot IT(Y_{ijkl}) \tag{6-6}$$

where w_Z and w_{IT} are the relative weights placed upon the objectives $Z(Y_{ijkl})$ and $IT(Y_{ijkl})$ respectively.

The less the weighted summation of the two objectives is, the greater the fitness. The fitness function $ft3$ of MGA-1 is defined as

$$ft3 = \frac{100}{OBJ(X_{ijkl}) + 1} \tag{6-7}$$

2) MGA-2

In MGA-2, some procedures are the same as those in MGA-1, including selection operation, fitness function and termination criterion. Other procedures are described as follows.

(1) Representation: The real-coded representation is adopted. Each gene represents the task proportion of an operation assigned to the corresponding workstation. Consider the assignment of nQ operations. nm_{ij} denotes the number of machines allocated to process operation O_{ij} and PS_{ij} denotes the summation of nm_{ij}-1 weights of O_{ij}. The number of genes in each chromosome of MGA-2 is the summation of nm_{ij} minus nQ since the nm_{ij} th weight is equal to $1-PS_{ij}$.

(2) Initialization: The initial population is generated by initializing randomly each task proportion (weight) in the chromosome between 0 and 1 based on the premise of $PS_{ij} \leq 1$.

(3) Crossover: The center of mass crossover (CMX) operator (Tsutsui and Ghosh 1998) was used. The procedures for this operation are detailed as follows:

$X = (x_1, x_2, \cdots, x_h)$ represents an h dimensional real number vector which represents a possible solution (chromosome). Let m_prt (m_prt >1) and N ($N > m\_prt$) be the numbers of parents and population size respectively. In this crossover, m_prt individuals $X^{pi} = (x_1{}^{pi}, x_2{}^{pi}, \cdots, x_h{}^{pi})$, $i = 1, \cdots, m\_prt$, are chosen at random from the parental pool $\{X_1, \cdots, X_h\}$. Then X_{CM}^{p}, center of mass of the m_prt parents, is calculated following ($\mu / \rho, \lambda$)-ES (Beyer 1995) as

$$X_{CM}^{p} = \frac{1}{m\_prt} \sum_{i=1}^{m\_prt} X^{pi} \tag{6-8}$$

Each X^{pi} generates a virtual parent X^{vi}, where X^{pi} and X^{vi} are symmetrical with respect to X_{CM}^{p} as

$$X^{vi} = 2X_{CM}^{p} - X^{pi} \tag{6-9}$$

By crossing over the real parent X^{pi} and its virtual parent X^{vi}, child X^{ci} is then generated. Thus in CMX, m_prt children are generated from m_prt parents (see Figure 6-3). Since X^{pi} and X^{vi} are symmetrical with respect to X_{CM}^{p}, center of mass of m_prt parents, CMX tends to generate offspring uniformly around the m_prt parents. Then another set of m_prt parents (not chosen earlier) is chosen and it generates m_prt more children. This process continues until N new children are generated.

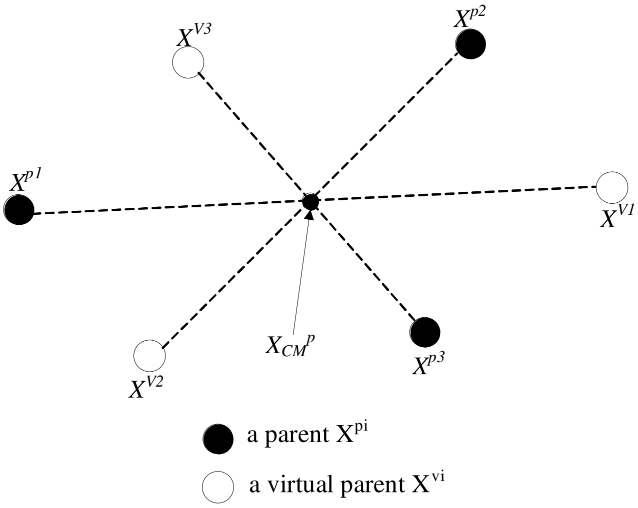


Figure 6-3. Center of mass crossover

(4) Mutation: The non-uniform mutation operator (Michalewicz 1992) is adopted, which has been described in section 5.2.6.

In MGA-2, after the genetic operations are performed, its nm_{ij} weights should be changed to the corresponding values between 0 and 1 if PS_{ij} of operation O_{ij} is greater than 1. A real number between 0 and 1 is generated randomly as the nm_{ij} th weight. Then the nm_{ij} weights are normalized and the normalized weights are the final weights.

6.2.2 Operation Routing

The proposed BiMGA can only obtain the optimized sewing operation assignment and task proportions of the shared operation in different workstations. After the previous operations of the shared sewing operation of each garment are completed, the shared operation should then be routed to an appropriate workstation so as to satisfy the optimized task proportion in each assigned workstation during production.

Assume that sewing operation O_{ij} is assigned to n machines (M_{k1}, M_{k2}, ... M_{kn}) according to the optimized operation assignment, ρ'_{ijkl} denotes the optimized task proportion that operation O_{ij} should be processed on machine M_{kl} (ρ'_{ijkl}>0), ρ''_{ijkl} denotes the task proportion that operation O_{ij} has been processed on machine M_{kl}, and Q_{ijkl} denotes the number of operation O_{ij} which has been assigned to machine M_{kl}.

To route the shared operation O_{ij} of a garment to an appropriate sewing workstation, a heuristic operation routing rule was adopted. Its procedure is described as follows:

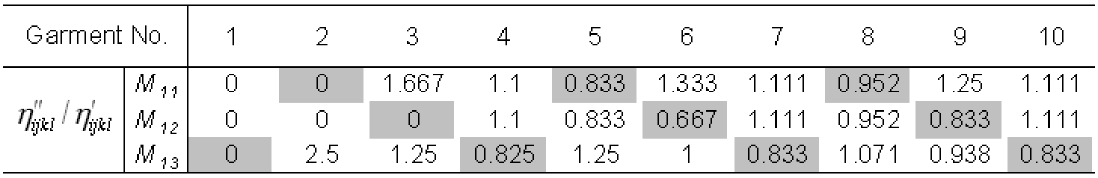
Step 1. Calculate $\rho''_{ijkl} = Q_{ijkl} / (\sum_{l=1}^{n} Q_{ijkl})$ for each sewing machine M_{kl} (for the first product, set ρ''_{ijkl}=0).

Step 2. Calculate $\rho''_{ijkl} / \rho'_{ijkl}$ for each machine M_{kl}.

Step 3. Assign operation O_{ij} of the current garment to the machine M_{kl} with the minimum $\rho''_{ijkl} / \rho'_{ijkl}$. If multiple machines have the same minimum value, one of these machines is selected randomly.

Table 6-1 shows an example of operation routing to process operation O_{11} of 10 garments. Operation O_{11} is assigned to machines M_{11}, M_{12} and M_{13}. The task proportions of operation O_{11} to be processed on these three machines are 0.3, 0.3 and 0.4 respectively generated by the proposed BiMGA. In Table 6-1, the rows of $\rho''_{ijkl}/\rho'_{ijkl}$ describe the current $\rho''_{ijkl}/\rho'_{ijkl}$ value of operation O_{11} of each garment on the relevant machine, and the shaded grid represents that the corresponding machine is selected to process the operation of the corresponding garment. According to the results of operation routing shown in Table 6-1, operation O_{11} of the first garment is assigned to M_{11}, that of the second garment is assigned to M_{13}. After the 10 garments are completed, the actual task proportion processed on each machine is equal to the optimized task proportion.

Table 6-1: Example of operation routing to process operation O_{11} of 10 garments



Garment No.		1	2	3	4	5	6	7	8	9	10
$\eta''_{ijkl} / \eta'_{ijkl}$	M_{11}	0	0	1.667	1.1	0.833	1.333	1.111	0.952	1.25	1.111
	M_{12}	0	0	0	1.1	0.833	0.667	1.111	0.952	0.833	1.111
	M_{13}	0	2.5	1.25	0.825	1.25	1	0.833	1.071	0.938	0.833

6.3 Experimental Results without Learning Effects

This section presents the validation of the effectiveness of the proposed optimization model, performance comparison between the proposed model and the industrial practice, and the analysis of the effects of different task proportion and operation routing on the AAL balancing performance. The learning factor was not considered and each operator's efficiency for different sewing operations kept unchanged during production.

6.3.1 Validation of the GA-Based Optimization Model

In order to evaluate the performance of the GA-based optimization model, a series of experiments were conducted. This section highlights four of these experiments in detail. The AAL consisted of eleven workstations with two types of machines, lockstitch sewing machine and overlock machine. The workstations of lockstitch sewing machines included eight workstations numbered as 1 to 8 and those of overlock machines included three workstations numbered 9 to 11.

In each experiment, two different apparel production orders were scheduled. Some basic data of these experiments are shown as follows.

Experiment 1: The desired cycle times of orders 1 and 2 were both 400 seconds. Each garment's assembly operations of order 1 included operations 1 to 7, and order 2 included operations 8 to 12.

Experiment 2: The desired cycle time of orders 1 and 2 were 55 and 130 seconds respectively. The garment's assembly operations of order 1 included operations 1 to 6, and order 2 included operations 7 to 11.

Experiment 3: The desired cycle time of two orders were both 50 seconds. The assembly operations of two orders were the same as those in experiment 2.

Experiment 4: The desired cycle times of orders 1 and 2 were 70 and 225 seconds respectively. The assembly operations of order 1 included operations 1 to 5, and order 2 included operations 6 to 10.

The operative efficiency of each workstation and the standard processing time of each operation in these experiments are shown in Table 6-2 to Table 6-5.

Table 6-2: Operative efficiency in workstations of experiment 1

Machine type	Workstation No.	Operation No. of order 1							Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10	11	12
Lockstitch sewing machine	1	90%	100%	95%	90%	0	0	100%	90%	0	100%	0	95%
	2	70%	75%	70%	70%	0	0	75%	80%	0	80%	0	70%
	3	80%	80%	80%	85%	0	0	80%	80%	0	75%	0	85%
	4	70%	70%	65%	60%	0	0	70%	70%	0	75%	0	65%
	5	80%	85%	75%	80%	0	0	85%	90%	0	95%	0	80%
	6	90%	90%	85%	90%	0	0	90%	90%	0	90%	0	95%
	7	95%	95%	100%	100%	0	0	95%	90%	0	85%	0	100%
	8	80%	75%	75%	75%	0	0	80%	85%	0	75%	0	80%
Overlock machine	9	0	0	0	0	100%	95%	0	0	100%	0	95%	0
	10	0	0	0	0	70%	80%	0	0	85%	0	75%	0
	11	0	0	0	0	90%	90%	0	0	90%	0	85%	0
Standard time (s/piece)		308	310	335	315	320	302	280	310	180	320	125	325

Table 6-3: Operative efficiency in workstations of experiment 2

Machine type	Workstation No.	Operation No. of order 1						Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10	11
Lockstitch sewing machine	1	90%	100%	95%	0	90%	100%	90%	0	100%	0	95%
	2	70%	75%	70%	0	70%	75%	80%	0	80%	0	70%
	3	80%	80%	80%	0	85%	80%	80%	0	75%	0	85%
	4	70%	70%	65%	0	60%	70%	70%	0	75%	0	65%
	5	80%	85%	75%	0	80%	85%	90%	0	95%	0	80%
	6	90%	90%	85%	0	90%	90%	90%	0	90%	0	95%
	7	95%	95%	100%	0	100%	95%	90%	0	85%	0	100%
	8	80%	75%	75%	0	75%	80%	85%	0	75%	0	80%
Overlock machine	9	0	0	0	100%	0	0	0	100%	0	95%	0
	10	0	0	0	70%	0	0	0	85%	0	75%	0
	11	0	0	0	90%	0	0	0	90%	0	85%	0
Standard time (s/piece)		25	36	30	75	45	54	125	58	132	65	120

Table 6-4: Operative efficiency in workstations of experiment 3

Machine type	Workstation No.	Operation No. of order 1						Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10	11
Lockstitch sewing machine	1	90%	100%	95%	0	90%	100%	90%	0	100%	0	95%
	2	70%	75%	70%	0	70%	75%	80%	0	80%	0	70%
	3	80%	80%	80%	0	85%	80%	80%	0	75%	0	85%
	4	70%	70%	65%	0	60%	70%	70%	0	75%	0	65%
	5	80%	85%	75%	0	80%	85%	90%	0	95%	0	80%
	6	90%	90%	85%	0	90%	90%	90%	0	90%	0	95%
	7	95%	95%	100%	0	100%	95%	90%	0	85%	0	100%
	8	80%	75%	75%	0	75%	80%	85%	0	75%	0	80%
Overlock machine	9	0	0	0	100%	0	0	0	100%	0	95%	0
	10	0	0	0	70%	0	0	0	85%	0	75%	0
	11	0	0	0	90%	0	0	0	90%	0	85%	0
Standard time (s/piece)		25	36	30	75	45	54	38	20	35	25	40

Table 6-5: Operative efficiency in workstations of experiment 4

Machine type	Workstation No.	Operation No. of order 1					Operation No. of order 2				
		1	2	3	4	5	6	7	8	9	10
Lockstitch sewing machine	1	90%	95%	0	100%	90%	90%	0	100%	0	95%
	2	70%	70%	0	70%	75%	80%	0	80%	0	70%
	3	80%	80%	0	85%	80%	80%	0	75%	0	85%
	4	65%	75%	0	70%	60%	75%	0	70%	0	65%
	5	80%	75%	0	85%	80%	90%	0	95%	0	80%
	6	85%	90%	0	90%	90%	90%	0	90%	0	95%
	7	100%	95%	0	95%	100%	85%	0	90%	0	100%
	8	80%	75%	0	80%	75%	80%	0	75%	0	85%
Overlock machine	9	0	0	95%	0	0	0	100%	0	100%	0
	10	0	0	75%	0	0	0	85%	0	70%	0
	11	0	0	85%	0	0	0	90%	0	90%	0
Standard time (s/piece)		20	75	52	30	90	180	160	408	240	205

In experiments 2-4, the number of sewing workstations was equal to or greater than the number of sewing operations. In order to evaluate the effect of work-sharing and workstation revisiting on the AAL balancing performance, different assignment strategies were implemented in different cases. In case 1, both work-sharing and workstation revisiting were allowed whereas neither was allowed in case 2 of experiments 2-3. In case 2 of experiment 4, only work-sharing was allowed.

The optimized operation assignments and line-balancing results of the four experiments generated by the proposed BiMGA are shown in Tables 6-6 and 6-7. In Table 6-6, the first column (Machine type) represents the sewing machine type; the second (Workstation No.) shows the workstation number, and other columns show the optimized operation assignment of different experiments to the workstation, in which the first value of each cell represents the operation number and the value in the bracket represents the task proportion ρ_{ijkl} of the operation being processed in the corresponding workstation. For instance, the value 12(1) in the column of 'Experiment 1' describes that workstation 1 processes all tasks of operation 12 (100%), and the value (7(0.67), 9(0.15)) in the column of 'Experiment 2' shows that workstation 2 processes 67% of the tasks of operation 2 and 15% of operation 9. In Table 6-7, the rows of 'Actual cycle time' show the optimized actual cycle time (seconds) of orders 1 and 2 in four experiments whereas the rows of 'Idle time' and 'Line efficiency' show the optimized average idle time (seconds) in each cycle and the optimized line efficiency of orders 1 and 2 in four experiments respectively. The line efficiency of order P_i was defined as the average processing time of workstations processing this order in each cycle divided by the actual cycle time of this order.

Table 6-6: Optimized operation assignment and task proportions of four experiments (without learning effect)

Machine type	Workstation No.	Experiment 1	Experiment 2		Experiment 3		Experiment 4	
			Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
Lockstitch sewing machine	1	12(1)	6(1)	9(1)	5(1)	1(1)	6(0.60), 10(0.45)	10(1)
	2	10(1)	7(0.67), 9(0.15)	6(1)	1(1), 6(0.15)	6(1)	1(0.87), 5(0.36)	4(1)
	3	2(1)	9(0.16), 11(0.49)	1(1)	9(1)	9(1)	6(0.40), 10(0.55)	1(1)
	4	7(1)	9(0.69)	5(1)	3(1)	5(1)	2(0.52), 4(0.42)	6(1)
	5	4(1)	3(0.05), 5(0.83)	3(1)	11(1)	11(1)	8(0.51)	8(1)
	6	3(1)	2(1), 5(0.17)	11(1)	7(1)	3(1)	1(0.13), 5(0.64)	2(1)
	7	8(1)	1(1), 3(0.95)	7(1)	6(0.85)	7(1)	8(0.49)	5(1)
	8	1(1)	7(0.33), 11(0.51)	2(1)	2(1)	2(1)	2(0.48), 4(0.58)	8(1)
Overlock machine	9	5(0.13), 6(1)	8(1), 10(1)	4(1)	4(0.64), 10(0.07)	4(1)	7(0.23), 9(0.67)	9(1)
	10	5(0.87)	4(0.5)	10(1)	4(0.36)	10(1)	3(1)	7(1)
	11	9(1), 11(1)	4(0.5)	8(1)	8(1), 10(0.93)	8(1)	7(0.77), 9(0.33)	3(1)

Table 6-7: Optimized AAL balancing results of four experiments (without learning effect)

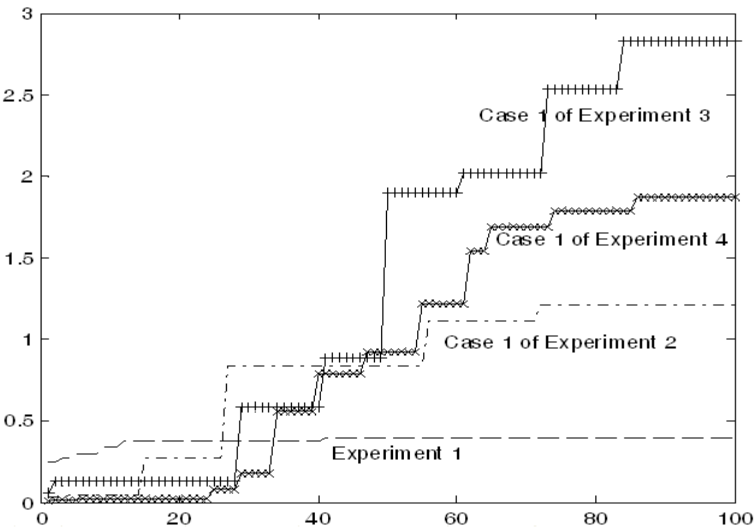
		Experiment 1	Experiment 2		Experiment 3		Experiment 4	
		Case 1	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
Actual cycle time	Order 1	400	54.82	75	50	75	70	90
	Order 2	400	129.44	138.89	50	50	224.89	240
Idle time	Order 1	82.42	27.65	108.75	22.6	116.93	5.8	147.63
	Order 2	166.39	47.52	146.13	11.69	55.56	46.59	75.98
Line efficiency	Order 1	97.06%	91.59%	75.83%	93.54%	74.02%	98.34%	67.19%
	Order 2	89.60%	92.66%	78.96%	95.32%	77.78%	96.60%	94.72%

As shown in Table 6-6, the proposed genetic optimization algorithm could implement flexible operation assignment when considering both work-sharing and workstation revisiting. For instance, in case 1 of experiment 2, the processing of operation 9 was shared by workstations 2, 3 and 4 wheareas workstation revisiting occurred in workstation 2. In the optimized operation assignment of case 1 of experiment 4, parallel workstations existed, which processed the same operation set, such as workstations 1 and 3, workstations 2 and 6, and workstations 4 and 8. It indicates that the proposed algorithm can also handle the ALB problem with parallel workstations.

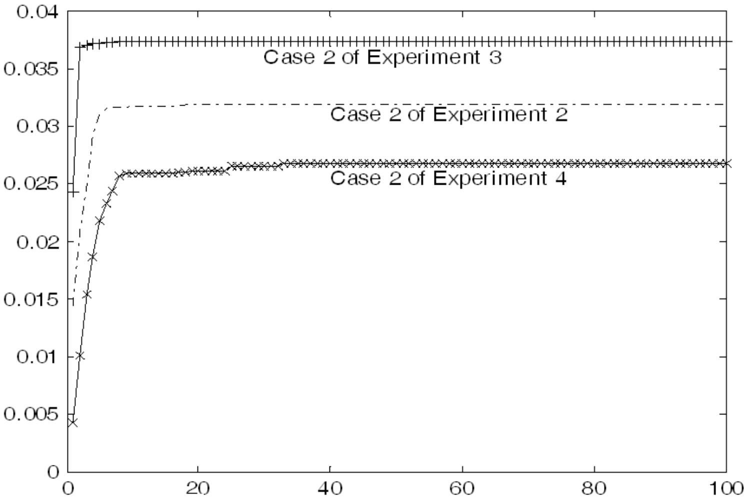
As shown in Table 6-7, the desired cycle time of orders 1 and 2 were achieved in case 1 of experiments 1 and 3, and the actual cycle time of two orders were very close to the desired cycle time in case 1 of experiments 2 and 4. These results show that the proposed BiMGA can solve the AAL balancing problem effectively.

In case 2 of experiments 2, 3 and 4, the actual cycle time went beyond the desired cycle time; the other two performances were inferior to the corresponding performances in case 1. Obviously, the work-sharing can improve the performance of the assembly line.

In the optimization processes of these experiments, the evolutionary trajectories of the maximum value of fitness over generations are shown in Figure 6-4. The optimized results in this chapter were obtained based on the settings: the population sizes of MGA-1 and MGA-2 were 200 and 100 respectively, the maximum numbers of generations of MGA-1 and MGA-2 were 100 and 50 respectively, the penalty weights ω_i and ξ_i of each order were 10 and 100, and the relative weights w_Z and w_{IT} were both set as 1. The probabilities of crossover and mutation were also adjusted according to the fitness values of the population based on the method developed by Syswerda (1991).



(a) Experiment 1 and case 1 of experiments 2-4



(b) Case 2 of experiments 2-4

Figure 6-4: Trends of chromosome fitness

6.3.2 Comparison Between the GA-Based Optimization Model and Industrial Practice

In industrial practice, the shop floor manager usually balances the assembly line using precedence diagrams and trial-and-error methods (Bhattacharjee and Sahu 1987). Considering case 1 of 4 experiments in section 6.3.1, their line balancing results in terms of the practical method are shown in the rows of 'Industrial results' of Table 6-8. The due dates of most orders could not be satisfied and a large number of earliness and tardiness penalties occurred. The results were inferior to the optimized results shown in section 6.3.1.

Table 6-8: Results of line balancing in sections 6.3.2 to 6.3.4

	Experiment	Actual Cycle		Idle Time		Line Efficiency	
	No.	Order 1	Order 2	Order 1	Order 2	Order 1	Order 2
Industrial results	1	400	387.5	106.58	132.35	96.19%	91.46%
	2	56.43	132.6	48.54	9.94	87.71%	98.13%
	3	54	50	48.89	14.8	87.07%	92.60%
	4	69.33	291.43	10.42	367.46	96.99%	78.98%
Same task proportion	1	400	400	183.62	166.39	93.44%	89.60%
	2	54	138.95	45.95	25.22	87.84%	95.46%
	3	54	48.33	45.79	16.33	97.89%	93.24%
	4	90	241.18	141.86	133.91	68.47%	90.75%
ORR2	1	449.71	747.15	430.37	1555	86.33%	47.97%
	2	111.72	425.24	369.05	1526.5	44.94%	28.20%
	3	111.13	94.7	450.49	235.19	42.09%	50.33%
	4	267.95	1160.8	995.56	5661.4	25.69%	18.71%

6.3.3 Effect of Task Proportion on AAL Balancing Performance

It is assumed in the existing literature that the task proportions of the shared operation are the same in the workstations processing the operation. For instance, if one operation is assigned to 4 workstations, the task proportion in each workstation should be 0.25. The optimized balancing results of case 1 of the above 4 experiments are shown in the rows of ‘Same task proportion’ of Table 6-8. These results were inferior to those of section 6.3.1. That is because this assumption restricts the flexibility of operation assignment and shrinks the search space of the possible ALB solutions.

6.3.4 Effect of Operation Routing on AAL Balancing Performance

The previous studies on ALB only focused on operation assignment and did not pay attention to operation routing based on the optimized operation assignment. However, different operation routing rules can generate different balancing performances. The operation routing in case 1 of the above 4 experiments was done based on the same operation assignment described in section 6.3.1 and the following routing rule (ORR2).

ORR2: OS_i denotes the order size of order P_i in this research. Operation O_{ij} of $\rho'_{ijkl} \cdot OS_i$ products should be processed on machine M_{k1}. Assign the first $\rho'_{ijk1} \cdot OS_i$ ones to machine M_{k1}, then $\rho'_{ijk2} \cdot OS_i$ ones to machine M_{k2} ,…, and the last $\rho'_{ijkn} \cdot OS_i$ ones to machine M_{kn}.

Assuming that OS_i is equal to 3000, the final balancing results are shown in the rows of 'ORR2' of Table 6-8. The actual cycle time was much greater than the desired cycle time and the line efficiencies were comparatively low. These results indicate that the effectiveness and efficiency of an operation routing rule have great impact on the performance of AAL balancing.

6.4 AAL Balancing with Learning Effects

6.4.1 Learning Curve-Based Operative Efficiency

When learning phenomenon is considered, the operative efficiency of an operator to perform an identical operation of different garments can be different. In this research, the operative efficiency is described by the time-constant learning curve model (Bevis 1970; Hitchings 1972), which is defined by the following equation:

$$E_L(t_L) = E_b + E_\Delta(1 - e^{-t_L/\tau_L}) \qquad (6\text{-}10)$$

where $E_L(t_L)$ is the predicted operative efficiency at time t_L of the learning period, E_b is the initial efficiency of the operator, E_Δ is the improvement in performance due to learning, and τ_L is the model time constant of the learning period, which is a measure of how quickly the performance improvement is achieved.

This research assumes that the ultimate efficiency of each operator is 100%. That is, $E_L(t_L)=1$ at $t_L \rightarrow \infty$. $E_\Delta=1-E_b$. Figure 6-5 shows the changing trends of two learning curves with different E_b and τ_L.

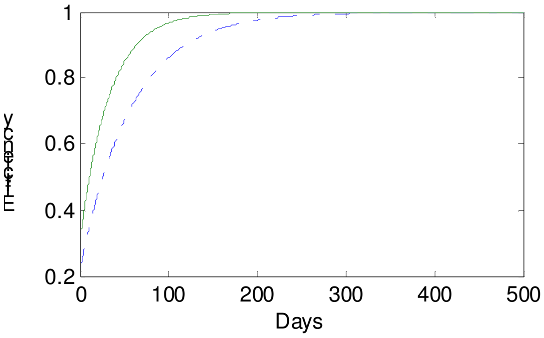


Figure 6-5: Learning curves with different E_b and τ_L

'-', E_b=31%, τ_L=33 days; '-.', E_b=22%, τ_L=58 days

6.4.2 Computation of Fitness Function Under Learning Effects

Without the learning effect, the operative efficiency of each sewing operator kept unchanged in production. For one production order, the process to produce the same operation of different garments was the same. Therefore, the fitness of MGA-1 and MGA-2 could be calculated by considering the production process of one garment. However, if the learning effect is considered, the production process of each garment of one order is different. To calculate the fitness of MGA-1 and MGA-2, the production of all garments of each order must be simulated completely.

Suppose that the number of assembly operations is V_i and the chromosomes in MGA-1 and MGA-2 are given. On the basis of chromosomes of MGA-1 and MGA-2, when the learning effect is considered, the procedure to calculate fitness is described in detail as follows.

Step 1. Parameter initialization: order index i equals 1, operator's accumulated operating time $AccT_2$ on the current day equals 0.

Step 2. Parameter initialization: For order P_i, initialize garment/product index u=1, operation index v=1, production days $iDays$=0.

Step 3. Select an operator (operator w) to process operation v of the uth garment according to the operator's task proportion assigned and the corresponding assignment rule.

Step 4. Calculate operating time of operator w for processing operation v of the current garment; calculate the operator's accumulated operating time $AccT_1$ for processing operation v; calculate the operator's accumulated operating time $AccT_2$ on the current day.

Step 5. If $AccT_2 > 8 \times 3600$ (working time in second unit per day), let $iDays = iDays + 1$, $AccT_2$=0.

Step 6. $v = v + 1$. If $v > V_i$, go to step 7; otherwise, go to step 3.

Step 7. $u = u + 1$. If $u > OS_i$, go to step 8; otherwise v=1, and go to step 2.

Step 8. Calculate the actual cycle time and the idle time of workstations processing order P_i on the basis of the accumulated operating time $AccT_1$ of each operation.

Step 9. $i = i + 1$. If i is greater than the number of orders, i.e., $i > m$, go to step 10; otherwise, go to step 1.

Step 10. Calculate the fitness on the basis of the actual cycle time of all orders and the total idle time of all workstations.

6.4.3 Experimental Results with Learning Effects

This section presents the experimental results with the learning phenomenon being considered. The basic data of experiments were the same as those of the experiments described in section 6.3.1, which are shown in Table 6-2 to Table 6-5. Yet the operative efficiency of each operator was variable because of the learning effect described in section 6.4.1. To investigate the influence of efficiency increase on production decision, the production of different quantities of products based on two different cases will be conducted respectively in each experiment. In case 1, 1000 garments are produced while 5000 garments are produced in case 2.

Assume that each operator has a same learning curve for different operations. That is, whichever operation is processed, the learning curve of the operator is identical. The parameters of the learning curve of each operator are shown in Table 6-9.

Table 6-9: Parameters of learning curve of each operator

Workstation No.	1	2	3	4	5	6	7	8	9	10	11
E_b	22%	31%	44%	20%	24%	26%	26%	38%	28%	26%	32%
τ_L (day)	58	33	46	42	56	52	41	26	54	41	28

The optimized production control results of the four experiments generated by the proposed methodology are shown in Tables 6-10 and 6-11. The structures of the two tables are, respectively, the same as those of Tables 6-6 and 6-7.

Table 6-10: Optimized operation assignment and task proportions of four experiments (with learning effects)

Machine type	Work-station No.	Experiment 1		Experiment 2		Experiment 3		Experiment 4	
		Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
Lockstitch sewing machine	1	12(1)	3(1)	6(1)	6(1)	7(1)	7(1)	6(0.52), 10(0.52)	6(0.55), 10(0.53)
	2	10(1)	2(1)	7(0.67), 9(0.15)	9(0.65)	1(1), 6(0.19)	1(1), 6(0.21)	1(0.47), 5(0.47)	6(0.45), 10(0.47)
	3	2(1)	8(1)	9(0.16), 11(0.49)	9(0.35), 11(0.49)	9(1)	9(1)	6(0.48), 10(0.48)	1(0.51), 5(0.51)
	4	7(1)	7(1)	9(0.69)	7(0.64)	3(1)	3(1)	2(0.49), 4(0.49)	2(0.49), 4(0.50)
	5	4(1)	12(1)	3(0.05), 5(0.83)	7(0.36), 11(0.51)	11(1)	11(1)	8(0.51)	8(0.52)
	6	3(1)	4(1)	2(1), 5(0.17)	2(1), 5(0.3)	5(1)	5(1)	1(0.53), 5(0.53)	1(0.49), 5(0.49)
	7	8(1)	1(1)	1(1), 3(0.95)	3(0.51), 5(0.7)	6(0.81)	6(0.79)	8(0.49)	8(0.48)
	8	1(1)	10(1)	7(0.33), 11(0.51)	1(1), 3(0.49)	2(1)	2(1)	2(0.51), 4(0.51)	2(0.51), 4(0.50)
Overlock machine	9	5(0.13), 6(1)	5(0.07), 6(1)	8(1), 10(1)	8(1), 10(1)	4(0.54), 10(0.36)	4(0.52), 10(0.41)	7(0.24), 9(0.66)	7(0.50), 9(0.50)
	10	5(0.87)	5(0.93)	4(0.5)	4(0.51)	4(0.46)	4(0.48)	3(1)	3(1)
	11	9(1), 11(1)	9(1), 11(1)	4(0.5)	4(0.49)	8(1), 10(0.64)	8(1), 10(0.59)	7(0.76), 9(0.34)	7(0.50), 9(0.50)

Table 6-11: Optimized AAL balancing results of four experiments (with learning effects)

		Experiment 1		Experiment 2		Experiment 3		Experiment 4	
		Case 1	Case 2	Case 1	Case 2	Case 1	Case 2	Case 1	Case 2
Actual cycle time	Order 1	399.3	391.99	54.94	54.74	49.99	49.94	69.99	69.66
	Order 2	395.74	392.52	129.94	129.22	49.99	49.94	224.98	224.96
Idle time	Order 1	271.58	343.53	28.47	28.82	12.97	15.91	6.58	12.33
	Order 2	74.02	149.64	49.51	65.44	20.56	23.54	49.78	44.77
Line efficiency	Order 1	90.28%	87.48%	91.36%	91.23%	96.29%	95.45%	98.12%	96.46%
	Order 2	95.32%	90.47%	92.38%	89.87%	91.77%	90.57%	96.31%	96.68%

As shown in Table 6-10, the operation assignments were quite different in different cases of each experiment because different product quantities were processed. Moreover, as shown in Table 6-11, the actual cycle time of two orders was very close to the desired cycle time in the cases of each experiment and the line efficiency was also very good, which was between

87.48 % and 98.12%. For instance, for case 1 of experiment 4, the actual cycle times of orders 1 and 2 were 69.99 and 224.98 respectively, that is, their percentage errors were 0.014% and 0.009% respectively. For order 1, the total idle time of all workstations in each cycle was 6.58, which was 9.4% less than its cycle time. It means that the production flow of this order was very smooth. This shows that the proposed methodology can solve the AAL balancing problem with learning effects effectively.

Table 6-11 also shows that the actual cycle time of each order in case 2 is less than that in case 1. The operative efficiency of operators increased with the increase of their accumulated operating time. Therefore, more operating time was accumulated in case 2 and this led to higher operative efficiency and lower cycle time.

6.4.4 Influence of Different Initial Operative Efficiencies

To consider the influences of different initial operative efficiencies, cases 3 to 5 were processed. The data of the three cases were the same as those of case 2 of experiment 1 except operative efficiencies of each operator. In cases 3-5, the initial operative efficiencies of each operator were 90%, 80%, and 70% of the efficiencies shown in Table 6-2. Tables 6-12 and 6-13 show the optimized operation assignment and balancing results of the three cases. Although the initial operative efficiencies were quite different, the optimized AAL balancing results in cases 3 and 4 were still very good, in which the desired cycle time were met well and the line efficiencies were all greater than 94%. As to case 5, the actual production cycle of order 1 lagged behind the desired cycle because the initial efficiencies were too low to reach the desired production performance. Yet the generated idle time and line efficiencies were still quite good. These results also show the effectiveness of the proposed methodology.

Table 6-12: Optimized operation assignment and task proportions (Additional cases of experiment 1)

Machine type		Lockstitch sewing machine								Overlock machine		
Workstation No.		1	2	3	4	5	6	7	8	9	10	11
Operation Assignment of Experiment 1	Case 3	8(1)	3(0.49), 7(0.46)	10(1)	1(0.26), 4(0.66)	12(1)	3(0.51), 7(0.54)	2(1)	1(0.74), 4(0.34)	5(0.52), 6(0.52)	5(0.48), 6(0.48)	9(1), 11(1)
	Case 4	3(1)	12(1)	8(1)	2(1)	4(1)	1(0.5), 10(0.5)	7(1)	1(0.5), 10(0.5)	5(1), 6(0.07)	6(0.93)	9(1), 11(1)
	Case 5	8(1)	1(0.77), 4(0.18)	3(0.81), 7(0.09)	2(1)	10(1)	12(1)	1(0.23), 4(0.82)	3(0.19), 7(0.91)	5(0.85), 6(0.18)	5(0.15), 6(0.82)	9(1), 11(1)

Table 6-13: Optimized AAL balancing results (Additional cases of experiment 1)

		Actual cycle time		Idle time		Line efficiency	
		Order 1	Order 2	Order 1	Order 2	Order 1	Order 2
Experiment 1	Case 3	399.49	388.17	164.71	77.85	94.11%	94.99%
	Case 4	398.70	398.70	154.82	48.97	95.15%	97.54%
	Case 5	411.19	399.19	30.90	17.14	99.41%	99.14%

6.5 Summary

In this chapter, the AAL balancing problem is investigated at the assembly line level. The mathematical model for the problem with work-sharing and workstation revisiting was proposed. The proposed model not only meets the desired cycle time of each order, but also minimizes the total idle time of all workstations on the AAL. These objectives are particularly useful to help sewing assembly lines to meet the due dates, and improve the efficiency of the assembly lines by optimizing the use of the limited resources.

A GA-based optimization model was developed to deal with the proposed AAL balancing problem, in which a BiMGA and a heuristic operation routing rule were presented.

The BiMGA generates the optimal operation assignment to workstations and the task proportions of each shared operation being processed in different workstations. In the BiMGA, the fitness-based scanning crossover and the inversion mutation were modified to suit the representation of the flexible operation assignment. The shared operation of each product was routed to an appropriate workstation by the proposed operation routing rule when it needed to be processed. Variable operative efficiency of sewing operators was also considered in AAL balancing. The learning curve theory was used to describe the change of operative efficiency. A heuristic procedure was also presented to calculate the fitness function of the BiMGA.

Experiments were conducted to validate the proposed optimization model based on production data from the real-life PBS. On the basis of different production tasks and production situations, different operation assignments and task proportions were generated. Whichever production tasks and production situations are considered, the optimized AAL balancing solution can meet the production objectives well. That shows the effectiveness of the proposed methodology. On the basis of the same production task, the generated production decisions with learning effects are different from those without learning effects owing to the increase of operative efficiency. Since the production decision without considering learning effects cannot be carried out in production practice, learning effects must be considered in both theory and practice.

This chapter also shows that a GA with multi-parent crossover can be used in tackling the operation assignment of the ALB problem. Since the AAL investigated not only processes two or more types of production orders simultaneously, but also two or more orders separately in batches, that is, the AAL has the feature of multi-model and the mixed-model assembly lines, the proposed optimization model can be extended easily to solve the balancing problem of the multi-model assembly line or the mixed-model assembly line.

Chapter 7

Conclusion and Future Work

This chapter starts with the conclusion of this research and presents contributions and limitations of this research as well as suggestions for future work.

7.1 Conclusion

The purpose of this research is to investigate and develop effective intelligent methodologies for production control decision-making in apparel manufacturing.

An RFID-based IPCDM framework for apparel manufacturing was proposed. Under this framework, an RFID-based data capture system was adopted to collect real-time operation processing records and production data from the AAL, and an IPCDM model was developed to generate effective solutions for production control in apparel manufacturing based on various collected real-time production data. Three different decision-making processes were integrated into the IPCDM model to investigate respectively order scheduling at the factory level, AAL scheduling at the shop floor level and AAL balancing at the assembly line level. The three decision-making problems at different management levels were investigated deeply in this research.

The order scheduling problem at the factory level was first investigated and the processes of each apparel production order were assigned to appropriate assembly lines. Various uncertainties, including uncertain processing time, uncertain orders and uncertain arrival time, were considered and described as random variables. The mathematical model for this problem was presented with the objectives of meeting the due date of each order and minimizing the expected value of the total throughput time of all orders. Since the time of production process is uncertain probabilistically, the completion time of each production order is also uncertain. It is difficult to evaluate directly if the due dates are met. In this research, the total satisfactory level was presented to evaluate the level (grade) of all orders to meet their due dates. To solve the order scheduling problem, uncertain completion time of one production process and beginning time of its next process were derived firstly by using the probability theory. A genetic optimization model, in which the representation with variable lengths of sub-chromosomes was presented, was developed to seek the optimal order scheduling solution. Experiments were conducted to validate the proposed algorithm by using industrial data from PBS.

The AAL scheduling problem at the shop floor level was investigated. The mathematical model for this problem was presented with the objectives of minimizing the E/T penalties and maximizing the smoothness of the production flow of the AAL. A bi-level genetic optimization model (BiGA) was developed to solve the AAL scheduling problem with two orders by determining the beginning time of each order and the assignment of sewing operations of each order to workstations. The BiGA comprises two genetic optimization processes on different levels, where the second-level GA (GA-2) was nested in the first-level GA (GA-1). GA-1 generated the optimal operation assignment of each order while GA-2 determined the optimal beginning time of each order on the basis of the operation assignment from GA-1. In GA-1, a novel chromosome representation was proposed to deal with flexible operation assignment in PBS including not only assigning one operation to multiple machines but also assigning multiple operations to one machine. On the basis of this representation, a heuristic initialization process and modified genetic operators were also developed. The proposed BiGA was evaluated by some numerical experiments.

Lastly, the AAL balancing problem at the assembly line level was investigated, which aimed at meeting the desired cycle time of each order and minimizing the total idle time of all sewing workstations by assigning and routing the operation of each garment to the appropriate sewing workstation. In terms of the addressed AAL balancing problem, the operation assignment was characterized by work-sharing and workstation revisiting; the deterministic operative efficiency and the variable operative efficiency were considered respectively. The change of operative efficiency was described by the time-constant learning curve. To solve this problem, a GA-based optimization model was developed, in which a BiMGA and a heuristic operation routing rule were presented. Two multi-parent crossover operators were used in the BiMGA, which had a very similar structure to that of a BiGA. In the MBiGA, MGA-1 generated the optimal operation assignment to workstations, in which the representation was the same to that of GA-1 of the BiGA. Based on each chromosome of MGA-1, the real-coded MGA-2 determined the task proportions (weights) of the shared operation being processed in different workstations. In terms of the generated operation assignment and task proportions, the shared operation of each garment was routed to an appropriate workstation by the proposed operation routing rule. Production data from the real-life AAL were collected to validate the proposed optimization model.

7.2 Contributions of this Research

7.2.1 Contributions to Production Control Decision-Making Architecture

In the proposed IPCDM architecture, the RFID-based data capture system and the IPCDM model were integrated to implement real-time and intelligent production control decision-making. This architecture was the first intelligent and real-time production control decision-making architecture for apparel manufacturing. It can overcome the drawbacks of the current production control decision-making processes in apparel manufacturing because the current process is based mainly on inconsistent, subjective, ad hoc and unorganized assessment. On the basis of the proposed architecture, the production control decision-making processes at different management levels can be integrated in a systematic and effective manner.

7.2.2 Contributions to Production Control Issues

Due to the features of multiple production processes and multiple assembly lines in apparel manufacturing, efficient order scheduling at the factory level is imperative to successful production control. The investigation into this problem is the first attempt in the field of production control and decision-making research. The three investigated production control problems are very close to reality. Some real-world production characteristics are considered in this research, such as multiple uncertainties in order scheduling, flexible operation assignment and order preemption in AAL scheduling, work-sharing, workstation revisiting, and variable operative efficiencies in AAL balancing. These considerations are necessary and have significant impact on the solutions to apparel production control problems. These objectives discussed in this research are particularly useful to help apparel factories to meet the due date and improve the efficiency of the assembly system. Obviously, these objectives are also probably pursued and these characteristics also occur in the production environments of other industries. The investigated problems in this research can be extended to the production control problems of other industries. For example, since the AAL investigated contains the feature of multi-model or mixed-model assembly lines, the optimization model proposed in Chapter 6 can be extended to solve the balancing problem of the multi-model assembly line or the mixed-model assembly line.

7.2.3 Contributions to Production Control Decision-Making Methodology

In this research, several IPCDM methodologies were developed to deal with the production control decision-making problems considering real-world features closer to reality. Experimental results showed the effectiveness of the proposed methodologies. Owing to the capacity of global optimization of GA, the proposed methodologies are able to obtain acceptable ‘near optimal’ solutions even though they cannot always guarantee optimal solutions.

Of the proposed methodologies, GAs are the most important parts determining the optimization performances of these methodologies. In this research, some effective modifications on GA were made on the basis of different production control decision-making problems. A novel representation was presented to deal with flexible operation assignment in PBS and a process order-based representation with variable lengths of sub-chromosomes was presented to assign effectively apparel production processes of each order to different assembly lines. The multi-parent crossover was used successfully in solving the AAL balancing problem and it shows that the GA with multi-parent crossover can be used to tackle assignment and sequence problems in industrial engineering.

7.3 Limitations of this Research and Suggestions for Future Work

While this research facilitates the development of IPCDM for apparel manufacturing, limitations of this research exist and there is a great deal of work left to be done.

In solving the order scheduling problem at the factory level, it was assumed that each production process could only be assigned to one assembly line for processing and the production of each process could not be preempted. However, in real-world apparel production, the production processes of an apparel order are probably done on multiple assembly lines if the size of the order is large. In addition, the production of a rush order can interrupt the current production process. How should these problems be tackled? This research defined equation (4-6) as the probability density function of the processing time of the production process, but the probability density function of the uncertain processing time can be other mathematical expressions. Which probability density function can describe the uncertain processing time better? Answers to these questions are left to future research.

It has been shown that the BiGA can solve the AAL scheduling problem with two orders effectively. It is possible that there are more than two orders processed simultaneously on an AAL in real-world apparel production. With the increase in the number of orders processed simultaneously, the number of scheduling modes and scheduling statuses on the AAL will increase greatly. The length of the chromosome in GA-1 will thus increase greatly and therefore it is too difficult and time-consuming to generate optimal or near-optimal scheduling decision-making. Exploring effective methodology for addressing AAL scheduling with more production orders is necessary.

In AAL balancing, the variety of operative efficiency was considered on the basis of the learning curve theory. However, the change of operative efficiency can also be influenced by some other factors, such as forgetting, re-learning, and status of the sewing machine and the operator. Though it was shown that the multi-parent GA can be used for solving the AAL balancing problem, the performance of the multi-parent GA have not been compared with that of the 2-parent GA. These problems will be taken into consideration in future research.

The uncertainties of AAL scheduling and balancing, such as uncertain production orders, operative efficiencies of operators, machine breakdown, operator absenteeism and shortage of materials, were not considered in this research. These uncertain factors often occur in real-world production and can have great influence on the performance of the production system. Future research should investigate the effects of these factors on production control decision-making on the AAL.

In this research, several GA-based methodologies were proposed to solve the order scheduling problems at the factory level, AAL scheduling problems at the shop floor level and AAL balancing problems at the assembly line level. Although these GA-based methodologies were proved to be effective, the optimization performances of these methodologies have various limitations due to some inherent characters of GA. For example, the genes from the few comparatively highly fit (but not optimal) individuals might rapidly come to dominate the population, causing it to converge at a local maximum. Once the population converged, the ability of the GA to continue to search for better solutions was almost eliminated. Crossover of almost identical chromosomes produces almost nothing new. Only mutation remains an entirely new ground for exploration. Some heuristic search techniques such as simulated annealing, particle swarm optimization and ant colony optimization can be used to improve the convergence speed and global optimization ability of GA. Future research should focus on the combination of GA and other heuristic research techniques and compare the performances of combined algorithms and the proposed methodologies in this research.

Lastly, in this research, it was assumed that the production data collected by the RFID-based data capture system were accurate. The proposed methodology provided effective production control decision-making on the basis of these accurate and real-time production data. However, in real-life production environment, incomplete or wrong data occur inevitably due to various factors. For example, if the sewing operator forgets to sweep (read) the RFID tag corresponding to his/her working records during production, it will lead to missing and absence of working records. If the sewing operator does not sweep the RFID tag at right time, for example, before and after processing an operation, the collected data will not be captured on real-time basis. Moreover, some given data can also be inaccurate due to input error by manual effort. It is undoubtedly that the inaccurate data will cause negative effects on the precision and accuracy of production control decision-making. However, this research has not considered these effects. What effects will be caused if incomplete or wrong data occur? Are the solutions generated by the proposed algorithms still effective for the real-life apparel production control? These problems need to be investigated further. Further research should focus on seeking effective data filtering mechanism to filter the incomplete and wrong data, analyzing the fault tolerance of the proposed methodology and exploring intelligent methodologies with high fault tolerance.

7.4 Related Publications

The author demonstrated the originality of this research through the following publications.

Refereed Journal Paper

Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2006). "Mathematical model and genetic optimization for the job shop scheduling problem in a mixed- and multi-product assembly environment: A case study based on the apparel industry". Computers & Industrial Engineering 50(3), 202-219.

Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2008). "A genetic-algorithm-based optimization model for scheduling flexible assembly lines." International Journal of Advanced Manufacturing Technology 36(1-2):156-168.

Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2008). "A genetic algorithm based optimization model for solving the flexible assembly line balancing problem with work-sharing and workstation revisiting." IEEE Transactions on Systems Man and Cybernetics Part C - Applications and Reviews 38(2):218-228.

Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2007). "Genetic optimization of order scheduling with multiple uncertainties." Expert Systems with Applications (Accepted and publication is pending).

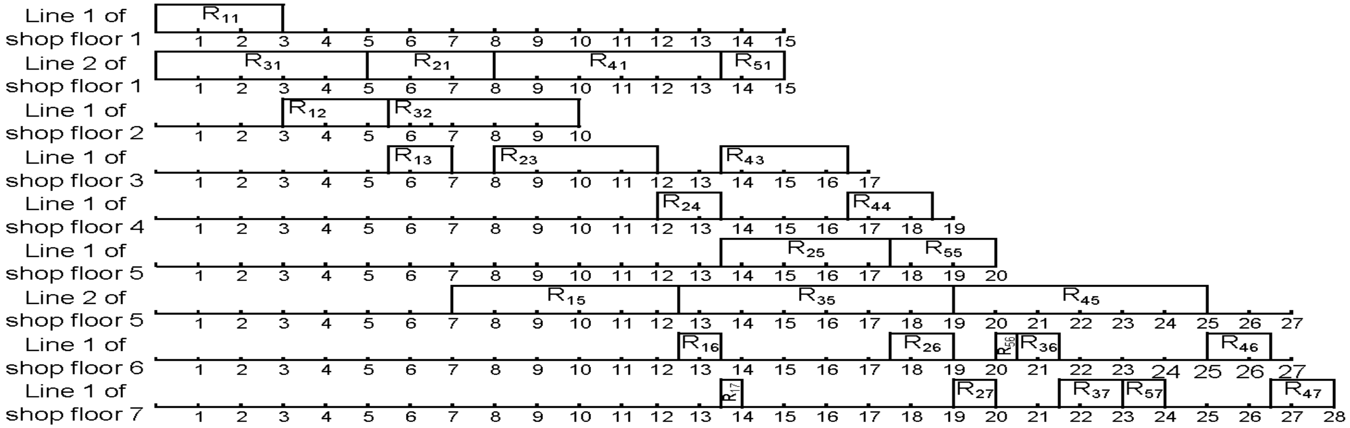
Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2007). "Intelligent production control decision support system for flexible assembly lines." submitted to Expert Systems with Applications (Accepted and publication is pending).

Conference Paper

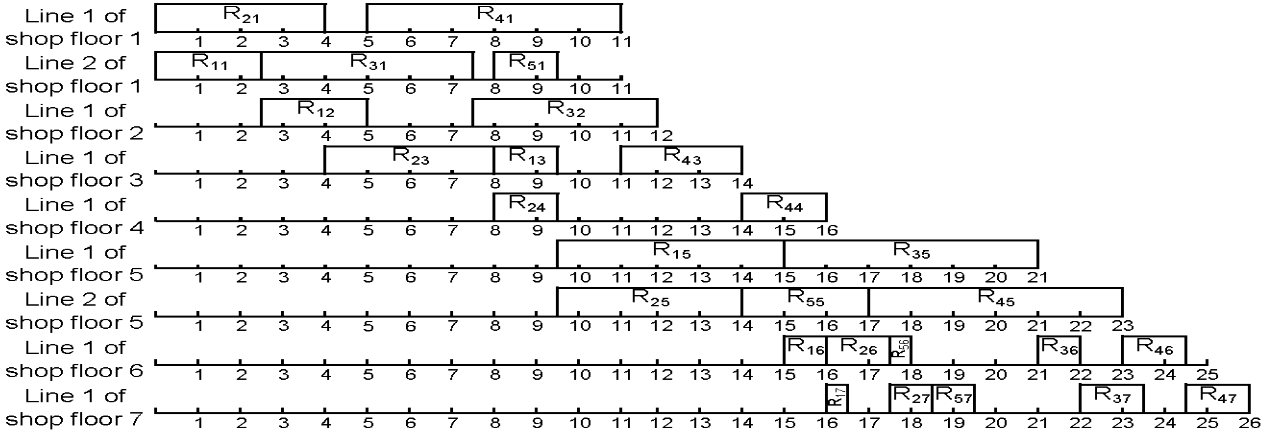
Guo, Z.X., W.K. Wong, S.Y.S. Leung, J.T. Fan, and S.F. Chan (2006). "A bi-level genetic algorithm for multi-objective scheduling of multi- and mixed-model apparel assembly lines." In Sattar, A. and Kang, B.H. (eds), Proceedings of 19th Australian Joint Conference on Artificial Intelligence, Lectures Notes in Artificial Intelligence 4304: 934-941.

Appendix

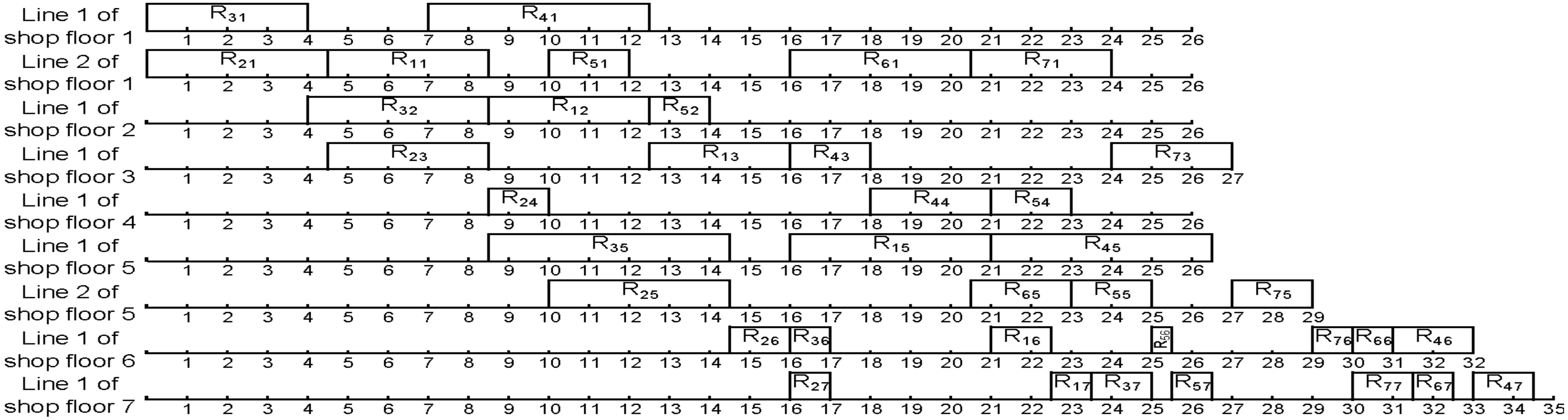
Gantt charts for Case 2 of Experiment 1 (Proposed method)



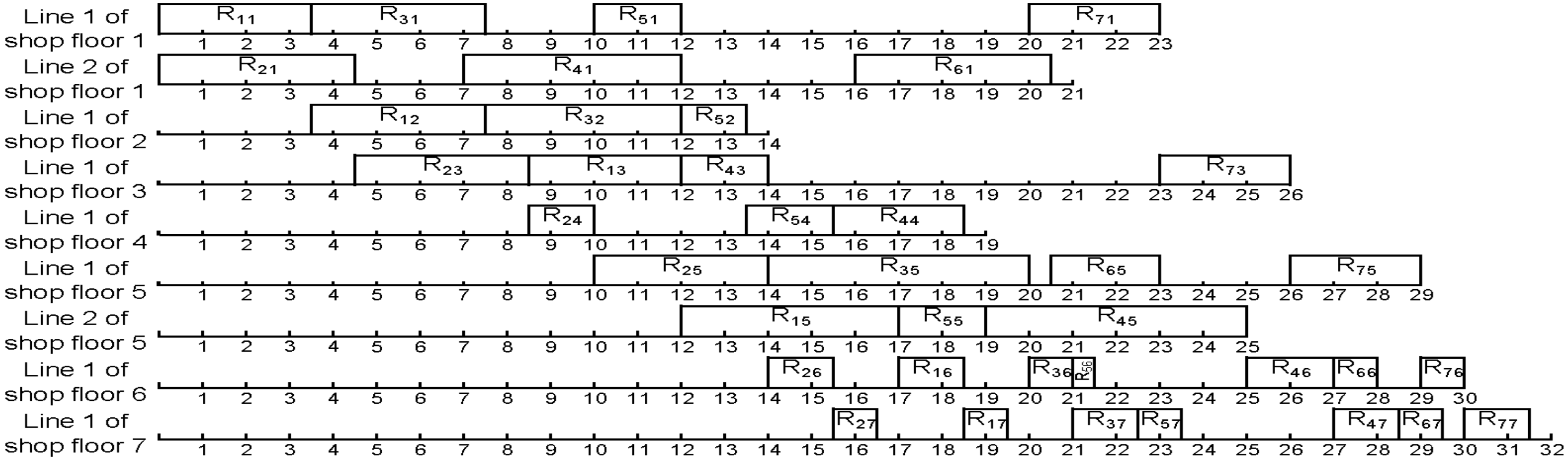
Gantt charts for Case 2 of Experiment 1 (Practical method)



Gantt charts for Case 3 of Experiment 1 (Proposed method)



Gantt charts for Case 3 of Experiment 1 (Practical method)



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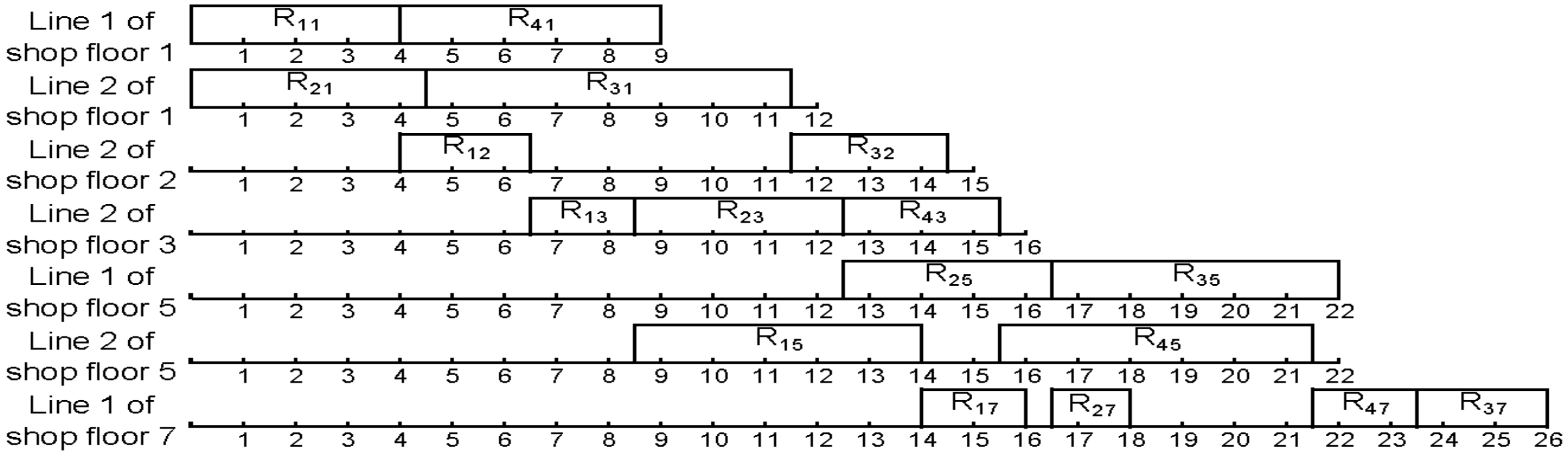

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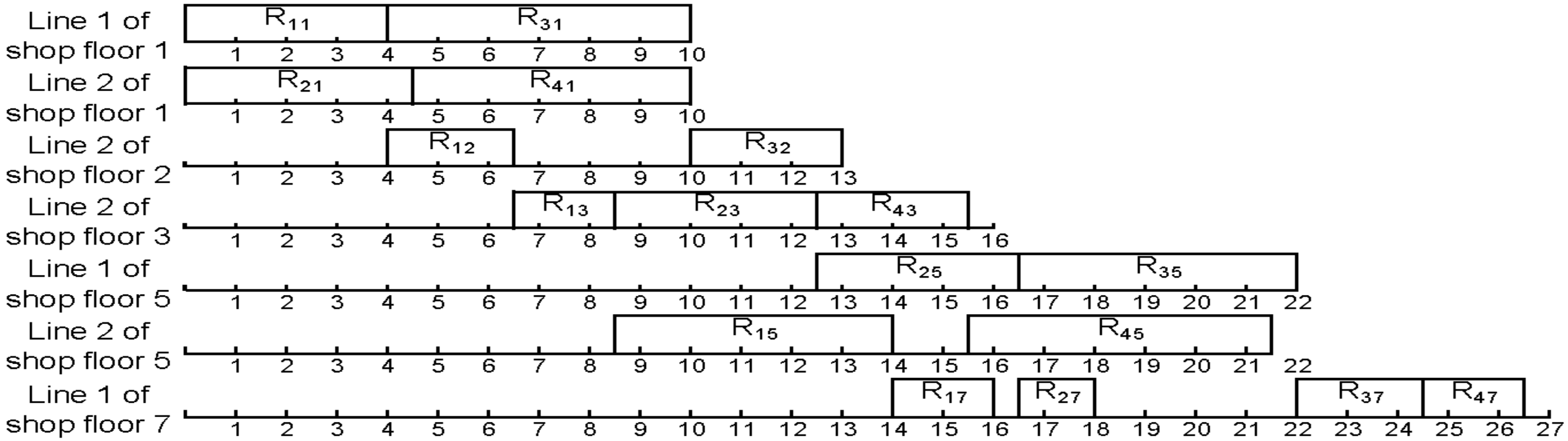

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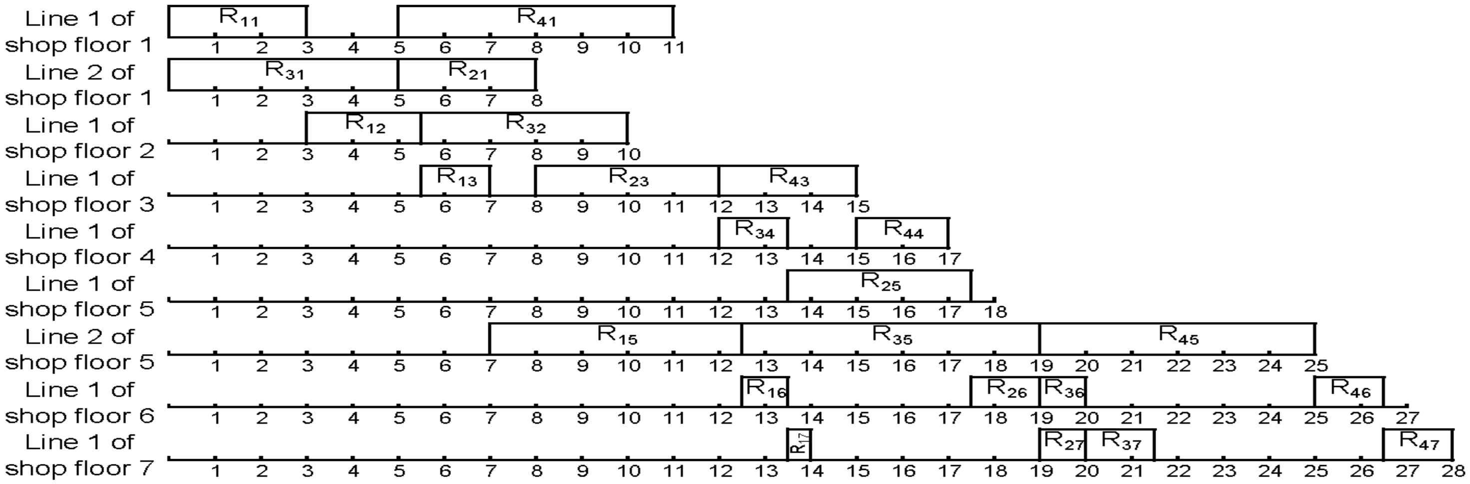

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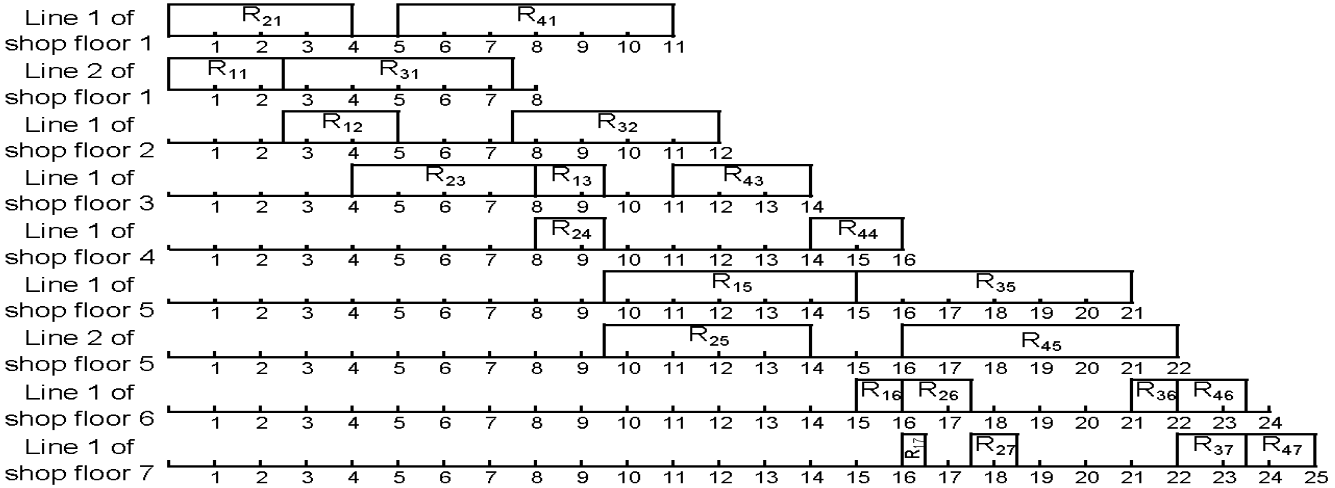
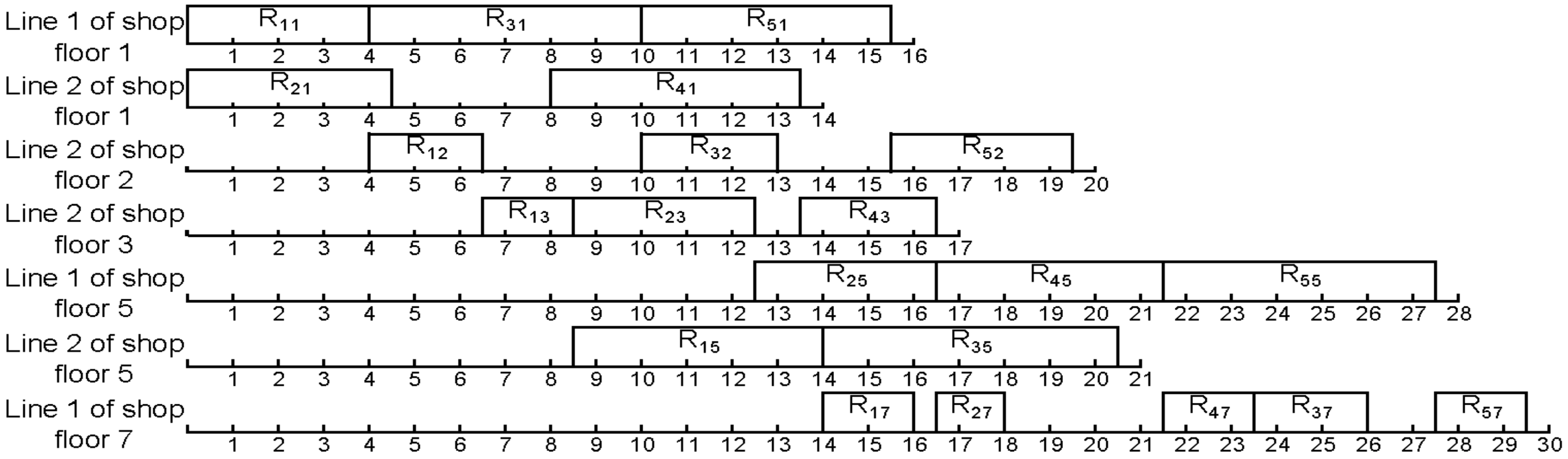
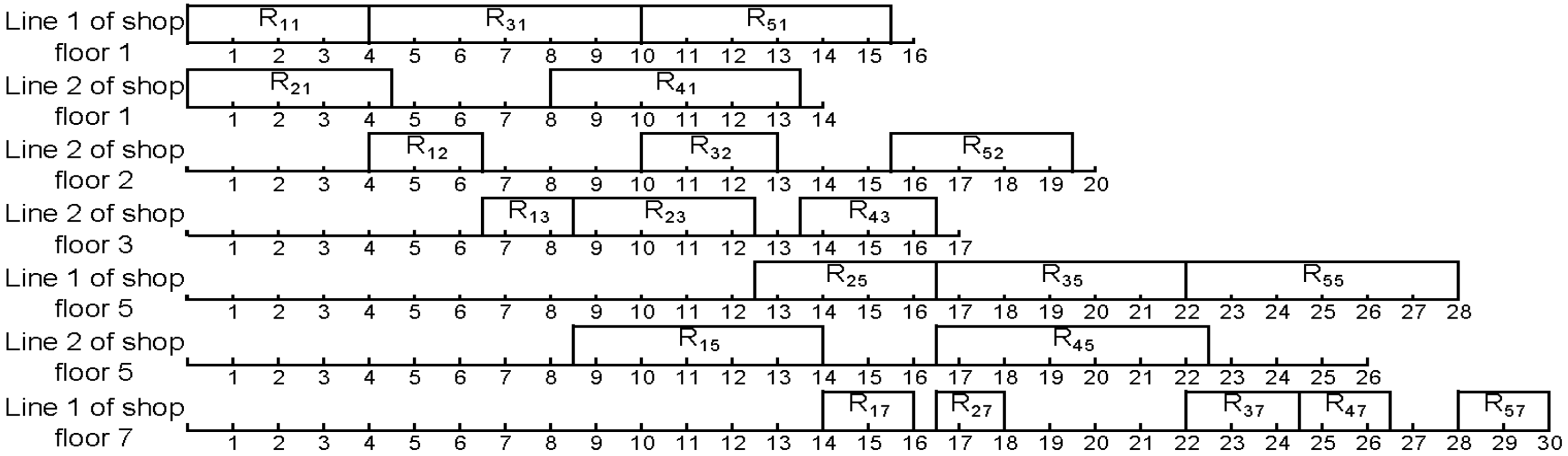


Gantt charts for Case 1 of Experiment 3 (Proposed method)



Gantt charts for Case 1 of Experiment 3 (Practical method)



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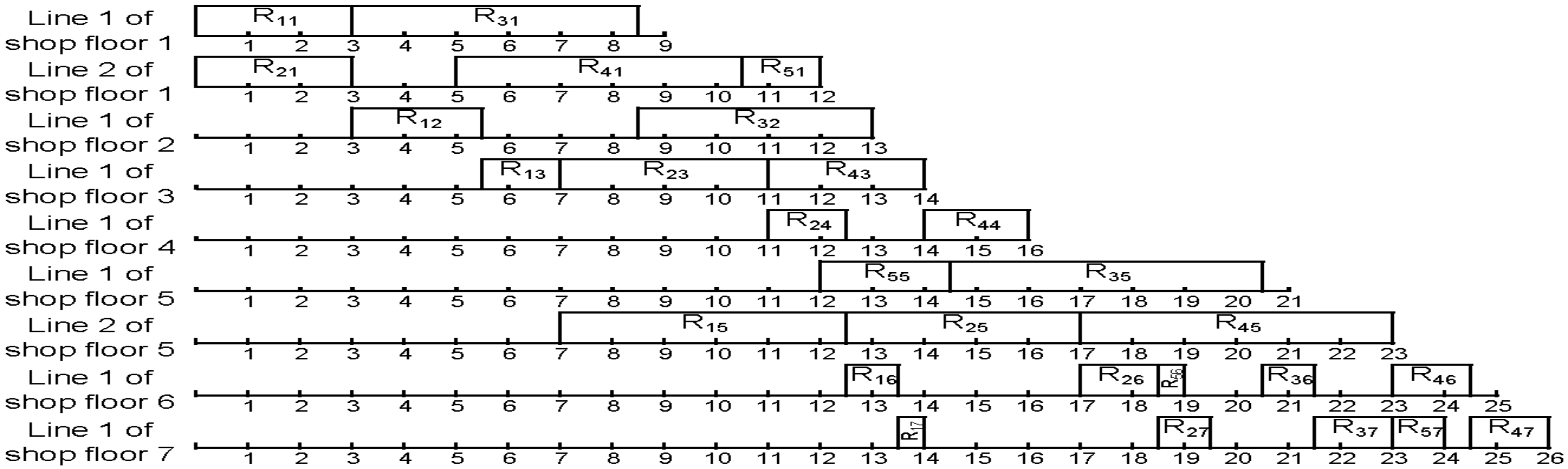
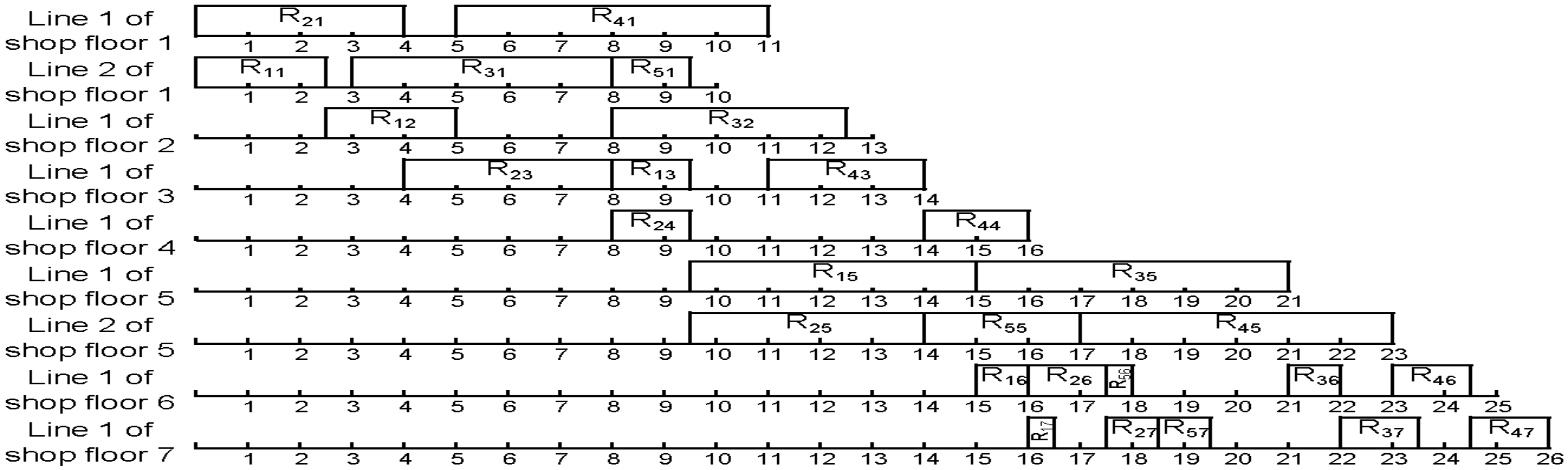


Gantt charts for Case 2 of Experiment 3 (Practical method)



References

Abdulrazaq, T., C. Potts and L. Vanwassenhove (1990). "A survey of algorithms for the single-machine total weighted tardiness scheduling problem." Discrete Applied Mathematics 26(2-3): 235-253.

Adiri, I. and N. Aizikowitz (1989). "Open-shop scheduling problems with dominated machines." Naval Research Logistics 36(3): 273-281.

Al-Turki, U., C. Fedjki and A. Andijani (2001). "Tabu search for a class of single-machine scheduling problems." Computers & Operations Research 28(12): 1223-1230.

Alan, K. (2007). "Simulation software development frameworks". Available at: http://www.topology.org/soft/sim.html (Accessed 30/07/2007).

Ambuhl, C. and M. Mastrolilli (2005). "On-line scheduling to minimize max flow time: An optimal preemptive algorithm." Operations Research Letters 33(6): 597-602.

Amen, M. (2000). "Heuristic methods for cost-oriented assembly line balancing: A survey." International Journal of Production Economics 68(1): 1-14.

Anderson, E. J. and M. C. Ferris (1994). "Genetic algorithms for combinatorial optimization: The assembly line balancing problem." ORSA Journal on Computing 6(2): 161-173.

Arcus, A. L. (1966). "COMSOAL: A computer method of sequencing operations for assembly lines." International Journal of Production Research 4(4): 259-277.

Argote, L. and D. Epple (1990). "Learning-curves in manufacturing." Science 247(4945): 920-924.

Ashby, J. and R. Uzsoy (1995). "Scheduling and order release in a single-stage production system." Journal of Manufacturing Systems 14(4): 290-306.

Axsater, S. (2005). "Planning order releases for an assembly system with random operation times." OR Spectrum 27(1-2): 459-470.

Azizoglu, M. (2003). "Preemptive scheduling on identical parallel machines subject to deadlines." European Journal of Operational Research 148(1): 205-210.

Badiru, A. (1992). "Computational survey of univariate and multivariate learning-curve models." IEEE Transactions on Engineering Management 39(2): 176-188.

Bailey, T. (1993). "Organizational innovation in the apparel industry." Industrial Relations 32(1): 30-48.

Baker, C. T. and B. P. Dzielinski (1960). "Simulation of a simplified job shop." Management Science 6(3): 311-323.

Baker, K., E. Lawler, J. Lenstra and A. Kan (1983). "Preemptive scheduling of a single-machine to minimize maximum cost subject to release dates and precedence constraints." Operations Research 31(2): 381-386.

Balasubramanian, J. and I. Grossmann (2002). "A novel branch and bound algorithm for scheduling flowshop plants with uncertain processing times." Computers & Chemical Engineering 26(1): 41-57.

Ballof, N. (1970). "Start-up management." IEEE Transactions on Engineering Management 17: 132-141.

Barnes, J. W. and J. B. Chambers (1995). "Solving the job-shop scheduling problem with tabu search." IIE Transactions 27(2): 257-263.

Bartholdi, J. and D. Eisenstein (1996). "A production line that balances itself." Operations Research 44(1): 21-34.

Bautista, J. and J. Pereira (2007). "Ant algorithms for a time and space constrained assembly line balancing problem." European Journal of Operational Research 177(3): 2016–2032.

Baybars, I. (1986). "A Survey of exact algorithms for the simple assembly line balancing problem." Management Science 32(8): 909-932.

Becker, C. and A. Scholl (2006). "A survey on problems and methods in generalized assembly line balancing." European Journal of Operational Research 168(3): 694-715.

Ben Abdallah, I., H. Elmaraghy and T. Elmekkawy (2002). "Deadlock-free scheduling in flexible manufacturing systems using Petri nets." International Journal of Production Research 40(12): 2733-2756.

Betts, J. and K. I. Mahmoud (1992). "Assembly line balancing in the clothing industry allowing for varying skills of operatives." International Journal of Clothing Science of Technology 4(4): 28-33.

Bevis, F. W. (1970). "An exploratory study of industrial learning with special reference to work study standards". M.SC. Thesis, University of Wales.

Beyer, H. G. (1995). "Toward a Theory of Evolution Strategies: On the Benefits of Sex-the (μ/μ,lambda) Theory." Evolutionary Computation 3(1): 81-111.

Bhattacharjee, T. K. and S. Sahu (1987). "A critique of some current assembly line balancing techniques." International Journal of Operations & Production Management 7(6): 32-43.

Biskup, D. (1999). "Single-machine scheduling with learning considerations." European Journal of Operational Research 115(1): 173-178.

Blazewicz, J., W. Domschke and E. Pesch (1996). "The job shop scheduling problem: Conventional and new solution techniques." European Journal of Operational Research 93(1): 1-33.

Bolton, W. (1994). Production Planning & Control. Essex, England, Longman Scientific &

Technical.

Boryczka, U. (2004). "Ant colony system for JSP." Lecture Notes in Computer Science 3305: 296-305.

Bowers, M. R. and A. Agarwal (1993). "Hierarchical production planning: Scheduling in the apparel industry." International Journal of Clothing Science and Technology 5(3/4): 36-43.

Bruce, M., L. Daly and N. Towers (2004). "Lean or agile - A solution for supply chain management in the textiles and clothing industry?" International Journal of Operations & Production Management 24(1-2): 151-170.

Brucker, P., S. Kravchenko and Y. Sotskov (1999). "Preemptive job-shop scheduling problems with a fixed number of jobs." Mathematical Methods of Operations Research 49(1): 41-76.

Caprihan, R. and S. Wadhwa (1997). "Impact of routing flexibility on the performance of an FMS - A simulation study." International Journal of Flexible Manufacturing Systems 9(3): 273-298.

Caridi, M. and A. Sianesi (2000). "Multi-agent systems in production planning and control: An application to the scheduling of mixed-model assembly lines." International Journal of Production Economics 68(1): 29-42.

Carson, J. S. I. (2003). Introduction to simulation: Introduction to modeling and simulation. Proceedings of the 2003 Winter Simulation Conference, New Orleans, Louisiana, USA.

Celano, G., S. Fichera, V. Grasso, U. La Commare and G. Perrone (1999). "An evolutionary approach to multi-objective scheduling of mixed model assembly lines." Computers & Industrial Engineering 37(1-2): 69-73.

Chakravarthy, S. (1986). "A single-machine scheduling problem with random processing times." Naval Research Logistics 33(3): 391-397.

Chakravarty, A. and A. Shtub (1985). "Balancing mixed model lines with in-process inventories." Management Science 31(9): 1161-1174.

Chan, C. C., C. L. Hui, K. W. Yeung and S. F. Ng (1998). "Handling the assembly line balancing problem in the clothing industry using a genetic algorithm." International Journal of Clothing Science and Technology 10(1): 21-37.

Chan, F. and H. Chan (2001). "Dynamic scheduling for a flexible manufacturing system - The pre-emptive approach." International Journal of Advanced Manufacturing Technology 17(10): 760-768.

Chan, F. and H. Chan (2004). "A comprehensive survey and future trend of simulation study on FMS scheduling." Journal of Intelligent Manufacturing 15(1): 87-102.

Chan, F., H. Chan and H. Lau (2002). "The state of the art in simulation study on FMS scheduling: A comprehensive survey." International Journal of Advanced Manufacturing Technology 19(11): 830-849.

Charnsirisakskul, K., P. Griffin and P. Keskinocak (2004). "Order selection and scheduling with leadtime flexibility." IIE Transactions 36(7): 697-707.

Chaudhry, S. and W. Luo (2005). "Application of genetic algorithms in production and operations management: A review." International Journal of Production Research 43(19): 4083-4101.

Chen, C., F. Swift and R. Racine (1992). "A computer application in apparel manufacturing management." Computers & Industrial Engineering 23(1-4): 439-442.

Chen, J. and F. Chen (2003). "Adaptive scheduling in random flexible manufacturing systems subject to machine breakdowns." International Journal of Production Research 41(9): 1927-1951.

Chen, R. and Y. Huang (2001). "Competitive neural network to solve scheduling problems."

Neurocomputing 37: 177-196.

Chen, Z. (1996). "Parallel machine scheduling with time dependent processing times." Discrete Applied Mathematics 70(1): 81-93.

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

Cheng, R., M. Gen and Y. Tsujimura (1996). "A tutorial survey of job-shop scheduling problems using genetic algorithms.1. Representation." Computers & Industrial Engineering 30(4): 983-997.

Cheng, R., M. Gen and Y. Tsujimura (1999). "A tutorial survey of job-shop scheduling problems using genetic algorithms: Part II. Hybrid genetic search strategies." Computers & Industrial Engineering 37(1-2): 51-55.

Cheng, T., Q. Ding and B. Lin (2004). "A concise survey of scheduling with time-dependent processing times." European Journal of Operational Research 152(1): 1-13.

Cheng, T. and G. Wang (2000). "Single machine scheduling with learning effect considerations." Annals of Operations Research 98: 273-290.

Cheng, T. C. E. and C. C. S. Sin (1990). "A State-of-art review of parallel-machine scheduling research." European Journal of Operational Research 47(3): 271-292.

Choi, J., M. Realff and J. Lee (2004). "Dynamic programming in a heuristically confined state space: a stochastic resource-constrained project scheduling application." Computers & Chemical Engineering 28(6-7): 1039-1058.

Chong, S. C., A. I. Sivakumar and R. K. L. Gay (2003). Simulation-based scheduling for dynamic discrete manufacturing. Proceedings of the 2003 Winter Simulation Conference, New Orleans, Louisiana, USA.

Coello, C., D. Rivera and N. Cortes (2003). "Use of an artificial immune system for job shop scheduling." Artificial Immune Systems, Proceedings 2787: 1-10.

Cohen, Y., G. Vitner and S. Sarin (2006). "Optimal allocation of work in assembly lines for lots with homogenous learning." European Journal of Operational Research 168(3): 922-931.

Conterno, R., A. Allasia and A. Proverbio (1991). "A queuing network branch-and-bound approach to lot scheduling in flexible manufacturing systems." Information and Decision Technologies 17(1): 1-21.

Crauwels, H., C. Potts, D. Van Oudheusden and L. Van Wassenhove (2005). "Branch and bound algorithms for single machine scheduling with batching to minimize the number of late jobs." Journal of Scheduling 8(2): 161-177.

Cruycke, B. (1979). "Production control with the computer - Investment decision." Melliand Textilberichte International Textile Reports 60(2): 189-192.

Cui, Z. and J. Zeng (2005). "A new organizational nonlinear genetic algorithm for numerical optimization." Advances in Natural Computation, PT 3, Proceedings 3612: 255-258.

Darel, E. and R. Karni (1980). "A Hybrid algorithm for independent task parallel machine scheduling." OMEGA-International Journal of Management Science 8(2): 239-242.

Davis, L. (1991). Handbook of genetic algorithms. New York, Van Nostrand Reinhold.

Decker, M. (1993). "Capacity smoothing and sequencing for mixed-model lines." International Journal of Production Economics 30-1: 31-42.

deWerra, D., A. Hoffman, N. Mahadev and U. Peled (1996). "Restrictions and preassignments in preemptive open shop scheduling." Discrete Applied Mathematics 68(1-2): 169-188.

Dorigo, M., V. Maniezzo and A. Colorni (1996). "Ant System: Optimization by a Colony of Cooperating Agents." IEEE Transactions on Systems, Man, and Cybernetics - Part B 26(1):

29-41.

Doumeingts, G., L. Pun, M. Mondain and D. Breuil (1978). "Decision-making systems for production control planning and scheduling." International Journal of Production Research 16(2): 137-152.

Doumeingts, G. and F. Roubellat (1979). "Production control and decision-making systems." Rairo-Automatique-Systems Analysis and Control 13(1): 77-92.

Drobouchevitch, I. and V. Strusevich (1999). "A polynomial algorithm for the three-machine open shop with a bottleneck machine." Annals of Operations Research 92: 185-210.

Drobouchevitch, I. and V. Strusevich (2001). "Two-stage open shop scheduling with a bottleneck machine." European Journal of Operational Research 128(1): 159-174.

Eiben, A. E., P.-E. Raue and Z. Ruttkay (1994). Genetic algorithms with multiparent recombination. Proceedings of the 3rd Conference on Parallel Problem Solving from Nature, New York, Springer-Verlag, New York.

Eilon, S. and R. M. Hodgson (1967). "Job shop scheduling with due-dates." International Journal of Production Research 6: 1-13.

ElMekkawy, T. and H. ElMaraghy (2003). "Real-time scheduling with deadlock avoidance in flexible manufacturing systems." International Journal of Advanced Manufacturing Technology 22(3-4): 259-270.

Epicdata Inc (2007). "RFID Systems". Available at: http://www.epicdata.com/data/rfid-systems.php (Accessed 30/07/2007).

Erel, E. and S. Sarin (1998). "A survey of the assembly line balancing procedures." Production Planning & Control 9(5): 414-434.

Eshelman, L. J. and J. D. Schaffer (1993). Real-coded genetic algorithms and interval schemata.

Foundations of Genetic Algorithms. L. D. Whitley. San Mateo,CA, Morgan Kaufmann. 2: 187-202.

Farmer, J. D., N. Packard and A. Perelson (1986). "The immune system, adaptation and machine learning." Physica D 2: 187-204.

Feng, S., L. Li, L. Cen and J. Huang (2003). "Using MLP networks to design a production scheduling system." Computers & Operations Research 30(6): 821-832.

Ferreira, C. (2002). Combinatorial optimization by gene expression programming: Inversion revisited. The Argentine Symposium on Artificial Intelligence, Santa Fe, Argentina.

Fleury, G. and M. Gourgand (1998). "Genetic algorithms applied to workshop problems." International Journal of Computer Integrated Manufacturing 11(2): 183-192.

Foster, B. and D. Ryan (1976). "Integer programming approach to vehicle scheduling problem." Operational Research Quarterly 27(2): 367-384.

Fozzard, G., J. Spragg and D. Tyler (1996). "Simulation of flow lines in clothing manufacture, Part 1. model construction." International of Clothing Science and Technology 8(4): 17-27.

Framinan, J., P. Gonzalez and R. Ruiz-Usano (2003). "The CONWIP production control system: review and research issues." Production Planning & Control 14(3): 255-265.

Freschi, F. and M. Repetto (2006). "Comparison of artificial immune systems and genetic algorithms in electrical engineering optimization." COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering 25(4): 792-811.

Gamberini, R., A. Grassi and B. Rimini (2006). "A new multi-objective heuristic algorithm for solving the stochastic assembly line re-balancing problem." International Journal of Production Economics 102(2): 226-243.

Gershwin, S. B., R. R. Hildebrant, R. Suri and S. K. Mitter (1986). "A control perspective on recent trends in manufacturing systems." IEEE Control Systems Magazine 6(2): 3-15.

Ghosh, S. and R. J. Gagnon (1989). "A comprehensive literature-review and analysis of the design, balancing and scheduling of assembly systems." International Journal of Production Research 27(4): 637-670.

Glover, F. (1989). "Tabu Search - Part I." ORSA Journal on Computing 1(3): 190-206.

Glover, F. (1990). "Tabu Search - Part II." ORSA Journal on Computing 2(1): 4-32.

Glover, J. H. (1966). "Manufacturing progress functions: An alternative model and its comparison with existing functions." The International Journal of Production Research 4: 279-300.

Gokcen, H. and K. Agpak (2006). "A goal programming approach to simple U-line balancing problem." European Journal of Operational Research 171(2): 577-585.

Gokcen, H., K. Agpak, C. Gencer and E. Kizilkaya (2005). "A shortest route formulation of simple U-type assembly line balancing problem." Applied Mathematical Modelling 29(4): 373-380.

Goldberg, D., B. Korb and K. Deb (1989). "Messy genetic algorithms: Motivation, analysis, and first results." Complex Systems 3(5): 493-530.

Gonzalez, T. and S. Sahni (1976). "Open shop scheduling to minimize finish time." Journal of the ACM 23(4): 665-679.

Gordon, V., J. Proth and C. Chu (2002). "A survey of the state-of-the-art of common due date assignment and scheduling research." European Journal of Operational Research 139(1): 1-25.

Grand, H. and M. Cook (1983). "Chossing an MRP system." Datamation 29(1): 84-&.

Graves, S. C. and B. W. Lamar (1983). "An integer programming procedure for assembly system design problems." Operations Research 31(3): 522-545.

Gu, Q. L. (1999). "The development of the China apparel industry". China Textile University and Harvard Center of Textile and Apparel Research. Available at: http://www.hctar.org/pdfs/gs01.pdf (Accessed 30/07/2007).

Guerriero, F. and J. Miltenburg (2003). "The stochastic U-Line balancing problem." Naval Research Logistics 50(1): 31-57.

Guinet, A. and M. Solomon (1996). "Scheduling hybrid flowshops to minimize maximum tardiness or maximum completion time." International Journal of Production Research 34(6): 1643-1654.

Guley, H. and J. Stinson (1980). "Computer-simulation for production scheduling in a ready foods system." Journal of the American Dietetic Association 76(5): 482-487.

Guo, Z. X., W. K. Wong, S. Y. S. Leung, J. T. Fan and S. F. Chan (2006). "Mathematical model and genetic optimization for the job shop scheduling problem in a mixed- and multi-product assembly environment: A case study based on the apparel industry." Computers & Industrial Engineering 50(3): 202-219.

Guo, Z. X., W. K. Wong, S. Y. S. Leung, J. T. Fan and S. F. Chan (2008). "A genetic algorithm based optimization model for solving the flexible assembly line balancing problem with work-sharing and workstation revisiting." IEEE Transactions on Systems Man and Cybernetics Part C - Applications and Reviews 38(2): 218-228.

Gupta, J. (1971). "An improved combinatorial algorithm for flowshop - Scheduling problem." Operations Research 19(7): 1753-1758.

Gupta, J. and E. Stafford (2006). "Flowshop scheduling research after five decades." European Journal of Operational Research 169(3): 699-711.

Gupta, Y., G. Evans and M. Gupta (1991). "A review of multi-criterion approaches to FMS scheduling problems." International Journal of Production Economics 22(1): 13-31.

Gupta, Y., M. Gupta and C. Bector (1989). "A review of scheduling rules in flexible manufacturing systems." International Journal of Computer Integrated Manufacturing 2(6): 356-377.

Gurney, K. R. (1997). An introduction to neural networks. London, UCL Press.

Gutjahr, A. L. and G. L. Nemhauser (1964). "An algorithm for the line balancing problem." Management Science 11(2).

Hackett, E. (1983). "Application of a set of learning-curve models to repetitive tasks." Radio and Electronic Engineer 53(1): 25-32.

Harmonosky, C. (1995). Simulation-based real-time scheduling: Review of recent developments. The 1995 Winter Simulation Conference, Arlington, VA, USA.

Harmonosky, C. and S. Robohn (1991). "Real-time scheduling in computer integrated manufacturing - A review of recent research." International Journal of Computer Integrated Manufacturing 4(6): 331-340.

Harpham, C., C. Dawson and M. Brown (2004). "A review of genetic algorithms applied to training radial basis function networks." Neural Computing & Applications 13(3): 193-201.

Harrell, C. R. and R. N. Price (2002). Simulation modeling using ProModel technology. The 2002 Winter Simulation Conference, Orlando, FL, USA.

Hart, E., P. Ross and D. Corne (2005). "Evolutionary scheduling: A review." Genetic Programming and Evolvable Machines 6: 191-220.

Haupt, R. (1989). "A survey of priority rule-based scheduling." OR Specktrum 11(1): 3-16.

Heizmann, J. (1981). SoziotechnologischeAblaufplanung verketteter Fertigungsnester zur Erhohung der Flexibilitat von Montage-FlieBlinien. Karlsruhe, Jochem Heizmann Verlag.

Hejazi, S. and S. Saghafian (2005). "Flowshop-scheduling problems with makespan criterion: a review." International Journal of Production Research 43(14): 2895-2929.

Helgeson, W. B. and D. P. Birnie (1961). "Assembly line balancing using the ranked positional weight technique." Journal of Industrial Engineering 12(6): 394-398.

Herrera, F. (1998). "Trackling real-coded genetic algorithms: Operators and tools for behavioral analysis." Artificial Intelligence Review 12(4): 265-319.

Herrera, L., M. Lozano and J. L. Verdegay (1996). "Tackling real-coded genetic algorithms: Operators and tools for behavioural analysis." Artificial Intelligence Review 12(4): 265-319.

Hitchings, B. (1972). Dynamic learning curve models describing the performance of human operators on repetitive industrial tasks. M.Sc. Thesis, University of Wales.

Ho, J. and Y. Chang (1991). "Heuristics for minimizing mean tardiness for m-parallel machines." Naval Research Logistics 38(3): 367-381.

Holland, J. H. (1975). Adaptation in natural and artificial systems. Michigan, University of Michigan Press.

Hollocks, B. (1995). "The impact of simulation in manufacturing decision-making." Control Engineering Practice 3(1): 105-112.

Holloway, C. and R. Nelson (1974). "Job shop scheduling with due dates and overtime capability." Management Science Series A - Theory 21(1): 68-78.

Hopp, W., E. Tekin and M. Van Oyen (2004). "Benefits of skill chaining in serial production lines with cross-trained workers." Management Science 50(1): 83-98.

Hopp, W. and M. Van Oyen (2004). "Agile workforce evaluation: A framework for cross-training and coordination." IIE Transactions 36(10): 919-940.

Huang, C. and A. Kusiak (1996). "Overview of Kanban systems." International Journal of Computer Integrated Manufacturing 9(3): 169-189.

Huang, M., D. Wang and W. Ip (1998). "A simulation and comparative study of the CONWIP, Kanban and MRP production control systems in a cold rolling plant." Production Planning & Control 9(8): 803-812.

Hunsucker, J. and J. Shah (1992). "Performance of priority rules in a due date flow-shop." OMEGA-International Journal of Management Science 20(1): 73-89.

Hwang, T. and S. Chang (2003). "Design of a Lagrangian relaxation-based hierarchical production scheduling environment for semiconductor wafer fabrication." IEEE Transactions on Robotics and Automation 19(4): 566-578.

Ibraki, T. and Y. Nakamura (1994). "A dynamic-programming method for single-machine scheduling." European Journal of Operational Research 76(1): 72-82.

Ignizio, J. P. (1991). An introduction to expert systems, Mcgraw-Hill College.

Ip, W., K. Yung, M. Huang and D. Wang (2002). "A CONWIP model for FMS control." Journal of Intelligent Manufacturing 13(2): 109-117.

Jain, A. and S. Meeran (1998). "Job-shop scheduling using neural networks." International Journal of Production Research 36(5): 1249-1272.

Jain, A. and S. Meeran (1999). "Deterministic job-shop scheduling: Past, present and future." European Journal of Operational Research 113(2): 390-434.

Jain, N., T. Bagchi and E. Wagneur (2000). "Flowshop scheduling by hybridized GA: Some new results." International Journal of Industrial Engineering-Theory Applications and Practice 7(3):

213-223.

Johnson, R. (1983). "A branch and bound algorithm for assembly line balancing problems with formulation irregularities." Management Science 29(11): 1309-1324.

Kao, E. (1976). "Preference order dynamic program for stochastic assembly line balancing." Management Science 22(10): 1097-1104.

Karacapilidis, N. and C. Pappis (1996). "Production planning and control in textile industry: A case study." Computers In Industry 30(2): 127-144.

Kaufman, M. (1974). "Almost optimal algorithm for assembly line scheduling problem." IEEE Transactions on Computers C 23(11): 1169-1174.

Kessler, J. (1991). "MRP-II - In the midst of a continuing evolution." Industrial Engineering 23(3): 38-40.

Khan, M. R. R. (1999). "Simulation modeling of a garment production system using a spreadsheet to minimize production cost." International Journal of Clothing Science and Technology 11(5): 287-299.

Kilbridge, M. D. and L. Wester (1961). "A heuristic method of assembly line balancing." Journal of Industrial Engineering 12(4): 292-298.

Kilincci, O. and G. M. Bayhan (2006). "A Petri net approach for simple assembly line balancing problems." The International Journal of Advanced Manufacturing Technology 30(11-12): 1165-1173.

Kim, C., H. Min and Y. Yih (1998). "Integration of inductive learning and neural networks for multi-objective FMS scheduling." International Journal of Production Research 36(9): 2497-2509.

Kiran, A. and M. Smith (1984). "Simulation studies in job shop scheduling. 1. A survey."

Computers & Industrial Engineering 8(2): 87-93.

Kirkpatrick, S., C. D. Gelatt and M. P. Vecchi (1983). "Optimization by Simulated Annealing." Science 220(4598): 671-680.

Klein, R. and A. Scholl (1996). "Maximizing the production rate in simple assembly line balancing - A branch and bound procedure." European Journal of Operational Research 91(2): 367-385.

Kottas, J. and H. Lau (1981). "A Stochastic Line Balancing Procedure." International Journal of Production Research 19(2): 177-193.

Kottas, J. F. and H. S. Lau (1973). "A cost-oriented approach to stochastic line balancing." AIIE Transactions 5(2): 164-171.

Koulamas, C. and G. Kyparisis (2007). "Single-machine and two-machine flowshop scheduling with general learning functions." European Journal of Operational Research 178(2): 402-407.

Koza, J. R. (1992). Genetic Programming: On the Programming of Computers by Means of Natural Selection, MIT Press.

Kravchenko, S. and F. Werner (2001). "A heuristic algorithm for minimizing mean flow time with unit setups." Information Processing Letters 79(6): 291-296.

Kuroda, M. and Z. Wang (1996). "Fuzzy job shop scheduling." International Journal of Production Economics 44(1-2): 45-51.

Kyparisis, G. and C. Koulamas (2002). "Assembly-line scheduling with concurrent operations and parallel machines." Informs Journal on Computing 14(1): 68-80.

Larranaga, P., C. Kuijpers, R. Murga, I. Inza and S. Dizdarevic (1999). "Genetic algorithms for the travelling salesman problem: A review of representations and operators." Artificial Intelligence Review 13(2): 129-170.

Lauff, V. and F. Werner (2004). "On the complexity and some properties of multi-stage scheduling problems with earliness and tardiness penalties." Computers & Operations Research 31(3): 317-345.

Lee, L., F. Abernathy and Y. Ho (2000). "Production scheduling for apparel manufacturing systems." Production Planning & Control 11(3): 281-290.

Leung, J., H. Li and M. Pinedo (2005). "Order scheduling in an environment with dedicated resources in parallel." Journal of Scheduling 8(5): 355-386.

Leung, J. and M. Pinedo (2003). "Minimizing total completion time on parallel machines with deadline constraints." SIAM Journal on Computing 32(5): 1370-1388.

Li, F. (1998). "A comparison of genetic algorithms with conventional techniques on a spectrum of power economic dispatch problems." Expert Systems with Applications 15(2): 133-142.

Liao, C., C. Sun and W. You (1995). "Flowshop scheduling with flexible processors." Computers & Operations Research 22(3): 297-306.

Liaw, C. (2003). "An efficient tabu search approach for the two-machine preemptive open shop scheduling problem." Computers & Operations Research 30(14): 2081-2095.

Liaw, C. (2005). "Scheduling preemptive open shops to minimize total tardiness." European Journal of Operational Research 162(1): 173-183.

Lima, R., R. Sousa and P. Martins (2006). "Distributed production planning and control agent-based system." International Journal of Production Research 44(18-19): 3693-3709.

Lin, B. and A. Jeng (2004). "Parallel-machine batch scheduling to minimize the maximum lateness and the number of tardy jobs." International Journal of Production Economics 91(2): 121-134.

Lin, F. (2001). "A job-shop scheduling problem with fuzzy processing times". Computational

Science – ICCS 2001, Lecture Notes in Computer Science 2074: 409-418.

Linn, R. and W. Zhang (1999). "Hybrid flow shop scheduling: A survey." Computers & Industrial Engineering 37(1-2): 57-61.

Liu, M., J. Hao and C. Wu (2006). "A new genetic algorithm for parallel machine scheduling problems with procedure constraints and its applications." Chinese Journal of Electronics 15(3): 463-466.

Liu, S., H. Ong and K. Ng (2005). "A fast tabu search algorithm for the group shop scheduling problem." Advances in Engineering Software 36(8): 533-539.

Lloyd, R. (1979). "Experience Curve Analysis." Applied Economics 11(2): 221-234.

Lorigeon, T., J. Billaut and J. Bouquard (2002). "A dynamic programming algorithm for scheduling jobs in a two-machine open shop with an availability constraint." Journal of the Operational Research Society 53(11): 1239-1246.

Lushchakova, I. (2006). "Two machine preemptive scheduling problem with release dates, equal processing times and precedence constraints." European Journal of Operational Research 171(1): 107-122.

Macaskil, J. (1972). "Production-line balances for mixed-model lines." Management Science Series B-Application 19(4): 423-434.

Malakooti, B. and A. Kumar (1996). "A knowledge-based system for solving multi-objective assembly line balancing problems." International Journal of Production Research 34(9): 2533-2552.

Mandel, M. and G. Mosheiov (2001). "Minimizing maximum earliness on parallel identical machines." Computers & Operations Research 28(4): 317-327.

Mcclain, J., L. Thomas and C. Sox (1992). "On-the-fly line balancing with very little WIP."

International Journal of Production Economics 27(3): 283-289.

Metaxiotis, K., D. Askounis and J. Psarras (2002). "Expert systems in production planning and scheduling: A state-of-the-art survey." Journal of Intelligent Manufacturing 13(4): 253-260.

Metaxiotis, K. and J. Psarras (2003). "Neural networks in production scheduling: Intelligent solutions and future promises." Applied Artificial Intelligence 17(4): 361-373.

Meybodi, M. (1995). "Integrating production activity control into a hierarchical production-planning model." International Journal of Operations & Production Management 15(5): 4-&.

Michalewicz, Z. (1992). Genetic algorithm + Data structures = evolution programs. New York, USA, Springer-Verlag.

Mok, P., C. Kwong and W. Wong (2007). "Optimisation of fault-tolerant fabric-cutting schedules using genetic algorithms and fuzzy set theory." European Journal of Operational Research 177(3): 1876-1893.

Mokotoff, E. (2001). "Parallel machine scheduling problems: A survey." Asia-Pacific Journal of Operational Research 18(2): 193-242.

Moodie, C. L. and H. H. Young (1965). "A heuristic method of assembly line balancing for assumptions of constant or variable work element times." Journal of Industrial Engineering 16(1): 23-29.

Mosheiov, G. (2001). "Parallel machine scheduling with a learning effect." Journal of the Operational Research Society 52(10): 1165-1169.

MSC Limited (2007). "Solution of Manufacturing Information and Management in Multi Variety and Small Batch Age." Textile & Clothing 19(1): 58-60.

Nakagiri, D. and S. Kuriyama (1996). "A study of production management system with MRP."

International Journal of Production Economics 44(1-2): 27-33.

Narahari, Y. and R. Srigopal (1996). "Real-world extensions to scheduling algorithms based on Lagrangian relaxation." Sadhana-Academy Proceedings in Engineering Sciences 21: 415-433.

Neumann, K. and W. Schneider (1999). "Heuristic algorithms for job-shop scheduling problems with stochastic precedence constraints." Annals of Operations Research 92(0): 45-63.

Nkasu, M. and K. Leung (1995). "A Stochastic Approach to Assmelby-line Balancing." International Journal of Production Research 33(4): 975-991.

Oh, K. H. (1997). "Expert line balancing system (ELBS)." Computers & Industrial Engineering 33(1-2): 303-306.

Okamura, K. and H. Yamashina (1979). "Heuristic algorithm for the assembly line model - Mix sequencing problem to minimize the risk of stopping the conveyor." International Journal of Production Research 17(3): 233-247.

Okeefe, R. and T. Kasirajan (1992). "Interaction between dispatching and next station selection-rules in a dedicated flexible manufacturing system." International Journal of Production Research 30(8): 1753-1772.

Ono, I., M. Yamamura and S. Kobayashi (1996). A genetic algorithm for job-shop scheduling problems using job-based order crossover. 1996 IEEE International Conference on Evolutionary, Nagoya, Japan.

Pan, C. (1997). "A study of integer programming formulations for scheduling problems." International Journal of Systems Science 28(1): 33-41.

Pandey, P., M. Ahsan and A. Hasin (1995). "A scheme for an integrated production planning and control system." International Journal of Computer Applications in Technology 8(5-6): 301-306.

Park, L. and C. Park (1995). "Genetic algorithm for job-shop scheduling problems based on 2 representational schemes." Electronics Letters 31(23): 2051-2053.

Park, M. and Y. Kim (2000). "A branch and bound algorithm for a production scheduling problem in an assembly system under due date constraints." European Journal of Operational Research 123(3): 504-518.

Park, Y., C. Pegden and E. Enscore (1984). "A survey and evaluation of static flowshop scheduling heuristics." International Journal of Production Research 22(1): 127-141.

Pastor, R., C. Andres, A. Duran and M. Perez (2002). "Tabu search algorithms for an industrial multi-product and multi-objective assembly line balancing problem, with reduction of the task dispersion." Journal of the Operational Research Society 53(12): 1317-1323.

Peng, J. and B. Liu (2004). "Parallel machine scheduling models with fuzzy processing times." Information Sciences 166(1-4): 49-66.

Pinto, P., D. Dannenbring and B. Khumawala (1978). "Heuristic network procedure for assembly line balancing problem." Naval Research Logistics 25(2): 299-307.

Piramuthu, S., N. Raman and M. Shaw (1994). "Learning-based scheduling in a flexible manufacturing flow line." IEEE Transactions on Engineering Management 41(2): 172-182.

Ponnambalam, S., P. Aravindan and S. Rajesh (2000). "A tabu search algorithm for job shop scheduling." International Journal of Advanced Manufacturing Technology 16(10): 765-771.

Ponnambalam, S., N. Jawahar and P. Aravindan (1999). "A simulated annealing algorithm for job shop scheduling." Production Planning & Control 10(8): 767-777.

Poon, P. and J. Carter (1995). "Genetic algorithm crossover operators for ordering applications." Computers & Operations Research 22(1): 135-147.

Por, A., J. Stahl and J. Temesi (1990). "Decision support system for production control - Multiple criteria decision-making in practice." Engineering Costs and Production Economics 20(2):

213-218.

Priore, P., D. De La Fuente, A. Gomez and J. Puente (2001). "A review of machine learning in dynamic scheduling of flexible manufacturing systems." AI EDAM-Artificial Intelligence for Engineering Design Analysis and Manufacturing 15(3): 251-263.

ProModel Corporation (2007). "Applications of ProModel in Industries". Available at: http://www.promodel.com/solutions/manufacturing/ (Accessed 30/07/2007).

Puente, J., H. Diez, R. Varela, C. Vela and L. Hidalgo (2003). "Heuristic rules and genetic algorithms for open shop scheduling problem." Current Topics in Artificial Intelligence 3040: 394-403.

Rachamadugu, R. and K. Stecke (1994). "Classification and review of FMS scheduling procedures." Production Planning & Control 5(1): 2-20.

Racine, R., C. Chen and F. Swift (1992). The impact of operator efficiency on apparel production planning. The Thrid Academic Apparel Research Conference, Atlanta, GA.

Ramasesh, R. (1990). "Dynamic job shop scheduling - A survey of simulation research." OMEGA-International Journal of Management Science 18(1): 43-57.

Reeve, N. and W. Thomas (1973). "Balancing stochastic assembly lines." AIIE Transactions 5(3): 223-229.

Reeves, C. R. (1995). "A genetic algorithm for flowshop sequencing." Computers and Operations Research 22(1): 5-13.

Rogers, P. and R. J. Gordon (1993). Simulation for real-time decision making in manufacturing systems. The 1993 Winter Simulation Conference, Los Angeles, USA.

Roman, R. (1971). "Mine-mill production scheduling by dynamic programming." Operational Research Quarterly 22(4): 319-328.

Rosenberg, O. and H. Ziegler (1992). "A comparison of heuristic algorithms for cost-oriented assembly line balancing." Zeit-schrift fur Operations Research 36: 477-495.

Ross, P. and D. Corne (2005). "Evolutionary scheduling: A review." Genetic Programming and Evolvable Machines 6(2): 191-220.

Rushinek, A. and S. Rushinek (1989). "Manufacturing resource planning systems (MRP) case-study - Feature-selection system (FSS) for microcomputer users and manufacturers." Computers & Industrial Engineering 16(2): 321-328.

Sakawa, M. and R. Kubota (2000). "Fuzzy programming for multiobjective job shop scheduling with fuzzy processing time and fuzzy duedate through genetic algorithms." European Journal of Operational Research 120(2): 393-407.

Salveson, M. E. (1955). "The assembly line balancing problem." Journal of Industrial Engineering 6(3): 18-25.

Sarin, S. and C. Chen (1987). "The machine loading and tool allocation problem in a flexible manufacturing system." International Journal of Production Research 25(7): 1081-1094.

Sawik, T. (2002). "Monolithic vs. hierarchical balancing and scheduling of a flexible assembly line." European Journal of Operational Research 143(1): 115-124.

Sawik, T. (2004). "Loading and scheduling of a flexible assembly system by mixed integer programming." European Journal of Operational Research 154(1): 1-19.

Scholl, A. and C. Becker (2006). "State-of-the-art exact and heuristic solution procedures for simple assembly line balancing." European Journal of Operational Research 168(3): 666-693.

Sellers, D. W. (1996). A survey of approaches to the job shop scheduling problem. The 28th Southeastern Symposium on System Theory, Baton Rouge, LA.

Sen, A. (2007). "The U.S. fashion industry: A supply chain review." International Journal of

Production Economics, Accepted.

Senthilkumar, P. and P. Shahabudeen (2006). "GA based heuristic for the open job shop scheduling problem." International Journal of Advanced Manufacturing Technology 30(3-4): 297-301.

Shakhlevich, N., Y. Sotskov and F. Werner (2000). "Complexity of mixed shop scheduling problems: A survey." European Journal of Operational Research 120(2): 343-351.

Sharafali, M., H. Co and M. Goh (2004). "Production scheduling in a Flexible Manufacturing System under random demand." European Journal of Operational Research 158(1): 89-102.

Shin, D. (1990). "An efficient heuristic for solving stochastic assembly line balancing problems." Computers & Industrial Engineering 18(3): 285-295.

Siegel, T. (1974). "Graphical branch-and-bound algorithm for job-shop scheduling problem with sequence-dependent set-up times." Journal of the Operations Research Society of Japan 17(1): 29-38.

Silverman, F. and J. Carter (1986). "A cost-based methodology for stochastic line balancing with intermittent line stoppages." Management Science 32(4): 455-463.

Simaria, A. and P. Vilarinho (2004). "A genetic algorithm based approach to the mixed-model assembly line balancing problem of type II." Computers & Industrial Engineering 47(4): 391-407.

Sinha, R. and R. Hollier (1984). "A review of production control-problems in cellular manufacture." International Journal of Production Research 22(5): 773-789.

Sipper, D. and R. L. Bulfin (1997). Production: Planning, control and integration, McGraw-Hill Companies.

Solinger, J. (1988). Apparel manufacturing handbook. Columbia, SC, Bobbin Media Corp.

Song, Y. and Y. Takahashi (1996). "Approximation for Kanban production systems." International Journal of Systems Science 27(12): 1443-1451.

Spearman, M., D. Woodruff and W. Hopp (1990). "CONWIP - A pull alternative to kanban." International Journal of Production Research 28(5): 879-894.

Sphicus, G. P. and F. N. Silverman (1976). "Deterministic Equivalents for Stochastic Assembly Line Balancing." AIIE Transactions 8: 280-282.

Stecke, K. and J. Solgerg (1981). "Loading and control policies for a flexible manufacturing system." International Journal of Production Research 19(5): 481-490.

Steedman, I. (1970). "Some improvement curve theory." International Journal of Production Research 8: 189-205.

Steffen, R. (1977). Produktionsplanung bei FlieBbandfertigung. Wiesbaden, Gabler.

Stoop, P. and V. Wiers (1996). "The complexity of scheduling in practice." International Journal of Operations & Production Management 16(10): 37-53.

Sugimori, Y., K. Kusunoki, F. Cho and S. Uchikawa (1977). "Toyota production system and kanban system materialization of just-in-time and respect-for-human system." International Journal of Production Research 15(6): 553-564.

Sullivan, P. and J. Kang (1999). "Quick response adoption in the apparel manufacturing industry: Competitive advantage of innovation." Journal of Small Business Management 37(1): 1-13.

Sun, X. and L. Sun (2005). "Ant Colony Optimization algorithms for scheduling the mixed model assembly lines." Advances in Natural Computation, PT 3, Proceedings 3612: 911-914.

Sung, S. and M. Vlach (2003). "Single machine scheduling to minimize the number of late jobs under uncertainty." Fuzzy Sets and Systems 139(2): 421-430.

Suresh, G. and S. Sahu (1994). "Stochastic assembly-line balancing using simulated annealing." International Journal of Production Research 32(8): 1801-1810.

Suzuki, S. and T. Saito (2006). "Synthesis of desired binary cellular automata through the genetic algorithm." Neural Information Processing, PT 3, Proceedings 4234: 738-745.

Syswerda, G. (1991). Schedule optimization using genetic algorithms. Handbook of genetic algorithms. L. Davis. New York, Van Nostrand Reinhold: 332-349.

Szmerekovsky, J. (2007). "Single machine scheduling under market uncertainty." European Journal of Operational Research 177(1): 163-175.

T'kindt, V., N. Monmarche, F. Tercinet and D. Laugt (2002). "An Ant Colony Optimization algorithm to solve a 2-machine bicriteria flowshop scheduling problem." European Journal of Operational Research 142(2): 250-257.

Takahashi, K. (2003). "Comparing reactive Kanban systems." International Journal of Production Research 41(18): 4317-4337.

Takahashi, K. and N. Nakamura (2002). "Comparing reactive Kanban and reactive CONWIP." Production Planning & Control 13(8): 702-714.

Tan, Z. and Y. He (2007). "Linear time algorithms for parallel machine scheduling." ACTA Mathematica Sinica-English Series 23(1): 137-146.

Tang, L. and H. Xuan (2006). "Lagrangian relaxation algorithms for real-time hybrid flowshop scheduling with finite intermediate buffers." Journal of the Operational Research Society 57(3): 316-324.

Thomopoulos, N. (1970). "Mixed model line balancing with smoothed station assignments." Management Science Series A - Theory 16(9): 593-603.

Thorndike, E. L. (1898). "Animal intelligence: an experimental study of the associative processes in animals." The Psychological Review: Ser. Monograph Supplements 2: 1-109.

Thurstone, L. L. (1919). "The learning curve equation." Psychological Monographs 26: 114.

Tomastik, R. N., P. B. Luh and G. D. Liu (1996). "Scheduling flexible manufacturing systems for apparel production." IEEE Transactions on Robotics and Automation 12(5): 789-799.

Tonge, F. M. (1965). "Assembly line balancing using probabilistic combinations of heuristics." Management Science 11(7): 727-735.

Tozkapan, A., O. Kirca and C. S. Chung (2003). "A branch and bound algorithm to minimize the total weighted flowtime for the two-stage assembly scheduling problem." Computers & Operations Research 30(2): 309-320.

Tsutsui, S. and A. Ghosh (1998). A study on the effect of multi-parent recombination in real coded genetic algorithms. The 1998 IEEE Conference on Evolutionary Computation, Anchorage, Alaska,USA, IEEE Press.

Tucci, M. and R. Rinaldi (1999). "From theory to application: Tabu search in textile production scheduling." Production Planning & Control 10(4): 365-374.

Turbide, D. (1995). "MRP-II - Still number one." IIE Solutions 27(7): 28-31.

Vanlaarhoven, P., E. Aarts and J. Lenstra (1992). "Job shop scheduling by simulated annealing." Operations Research 40(1): 113-125.

Vargas, J., R. Pishori, R. Natu and C. Kee (1992). "Expert system mixed-model assembly line scheduling." Expert Systems with Applications 5(1-2): 79-85.

Vojdani, N. (1997). Intelligent manufacturing control in clothing industry. The 2nd International ICSC Symposium on Fuzzy Logic and Applications, Bangor, Wales, UK.

Wang, D., X. Chen and Y. Li (1996). "Experimental push/pull production planning and control system." Production Planning & Control 7(3): 236-241.

Wang, K., H. Hsia and Z. Zhuang (1995). "Decision learning about production control as machines breakdown in a flexible manufacturing system." International Journal of Flexible Manufacturing Systems 7(1): 73-92.

Wardlaw, R. and K. Bhaktikul (2004). "Comparison of genetic algorithm and linear programming approaches for lateral canal scheduling." Journal of Irrigation and Drainage Engineering-Asce 130(4): 311-317.

Weiss, G. (1995). "On almost optimal priority rules for preemptive scheduling of stochastic jobs on parallel machines." Advances in Applied Probability 27(3): 821-839.

Weng, M. and H. Ren (2006). "An efficient priority rule for scheduling job shops to minimize mean tardiness." IIE Transactions 38(9): 789-795.

Wight, O. (1984). Manufacturing Resource Planning - MRPII. Vt. USA, Oliver Wight Publications, Essex Junction.

Willems, T. and J. Rooda (1994). "Neural networks for job-shop scheduling." Control Engineering Practice 2(1): 31-39.

Wong, W. K., C. K. Chan and W. Ip (2001). "A hybrid flowshop scheduling model for apparel manufacture." International Journal of Clothing Science and Technology 13(2): 115-131.

Wong, W. K., P. Y. Mok and S. Y. S. Leung (2006). "Developing a genetic optimisation approach to balance an apparel assembly line." International Journal of Advanced Manufacturing Technology 28(3,4): 387-394.

Wright, T. (1936). "Factors affecting the cost of airplanes." Journal Aeronautical Science 3: 122-128.

Xu, Z. and X. Gu (2005). "Flow shop scheduling problems under uncertainty based on fuzzy cut-set." Advances in Natural Computation, PT 2, Proceedings 3611: 880-889.

Yamamoto, S., K. Nakadai, M. Nakano, H. Tsujino, J. Valin, R. Takeda, K. Komatani, T. Ogata and H. Okuno (2006). "Genetic algorithm-based improvement of robot hearing capabilities in separating and recognizing simultaneous speech signals." Advances in Applied Artificial Intelligence, Proceedings 4031: 207-217.

Yelle, L. (1983). "Adding life-cycles to learning-curves." Long Range Planning 16(6): 82-87.

Yen, B. and G. Wan (2003). "Single machine bicriteria scheduling: A survey." International Journal of Industrial Engineering-Theory Applications and Practice 10(3): 222-231.

Ying, K. and C. Liao (2003). "An ant colony system approach for scheduling problems." Production Planning & Control 14(1): 68-75.

Yu, J., Y. Yin and Z. Chen (2006). "Scheduling of an assembly line with a multi-objective genetic algorithm." International Journal of Advanced Manufacturing Technology 28(5-6): 551-555.

Zhang, B. and S. Gong (2006). "Stochastic process time based job shop dynamic scheduling." Dynamics of Continuous Discrete and Impulsive Systems-Series A-Mathematical Analysis 13: 67-76.

Zhang, J., L. Zhao and W. Kwon (2001). Scheduling and optimization for a class of single-stage hybrid manufacturing systems. The IEEE International Conference on Robotics and Automation, Seoul, Korea, IEEE Press.

Zhang, Y., P. Luh, K. Yoneda, T. Kano and Y. Kyoya (2000). "Mixed-model assembly line scheduling using the Lagrangian relaxation technique." IIE Transactions 32(2): 125-134.