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Scheduling Mass Customized Large Product Assembly Line Considering Learning
Effect and Shifting Bottleneck

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Abstract

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The large product assembly industry is a complex and heavily manually based assembly manufacturing process. Examples are commercial airplanes, ships, and wind turbines. These manufacturing enterprises are increasingly striving to satisfy the individual needs of customers by providing customized products. Under this circumstance, production completion times are not easy to predict precisely and likely to be variable. This leads to problematic scheduling decisions since scheduling precision depends on reliable job processing time projection.

Mass customization has been a contemporary manufacturing industry management technique, enabling a company to compete with their competitors. It is described as the ability to provide individually designed products and services to satisfy every customer through high process agility, flexibility and integration with acceptable production cost (Davis, 1989). However, implementing the concept of mass customization into the production system is not free and increases both the complexity and the difficulty of the production process compared to mass production.

Thanks to the characteristic of learning effect, which is a phenomenon that people improve operational efficiency when they do the same task repeatedly (Wright, 1936), mass production can simply reach steady production and operational efficiency by scheduling a series of standardized process consecutively. However, it is a challenging task to improve the operational performance in mass customization by utilizing learning effect due to a large variety of different jobs.

In order to achieve mass customization at near mass production efficiency, eliminating the bottleneck is one of manufacturing tactics to improve production efficiency. Most manufacturing systems' performance is constrained by one or more bottlenecks and the critical bottleneck may shift from one work station to another. Therefore, this dissertation addressed the linking of learning effect consideration in a bottleneck selection scheduling heuristic for the mass customized large scale product industry to improve production performance measures such as the completion time, throughput, or due date assignment.

A systematic scheduling heuristic was developed to allocate the same task consecutively to reduce processing time on the critical bottleneck stage and further improve the whole production performance. The scheduling heuristic is based on the classic job shop scheduling problem, the Shifting Bottleneck Procedure, and learning curve consideration. The objective of the sought scheduling heuristics is to provide manufacturers better scheduling decision support for not only satisfying their customer's demand but also improving the performance of the production system. Through the presentation of a simulation model carried out in a wind turbine assembly line, the impact of the proposed scheduling heuristic to the large product assembly performance under mass customization is evaluated and validated.

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Chapter 1: Introduction

The development of a scheduling heuristic for large product industries that facilitates mass customized production is presented in this dissertation. The proposed scheduling heuristic is based on the classic job shop scheduling problem, the Shifting Bottleneck Procedure, and learning curve consideration. The objective of the sought scheduling heuristics is to provide manufacturers better scheduling decision support for not only satisfying their customer's demand but improving the performance of the production system. Through the presentation of a simulation model carried out in wind turbine assembly, the impact of the proposed scheduling heuristic was evaluated and validated.

The background of the dissertation is discussed in this introductory chapter. In section 1.1, the problem overview considered from large product industry and mass customization is described. In section 1.2, operational performance measures for this study are addressed. In section 1.3, the connection between large product industry, mass customization, learning effect and Shifting Bottleneck Procedure is presented and their limitations are discussed. Finally, a description of the organization of this dissertation is provided.

1.1 Overview of Mass Customization and Large Product Assembly Industry

Mass customization (MC) was introduced in the late 1980s due to the dissatisfaction in a homogenous market from general consumers and people desiring more options of products. Mass customization was defined as a system or a company's strategy to meet customer's requirements at an acceptable cost and time frame by using product information technology, flexible systems, and well-designed structures to deliver a range of products and services to compete with their competitors (Silveira et al., 2001). Many manufacturing companies have

focused their effort on meeting individual requirements of their customers to not only make more profit but also expand a company's market by providing various product options. However, implementing MC in a manufacturing production line might cause unnecessary production cost, higher process complexity and poor quality compared to mass production. In addition, mass customization also strongly affects a large product assembly line which is a heavily manually based assembly process since workers need to frequently adapt to different processes and cannot achieve high operational efficiency (Chao and Graves, 1998).

A large product assembly line often consists of a group of structured organizations to produce a family of complex and customized products in the certain geographic region (Lu et al., 2008). Examples are commercial airplanes, ships, and wind turbines. Several unique characteristics of the large scale production have been important among these industries. Most significant characteristics are the long cycle time and low throughput. For instance, the total assembly duration of a wind turbine nacelle may be up to five days to be completed. Long cycle time leads to the limited total production volume in the large product manufacturing industry which means throughput, the average output of a production process per unit time, is limited (Hopp and Spearman, 2011). Throughput is also restricted by a bottleneck which is defined as a work station or process that limits the production rate of the entire system. The queue line or buffer space is also restricted to just one or two available spaces for unfinished products because the capacity of large production working area is limited and there is usually little space for idle unfinished product. In addition, every component or process is very important in the large scale production system since the large scale product design is usually complex and needs precise manufacturing. Under this circumstance, production completion times are not easy to estimate

precisely and likely to be variable. This leads to problematic scheduling decisions since scheduling precision depends on reliable job processing time estimation.

1.2 Production Performance Measures

In this study, the highest priority goal is to achieve 100% customer's requirement under various product demands. Manufacturers strive to schedule the various orders (jobs) in their factory to satisfy their customers; meanwhile, they have to improve the company's performance. Planning and scheduling methods have been the critical key to achieve better company performance. The other typical objective of performance measures at the operational level is to minimize the completion time of a sequence of jobs or tasks, called the makespan, which can improve the throughput, the rate at which jobs are passing through the system. In addition, there are other potential objectives of the job shop scheduling problem. For instance, minimizing tardiness and minimizing variation between due date and finished date of jobs on each machine will be discussed under the environment of mass customized large product assembly line.

1.3 The Problem Statement and Contribution of the Research

Large product manufacturers are striving to develop various products with acceptable cost to satisfy their customers due to the increasing variety of demand. In order to improve the production performance while achieving the product variety and also increasing the throughput, researchers have focused on the development of more efficient manufacturing methods under the environment of applying mass customization. Customized product was best produced in a job shop environment which is craft production, whereas standardized product was best produced in an assembly line (Kotha, 1995). From a practical perspective, the job shop is a common way to describe the process layout which produces custom orders with higher cost in factories. On the

other hand, mass production increases the output and sales by the development and manufacturing of standardized products. Hence, mass customization is a synthesis of the two systems of management: the mass production of individually customized goods and services (Pine, 1993). The relationship between product volume and variety for different production systems is shown in the following

Figure 0.1. The main benefit to applying mass customization to manufacturing industry is to satisfy customer's wants and needs with acceptable production cost. However, implementing the concept of mass customization into the production system increases not only the complexity but also the difficulty of the production process compared to mass production system. In addition, the processing time does not decrease because operators do not perform the same task repetitively due to different customer's orders. This leads the lower production performance of the manufacturing enterprise. Manufacturers will be more successful if they can retain low cost and sufficient throughput while providing the variety of customer's demand. A potential research opportunity is created from the integration of the human experience, learning effect modeling, and scheduling technique (Anzanello and Fogliatto, 2010).

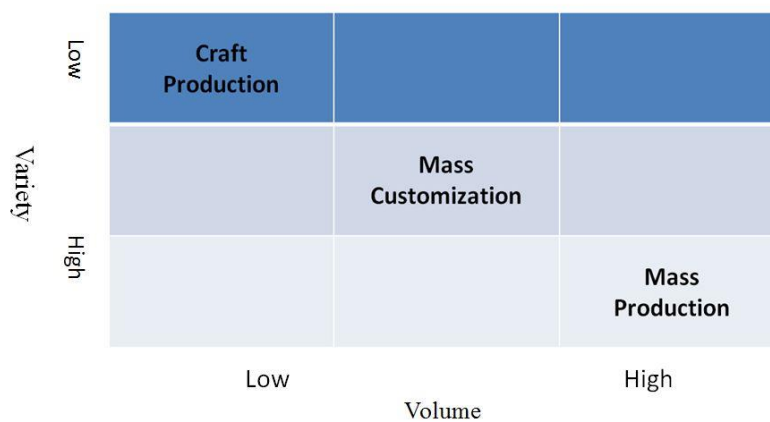


Figure 0.1 The relationship between product volume and variety under different production systems (Browne, 1996)

Biskup (1999) is the pioneer who considered the connection between learning effect and scheduling problem and proved that the single-machine problem with the consideration of learning effects remains polynomially solvable. Dr. Wright (1936) first introduced learning curve and the phenomenon of learning effect happens when operators learn skills and decrease the operation time by repetitive work. However, the processing time will not easily be reduced in mass customization because various customized products increase the complexity of production process. The nature of learning effect is utilized to reduce the process time in each work station as operators become more experienced when operating the same task repetitively. In this research, the proposed scheduling heuristic with learning effect consideration is demonstrated to enhance the performance of the large product assembly line. To achieve mass customization in a large product assembly line, good production design and information technology are necessary. Several researchers have worked on improving the capability of product design and production system for the automotive, computer, and other industries. However, large product assembly industry is rarely discussed. In this study, many approaches of production design are introduced to present effective ways for accomplishing mass customization. All product designs are assumed to be with sufficient information from the design group and are feasible for entering a production line in this study.

Assigning different person to be responsible for specific work stations or tasks is one common way in the modern organization. However, many managers or leaders may neglect the importance of the major bottleneck in the whole production line while only seeking better performance of each individual process. The total production rate will not be improved if the production rate of the bottleneck stage is not improved due to the lack of communication between each manager. As shown in Figure 0.2, the total production rate is still restricted by

stage 2 even though the production rates of all other stages are improved afterward. This study is then inspired by one scheduling heuristic, the Shifting Bottleneck (SB) procedure introduced by Adams et al. (1988) in order to eliminate the major bottleneck in production system. SB procedure decomposes the job shop problem into single machine sub-problems. In each iteration, a critical sub-problem is identified as a bottleneck and solved, and the previously introduced sub-problems are re-optimized until all machines are scheduled (Demirkol et al., 1997). The job shop scheduling problem is known as a NP-hard problem (Pinedo, 2008); hence, most research based on scheduling problem with learning consideration are focused on a single machine or at most two machines problem under different objectives such as minimizing completion time or minimizing the difference from due date. In addition, balancing the bottleneck of the production system has been known as one of the industrial engineering strategies to improve the throughput. Therefore, the development of the Shifting Bottleneck procedure and learning effect (SBLE) aims to provide a systematic heuristic to allocate the same tasks consecutively to reduce processing time on critical bottleneck stage and further improve the whole production performance in mass customized large product assembly line.

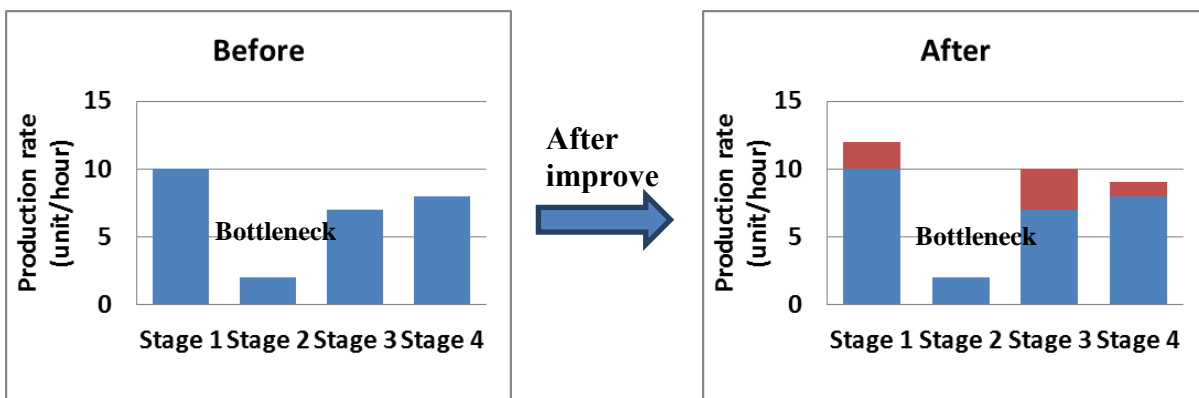


Figure 0.2 An example of the impact of the bottleneck stage

The goal in this research is to provide insights into the scheduling problem with learning curve consideration in a mass customized large product assembly line. The major mathematical and heuristic tools are the learning curve and the Shifting Bottleneck procedure as well as some basic optimization techniques. The proposed scheduling heuristics are based on the perspective of the learning curve and SB procedure in a mass customized large scale production system environment. The benefits and differences between the new heuristic and traditional scheduling problem will be introduced through some numerical examples. The objective of the new heuristic is to get better performance with acceptable computational time compared to the baseline. The long term goal of these new models and measures is to provide large product manufacturers better scheduling decision supports for not only satisfying their customer's demand but improving the performance of the production system. Specifically, the contributions are as follows.

- To provide the framework of the manufacturing scheduling problem with learning effect consideration in a mass customization environment.
- To demonstrate the impact of learning curve to the scheduling problem and provide better processing time prediction.
- To develop a scheduling heuristic to improve the performance of the large scale assembly manufacturing in a mass customization environment based on the Shifting Bottleneck (SB) procedure by utilizing the nature of learning curve effect to balance the bottleneck.
- To compare the performance of the improved Shifting Bottleneck heuristic with learning effect consideration under different practical objective functions such as minimum makespan and minimum tardiness and different priority dispatching rules.
- To show the capability of the improved scheduling heuristic with learning effect and demonstrate the heuristic through some examples and engineering applications by discrete even simulation models.

1.4 Organization of the Dissertation

The remainder of the dissertation is organized as follows. Chapter 2 provides a review of literature on the mass customization related research and introduces the role of mass customization in the manufacturing industry. A review of the classic scheduling approach, Shifting Bottleneck (SB) procedure, is provided. Also, a review of scheduling problem with learning curve consideration is discussed in this chapter to emphasize the impact of learning curve to scheduling problem.

A methodology to describe the process of setting up the research question, selecting the case study, and developing a discrete simulation model is provided in the Chapter 3. This chapter also provides a description of data collection from the case study as a baseline to compare to the result of proposed scheduling heuristics for the subsequent chapter. A simulation model from wind turbine assembly line case study is included to validate and demonstrate the capability of the proposed method.

Chapter 4 builds a simple count example to illustrate the importance of learning curve in a two machine scheduling problem compared to Johnson's algorithm in the beginning of the research methodology and the proposed model is evaluated as to whether it has better production effectiveness. A generalized heuristic of scheduling problem with learning effect for i machines and j jobs will be developed in the following section. The evaluation of the performance of several types of the Shifting Bottleneck (SB) procedure with learning effect consideration is proposed through computational experiments. The original SB procedure model is introduced as well as the modified SB procedure. The research opportunity of connecting SB procedure and learning curving is shown.

Chapter 5 provides a case study for modeling and predicting operation performance measures i.e. mean flow time, mean tardiness, total tardy jobs, and linear combination objectives to industrial data. Through the presentation of a simulation model carried out in a wind turbine assembly line, evaluation and validation of the impact of the proposed SBLE scheduling heuristic to mass customized large product assembly line is given. The simulation results of traditional scheduling rules (FCFS, SPT, EDD) are explained and compared to proposed SBLE scheduling rules on the same industrial data set.

Chapter 6 gives an overview of the main conclusion of this research study. The original contributions that result from the research work are provided. The limitations of the research will be mentioned and finally possibilities for future work are discussed.

Chapter 2 : Literature Review

This chapter provides an overview of previous research dealing with the important aspects of large product assembly industry, mass customization, learning curve, and shifting bottleneck procedure. The main purpose of the literature review work was to survey previous studies and provides the connection between these different research areas. This chapter is organized as follows:

1. Large product assembly industry
2. Mass customization
3. Significance of learning effect
4. Bottleneck based heuristics

2.1 Large Product Assembly Industry

Large scale product industries are known to produce or assembly large size products. Examples are ships, aircraft, and wind turbines. A large product assembly line often consists of a group of structured organizations to produce a family of complex and customized product in the certain geographic region (Lu et al., 2008). There are several crucial characteristics among these industries. The nature of a large scale production system is influenced by its products. The most common characteristic of a large scale production system is the long cycle time and low throughput. For instance, the total assembly cycle time of a wind turbine nacelle may cost up to sixteen hours to be completed and five units yield per week. Long cycle time leads to the limited total production volume in the large scale product manufacturing industry which means throughput, the average output of a production process per unit time, is limited.

Generally speaking, manufacturing companies can be divided into two types: Make to Order (MTO) and Make to Stock (MTS). Kingsman et al. (1996) mentioned that MTO has more flexibility to customize products to meet specific need of individual customers and some or all of production takes place after the customer order has been received. The large scale production system is usually defined under the Make to Order category because the inventory space is usually not big enough for large scale manufacturers to stock those large size products. In addition to the inventory issue, customers who are willing to buy this type of large size product ordinarily have specific requirements and this makes these large scale manufacturing companies cannot just keep producing their products without receiving customer's orders.

Manufacturing enterprises are increasingly striving to satisfy the individual needs of customers by providing varied products or customization. However, the inappropriate product design will lead the company to costly production expense and more complex process. Thus some researchers introduced the structure of product family. Systematic steps were developed by Jiao et al. (1999) to formulate the product family architecture in terms of functional, technical and physical views. The idea of product family simplifies the product offering and reduces part variety by standardizing components so as to reduce manufacturing and inventory costs and variability while satisfying the individual needs of customers. Boeing Company offers various airplane models for different customer's demand from the commercial airplane to the cargo airplane and their product family models are illustrated in Figure 2.1. Customers can initially choose the model type of the airplane to meet their macro demand and then communicate with the Boeing's project team in terms of the detailed product requirements.



Figure 2.1 A Boeing company airplane family (www.boeing.com/commercial)

In the all airplane programs, the Boeing 737 series might be known as the most popular and best selling airplane in the history. The 737 is a single aisle airplane with a twin engine design for the short to medium ranges from sea level runways of less than 6,000 feet. In this model series, there are even more options for customers to meet their detailed requirements such as engine type, seat capacity, fuel capacity, and gravel runway capability etc. For example, each model in the 737 family can seat as many as the number of passengers in an all-economy condition showed in the Table 2.1. In addition, other option engines offer more thrust to improve flight runway length requirement and exhibit lower noise performance. In this large scale production manufacturing example, Boeing Company is certainly trying to achieve the mass customization to satisfy their customers by implementing their product family strategy. This also shows the potential opportunities of implementing mass customization in the large scale production system to improve the company's performance.

Table 2.1 The 737 family (www.boeing.com/commercial)

| | No. of seat | Engine |
|---------|-------------|--|
| 737-300 | 149 | High bypass ratio engines (CFM56-3) |
| 737-400 | 168 | |
| 737-500 | 132 | |
| 737-600 | 130 | Advanced high bypass ratio engines (CFM56-7) |
| 737-700 | 148 | |
| 737-800 | 184 | |
| 737-900 | 189 | |

2.2 Background of Mass Customization

Mass customization is already a well known contemporary manufacturing industry management for the company to compete to their competitor through various products. In these two decades, mass customization has been implemented in the different manufacturing industries to meet customer's demand with various customized products. Broadly, the concept of mass customization was first introduced by Davis (1989) and was described as manufacturing companies trended to produce goods to serve their relatively large market; meanwhile, satisfied those specific need of individual consumers by customized products with acceptable cost. Several papers defined the Mass Customization (MC) as a system that meet customer's requirement at an acceptable cost and time frame by using product information technology, flexible systems, and well designed structures to deliver a various range of products and services (Silveira et al., 2001). Silveira et al. also introduced a framework of different levels at which mass customization may be implemented and how mass customization can be applied by several methodologies and technologies that support those enablers.

Other researchers promoted mass customization as the ability to provide individually designed products and services to every customer through high process agility, flexibility and integration. Some similar and more practical concept of mass customization system is often defined by a series of options at a cost near to that of mass-production items. Besides, mass customization can highlight an alternative to differentiate companies in a highly competitive and segmented market. Duray et al. (2000) have provided a conceptual model with empirical study investigation to identify and categorize mass customizers from perspective of operations. However, manufacturing systems are always changing and mass customers may need to clarify

those issues between manufacturing priority and the related manufacturing capability to the implementation of this strategy.

Table 2.2 Previous Literatures on Mass Customization

| Topics | Author | Years | Area |
|---|-----------------------|--------------|---|
| From "future perfect" : Mass customizing | Stanley M. Davis | 1989 | Mass customization |
| Making Mass Customization Work | B. Joseph Pine | 1993 | Mass customization |
| Mass customization Implementing the emerging paradigm for competitive advantage | Kotha | 1995 | Mass customization v.s. Mass production |
| Approaches to mass customization configurations and empirical validation | Rebecca Duray | 2000 | Empirical study in mass customization |
| The limits of Mass Customization | Paul Zipkin | 2001 | Mass customization |
| Mass customization: Literature review and research directions | Giovani Da Silveira | 2001 | Mass customization |
| Modeling customized product configuration in large assembly manufacturing with supply-chain consideration | Robert F. Lu | 2007 | Customization, supply chain, large size product, and learning curve |
| Mass customization: A method for market segmentation and choice menu design | Flavio S. Fogliatto | 2007 | Customization, marketing analysis |
| Customer-driven product configuration optimization for assemble-to-order manufacturing enterprises | ChungJing Zhou et al. | 2007 | Customization, assemble-to-order manufacturing |
| User design of customized products | Taylor Randall | 2007 | Customization |

| | | | |
|---|------------------|------|--|
| An assessment of effect of mass customization on supplier' inventory levels in a JIT supply chain | Henry Aigbedo | 2007 | Customization, inventory, supply chain |
| Linking learning and effective process implementation to mass customization capability | Xiaowen Huang | 2008 | Mass customization, internal and external learning consideration |
| Supply chain modeling and control for producing highly customized products | D.Mourtzis et al | 2008 | Customization, supply chain |
| Agent-based distributed manufacturing control: A state-of –the-art survey | Paulo Leitão | 2009 | Customization, globalization |

Continuous improvement at Toyota Company is still a successes business story nowadays. Toyota educated its employees to keep improving and developing the production system to achieve the goal of low cost, defect free cars and zero inventory. In the late 1980s, many researchers paid more attention on the concept of mass customization and how to implement it into the practical production industry according the rising various market segments. Toyota saw this approach as a more advanced stage of continuous improvement and began to use their highly skilled, flexible work force to make varied and often individually customized products at the low cost of standardized, mass-produced goods (Pine et al., 1993). Pine et al. mentioned that managers should first turn their process into modules, and then need to create an architecture for linking them to integrate rapidly in the combination or sequence required to tailor products or services in order to achieve successful mass customization. To make mass customization work, the process first must be able to be linked together as quickly as possible and responses and collaborate with customers' need rapidly. Secondly, beyond the initial investment required to create modules, the linkage system must add as little as possible to the cost of making the product or service. Thirdly, the company should be responsible for the

relationship with customer and for the creation of customized product or service. Finally, company will need an instant team for every individual customer in a dynamic network. These teams must be frictionless from the moment of their creation, so they can achieve their customer's attributes by efficient communications.

However, mass customization may not always be the best way to achieve the variety of customer's requirement and not all industries have enjoyed the same intensity of innovation. In every industry, moreover, only certain processing stages are sufficiently flexible, and so only certain product attributes can be customized. Three main elements of mass customization, elicitation, process flexibility, and logistic must be considered by companies to actualize high capability (Zipkin, 2001). Many managers have discovered that mass customization can produce more unnecessary cost and complexity (Gilmore and Pine, 1997). Gilmore et al. have identified four distinct approaches to customization, which are collaborative, adaptive, cosmetic, and transparent. Companies should choose the right approach to identify the critical customer in their business and then carefully identify not only what but also when to customize the product at the lowest price. However, those companies also can combine two or more approaches to achieve their customer's requirement as shown below in Figure 2.2:

1. Collaborative customizers conduct a dialogue with individual customers to help them articulate their need, to identify the precise offering that fulfills those needs, and to make customized products for them.
2. Adaptive customizers offer one standard, but customizable, product that is designed so that users can alter it themselves.
3. Cosmetic customizers present a standard product differently to different customers.
4. Transparent customizers provide individual customers with unique goods or services without letting them know explicitly

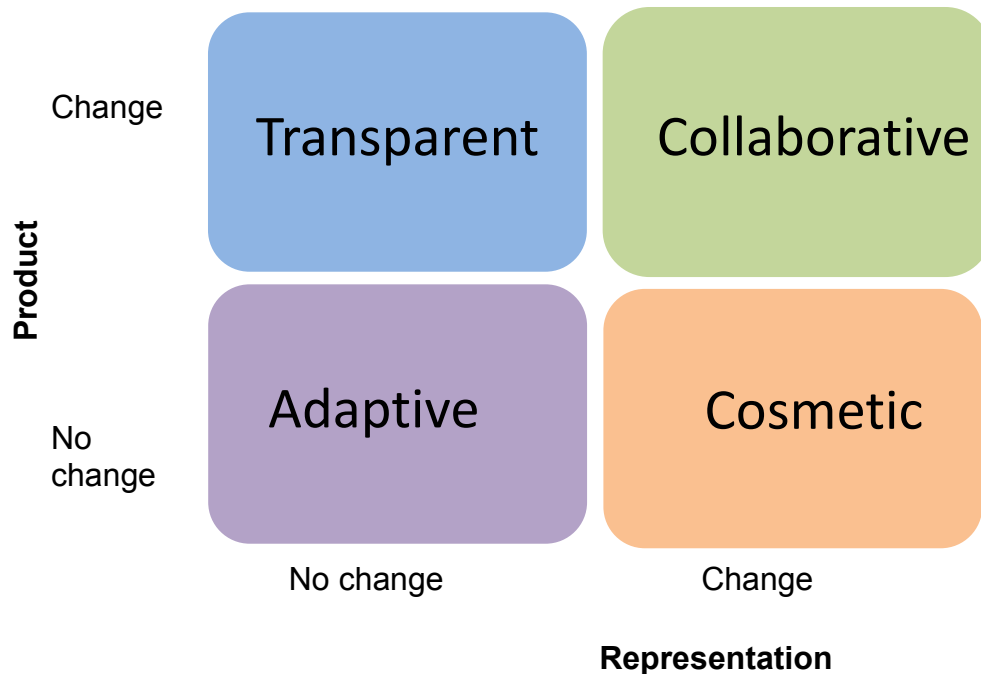


Figure 2.2 The four approaches to customization (Gilmore et al., 1997)

Besides, many researchers have studied that the relationship between product customization and other priorities is not free and common to the impact of mass customization on manufacturing trade-offs are four key competitive priorities: cost, quality, delivery and volume flexibility (Squire et al., 2006). Companies must consider the performance of those factors when they begin to implement a mass customization strategy although Squire et al. mention that the customization has limit effect to those priorities.

2.2.1 Approach to customized product

The first challenge for those manufacturers who are struggling to achieve mass customization is how to design an appropriate product for their customer. Ulrich et al. (2000) introduced a development process to identify the customer needs. The concept development

process implies a distinction between customer needs and product specification. The Figure 2.3 shows a development process steps to facilitate manufacturers to build effective product design for satisfying customer needs.

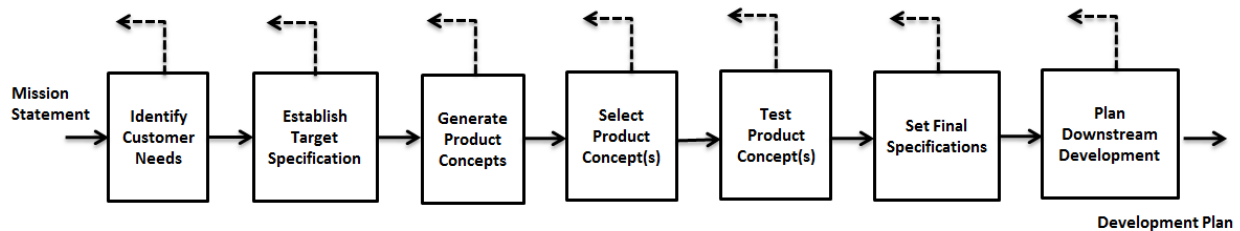


Figure 2.3 The customer-needs activity in relation to other concept development (Ulrich et al. 2000)

Silveira et al. (2001) introduced four main processes and methodologies relating to the MC concept: agile manufacturing, supply chain management, customer-driven design and manufacture, and lean manufacturing. Agile manufacturing has been defined as the ability to thrive in a competitive environment of continuous and unanticipated change to respond quickly to rapidly changing markets driven by customer-based valuing of products. DeVor et al. (1997) identified the main strategic dimensions of agile manufacturing as following:

1. Valued-based strategies that enrich customers focus on delivering value.
2. Cooperating to enhance competitiveness.
3. Organizing to master change and uncertainty.
4. Leveraging the impact of people and information.

These dimensions lead to the concept of internal and external agility. The internal agility may be viewed as the ability to quickly respond to market and customer demands for new products and product features. The external agility is associated with the idea of virtual enterprise which consists of several individual companies linked in a collaborative effort to design high quality and customized products.

Supply chain management concerns the coordination of resources and the optimization of activities across the value chain to obtain competitive advantages (Mourtzis et al., 2008, Lu et al., 2008, Alford et al., 2000). As previous supply chain management papers discussed, the improving supply chain management provides organizational coordination required in MC system and develops an interconnected information network between each involved group. Supply chain management also offers successful balance of low stocks with high delivery service, design of innovative products with active collaboration of suppliers, and cost effective delivery of the right product to the right customer at the right time (Aigbedo, 2007).

The application of customer-driven design and manufacturing in mass customization system (MC) aims fundamentally to provide conditions for customer to initiate the design process of a product and to build an infrastructure to develop new products driven by the market. Several customer-driven design and manufacturing principles are discussed in the previous MC related papers to achieve better configuration and parametric model design. Many researches about configuration design have been discussed. Most of configuration design systems are the catalog design systems, which specify properties of products such as personal computers and passenger cars. Configuration design method is to define the relationship between parts to satisfy the constraints and the product specification (Lu et al., 2008). Some of relations between parts can be given from the start and required functions, performance, and cost can be obtained when a design proceeds within a pre-defined database. Zhou et al. (2007) proposed a new optimization approach for customer-driven product configuration. A mathematic model that maximizes the ratio between overall utility and cost from both perspectives of customers and manufacturers is formulated, and a genetic algorithm is adopted to solve the combinatory optimization. A challenge of mass customization is to quickly and accurately generate product configuration

information for customized product since the potential number of combination of components and design parameters can be very large. In an engineering product configuration problem, it is essential to model customer requirements, component types, design parameters, and the design constraints (Xie et al., 2005). The author proposes an extension of CSP (constraint satisfaction problem) to support n-array constraint over both discrete and continuous variables.

Parametric models also have been discussed in many research papers to achieve customer's satisfaction in an efficient way. The compromise Decision Support Problem (DSP) is a multi-objective mathematical framework which is a hybrid formulation based on mathematical programming and goal programming (Mistree et al., 1993). The compromise DSP is used to determine the values of the design variables that satisfy a set of constraints and achieve a set of potentially conflicting goals as closely as possible (Xiao et al., 2007). In the engineering, the concept of robustness is used to mitigate the consequences of variability to variations without removing its underlying sources (Nair, 1992). Allen et al. (2006) discussed opportunities and challenges for using robust design to improve two or more distinct perspectives or aspects of a system design. Williams et al.(2007) presented augmentations to an existing platform design approach, Product Platform Constructal Theory Method (PPCTM) (Hernandez et al., 2003), that enable a designer to systematically manage modularity and commonality in the development of both customizable products and production process in the presence of non-uniform market demand. Most commercial CAD (Computer Aided Design) systems support the parametric modeling of parts, but the parametric modeling of assembly models is not well supported (Myung and Han, 2001). They presented a system which consists of a commercial expert system shell, a design knowledge-base, and a commercial CAD system to integrating the initial configuration and the detailed CAD design.

Jose et al. (2005) provided a review of modular design methodologies. A good analysis should not only consider an easy platform adaptation to develop other products or economic benefits of easy conception, but also the maximization of economic benefits of the reduction of the number of the total different assets. There are two ways to increase the modularity: one is the division of a module version into small parts, the other is to include more module versions. The platform development allows several advantages, therefore standard and differentiation components should be carefully balanced inside a modular architecture. Emerging technologies in the automotive assembly are discussed by Michalos et al. (2010), and they mention that modularity is an appealing approach, which needs to be strongly supported by software system. The modular product and assembly system design are key issues for modular concept. In the automotive assembly case (Michalos et al., 2010), a product platform design provides a common base for the assembling of a great number of vehicle variations, involving completely different models, and different model versions in the same assembly line. Examples of car assembly line as Table 2.3, different factory departments have to handle the process flexible enough to achieve the goal of producing various products.

| | Description | Department | Example |
|-----------------|--------------------------------------|----------------|--|
| PLATFORM | Car of a different class | Body Shop | C-Class |
| MODELS | Different car model | Body Shop | <pre> graph TD CClass[C-Class] --> Model1[Model 1] CClass --> Model2[Model 2] </pre> |
| VERSIONS | Different versions of the same model | Body Shop | <pre> graph TD Model1[Model 1] --> 3door[3 door] Model1 --> 5door[5 door] Model2[Model 2] --> Coupe[Coupe] Model2 --> Sedan[Sedan] </pre> |
| OPTIONS | Options within versions | Final Assembly | <pre> graph TD 3door[3 door] --> Clima[Clima] 3door --> Navigation[Navigation] 5door[5 door] --> Navigation 5door --> HeatedSeats[Heated Seats] Coupe[Coupe] --> HeatedSeats Sedan[Sedan] --> HeatedSeats </pre> |

Table 2.3 A basic automotive variants derived from the same vehicle platform (Michalos 2010)

Due to the globalized economy competitive, short life cycles of product, and highly customized demand of high quality at low cost, the manufacturing has faced significant changes

during the last decades (Leitão, 2009). In this environment, the current challenge of company is to develop manufacturing control systems which can response customer's requirement rapidly and correctly with acceptable production cost. The multi-agent system paradigm derives from distributed artificial intelligence (DAI) field, being characterized by decentralization and parallel execution of activities based on autonomous entities, called agents. A multi-agent system can be defined as a set of agents that represent the objects of a system, capable of interacting, in order to achieve their individual goal. Since each agent has a partial view of system, the agents need to be able to communicate in order to achieve a pre-defines goal or solve a problem (Leitão, 2009). Agent-based solutions for manufacturing, operation management, supply chain management, and virtual enterprise are being developed quickly and providing four main benefits: feasibility, robustness and flexibility, reconfigurability, and redeployability (Marik and McFarlane, 2005). However, current industrial agent-based solutions have few actual industrial applications or even prototype and have several crucial drawbacks. Cost is the first concern; the investment needed for implementing agent-based solutions is much higher than classical centralized solution. No central control element, unpredictable, emergent behaviors cause many obstacles to company management's easy acceptance of agent-based solutions. Besides, there are still no mature commercial platforms to guarantee on operation performance. Lean manufacturing is an efficient way to satisfy customer needs while giving producers a competitive edge (Storch and Lee, 1999). For a successful implementation of an MC production system, it is to define value based on the customer, to concentrate in the activities that create value and to eliminate all wastes, in all production steps, and to reorganize the value-creating activities into efficient processes without interruptions and incorporating production variant at high levels (Silveira et al., 2001).

2.2.2 Mass Customization Considering Learning Effect

As the description in last section, mass customized production process must be very flexible in order to meet various requirements (Zipkin, 2001) and those manufacturers with high degree of flexibility lead to frequent small batch production. A complex product such as an aircraft engine usually is made in a small batch (low volume) production line and employ related large amount of workers to produce the engine (Kelley, 1994). In batch manufacturing processes, production is punctuated by frequent changes in the different type of product. This causes not only discontinuous learning process but also less efficiency compare to production line with less diverse needs. Therefore, a combination of making the same item in large batches and from frequent repetitions of the same setup tasks on repeated batch orders could improve production efficiency by utilizing learning curve modeling (Adler and Clark, 1991, Silveira et al., 2001).

Although many practical application of learning curve have been reported in the literature (Adler and Clark, 1991, Biskup, 1999, Biskup, 2008), a major research gap still remains in the LC literature and the assignment of products to workers according to product characteristics and batch sizes (Anzanello and Fogliatto, 2007). They proposed a method using learning curve modeling to guild the assignment of products to workers teams in assembly lines. Huang et al. (2008b) provided a systematical investigation between internal and external learning, effective process implementation, and mass customization capability base on an empirical data collected in the high performance manufacturing survey. They also postulated that effective process implementation can be achieved by both internal and external learning which can translate knowledge into manufacturing processes. As a valuable knowledge-based capability, effective process implementation turns out to improve manufacturer's mass customization capability. Anzanello and Fogliatto (2010) proposed a method that integrated a new scheduling heuristic and work's learning curve to schedule jobs in highly customized applications and aimed at

minimizing the total weighted earliness and tardiness. Moreover, learning curve provides a more reliable prediction of process time required for work on each work station. This creates a production scenario that could potentially benefit from the implementation of learning curve (LC) modeling to mass customization environment.

2.3 Learning Effect

Learning effect has received considerable attention in the management science during World War II (Yelle, 1979) and it can be described as a steady decline in process time when operators perform the same task repeatedly (Wright 1936). He first introduced a mathematical learning curve model to represent the worker's learning experience in aircraft industry in 1936 and this model is still one of the best ways to predict operator's performance.

Many learning curve models have been proposed and represent a dependent variable of production performance (e.g. processing time, cost) in terms of an independent variable of cumulative production (Yelle, 1979, Badiru, 1992, Nembhard and Uzumeri, 2000, Anzanello and Fogliatto, 2011). These learning curve models have various mathematical forms in order to represent particular learning circumstances. A numerous amount of applications considered learning curves have been divided into two segments: univariate and multivariate models of learning curves. Several popular univariate models are discussed as below include:

1. The log-linear model (Wright, 1936)
2. DeJong's learning formula (DeJong, 1957)
3. The S-curve (Carr, 1946)
4. The Stanford-B model (Asher, 1956)
5. Levy's function (Levy, 1965)
6. Exponential learning curves (Knecht, 1974, Nembhard and Uzumeri, 2000)
7. Hyperbolic models (Mazur and Hastie, 1978)

Wright's model is often referred to as the log-linear model and the average cost model is one popular form to specify the relationship between the cumulative average cost per unit and cumulative production. The following is mathematical representation for average cost model (Badiru, 1992, Wright, 1936):

$$y = C_1 x^a \quad (2.1)$$

where :

y = cumulative average time (cost) of producing x th units

C_1 = time (cost) of the first unit

x = cumulative production count

$a = \frac{\log \phi}{\log 2}$, the learning index ($-1 < a < 0$)

ϕ = The learning rate

$1 - \phi$ = The progress ratio

DeJong's model (1957) presented a power function which is designed to incorporate the proportion of manual work in a man-machine operation. When operations are partially controlled by machine throughout rates, the processing time will not be completely compressible even if successive units are completed. DeJong's formula introduces an incompressibility factor M and takes into account the manual and machine ratio (Badiru, 1992, Nembhard and Uzumeri, 2000, Anzanello and Fogliatto, 2011). The model is as following:

$$y = C_1 [M + (1 - M)x^a] \quad (2.2)$$

where M ($0 \leq M \leq 1$) is an incompressibility factor. When $M = 0$, the model reduces to the log-linear model which implies there is no machinery engaged in the operation. While $M = 1$, the model represents the operation is completely performed by machine .

Carr (1946) introduced the S-curve model base on considering the gradual start-up. The gradual start-up is on the basis of the fact that some intervention state typically occurs in the first cycle of production. Examples are regular maintenance, changes in tooling, material, method, design, and operators. The S-curve model introduces a variable B which presents the equivalent experience units (Badiru, 1992, Nembhard and Uzumeri, 2000). The model has an incompressibility factor M as the DeJong's model. The basic S-curve model is:

$$y = C_1[M + (1 - M)(x + B)^a] \quad (2.3)$$

The Stanford-B model (1956) is an early study contracted by U.S. Defense Department at Stanford Research Institute (Badiru, 1992). The model includes the B parameter and is a special case of S-curve model with $M = 0$. The model is represented as:

$$y = C_1[(x + B)^a] \quad (2.4)$$

where B ($0 \leq B \leq 10$) is the equivalent units of previous experience at the beginning of the process. It noted that when $B = 0$, the Stanford-B model reduces to the log-linear model. In addition, the Stanford-B model was also found to be the best available model for the manufacturing of Boeing 707 resulted in the smaller sum of squared deviations (Nembhard and Uzumeri, 2000).

Levy's adaptation function (1965) presented a new type of firm learning function for better description of adapting new processes in companies and accounts for the steady state production rate. The model is expressed as:

$$y = \left[\frac{1}{\beta} - \left(\frac{1}{\beta} - \frac{x^a}{C_1} \right) k^{-kx} \right]^{-1} \quad (2.5)$$

where β is a production coefficient for the first unit. k is the operator's performance in steady state and is used to flatten the learning curve for large value of x (Badiru, 1992, Anzanello and Fogliatto, 2011).

Exponential learning curves depend on a more complete set of parameters compare to the conventional log-linear models. Knecht (1974) introduced a modified form of learning curve to improve predictions in long duration production runs (Anzanello and Fogliatto, 2011). If y is defined as the unit cost of the x th unit, then it approaches to 0 when x increases (Badiru, 1992). In order to avoid this zero limit unit cost, Knecht modified the basic function given as:

$$y = \int_0^x C_1 z^a dz = \frac{C_1 x^{a+1}}{(1+a)} \quad (2.6)$$

Knecht then altered the expression for cumulative curve and suggested to integrate exponential and log-linear function as below:

$$y = C_1 x^a e^{cx} \quad (2.7)$$

where c is a second constant and e is the base of the natural logarithm. Other popular exponential learning curve models are the 3-parameter exponential, the 2-parameter exponential, and the constant time models. The extra parameters in those exponential learning curves obtain additional information, and therefore result more precise production rate prediction. It is noted that there are many other existing learning curve models in addition to those listed above and selected models are appropriate representation to this study.

Biskup (1999) might be the pioneer to consider the connection between learning effect and scheduling problem and proved that single-machine problem with the consideration of leaning effects remains polynomially solvable for two objectives which are the minimized

deviation from a common due date and minimized sum of flow time. Learning effects are important if the production environment changes. Typical examples are (Biskup, 2008):

- New (inexperienced) employees
- Investments in new machines or replacement of equipment
- Workflow changes resulting from internal optimization or externally given requirements
- The acceptance of jobs that have never been produced before

A modified formulation to describe the learning effects was introduced in scheduling problem with $p_i, i = 1, \dots, n$ being the normal process time and p_{ir} as the process time of job i if it is scheduled in position r in a sequence as below:

$$p_{ir} = p_i r^a \quad (2.8)$$

where $a \leq 0$ is the learning index, given as the logarithm to the base 2 of the learning rate, and thus for the 80% hypothesis $a = \log_2 0.8 = -0.322$ holds (Wright 1936). According to the equation above, the needed process time in position r decreases by the number of repetitions which represents that operators gain experience and skills after repetitive operations.

Biskup (2008) gave a good literature review on scheduling with learning effects and mentioned that there was a discrepancy between autonomous learning and induced learning. Autonomous learning occurs when operators perform similar operations routinely to get more experience, but cannot be influenced by external factors such as company's training. On the contrary, induced learning can be described as reducing performance time by additional training, investments on higher performance machine, or improved process design etc. Huang et al. (2008a) argued that internal and external learning are two knowledge generation routines that

might influence the effective process implementation and provide empirical result supporting the effect of internal and external learning on mass customization. Internal leaning involves the training of employees and the incorporation of employee suggestions to improve the production system within the plant. External learning involves the interactive between customers and suppliers to solve the problem together. In this study, the autonomous learning effect within the internal leaning is initially considered on scheduling problem.

Mosheiov (2001b) considered to compare the optimal schedule of some classical single-machine problem with learning effect such as minimum makespan, minimum flow-time, minimum sum of weight completion times, minimum maximum lateness, and minimum number of tardy jobs. He showed that several classical scheduling problems with a learning effect do not remain the optimal for certain minimum objective. Mosheiov (2001b) introduced a more general form of position-based learning effects. They assumed that learning takes place by

$$p_{ir} = p_i r^{a_i} \quad (2.9)$$

where $a_i \leq 0$, $i = 1, \dots, n$ being the job dependent learning index,

Koulamas et al. (2007) showed that shortest process time (SPT) sequence is optimal for the single-machine makespan and total completion time minimization problem when leaning effect is expressed as a function of the sum of the processing times of the already process jobs. Then they proved that SPT sequence rule is still optimal of the two-machine flowshop makespan and total completion time minimization problem when job processing times are ordered. A time-dependent learning effect of a job was introduced by Kuo et al. (2006) to assume a function of total processing time of jobs scheduled in front it. In this paper, they also showed that the SPT-sequence is still the optimal sequence in time-dependent learning effect problem. It has been

shown that makespan, the sum of completion times, and the sum of completion times square minimization problems all can be optimally solved by the SPT rule (Wang, 2007).

Lee et al. (2004) discussed the goal of minimize total completion time for the two machine flow shop problem. They assumed that same job has different learning effect on different machines and this assumption is common for those multi-machine scheduling problem with learning consideration. A modified equation with learning effect was introduced by Lee and Wu to represent p_{ijr} as the process time of job i if it is scheduled in position r in a sequence on the machine j :

$$P_{ijr} = p_{ij}r^{ai} \quad (2.10)$$

where $j = 1, \dots, m$ being the machine index. With respect to the equation above, the needed process time in position r on machine j decreases by the number of repetitions, hence, different process on each machine might affect learning situation. A previous literature review of learning curve is provide as shown in the Table 2.4 and indicate that production planning activities may benefit from applications of learning curves (Adler and Clark, 1991, Biskup, 1999, Lonchamp, 2006, Anzanello and Fogliatto, 2007, Lu, 2008).

Table 2.4 Previous literature on learning curve

| Topics | Author | Years | Area |
|---|---|-------|---|
| Factors Affecting the Cost of Airplanes | T.P. Wright | 1936 | Mathematical learning curve |
| Peacetime cost estimating requires new learning curves | G. W. Carr | 1946 | S-Curve model |
| The effects of increasing skill on cycle time and its consequences for time standards | J.R. DeJong | 1957 | DeJong's model |
| Adaption in the production process | F. K. Levy | 1965 | Levy's model |
| Costing, technological growth and generalized learning curves | G. R. Knecht | 1974 | Exponential models |
| Learning as accumulation: A reexamination of the learning curve | J. E. Mazur R. Hastie | 1978 | Hyperbolic models |
| Behind the learning curve a sketch of the learning process | Paul S. Adler Kim B. Clark | 1991 | Learning curve: engineering change and workforce training |
| Computational Survey of Univariate and Multivariate Learning Curve Models | Adedeji B. Badiru | 1992 | Literature review of previous learning curve |
| Productivity and Information Technology: The Elusive Connection | Maryellen R. Kelley | 1994 | Learning curve and customization |
| Single-machine scheduling with learning considerations | Dirk Biskup | 1999 | Scheduling problem considering learning curve |
| An Individual-Based Description of Learning within an Organization | David A. Nembhard Mustafa V. Uzumeri | 2000 | Literature review of learning curve |
| Scheduling problems with a learning effect | Gur Mosheiov | 2001 | Modified scheduling with learning curve |
| Parallel Machine Scheduling with a Learning Effect | Gur Mosheiov | 2001 | Parallel machine scheduling problem with learning curve |
| Minimizing total completion time in a two-machine flowshop with a learning effect | Wen-Chiung Lee Chin-Chia Wu | 2004 | Machine dependent learning curve |
| Flow-shop scheduling with a learning effect | Wang, J. B. Xia, Z. Q. | 2005 | Flow shop and learning curve |
| Minimizing the total completion time in a single-machine scheduling problem with a time-dependent learning effect | Wen-Hung Kuo Dar-Li Yang | 2006 | Time-dependent learning curve |

| | | | |
|--|---|------|--|
| Minimizing total tardiness in a scheduling problem with a learning effect | Eren, T. Guner, E. | 2006 | Learning curve with due date assignment |
| Learning curve modelling of work assignment in mass customized assembly lines | Michel J. Anzanello Flavio S. Fogliatto | 2007 | Learning curve and customization |
| Single-machine and two-machine flowshop scheduling with general learning functions | Koulamas, Christos Kyparisis, George J. | 2007 | shortest processing time (SPT) rule and learning curve |
| Single-machine scheduling problems with the effects of learning and deterioration | Ji-Bo Wang | 2007 | Learning curve with weighted shortest processing time (WSPT) and earliest due date (EDD) |
| A state-of-the-art review on scheduling with learning effects | Dirk Biskup | 2008 | Literature review of scheduling problem considering learning curve |
| Linking learning and effective process implementation to mass customization capability | Xiaowen Huang et al. | 2008 | Learning curve and customization |
| Asynchronous stochastic learning curve effects in a large scale production system | Roberto F. Y. Lu | 2008 | Learning curve and large product industry |
| Asynchronous stochastic learning curve effects in engineering-to-order customization processes | Lu, R. F. Petersen, T. D. Storch, R. L. | 2009 | Learning curve, customization, and large product industry |
| Scheduling learning dependent jobs in customized assembly lines | M.J. Anzanello F.S. Fogliatto | 2010 | Learning curve, customization in shoe industry |
| Learning curve models and application: Literature review and research directions | M.J. Anzanello F.S. Fogliatto | 2011 | Literature review of learning curve in customization |

2.4 Bottleneck based heuristics

The manufacturing industry generally involved many operations on many machines and required many decisions. There have been many classical scheduling theory of deterministic problem of scheduling a fixed number of jobs on a given set of machines to improve the production performance such as minimizing makespan, minimizing tardiness, and minimizing lateness. The classical job shop problem can be described as a set of machines that process operations on jobs. Each job has a predefined operation schedule on each machine with the required process time on it. There are several constraints on jobs and machines as Blazewiz et al. (1996) mentioned. First of all, there are no precedence constraints among operations of different jobs. Secondly, operations cannot be interrupted and each machine can handle only one machine at one time. Finally, each job can be processed only on one machine at one time. Most job shop scheduling problem research has focused on the problem of minimizing makespan (C_{max}). The problem is denoted by $Jm//C_{max}$ in the notation of Lageweg et al. and has been shown to be strongly NP-hard which is among the hardest combinatorial optimization problems. In the past decades, several effective algorithms for job shop scheduling problem have been proposed and many researchers are still working on this problem. These algorithms can be classified as optimization and approximation algorithm (Jain and Meeran, 1999, Wenqi and Alihua, 2004). Wenqi et al. (2004) described that the optimization problems are based on the branch and bound scheme. These algorithms have been considered to achieve the solution, however, their implementation needs too computational cost and time consuming. On the other hand, those approximation algorithms are more effective for large size problem to approach.

A bottleneck is defined as a phenomenon which happens in a process or a working station that limits the performance and production rate of entire system. This can result from either of

following two conditions: (1) capacity of the bottleneck is only slightly greater than demand over the horizon, or (2) the capacity of the bottleneck is exceeded by demand (Billington et al., 1986). Among those approximation algorithms, Adams et al. (1988) proposed the Shifting Bottleneck (SB) procedure and it is probably the most well known among all heuristics for job shop scheduling problem. A brief statement of the Sifting Bottleneck procedure is as optimizing the sequence on each machine repeatedly, while keeps the sequence of other machines fixed. Each one machine solution is compared with the all others and the machine is identified as the bottleneck machine based on their solution. The SB procedure terminates once all machines have been scheduled. It is generally characterized by following steps to minimize the makespan: bottleneck identification, bottleneck selection, and sequence reoptimization. The main contribution of this approach is the way the one machine relaxation is used to decide the order in which machine should be scheduled (Jain and Meeran, 1999).

The first Shifting Bottleneck procedure paper by Adams et al. (1988) has been extended by many researchers into two directions generally: algorithm improvement of SB procedure and real life application of SB procedure. (Schutten, 1998). In the first concern, for instance, the SB procedure is improved by Dauzere-Peres et al.(1993). Researchers found some weakness in the original SB procedure. Dauzere-Peres et al. take account of the dependence between jobs to deal with delayed precedence constraints (DPCs) to distinct from the original procedure. Under the DPCs consideration, Balas et al.(1995) replaced Shifting Bottleneck procedure by DPCs on the one machine problem for identifying the bottleneck machines and scheduling them. Some different version of the heuristics were used in their Modified Shifting Bottleneck procedure such as longest tail heuristic, and Branch and Bound with different number of reoptimization cycles and their computational results showed that some of their modified procedures have better

scheduling. Wenqi & Alihua (2004) proposed a improved Shifting Bottleneck procedure to solve one machine problem with an approximate algorithm instead of the exact algorithm. This improved hybrid SB procedure enhanced the procedure of solving one machine problem with the Schrage algorithm with disturbance.

Nowadays, an algorithm without hybrid schemes not able to meet practical demands for both acceptable computing time and quality solution because the size of job shop scheduling problem is usually large in practice. Several researchers have focused on the hybrid algorithm with Shifting Bottleneck procedure. Dorndore et al. (1995) presented several individual priority rules based on a genetic algorithm which incorporates the SB procedure. It turns out that the hybrid algorithm may not work best because of the amount of the computation time needed based on 1995's technological level. However, a simple genetic algorithm can do its work well to be a sequence of local decision under some specific purposes. Gao et al. (2007) introduced a flexible job shop scheduling problem with genetic algorithm under the objective of min makespan, min maximal machine workload and min total workload. The computational results showed the main positive effect of hybridizing GAs with local search is the improvement in the convergence speed local optimum, on the other hand, the main negative effect is the increase in the computation time per generation. Some researchers (Pezzella and Merelli, 2000, Bülbül, 2011) embedded the tabu search algorithm into the Shifting Bottleneck procedure and demonstrated it on several benchmark instances. Those hybrid tabu-SB procedure algorithm are capable to obtain the optimal or near optimal solutions for many problem instances in a acceptable amount of computing time.

Table 2.5 Previous literatures on the Shifting Bottleneck (SB) procedure

| Topics | Author | Years | Area |
|---|--------------------|-------|---|
| The Shifting Bottleneck Procedure for Job Shop Scheduling | Joseph Adams | 1988 | Minimum makespan problem of job shop scheduling, Shifting bottleneck |
| A modified shifting bottleneck procedure for job-shop scheduling | S. Dauzere Peres | 1993 | Modified Adams' SB of one machine sequencing problems with delayed precedence constraints (DPC) |
| Evolution Based Learning in a Job Shop Scheduling Environment | Ulrich Dorndore | 1995 | An approximation algorithm for shifting bottleneck heuristic |
| The one-machine problem with delayed precedence constraints and its use in job shop scheduling | (Balas et al.) | 1995 | The longest tail heuristic under DPCs |
| Machine Criticality Measures and Subproblem Solution Procedures in Shifting Bottleneck Methods: A Computational Study | Harry H. Holtsclaw | 1996 | Minimize maximum lateness, Shifting bottleneck |
| The Generalized Shifting Bottleneck Procedure | Amar Ramudhin | 1996 | Shifting bottleneck scheduling of openshop and job shop |
| Extending the shifting bottleneck procedure to real-life applications | Philip Ivens | 1996 | Shifting bottleneck scheduling of non-standard job shop problem for real life application |
| The job shop scheduling problem: Conventional and new solution techniques | Jacek Blazewicz | 1996 | A review of job shop scheduling problem techniques |
| A Computational Study of Shifting Bottleneck Procedures for Shop Scheduling Problems | (Demirkol et al.) | 1997 | A evaluation of the performance of several variations of SB procedure |

| | | | |
|---|-------------------|------|--|
| Practical job shop scheduling | J.M.J Schutten | 1998 | Shifting bottleneck method with practical features |
| Guided local search with shifting bottleneck for job shop scheduling | Egon Balas | 1998 | A new search procedure GLS (guided local search) on SB |
| Decomposition methods for large job shop | Marcos Singer | 2001 | A rolling horizon heuristic with shifting bottleneck heuristic |
| A modified shifting bottleneck heuristic for minimizing total weighted tardiness in complex job shops | Scott J. Mason | 2002 | A modified heuristic for minimizing total weighted tardiness in a semiconductor industry |
| An improved shifting bottleneck procedure for the job shop scheduling problem | Huang Wenqi | 2004 | A hybrid shifting bottleneck heuristic |
| A distributed shifting bottleneck heuristic for complex job shops | Lars Monch | 2005 | A modified shifting bottleneck for complex job shops |
| A hybrid genetic algorithm and bottleneck shifting for multiobjective flexible job shop scheduling problems | Jie Gao | 2007 | A improved hybrid algorithm with genetic algorithm |
| A hybrid bottleneck-tabu search heuristic for the job shop total weighted tardiness problem | (Bülbül) | 2011 | tabu search |

In the second concern, many researchers have extended the Adam's original SB procedure to take account of the real life assembly features due to the potential of SB procedure to solve real-world scheduling problem. Ivens et al. (1996) modified the shifting bottleneck procedure to handle some practical cases. They also examined several extensions of the shifting bottleneck procedure towards real life application such as setup time, overlapping, initial work in process, internal transportation delays and parallel machining. Mason (2002) gave a

semiconductor manufacturing example and it showed that this process is one of the most expensive and complex manufacturing processes in existence. The real world wafer fabs contain a large number of different products and each product might need to process equipment sets up of 60-80 different equipment types. The proposed heuristic indicated the potential for promoting on-time deliveries of customer orders by semiconductor manufacturing but further investigations for other manufacturing features are needed in the future. Schutten (1998) mentioned that the manufacturing processes and planning have become more complex due to the increasing demand of high product variety, high quality, short lead time, and an accurate delivery performance. They showed that the SB procedure can be extended to deal with practical features. This implies that a modified SB procedure has potential to improve the manufacturing process under the mass customization environment.

Table 2.6 Previous research in Shifting bottleneck and opportunities

| Topics area | Authors | Opportunities |
|---|---|--|
| The Shifting Bottleneck Procedure for job shop scheduling | Adams et al.(1988) | Learning effect in heuristic |
| Improved Shifting Bottleneck procedure | Dauzere-Peres & Lasserre(1993), Balas et al.(1995), Dorndore et al. (1995), Ramudhin et al.(1996), Blazewicz et al. (1996), Wenqi & Alihua(2004), Monch et al. (2005) | Learning effect in heuristic |
| Bottleneck selection criteria and subproblem solution procedure | Balas et al.(1995) (1998), Holtsclaw (1996), | Subproblem lateness value, preemptive relaxation, and Learning effect in heuristic |

| | | |
|---|--|--|
| The hybrid heuristics of Shifting Bottleneck procedure | Dorndore et al. (1995), Wenqi & Alihua (2004), Gao et al. (2007), Bülbül (2011) | Genetic algorithm, Tabu search, branch and bound, simulated annealing |
| Shifting Bottleneck with various objectives | Holtsclaw (1996), Demirkol et al.(1997), Singer(2001), Mason (2002), Gao et al. (2007) | Makespan, lateness, tardiness, weighted tardiness |
| Shifting Bottleneck procedure for real life application | Ivens et al.(1996), Schutten(1998), | Practical features such as due date, lead time and so on. |
| Different types of scheduling problem | Ramudhin et al.(1996), Monch et al. (2005) | Job shop, open shop, assembly shop, flexible shops |
| Scheduling priority rules | Ivens et al.(1996), Bülbül (2011) | SPT (shortest process time), LPT (longest process time), EDD (earliest due date), FCFS (first come first served), etc. |

Chapter 3 Methodology and Research Design

3.1 Processes of establishing the research

The methodology used for the dissertation is introduced in this chapter and describes the detail of processes to set up the research question. The subsequent three sections describe developments of establishing the research, data collection for this dissertation based on a case study of a nacelles assembly line in a wind turbine manufacturing company, and a development of discrete simulation model and data analysis. A flow chart of research design is shown in Figure 3.1 to describe steps to establish the dissertation as below:

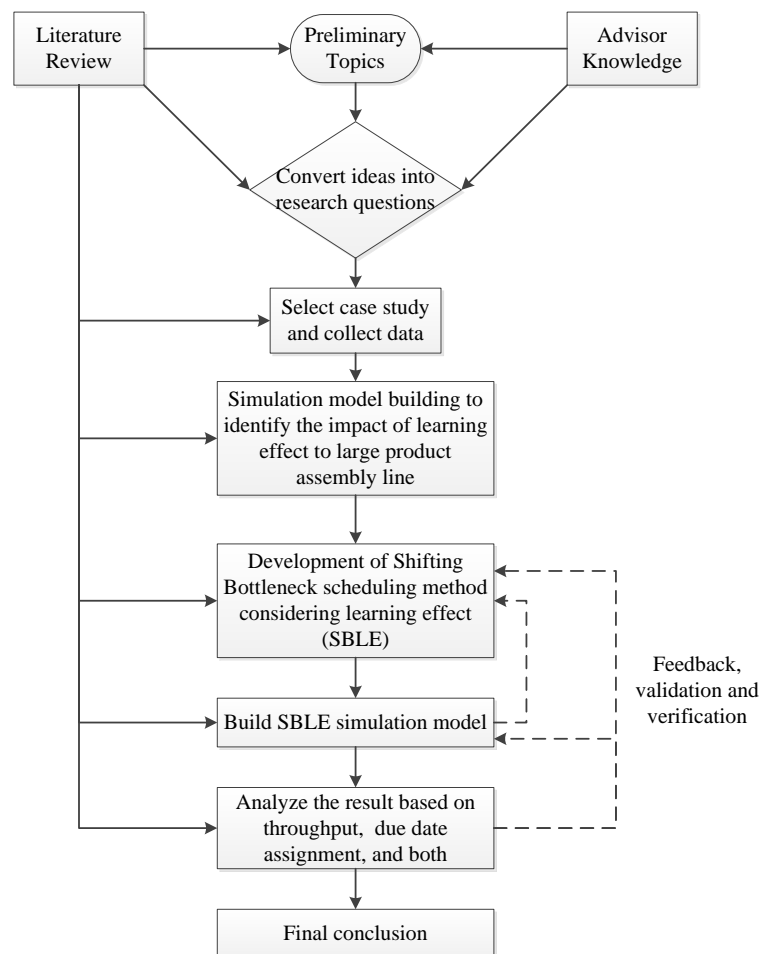


Figure 3.1 Research design flow chart

Firstly, the research question was developed from the linking of different thematic fields, including large product assembly industry, mass customization, learning effect, and Shifting Bottleneck procedure. The fundamental background of these thematic areas is discussed in the Chapter 1. The large product assembly companies are increasingly trying to provide customized products to satisfy individual needs from their customers. Mass customization is introduced as a contemporary manufacturing industry management tool for the company to compete with their competitor through various products. However, implementing the concept of mass customization into the production system is not free and increases both the complexity and the difficulty of the production process compared to mass production. In addition, the processing time in this mass customized product assembly line is not easy to estimate precisely and likely to be variable. This leads to problematic scheduling decisions since scheduling precision depends on reliable job processing time prediction.

Learning effect is considered in this dissertation because the large product assembly industry is still a complex and heavily manually based assembly manufacturing process. The challenging task of improving the operational performance in mass customized product assembly line is due to a large variety of different jobs and cannot utilize characteristics of learning effect. Therefore, the proposed systematic scheduling heuristic based on the Shifting Bottleneck procedure is developed to reduce process time by allocating the same process consecutively on the critical bottleneck stage. The purpose of proposed scheduling heuristic tends to eliminate the major bottleneck and further improve the whole production performance.

The literature review in Chapter 2 is provided to establish a systematic review of existing research opportunities and limitations in the similar area. The particular production characteristic of large product assembly line is introduced to compare with other manufacturing industries. An

airplane example indicates that large product manufacturing is usually defined under the Make to Order category and tends to provide specific product after the customer order has been received. A background of mass customization is presented and several approaches are shown to be viable to achieve mass customization production. Then a review of learning effect is discussed; several famous learning curves are introduced to prove the impact of learning effect to the manufacturing production and scheduling decision. Finally, a review of Shifting Bottleneck Procedure and its research opportunities under mass customization environment considering learning effect is presented.

The case study and data description is introduced in the section 3.2 and enables the use of several scheduling methods and data analysis. Section 3.3 represents the development of a discrete simulation model to address the influence of learning effect to the large product assembly line example base on Arena Simulation Software by Rockwell Automation. Chapter 4 builds a simple count example to illustrate the importance of learning curve in a two machine scheduling problem compared to Johnson's algorithm in the beginning of the research methodology and the proposed model is evaluated as to whether it has better production effectiveness. The original SB procedure model is introduced as well as the modified SB procedure. A proposed SB scheduling procedure with learning effect (SBLE) for i machines, j jobs, and k options will be developed in the following section. A development of a discrete simulation model to demonstrate the proposed SBLE is also discussed.

Chapter 5 provides an application for modeling and predicting production performance level, i.e. throughput, due date assignment, and the balance of throughput and due date assignment. The application of Shifting Bottleneck procedure considering learning effect on the industrial case study is explained.

3.2 Case study and data description

3.2.1 Selection of Case Study

The selected wind turbine company is a large product manufacturer and provides a range of market oriented products to their customer based on different power output and models according to various wind farm location. The company has ability to design and manufacture its own blades, root joints (towers), and nacelles. The nacelles assembly line is chosen for investigation in this dissertation because this production line is the most important and complex production among three main assembly lines. The nacelle assembly line consists of seven major assembly stages: gearbox preassembly, main shaft preassembly, gearbox-main shaft union assembly, main frame assembly, rear frame assembly, main frame-rear frame union assembly, and final housing assembly. A simplified process flow of the nacelles assembly line is presented in Figure 3.2.

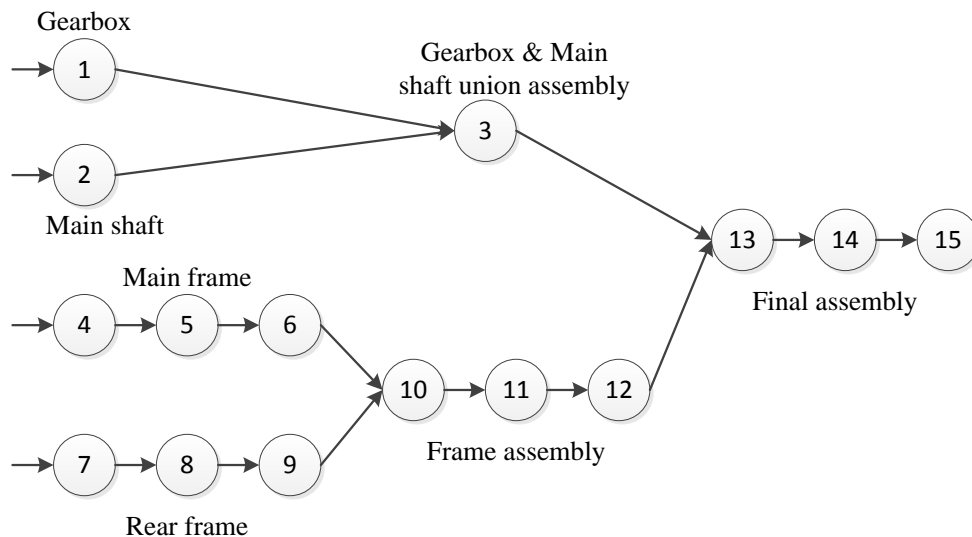


Figure 3.2 Simplified example of nacelles assembly line

In this case, this wind turbine company is assumed to have capability to offer its customers customized nacelles with 3 options ($k=1...3$) on each 15 stations ($j=1,...,15$) without supply shortage or other unexpected emergent situation such as labor absence or delay of delivery. The process begins from station 1, 2, 4, and 7 as shown in Figure 3.2. Main frame assembly stage consists of three specific assemble stations as well as rear frame assembly stage, frame union assembly stage, and final assembly stage. In addition, all jobs need to process through 15 work stations to be completed with same process sequence in this complex system.

3.2.2 Data Collection

The data come from a nacelles assembly line in a wind turbine manufacturing company source. Every order consists of a set of operations to be performed on the station in the assembly line. The routing of a job through the stations is determined in the very beginning and is all the same in this case. Processing time for operations are generated from historical data from the nacelles assembly line and the raw data is provided in the Appendix A. The processing time of each operation of 15 jobs were collected and the following table 3.1 shows the standard processing time of each operation that is used in this dissertation.

Table 3.1 Average and Standard deviation of processing time on each operation in the nacelles assembly example

| Operations \ Processing Time (hours) | Average | S.D. |
|--------------------------------------|---------|------|
| Gearbox | 5.1 | 0.9 |
| Main Shaft | 6.3 | 1.1 |
| Shaft-Gearbox union assembly | 7.8 | 0.8 |
| Main Frame assembly_1 | 24.2 | 6.7 |
| Main Frame assembly_2 | 21.7 | 6.2 |
| Main Frame assembly_3 | 13.2 | 4.6 |
| Rear Frame assembly_1 | 5.5 | 2.6 |
| Rear Frame assembly_2 | 5.7 | 3.4 |
| Rear Frame assembly_3 | 5.1 | 2.2 |
| Main-Rear Frame union assembly_1 | 21.1 | 6.4 |
| Main-Rear Frame union assembly_2 | 24.8 | 8.4 |
| Main-Rear Frame union assembly_3 | 27.2 | 6.9 |
| Final union assembly_1 | 27.7 | 7.1 |
| Final union assembly_2 | 40.9 | 8.9 |
| Final union assembly_3 | 42.0 | 10.5 |

3.3 Model building

3.3.1 Assumptions

The present dissertation focuses on scheduling a complex large product assembly system following assumptions below:

- The sequence of stations, customized configuration, and due date for each job is prescribed.
- Each station can process only one job at a time.
- The processing of a job on a station is called an operation and it cannot be interrupted once it has begun on a station.
- Each station is available all the time for production which means there is no machine breakdown.
- There is restriction on buffer space or queue length in front of stations.
- There is no lack of inventory.
- There is no transportation time between each station.

- The processing time (duration) of each job on each station is not fixed. The duration might decrease owing to learning effect when similar processes are scheduled on the same station consecutively in this developed heuristic.

3.3.2 Discrete event simulation considering learning effect

This section represents the development of a discrete simulation model in order to identify the impact of learning effect to the nacelles assembly line example based on Arena Simulation Software by Rockwell Automation. Simulation data modules and flowchart modules that were used to model the process are listed in the Table 3.2 and Table 3.3 respectively.

Table 3.2 Simulation data modules (ARENA user's guide)

| Data modules | Functions |
|---------------------|--|
| Attribute | Define an attribute's dimension, datatype, and values which is unique for each entity |
| Entities | Represent a unit (i.e. orders, parts, or customers) or logic decision |
| Queue | Stack of entities waiting for available resource in the Process modules or specified signal or condition in the Hold modules |
| Resource | Define the resources need to process an entity |
| Variable | Define an variable's dimension and values which is global to the simulation model |

Table 3.3 Simulation flowchart modules (ARENA user's guide)

| Flowchart modules | Functions |
|--------------------------|---|
| Create | Plan as the starting point and generate entities using a schedule or arrival rate |
| Dispose | Intend as the ending point and entities are disposed here |
| Process | The main processing method to indicate how the entities seize, delay, and release resources in the simulation |
| Decides | Decision making process in the system based on one or more conditions or one or more probabilities |
| Batch | Entities can be temporarily or permanently grouped to represent different situation |
| Separate | The module can be used to duplicate an entity or split a previous batched entity |
| Assign | Assign system variables and attributes |
| Record | Collect statistic in the simulation model |
| Hold | Hold entities in the queue for a signal or a specified condition becomes true and the entity will be removed from the Remove module |
| Remove | Remove a single entity from a specified position in the queue |
| Read/Write | Read data from an input file or Write date to an output file such as EXCEL |

We start by defining the system variables; such that, i denotes the serial number of a job, j denotes the machine or work stage, and k denotes the customization option. In job shop scheduling problem, the processing time of each job on each machine is known and is fixed. However, the processing time of each job might be effected by learning curve when similar processes are scheduled on the same machine in the developed heuristic and this means the processing time of each job on each machine might be changed. The following notations are used for the description of the proposed scheduling method:

$N = \{0, 1, \dots, n\}$ set of jobs

$M = \{0, 1, \dots, m\}$ set of machines

$K = \{0, 1, \dots, q\}$ set of customization options

A = set of machines constrained by precedence relations

p_{ijk} = processing time of job i on machine j with customization category k ,

$i \in N, j \in M, k \in K$

t_{ij} = start time of job i on machine j , $i \in N, j \in M$

c_{ij} = release time of job i on machine j , $i \in N, j \in M$

r = the position of a job when it is scheduled in a sequence with the same operation

$a = \log_2 0.8 = -0.322$

The arrival time and customized configuration of each order should be determined by both manufacturers and customers in this large product industry. However, in order to describe this near realistic situation, a random arrival time $t_{i,0}$ of job i is determined as following and $t_{0,0}$ is given as 0:

$$t_{i+1,0} = t_{i,0} + U(l, u) \quad (3.1)$$

for all i , where $i = 0 \dots n$ being job index where $t_{i,0}$ denotes the arrival time of job i , $U(l, u)$ generates

random number with the lower l and upper u limit of uniform distribution as the time between arrivals of job and $l < u$. The lower and upper limit can be set by the scheduler. The customized options k ($k = 1, \dots, 3$) on each category j ($j = 1, \dots, 15$) is determined by customer and is randomly generated from the function `RANDBETWEEN(1,3)` in EXCEL for this case. The standard processing time on each operation follows the data presented in section 3.2.2. Figure 3.3 shows a flow chart of schedule decision followed by First Come First Served (FCFS) and take into account learning effect in this simulation model.

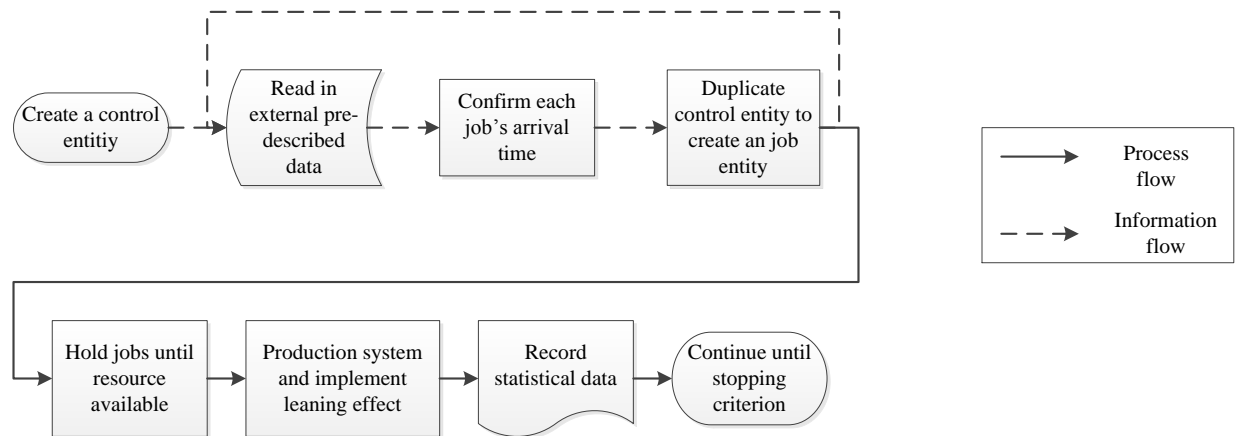


Figure 3.3 Flow diagram of simulation model considering learning effect

More detailed descriptions and heuristics of the discrete simulation methods are discussed as following steps:

1. The initialization module creates only one “control entity” at the very beginning of the simulation model at time 0. This control entity represents a command to repeat routine jobs instead of representing a unit, i.e. jobs, parts, or customers.
2. Read in customer order data from external EXCEL spreadsheet. The simulation model has capability to connect outside data file such as Microsoft Excel,

Microsoft Access, and other data source by using Read/Write module associated with File module which specified data location. In this case, each customer order should have pre-described arrival time t_{i0} and customized configuration as shown in

3. Figure 3.4. When a control entity arrives at the Read/Write module, the specified file is examined and input only one set of date according to serial number.

| Serial Number (i) | arrival time (minutes) | Machines (j) | | | | | | | | | | | | | | |
|-------------------|------------------------|--------------|------------|--------------------------|--------------|--------------|--------------|--------------|--------------|--------------|-------------------------|-------------------------|-------------------------|------------------|------------------|------------------|
| | | Gearbox | Main Shaft | Gearbox_Main Shaft union | Main frame 1 | Main frame 2 | Main frame 3 | Rear frame 1 | Rear frame 2 | Rear frame 3 | Main-Rear frame union 1 | Main-Rear frame union 2 | Main-Rear frame union 3 | Final assembly 1 | Final assembly 2 | Final assembly 3 |
| 0 | 0.00 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 1546.73 | 3 | 3 | 2 | 1 | 3 | 2 | 1 | 2 | 3 | 1 | 3 | 3 | 3 | 1 | 1 |
| 2 | 2057.06 | 3 | 3 | 2 | 3 | 3 | 3 | 2 | 1 | 3 | 2 | 2 | 2 | 1 | 1 | 3 |
| 3 | 2583.03 | 1 | 2 | 1 | 2 | 2 | 3 | 3 | 1 | 3 | 1 | 3 | 2 | 1 | 2 | 1 |
| 4 | 2614.83 | 2 | 2 | 3 | 2 | 1 | 1 | 2 | 1 | 2 | 2 | 2 | 2 | 3 | 2 | 2 |
| 5 | 5411.89 | 1 | 2 | 1 | 2 | 3 | 2 | 3 | 1 | 2 | 2 | 2 | 1 | 2 | 3 | 3 |
| 6 | 6451.04 | 2 | 3 | 1 | 2 | 1 | 3 | 2 | 1 | 2 | 2 | 1 | 3 | 1 | 1 | 2 |
| 7 | 6589.20 | 2 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 1 | 3 | 1 | 3 | 1 | 3 | 3 |
| 8 | 8674.25 | 2 | 2 | 1 | 1 | 2 | 2 | 1 | 2 | 2 | 3 | 1 | 1 | 2 | 3 | 3 |
| 9 | 10807.39 | 1 | 3 | 1 | 1 | 3 | 2 | 2 | 2 | 1 | 3 | 1 | 1 | 2 | 3 | 1 |
| 10 | 12174.76 | 2 | 1 | 2 | 1 | 3 | 2 | 2 | 2 | 3 | 1 | 2 | 3 | 3 | 3 | 3 |
| ... | ... | ... | | | | | | | | | | | | | | |

Figure 3.4 Example of input external data

4. Delay a duration time based on the following equation to ensure that the starting time of each job is exactly equal to the arrival time:

$$\text{Delay time} = \text{Arrival Time} - \text{TNOW} \quad (3.2)$$

Where TNOW is the current simulation time and it records the simulation clock time as the model progresses.

5. The Separate module duplicates the control entity in order to create a job entity to enter the following simulation model. Every time the control entity arrives at the

Separate module, it will be duplicated into two identical entities. The original control entity will go back to Read/Write module and ready to input the data from external file for next job. The other duplicated entity will go forward to the following module and represents the real job entity. The purpose of the use of combining Read/Write module and Separate module is to make sure to input the exact pre-described data from external file.

6. Every entity leaves Separate module represents a job and the value that read into simulation model will be assigned as an attribute on respective entity. Attribute values are unique to each entity and will bind with entity through the entire simulation model unless a new value is assigned to the same attribute.
7. Hold module holds entities in the queue waiting for a signal or until a specified condition becomes true and the entity will be removed from the Remove module. Due to the large product assembly line environment, buffer space or queue length in front of stations is limited. In this case, each entity will leave Hold module by First Come First Served (FCFS) schedule dispatching rule if the buffer space becomes available in front of starting machines which are station 1, 2, 4, and 7.
8. Once each entity enters the production system, there will be a learning curve model agent to assign the new processing time based on the standard processing time by checking if learning effect happened on the entity. This step is to implement the learning effect to jobs which are in the same customization

category on the certain machine and are processed consecutively. There are numerous descriptions and practical applications of learning curve discussed in the literature (Roser et al., 2002, Biskup, 2008). However, the proposed schedule procedure in this dissertation uses a modified learning curve from the classic Wright's log2 learning curve model with $p_{ijk}, i \in N, j \in M, k \in K$ being the normal process time and p_{ijk} as the process time of job i if it is scheduled in position r in a sequence on the machine j in the customization category k as below:

$$P_{ijk} = p_{ijk} r^a \quad (3.3)$$

where $a \leq 0$ is the learning index, given as the logarithm to the base 2 of the learning rate, and thus for the 80% hypothesis $a = \log_2 0.8 = -0.322$ holds. The simulation model represents this processing time with leaning effect function as:

$$EP(\text{LN}(\text{Ptime}(1,k)) - 0.322 * \text{LN}(r)) \quad (3.4)$$

Where EP represents the exponential function, LN denotes the natural logarithm, and Ptime indicates the initial standard processing time in Figure 3.5. For example, Ptime (1,3)=6 represents the standard processing time of any job on machine $j=1$ with the customized option $k=3$ is 6 hours. The procedure is repeated until all unprocessed jobs in the queue are completed and the queue is empty.

| | | Customized options (k) | | |
|--------------------|----|------------------------|----|----|
| | | 1 | 2 | 3 |
| Machine number (j) | 1 | 4 | 5 | 6 |
| | 2 | 5 | 6 | 7 |
| | 3 | 6 | 7 | 8 |
| | 4 | 23 | 25 | 27 |
| | 5 | 20 | 22 | 24 |
| | 6 | 11 | 13 | 14 |
| | 7 | 4 | 5 | 6 |
| | 8 | 5 | 6 | 7 |
| | 9 | 4 | 5 | 6 |
| | 10 | 19 | 21 | 23 |
| | 11 | 22 | 25 | 27 |
| | 12 | 25 | 27 | 29 |
| | 13 | 26 | 28 | 30 |
| | 14 | 39 | 41 | 43 |
| | 15 | 40 | 42 | 44 |

Figure 3.5 Initial standard processing time

3.3.3 Summary of simulation model considering learning effect

There are a total of 500 unprocessed jobs with continuous arrival time waiting to enter the assembly line. The information of each job is assumed to be sufficient for the following manufacturing process including arrival time and product configuration. This nacelles assembly line example also assumed that the buffer space in front of each work station is restricted. First Come First Served (FCFS) and First Come First Served considering Learning Effect (FCFS_LE) are two scheduling rules to determine job priority in the queue to enter the production system in this experiment. Figure 3.6 shows the simulation result of flow time for each job/observation resulted by two scheduling rules. Schedule observation denotes the proposed schedule sequence generated by simulation model with different scheduling rule. Different scheduling rules will be used to determine job priority for entering the production system and the predicted scheduling sequence will be different from job serial number. In this case, the predicted schedule

observation is same as job's serial number in FCFS rule as well as FCFS_LE. The solid trend represents a schedule decision with FCFS dispatching rule which means a job is scheduled according to their arrival time. The earlier a job arrives in the queue in front of the main system, the earlier it can be processed into the main system. The dash trend represents a schedule decision using FCFS dispatching rule considering learning effect (FCFS_LE) and it shows that the average flow time has been improved and reduced from around 27866.3 minutes to 26081.7 minutes in this nacelles assembly line example. FCFS_LE scheduling rule decrease around 6.5% of flow time compared to the result from FCFS scheduling rule. This shows the scheduling rule considering learning effect is not only viable but providing more closed to reality processing time prediction.

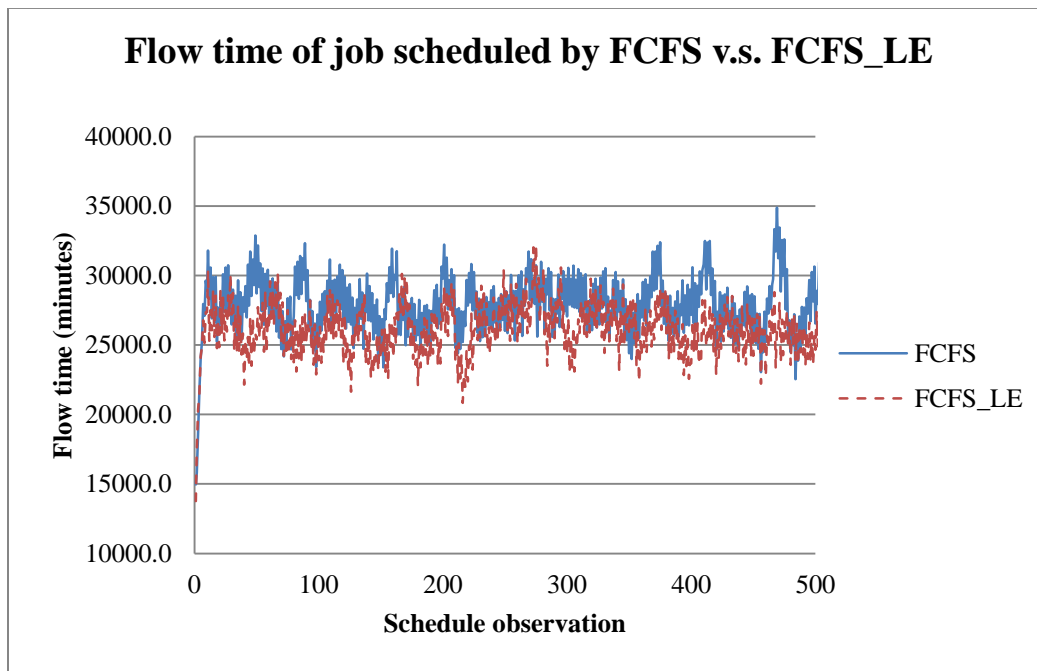


Figure 3.6 Flow time comparison between FCFS and FCFS_LE

Figure 3.7 shows which workstation is the current major bottleneck at the time when a job is released into the assembly line system. The major bottleneck of FCFS moves to work

station 15 after observation 30 and the major bottleneck of FCFS_LE shifts between work station 14 and 15 before observation 200. After around observation 200, work stage 15 continues to be identified as the major bottleneck of FCFS and FCFS_LE until the end of this experiment. This indicates both FCFS and FCFS_LE scheduling rules are not improving the production performance because the major bottleneck is not improved. In the Chapter 4, a proposed Shifting Bottleneck scheduling procedure with learning effect (SBLE) for i machines, j jobs, and k options will be developed to illustrate how to make schedule decision by improving the major bottleneck. A development of a discrete simulation model to demonstrate the proposed Shifting Bottleneck scheduling with Learning Effect (SBLE) is also discussed.

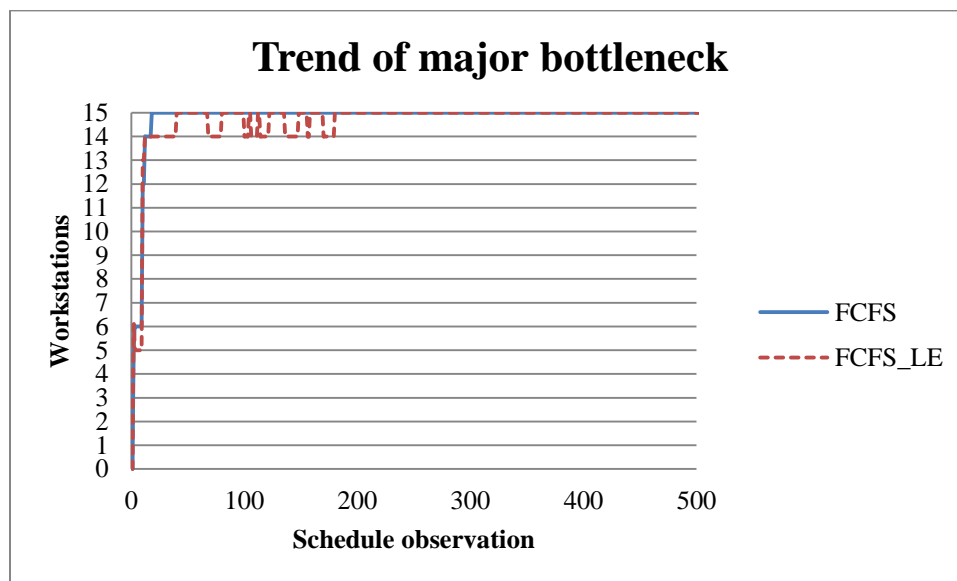


Figure 3.7 Major bottleneck shift diagram

Chapter 4 : Shifting Bottleneck Procedure Considering Learning Effect (SBLE)

This chapter begins with an example to introduce the impact of learning effect to a two machines scheduling problem and compares with the result of Johnson's algorithm. In section 4.2, the original Shifting Bottleneck procedure is introduced and a modified SB procedure is presented for the following improved heuristic. A proposed Shifting Bottleneck procedure considering learning effect is discussed in the section 4.3. Finally, a development of discrete simulation model to address Shifting Bottleneck procedure considering learning effect (SBLE) is presented in the section 4.4.

4.1 Minimizing the total completion time or makespan in a two-machine scheduling problem

Many researchers have proved the Shortest Process Time (SPT) is still an optimal of scheduling problem in a single machine with learning effect (Biskup, 1999). This section will compare the Johnson's algorithm and a bottleneck consideration on scheduling problem with learning effect on a two machines problem. This section 3.1 will use the following variables:

- x_{ijk} = The produced j th component of i th product at stage k ;
the decision variable takes on a value 1 if this unit will
be processed, or a value of 0 otherwise.
- X_i = The i th product design matrix.
- p_{jk} = Time needed to produce j th component at stage k .
- P_{ik} = Time needed to produce i th component at stage k .
- r = The position in a sequence when learning effect triggered.

a = The learning index; We assume $a = -0.322$ by 80% hypothesis (Wright 1936)

t_{ik} = The arrival time of the i th product when entering the stage k and start to produce.

d_{ik} = The departure time of the i th product at stage k .

$$t_{ik+1} - d_{ik} > 0$$

It is assumed that each product X_i need to be processed through k stages and each product has j options of components in each stage and give them a product design matrix based on the product configuration, as following:

$$X_i = \begin{pmatrix} x_{i11} & x_{i12} & \dots & x_{i1k} \\ x_{i21} & x_{i22} & \dots & \\ \dots & & & \\ x_{ij1} & x_{ij2} & \dots & x_{ijk} \end{pmatrix} \text{ for all } i$$

where i denotes the l th product when $i = 1 \dots l$

j denotes the m th option in each stage when $j = 1 \dots m$

k denotes the n th stage when $k = 1 \dots n$

$$\text{and } x_{ijk} = \begin{cases} 1 & \text{if } x_{ijk} \text{ is designed } j\text{th component in stage } k \\ 0 & \text{otherwise} \end{cases}$$

A correspond process time matrix is also given as:

$$P = \begin{pmatrix} P_{11} & P_{12} & \dots & P_{1k} \\ P_{21} & & & \\ \dots & & & \\ P_{j1} & P_{j2} & & P_{jk} \end{pmatrix}$$

Then each product X_i is assumed that just can choose only one component for each stage.

$$\sum_{j=1}^m x_{ijk} = 1 \quad \text{for all } i, k$$

The process time for each product can be defined as following:

$$P_i = \left(\sum_j^m x_{ij1} P_{j1}, \sum_j^m x_{ij2} P_{j2}, \dots, \sum_j^m x_{ijk} P_{jk} \right) \text{ for all } i$$

A classical two machines scheduling problem by Johnson's algorithm is to find the shortest operation duration and schedule it to the correspond machine and keep scheduling by this way until all jobs are done. Given a product assembly example, each product is assumed to be processed two machines and has three component options for each stage. And then the product design matrix and operation time matrix is shown as below:

$$X_i = \begin{pmatrix} x_{i11} & x_{i12} \\ x_{i21} & x_{i22} \\ \dots & \\ x_{ij1} & x_{ij2} \end{pmatrix} \text{ for all } i \text{ where } j = 1 \dots m, m = 3$$

$$P = \begin{pmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \\ \dots & \\ p_{j1} & p_{j2} \end{pmatrix} = \begin{pmatrix} 3 & 4 \\ 6 & 7 \\ 9 & 10 \end{pmatrix} \text{ where } j = 1 \dots m, m = 3$$

$$P_i = \left(\sum_j^m x_{ij1} P_{j1}, \sum_j^m x_{ij2} P_{j2} \right) \text{ for all } i \text{ where } j = 1 \dots m, m = 3$$

Now, supposed that there are 6 jobs with customized configuration design and give them some reasonable process time as below. Each product has to be processed in two stages with respective processing time. An example is as following in Figure 4.1:

$$P = \begin{pmatrix} 3 & 4 \\ 6 & 7 \\ 9 & 10 \end{pmatrix} \text{ where } j = 1 \dots m, m = 3$$

| Jobs | J1 | J2 | J3 | J4 | J5 | J6 |
|-----------|----|----|----|----|----|----|
| Machine 1 | 3 | 6 | 6 | 3 | 9 | 9 |
| Machine 2 | 10 | 4 | 4 | 7 | 7 | 7 |

Figure 4.1 A project scheduling example with processing time

According to the *Johnson's algorithm*, the lowest process time is chosen to assign it to the corresponding machine and keep finding the product with lower process time to assign it to the corresponding machine until all products are assigned. The optimal sequence will be J1,J4,J5,J6,J2,J3, and the makespan is 44 according to the Gantt chart in Figure 4.2.

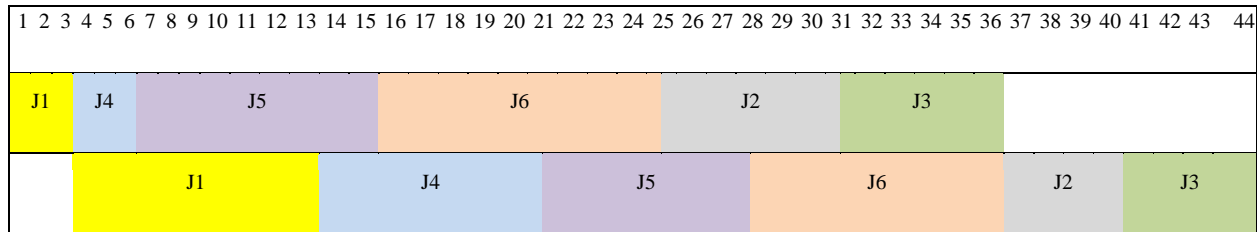


Figure 4.2 Sequence by Johnson's rule

Now, the learning effect to the scheduling problem is considered and schedule sequence is decided according to the bottleneck. Let p_{ir} be the processing time of job i if it is schedule in the position r in a sequence (Dirk B. 1999). Then

$$p_{ir} = p_i r^a$$

Where $a \leq 0$ is the learning index, given as the logarithm to the base 2 of the leaning rate, and thus for the 80% hypothesis $a = \log_2 0.8 = -0.322$ holds (Wright 1936).

Step 1:

Following the first come first served (FCFS) schedule dispatching rule in the very beginning, job 1 enters the system at time 0 and leaves the waiting line. The job 1 finished its process in the stage 1 at time 2 and enters the stage 2 without waiting process. The job 1 then is done the process in the stage 2 at time 13.

Step2:

Job 2 enters the system, meanwhile, the stage 2 becomes a bottleneck because job 2 need to wait for job 1 processing in the stage 2 after job 2 finishes its process in the stage 1 at time 9. By the learning effect, the more consecutive same jobs are assigned together, the more processing time is reduced. Then those majority jobs which did not enter the whole production line with the same process in the stage 2 have priority to enter the system. Job 4, job 5, and job 6 are qualified this criteria.

Step 3:

Job 4 is assigned to enter the production system at time 9 and leaves stage 1 at time 12. And then job 4 enters the stage 2 at time 17 and finishes in the stage 2 at time 24.

Step 4:

Job 5 enters the system and will trigger the learning effect to decrease its operation time in the stage 2. By the learning effect of Biskup (1999), the required processing time of job 5 in the stage 5 will reduce to 5.6 from 7 time unit.

$$p_{5,2} = p_5 * 2^{-0.322} = 7 * 2^{-0.322} = 5.6$$

Step 5:

Job 6 enters the system and also will continue to trigger learning effect to its operation time in the stage 2. The required processing time of job 5 in the stage 5 will reduce to 4.9 from 7 time unit.

$$p_{6,3} = p_6 * 3^{-0.322} = 7 * 3^{-0.322} = 4.9$$

Step 6:

To assign the job 3 to enter the production and the total makespan is 39.5 as in Figure 4.3.

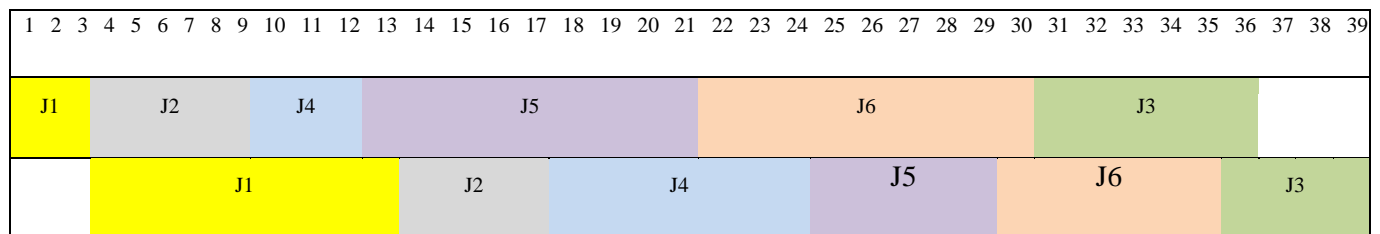


Figure 4.3 Sequence decided by process family with learning effect

In this count example, the conclusion is that two machine scheduling problem with learning effect under bottleneck consideration has shorter makespan than Johnson's algorithm. The further work will be to model this concept as a heuristic under according to the Shifting Bottleneck scheduling problem with different objectives such as minimize flow-time, minimize tardiness or minimize completion time.

4.2 Shifting Bottleneck Procedure

The job shop scheduling or machine problem is as follows, jobs are to be processed on machines with the objective of minimizing some function of the completion times of the jobs, subject to the constraints that (i) the sequence of machines for each job is prescribed; and (ii) each machine can process only on job at a time. Besides, the processing of a job on a machine is

called an operation; its time (duration) is fixed, and it cannot be interrupted. The notation of Adams, et al.(1988) is as below:

$N = \{0, 1, \dots, n\}$ set of operations (with 0 and n as dummy 'start' and 'finish' operations)

$M =$ set of machines

$A =$ set of pairs of operations constrained by precedence relations

$E_k =$ set of pairs of operations to be performed on machine k
and which therefore can not overlap in time

$p_i =$ processing time of operation i , $i \in N$

$t_i =$ start time of operation i , $i \in N$

The problem can be stated as:

$$\begin{aligned}
 (P) \quad & \text{Min } t_n \\
 & \text{s.t.} \\
 & t_j - t_i \geq p_i \quad (i, j) \in A \\
 & t_i \geq 0 \quad i \in N \\
 & t_j - t_i \geq p_i \vee t_i - t_j \geq p_j \quad (i, j) \in E_k, k \in M
 \end{aligned} \tag{4.1}$$

Any feasible solution to (P) is called a schedule. Adams, et al.(1988) also mentioned that it is useful to represent this problem on a disjunctive graph $G = (N, A, E)$, with node set N , (directed) ordinary arc set A , and disjunctive arc set E . The length of an arc $(i, j) \in A$ is p_i and the length of an edge $(i, j) \in E$ is either p_i or p_j , depending on its orientation. Each machine k corresponds to a set N_k of nodes (operations) and a set E_k of edges that together form a disjunctive clique. A clique is a term in graph theory that refers to a graph in which any two nodes are connected to one another; in this case each connection within a clique is a pair of disjunctive arcs (Pinedo, 2005). Figure 4.4 shows a disjunctive graph representing a job shop scheduling problem with 3 jobs and 3 machines. The disjunctive cliques corresponding to the 3

machines have node sets $N_1 := \{1, 5, 8\}$, $N_2 := \{2, 4, 9\}$, $N_3 := \{3, 6, 7\}$, with their edges drawn in the dotted lines.

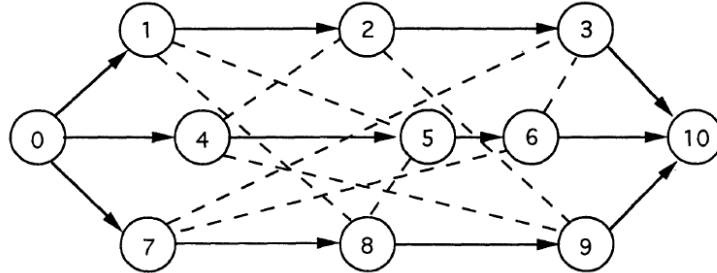


Figure 4.4 Disjunctive graph for a three-job Three-machine problem (Balas et al., 1995)

The job shop scheduling problem is well known to be strongly NP-hard and the Shifting Bottleneck (SB) procedure (Adams et al., 1988) is one of them.

During the SB procedure, let M_0 be the set of machines already sequenced ($M_0 = \emptyset$ at the start).

A brief statement of Shifting Bottleneck Procedure is as follows:

1. Identify a bottleneck machine m among the machines $k \in M \setminus M_0$ and sequence it optimally. Set $M_0 \leftarrow M_0 \cup \{m\}$ and go to step 2.
2. Reoptimize the sequence of each critical machine $k \in M_0$ in turn, while keeping the other sequences fixed; i.e. set $M'_0 = M_0 - \{k\}$ and solve $P(k, M'_0)$. Then if $M = M_0$ stop; otherwise go to 1.

Then the standard one-machine scheduling problem to be solved for machine k can be stated as:

$$\begin{aligned}
 & (P(k, M_0)) \text{ Min } t_n \\
 & \text{s.t.} \\
 & \quad t_j - t_i \geq p_i + q_i \quad \quad \quad (4.2) \\
 & \quad t_i \geq r_i \quad \quad \quad i \in N^* \\
 & \quad t_j - t_i \geq p_i \vee t_i - t_j \geq p_j \quad \quad (i, j) \in E_k, k \in M
 \end{aligned}$$

Where N^* is the set of jobs to be processed on machine k , r_i is the release time of job i equal to the length $L(0, i)$ of the longest path from node 0 to node i . And $q_i = L(i, n) - p_i$ is the time to be spent in the system after the end of operation i . Dauzere-Peres & Lasserre (1993) mentioned the drawbacks of SB procedure and introduced a modified SB procedure. The SB procedure uses the Carlier's algorithm which is an efficient algorithm to solve one machine problem and jobs here are treated as independent. However, some jobs may be dependent in the one machine scheduling problem of SB procedure. For instance, if in the graph of Figure 4.4 the edges joining the node set $N_1 := \{1, 5, 8\}$ are replaced, as a result of sequencing machine 1, by the direction arcs $\{(5, 1), (5, 8), (1, 8)\}$, that replacement creates the path $\{(4, 5), (5, 1), (1, 2)\}$ from 4 to 2, of length $L(4, 2) = p_2 + p_5 + p_1$, which in turn imposes the constraint $t_2 - t_4 \geq L(4, 2)$ as Figure 4.5. It is apparently that the constraint $t_j - t_i \geq L(i, j)$ is different from the original precedence constraint $t_j - t_i \geq p_i$. The delay $L(i, j)$ involved in the constraint is different from and usually large than p_i . In order to make this distinction, the constraints described here precedence constraints with delay is called delayed precedence constraints (DPC).

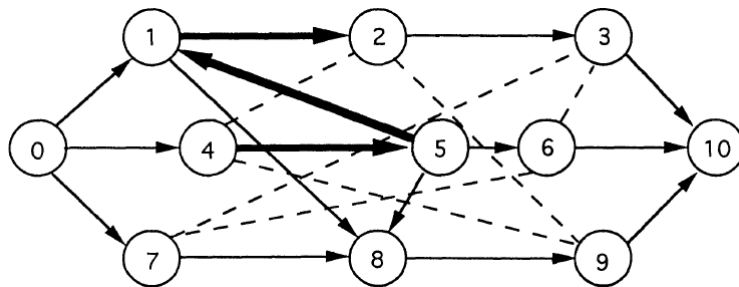


Figure 4.5 Disjunctive graph after sequencing machine 1 (Balas et al., 1995)

Thus, it is sometimes impossible to find an optimal sequence with Calier's algorithm and may select incorrect bottleneck machine in the first step of the SB procedure. Therefore, Dauzere-Peres & Lasserre (1993) introduced a modification of the one machine scheduling problem which is to take account of dependent between jobs as following state and the modified Carlier's algorithm to get better results in local optimization procedure.

$$\begin{aligned}
 & (DPC(k, M_0)) \text{ Min } t_n \\
 & \text{s.t.} \\
 & \quad t_j - t_i \geq p_i + q_i \\
 & \quad t_i \geq r_i \quad \quad \quad i \in N^* \\
 & \quad t_j - t_i \geq L(i, j) \quad \quad (i, j) \in F \\
 & \quad t_j - t_i \geq p_i \vee t_i - t_j \geq p_j \quad (i, j) \in E_k, k \in M
 \end{aligned} \tag{4.3}$$

Where F is the set of precedence arcs, i.e., pairs with delayed precedence constraints, and $L(i, j)$ is the length of a longest path from i to j . The modification consist of updating the start time of operations each time by Scharage's algorithm and trying to decrease the modified start time of operations on a critical path. Modified Scharage's algorithm is as following:

1. Set $t = \min_{i \in I} r_i; U = \emptyset$
 2. At time t , among ready job i ($r_i \leq t$) of \bar{U} , schedule job j with greatest q_i (if there are ties, break them by giving preference to the greatest p_i)
 3. Set: $U = U \cup \{j\}$; for all $i \in \bar{U}$, if ($p_{ij} \neq 0$) and ($r_i < t + p_{ij}$) then $r_i = t + p_{ij}$
 $t_j = t; t = \text{Max}(t_j + p_j, \min_{i \in \bar{U}} r_i)$
- If U is equal to I , then stop; otherwise, go to 2.

where U is the set of jobs already scheduled and \bar{U} is the set of all other jobs. p_{ij} ($i, j \in I$, I is a set of jobs on a machine) is the length of the longest path between i and j in the whole graph (=0 if there is no path). To be able to reduce the makespan in reducing t_i , there must exist a job $j \in I$ which satisfy the following conditions:

1. $p_{ij} \neq 0$
2. $r'_j = t_i + p_{ij}$
3. $r'_j \neq r_j$
4. job j on critical path

Condition 1 and 2 just state the dependence of i and j . Condition 3 ensures that a decrease of t_i will reduce release date of j . If condition 4 is not satisfied, there is no advantage in reducing r'_j . For all i which satisfies the necessary conditions described above, set $q'_i = C_{\max} - t_i - p_i$ and use the modified Carlier's algorithm to continue to find better results from Dauzere-Peres & Lasserre (1993).

4.3 Approach to Shifting bottleneck procedure considering learning effect (SBLE)

In job shop scheduling problem, the processing time of each job on each machine is known and is fixed. However, the processing time of each job might be effected by learning curve when similar processes are scheduled on the same machine in the developed heuristic and this means the processing time of each job on each machine might be changed. Biskup (1999) introduced a modified formulation $p_{ir} = p_i r^a$ to describe the learning effects in scheduling

problem with $p_i, i = 1, \dots, n$ being the normal process time and p_{ir} as the process time of job i if it is scheduled in position r in a sequence.

According to the equation (1), the processing time in position r decreases by the number of repetitions which represents that operators gain experience and skills after repetitive operations. The variety of the product in the mass customization production system is much higher than the variety in the mass production system. Whereas the various customized products, the processing time can be reduced when same processes are scheduled on the certain machine. Note that the learning effect of job i in position r only depends on its processing time, the learning index, and the number of jobs with same process on a machine processed prior to the job i . In Table 4.1, it shows the relationship between the processing time of job i and position r . There will be no learning effect triggered if the prior job processes different task from job i . A matrix of processing time for different components family is necessary for the model due to the learning effect starts only when the same processes are scheduled consecutively.

Table 4.1 Matrix of processing times (Biskup, 1999)

| | $r = 1$ | $r = 2$ | ... | $r = n$ |
|-------|---------|-----------|-----|-----------|
| p_1 | p_1 | $p_1 2^a$ | | $p_1 n^a$ |
| p_2 | p_2 | $p_2 2^a$ | | $p_2 n^a$ |
| ... | | | | |
| p_n | p_n | $p_n 2^a$ | | $p_n n^a$ |

Initially, defining the due date is provided and each job's due date has to be pre-assigned by a scheduler who could be manufacturers or customers in a practical case before a job arrives to the production system. In order to describe this near realistic situation, a random due date d_i of job i is determined as following:

$$d_i = t_{i0} + U_d(l_d, u_d) \quad (4.4)$$

where t_{i0} denotes the arrival time of job i , $U_d(l_d, u_d)$ generates random number with the lower l_d and upper u_d limit of uniform distribution as time duration to promised due date. The lower and upper limit can be set by the scheduler and the lower limit is always smaller than upper limit $l_d \leq u_d$. It should be noted that if the lower limit l_d is a very large number, i.e. one million hours, then it means that due date is not the major concern for a manufacturer's scheduling decision.

Many bottleneck identification methods have been suggested and two popular methods to define the bottleneck in a manufacturing system are described as follows (Roser et al., 2002, Li et al., 2009). The first method is to define the station with highest utilization as a bottleneck among the production system. However, there might be more than one work stations with the same utilization in the system and this leads to insensitive detection of the real bottleneck. The second method defines bottleneck by measuring the longest queue line of unprocessed jobs in front of each work station or longest waiting time of each work stage. It is also a simple method to observe the length of queue on each machine in a manufacturing production line. The drawback of this method is lack of accuracy when the maximum of buffer size is limited. The number of unprocessed jobs on more than one busy work stations is restricted by buffer size and this causes difficulty to define a real bottleneck. This commonly happens in large scale production system, for example, an airplane assembly line may just have one buffer space in front each stage.

In this study, there are two types of operations in the assembly line as an example of nacelles assembly line in a wind turbine production system shown in Figure 3.2. A regular operation is defined as the one has only one immediate predecessor. Therefore, the largest

waiting time is chosen as a bottleneck identification criterion for the regular operation in this research:

$$\max \left(\frac{\sum_{i=1}^n t_{i1} - c_{i0}}{i}, \frac{\sum_{i=1}^n t_{i2} - c_{i1}}{i}, \dots, \frac{\sum_{i=1}^n t_{ij} - c_{ij-1}}{i} \right) \quad (4.5)$$

for all j , where $j = 1 \dots m$ being machine index, t_{ij} denotes the start time of job i on machine j and c_{ij} is the release time of job i on machine j .

The other type of operation is the one has two or more predecessor and need to wait for completed jobs from their predecessors to continue the operation. Examples of these operations are operation 3, 10, and 13 in Fig. 3.2. For the other kind operation which has more than one parallel machine should combine and precede a certain work stage, the succeeded stage is determined as a bottleneck stage if the arrival time is larger than any other completion time from preceding machines:

$$\max(t_{ij} - \max_{l \in A} c_{il}, 0) \quad (4.6)$$

$c_{il \in A}$ denotes the release time of job i on machine l precedes machine j . Where l are machines precedent to machine j and is defined in the set A . On the other hand, one of predecessors of current operation is determined as a bottleneck if the equation above is equal to 0. Once the bottleneck station is determined, the next step is to identify the major bottleneck of the production system according to the bottleneck decision tree which needs to be developed by manufacturing engineer. Figure 4.6 shows an example of major bottleneck decision tree based on the example of nacelles assembly line in Figure 3.2.

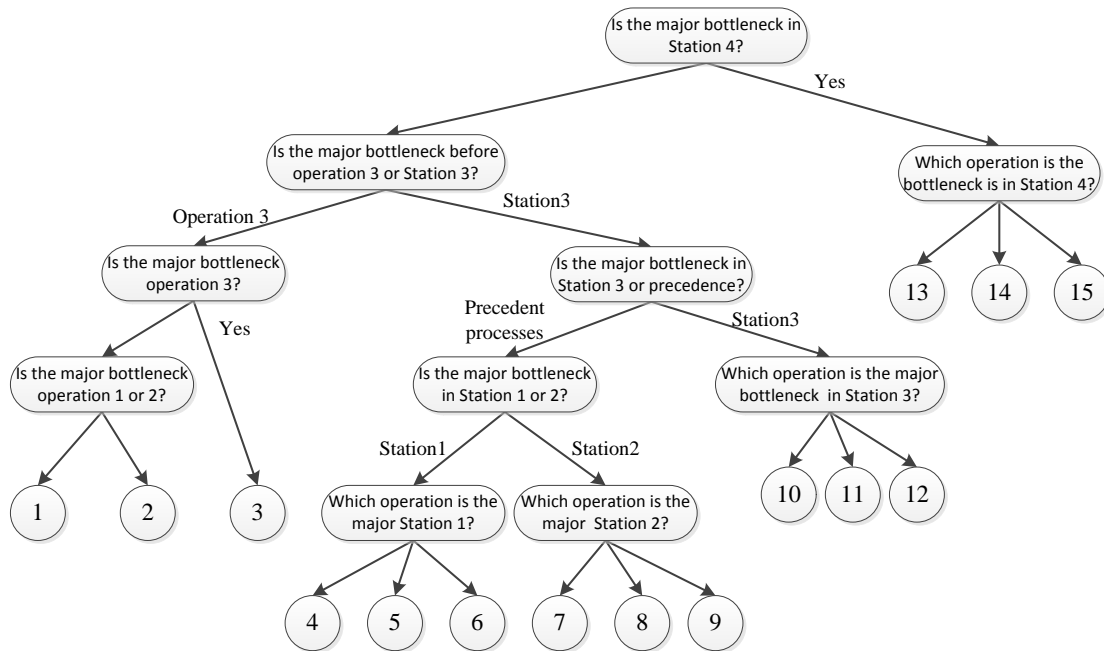


Figure 4.6 An example of major bottleneck decision tree based of nacelles assembly line

The approach to Shifting Bottleneck procedure considering learning effect (SBLE) is described as follows based on assumptions in section 3.3, the Shifting Bottleneck Procedure in section 4.2, and additional description of due date assumption and the major bottleneck decision tree in section 4.3:

1. Set $t = \min_{i \in N} t_{i0}$; $U = \emptyset$, $M_0 = \emptyset$
2. Check if the most front job i will exceed its due date. If $C_i = T_{now} + \bar{C} \geq d_i$ and go step 6; otherwise $C_i < d_i$ go to step 3.
3. Identify the major bottleneck machine j^* among machines $j \in M$ by major bottleneck selection tree and set $M_0 \leftarrow j^*$. If $j^* = M_0$ and go to step 5; otherwise go to step 4.
4. Find set of job i^* among jobs $i \in N$ with the most frequent k on the major bottleneck machine j^* and identify with higher schedule priority. Set $r = 0$. Go to step 5.
5. Set $r = r + 1$. If $i^* = \emptyset$ go to step 3; otherwise go to step 6.
6. Set: $U = U \cup \{i\}$; $i \in i^*$ with $\min(t_{i0})$ for all $i \in \bar{U}$ and define $p_{ijk_r} = p_{ijk} r^a$ when $j^* = M_0$. If U is equal to N , the procedure stops; otherwise go to step 2.

where U is the set of jobs already scheduled and \bar{U} is the set of all other jobs.

4.4 SBLE Discrete Simulation Model

The development of a discrete simulation model to apply proposed Shifting Bottleneck procedure considering learning effect (SBLE) in the nacelles assembly line example is presented in this section. A modified discrete simulation system model with learning effect consideration from section 3.3 is discussed in the section 4.4.1. The SBLE scheduling decision model will be discussed in section 4.4.2. Detailed descriptions and heuristics of the discrete simulation methods are discussed as following two sections.

4.4.1 Discrete simulation system model considered learning effect

The discrete simulation system model presented in the section 3.3 is modified by adding two additional models in order to connect SBLE decision model. Step 6 and step 8 are key added models to be described as following:

1. The initialization module creates only one “control entity” at the very beginning of the simulation model at time 0. This control entity represents a command to repeat routine jobs to read data from EXCEL file instead of representing a unit, i.e. jobs, parts, or customers.
2. Read in customer order data from external EXCEL spread sheet. In this case, each customer order should have pre-described arrival time t_{i0} and customized configuration. When a control entity arrives the at Read/Write module, the specified file is examined and input only one set of data according to serial number.

3. Delay a duration time based on the following equation to ensure that the starting time of each job is exactly equal to the arrival time:

$$\text{Delay time} = \text{Arrival Time} - \text{TNOW}$$

Where TNOW is the current simulation time and it records the simulation clock time as the model progresses.

4. The Separate module duplicates the control entity in order to create a job entity to enter the following simulation model. Every time the control entity arrives the Separate module, it will be duplicated into two identical entities. The original control entity will go back to Read/Write module and ready to input the data from external file for next job. The other duplicated entity will go forward to the following module and represents the real job entity.
5. Every entity leaves Separate module represents a job and the value that read into simulation model will be assigned as an attribute on respective entity. Attribute values are unique to each entity and will bind with entity through the entire simulation model unless a new value is assigned to the same attribute.
6. A frequency counter model is built to keep tracking the number of each customization option corresponding to its work station based on unprocessed job in the queue. An example of frequency model to accumulate the information of five unprocessed jobs in the queue is presented in Figure 4.7. For instance, the first column indicates that one job need to be processed option $k = 1$, three jobs

need to be processed option $k = 2$, and one job need to be processed option $k = 1$ on the work station $j = 1$. The purpose of this step is to provide current unprocessed job information for SBLE model to make schedule decision.

| | | Machine or work station number (j) : | | | | | | | | | | | | | | | # of unprocessed |
|-------------------------------|---|--|---|---|---|---|---|---|---|---|----|----|----|----|----|----|------------------|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | |
| Customization options (k) : | 1 | 1 | 4 | 4 | 2 | 1 | 1 | 1 | 1 | 1 | 0 | 2 | 3 | 1 | 3 | 2 | 5 |
| | 2 | 3 | 1 | 0 | 2 | 3 | 1 | 2 | 2 | 3 | 1 | 2 | 0 | 2 | 1 | 2 | |
| | 3 | 1 | 0 | 1 | 1 | 1 | 3 | 2 | 2 | 1 | 4 | 1 | 2 | 2 | 1 | 1 | |

Figure 4.7 An example of frequency counter model to accumulate unprocessed job information

7. Hold module holds entities in the queue waiting for a signal or until a specified condition becomes true and the entity will be removed from the Remove module. Due to the large product assembly line environment, buffer space or queue length in front of stations is limited. In this case, each entity will leave Hold module by SBLE method discussed in the section 4.3 meanwhile the buffer space have to be available in front starting machines which are station 1, 2, 4, and 7 as shown in Figure 3.2.
8. Figure 4.8 shows this frequency counter model subtracts one from each work station when one job is removed from Hold module. In this example, the current number of unprocessed job is four and the released job from Figure 4.7 has customization option $k = (2, 1, 1, 3, 2, 2, 3, 2, 3, 3, 1, 1, 3, 1, 1)$ correspond to machine $j = 1, \dots, 15$. Now, noted that one job need to be processed option $k = 1$, two jobs need to be processed option $k = 2$, and one job need to be processed option $k = 1$ on work station $j = 1$. The current number of customization option $k = 2$ on work station $j = 1$ is 2 because the job removed from Hold module has to process customization option two on machine one $(k, j) = (2, 1)$.

| | | Machine or work station number (j) : | | | | | | | | | | | | | | | # of unprocessed jobs in the queue |
|-------------------------------|---|--|---|---|---|---|---|---|---|---|----|----|----|----|----|----|------------------------------------|
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | |
| Customization options (k) : | 1 | 1 | 3 | 3 | 2 | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 2 | 1 | 2 | 2 | 4 |
| | 2 | 2 | 1 | 0 | 2 | 2 | 0 | 2 | 1 | 3 | 1 | 2 | 0 | 2 | 1 | 1 | |
| | 3 | 1 | 0 | 1 | 0 | 1 | 3 | 1 | 2 | 0 | 3 | 1 | 2 | 1 | 1 | 1 | |

Figure 4.8 An example of frequency counter model to subtract one from each machine based on the released job information

9. Once each entity enters the production system, learning curve model agent will assign the new processing time based on the standard processing time by checking if learning effect happened on the entity. This step is to apply the learning effect to jobs which are in the same customization category on the certain machine and are processed consecutively as presented in the section 3.3.3. The procedure is repeated until all unprocessed jobs in the queue are completed and the queue is empty.

A flow diagram of schedule decision by linking the discrete simulation system model and Shifting Bottleneck procedure considering learning effect (SBLE) decision model with due date assignment is shown as in Figure 4.9. The discrete simulation system model generates and records specified production information to support SBLE decision model to make schedule decision. And then SBLE decision model identifies the highest priority job and sends a signal back to Hold module to release entity. The entity will be removed from the Remove module to enter the production system. Detailed steps and functions of SBLE decision model is discussed in the following section 4.4.2.

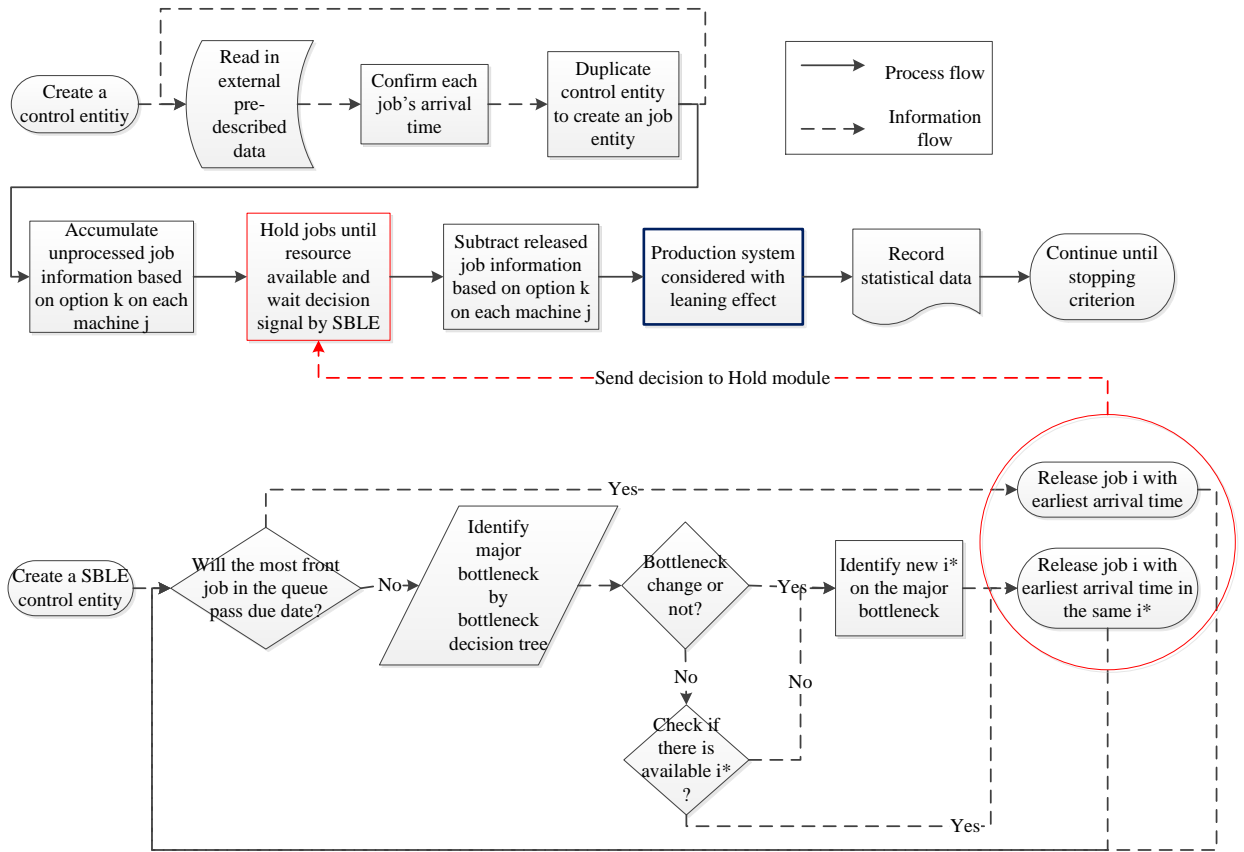


Figure 4.9 Flow diagram of simulation model considering learning effect and schedule decision made by SBLE

4.4.2 SBLE decision model

This section illustrates a discrete simulation model to address Shifting Bottleneck procedure considering learning effect (SBLE) which is discussed in the section 4.3. The lower part model in Figure 4.9 shows a flow diagram of SBLE decision model and thorough steps are discussed as following:

1. The initialization module creates only one “control entity” at the very beginning of the simulation model at time 0. This control entity represents a command to follow steps of SBLE schedule method as given in section 4.3.

2. Step 2 determines whether the predicted completion time C_i of each job in the Hold module queue line may exceed its own due date. The job is removed to enter the production system if a job's predicted completion time is greater or equal to its due date according to specified scheduling rules, i.e. FCFS, SPT, or EDD and the formulation is determined as:

$$C_i = T_{now} + \bar{C} \geq d_i \quad (4.7)$$

where TNOW is the current simulation time. \bar{C} denotes the average flow time which is updated at any time.

Otherwise, this decision flow continues to the next step 2 if $C_i < d_i$.

3. In step 3, starting to check whether there is any current processing job in the system. If not, the first job is allowed to access into the system according to first come first served (FCFS) rule. Otherwise, this decision module identified which work station is the major bottleneck by certain criteria and a decision tree as the example shown in Figure 4.6. This step also determines whether the current major bottleneck is the same as the previous bottleneck. The decision flow leads to step 4 if the current bottleneck changes compare to last major bottleneck result, otherwise it leads to step 5.

4. Jobs are assigned with higher priority when they belong to the largest group with same customized option on the major bottleneck in the step 4. This step also receives those unprocessed job's customization information from the frequency counter model in the discrete simulation system model and know how many and what kind of process the assembly line need to work to complete those jobs. For example, a product needs to be completed in three stations with three options for each station. The first job with configuration (1,2,3) indicates that this job needs to be processed as option 1 in station one, option 2 in station two, and option 3 in station three and the second job has (3,2,1) product configuration. In the Figure 4.10 below, the matrix (a) shows that the system needs to process option 1 and 3 in station one, two option 2 in station two, and option 1 and 3 in station three to complete these two jobs. The matrix is re-counted as (b) once the first job is released to enter the production system. The purpose of step 4 is aiming to reduce process time and then eliminate major bottleneck by accumulating the same process at the same station to activate learning effect. This step goes to the final step 6 once job's priority is defined.

$$(a) \begin{pmatrix} 1 & 0 & 1 \\ 0 & 2 & 0 \\ 1 & 0 & 1 \end{pmatrix} \rightarrow (b) \begin{pmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

Figure 4.10 An example of counting model with two jobs

5. The decision flow goes to step 5 if the current major bottleneck does not change and check if there are jobs defined as higher priority available in the Hold module queue. The decision process leads to step 4 if there is no job defined as higher priority, otherwise, go to step 6.
6. Step 6 selects the job with higher priority with earliest arrival time to enter the production system. The control entity then goes back to step 2 to re-determine the scheduling priority. Noted that this SBLE is a logic loop and will not end unless all jobs in the simulation system model are all removed from the production system. Besides, the learning effect happens on every machine especially for major bottleneck machine to reduce process time when a job is still in the same process as the previous one.

Chapter 5 Application of Shifting Bottleneck Procedure Considering Learning Effect (SBLE) in Mass Customized Large Product Assembly Line

The SBLE is applied with a case study of nacelles assembly line in a wind turbine industry and this model is carried out to analyze the simulation result. Section 5.1 begins with an example to introduce the impact of SBLE to a nacelles assembly line and compares with the result of First Come First Served dispatching rule considering leaning effect (FCFS_LE). In section 5.2, a due date oriented SBLE scheduling model is applied with the same example and evaluates the result with the other two scheduling rules: FCFS_LE and throughput oriented SBLE. Section 5.3 seeks to provide an insight into the problem of finding the balance of maximizing throughout and meeting customers due date assignment in the mass customized large product assembly line.

5.1 Throughput Objective SBLE Application

This section presents the use of SBLE scheduling method to improve the flow time or system throughput for the mass customized large product assembly industry. In this case study, this nacelles assembly line is assumed to be able to offer its customers customized nacelles with 3 options ($k=1...3$) on each of the 15 workstations ($j=1,...,15$). Operators have initial standard processing time performance based on the customization options and operation stages as shown in the Figure 3.5 when the task has never been performed before or the task is different from previous one. The processing time will decrease when an operator performs the same task repeatedly based on learning curve. There are a total of 500 unprocessed jobs with continuous arrival time and customer's requirements are well defined. The buffer space of each work station is assumed to be restricted to store at most 2 unfinished jobs. Note that the lower limit and upper

limit (l_d and u_d) in the equation 4.4 is defined as a very large number, i.e. one million hours in this case study. This indicates that due date assignment is not the most important concern for this large product manufacturer's scheduling decision.

Figure 5.1 shows the record of the major bottleneck at each time when an order is released into the system. The solid trend represents a schedule decision with SBLE and the dash trend represents a schedule decision using FCFS dispatching rule considering learning effect (FCFS_LE). The major bottleneck in two scheduling rules stays relatively the same and shifts between different workstations until observation 25. The major bottleneck of FCFS_LE shifts between workstation 14 and 15 before observation 200, however, workstation 15 has not been changed to be identified as the major bottleneck of FCFS_LE until the end of this experiment. The major bottleneck of SBLE shifts between workstation 12 and workstation 15 after observation 25. Workstation 14 and 15 are identified as the major bottleneck most frequently. In this simulation with 500 schedule observations, workstation 14 is identified as the major bottleneck 227 times and workstation 15 is identified as the major bottleneck 250 times. This also indicates the major bottleneck is continuously improved by proposed SBLE schedule sequence so that the major bottleneck keeps changing from workstation 14 to another workstation 15. On the other hand, the major bottleneck is not improved in the FCFS_LE case because the major bottleneck is identified as workstation 15 after observation 200 to the end of simulation.

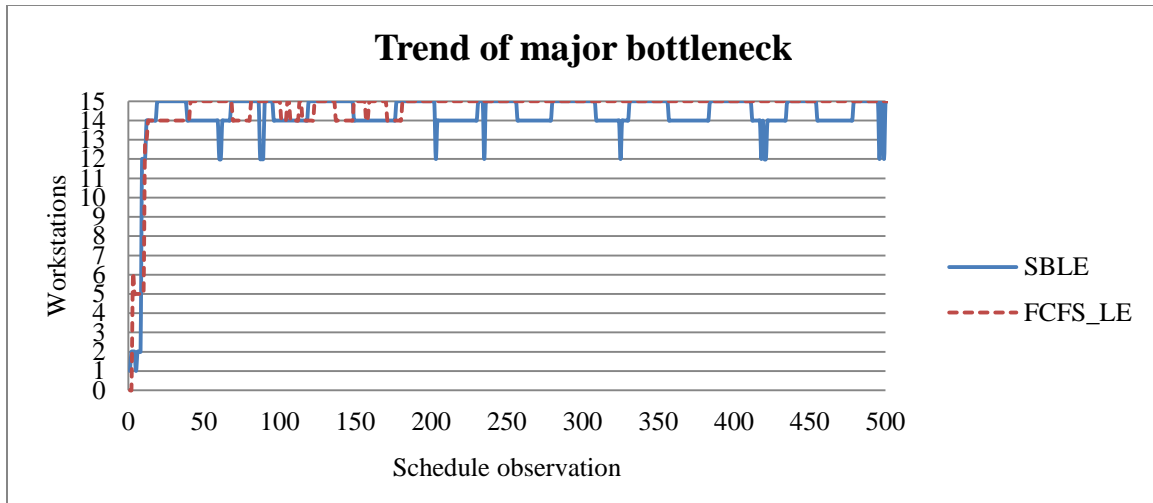


Figure 5.1 Major bottleneck shift diagram

Figure 5.2 (a) (b) (c) depicts the processing time of individual jobs on workstation 13, 14, and 15 respectively. The solid trend represents a schedule decision with SBLE and the dash trend represents a schedule decision using FCFS_LE. It can be seen that learning curve happens on all of three work stations by scheduling with SBLE, especially on workstation 14 and workstation 15. This also points out that a workstation is identified as a critical bottleneck when there is an exponential decrease period influenced by learning effect. However, a bottleneck might go along with a short learning effect period and this just means the bottleneck changes to another workstation quickly in a short time. In addition, learning effect may happen on a non-bottleneck workstation because of random combinatorial sequence and this non-bottleneck workstation can also benefit by the nature of learning effect. Note that the processing time in workstation 15 with FCFS_LE is not improved efficiently by learning curve in Figure 5.2 (c) and this causes that workstation 15 continues to be identified as a major bottleneck.

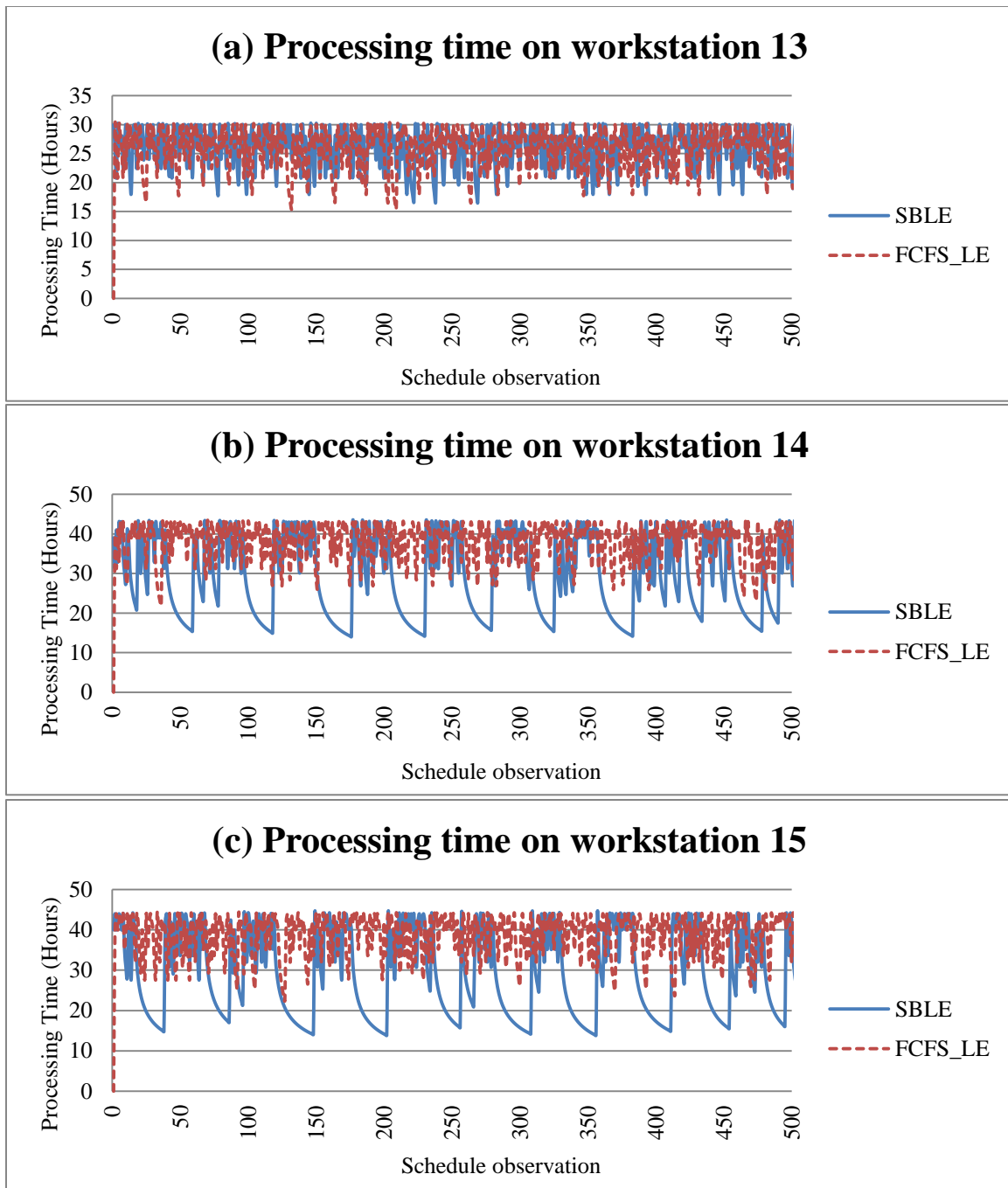


Figure 5.2 Processing time on (a) workstation 13 (b) workstation 14 (c) workstation 15

Gantt charts for major bottleneck, workstation 14 and 15, are provided to illustrate the impact of SBLE to job 130 through job 160 compared to FCFS_LE in Figure 5.3. It can be seen that the starting time of job 130 on workstation 14 by using SBLE has been improved from 5320 hours to 5078 hours compared to FCFS_LE as well as the improved starting time of job 130 on workstation 15 from 5378 hours to 5125 hours. Shorter time duration in the SBLE Gantt chart also indicates the situation that learning effect happens on the bottleneck workstation.

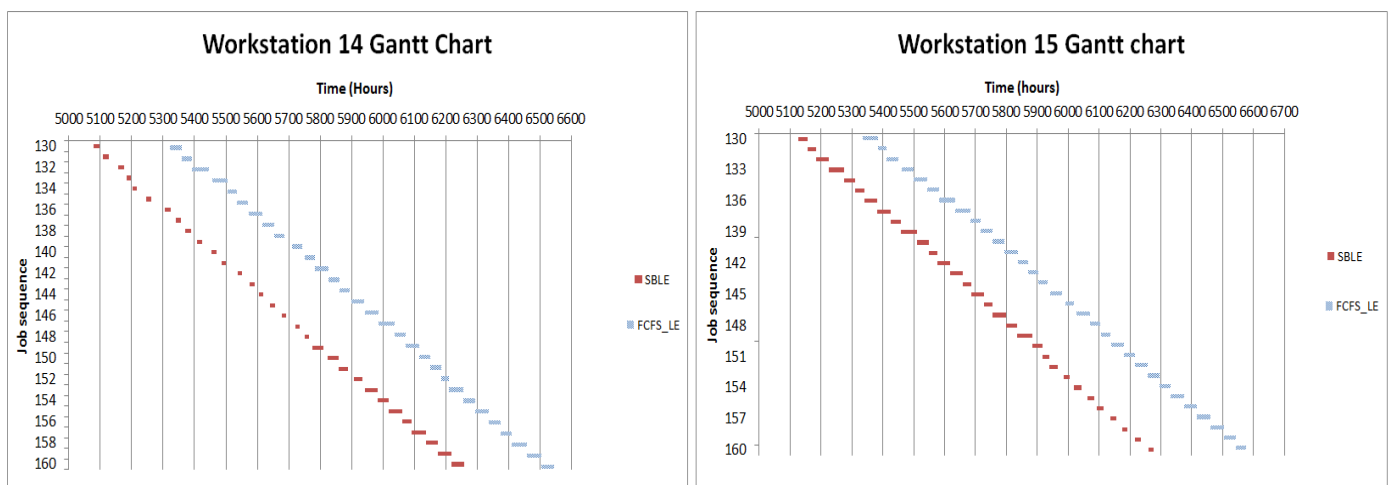


Figure 5.3 Bottleneck Gantt chart

Continuous improvement on major bottleneck by using SBLE improved the total production performance as shown in Figure 5.4. The completion time of job 150 has been improved from 6226 hours to 5916.5 hours and the completion time of job 400 has been improved from 16296 hours to 15149 hours by using SBLE. In a long term project, SBLE could be a better scheduling option to improve a throughput oriented mass customized large product assembly line compared to FCFS.

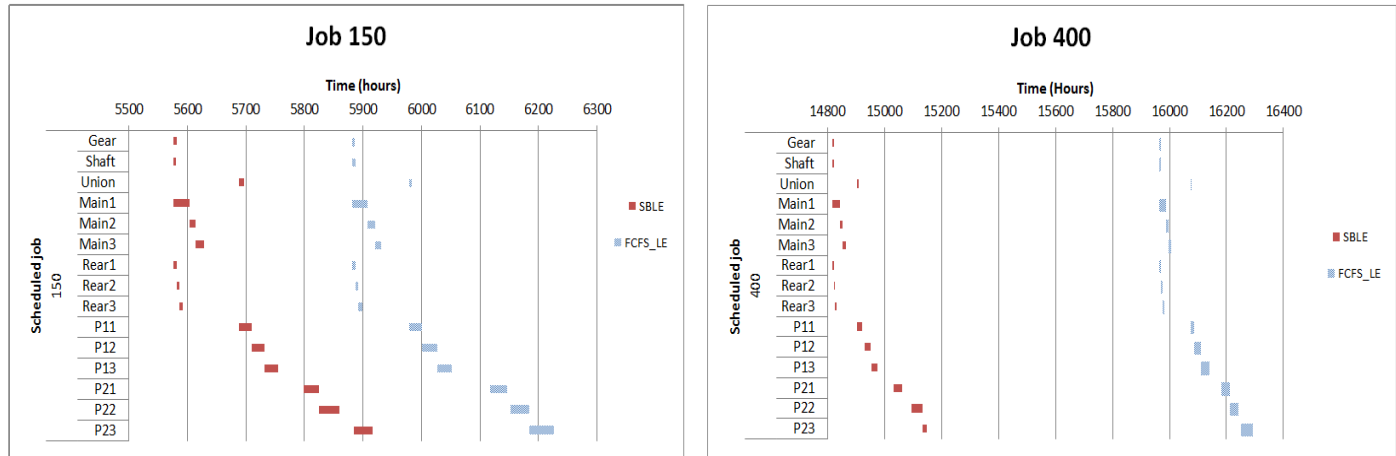


Figure 5.4 Gantt chart for individual job

Biskup (2008) provided a detailed summary on scheduling with position based learning effect and showed that most throughput oriented applications can be solved scheduling according the shortest processing time (SPT) rule. In this section, the performance measures are mean flow time and standard deviation of flow time. Four scheduling rules are performed for scheduling the jobs in the queue in front the main system as follows: First Come First Served (FCFS), First Come First Served considering learning effect (FCFS_LE), shortest processing time rule considering learning effect (SPT_LE) and SBLE. Figure 5.5 shows the simulation result of flow time for each job/observation resulted by four scheduling rules: FCFS, FCFS_LE, SPT_LE, and SBLE. Schedule observation denotes the suggested schedule sequence generated by simulation model with different scheduling rules. Scheduling rules will be applied to determine job priority for entering the production system and proposed scheduling sequence may be different from job serial number. Suggested schedule observation/sequence is same as job's serial number in FCFS scheduling rule as well as FCFS_LE. However, the proposed schedule observation/sequence from SBLE will be different from job serial number and suggested schedule sequence from SPT orders job sequence by shortest sum of regular processing time. The round dot trend represents a

schedule decision with FCFS dispatching rule, the dash trend represents a schedule decision with FCFS_LE, the solid line with cross marker is scheduled according to SPT_LE, and the solid trend represents a schedule decision using SBLE scheduling rule. It can be seen that SBLE provides a lowest average flow time trend.

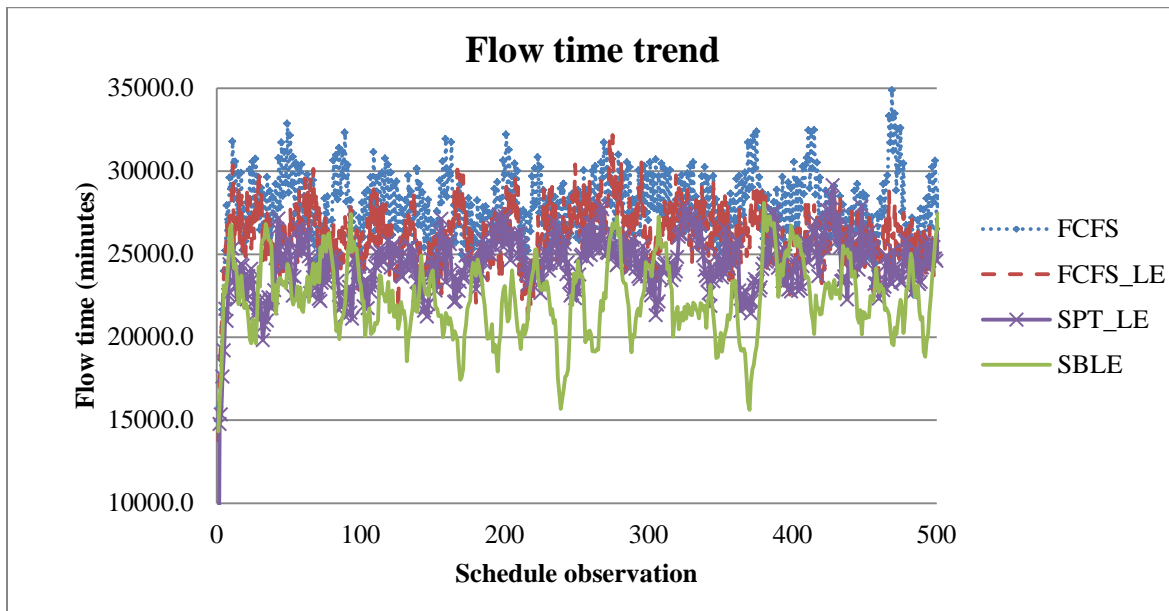


Figure 5.5 Flow time comparison of FCFS, FCFS_LE, SPT_LE, and SBLE

Figure 5.6 shows a boxplot to compare the result of four scheduling rules. First of all, it can be seen that SBLE provides the best results of mean flow time and SPT_LE provides similar results of mean flow time as FCFS_LE. The mean flow time of SBLE has been improved and reduced to 22827 minutes compared to the mean flow time of FCFS's 27866.3 minutes, FCFS_LE's 24419 minutes, and SPT's 24563 minutes in this nacelles assembly line example. SBLE scheduling rule reduces around 6.5% of mean flow time compared to the result from FCFS_LE and 7.1% compared to SPT_LE. On the other hand, the simulation model results 1701

minutes of standard deviation of flow time according to SPT_LE and 1699 minutes according to FCFS_LE. Both SPT_LE and FCFS_LE provide better performance on the standard deviation of flow time compared to FCFS's 2196 minutes, and SBLE's 2238.7 minutes. In reality, manufacturers also want to have lower production variability in order to make the production line stable and this shows that scheduling results that provide lower standard deviation is an important concern. Therefore, it is concluded that there is significant improvement in the mean flow time after applying SBLE scheduling rule to this large product assembly line case; however, SBLE scheduling rule could be better suited to this case study when manufacturers are only aiming to minimize mean flow time or maximize system throughput.

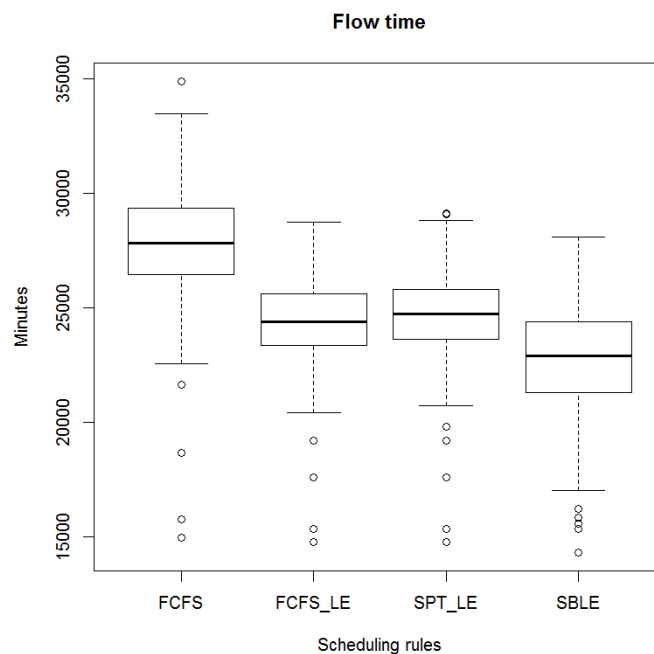


Figure 5.6 Mean and standard deviation of flow time

In the following section, the use of a due date oriented SBLE (SBLE_DD) scheduling model is discussed in the same nacelles assembly line case study and compares the result with other scheduling rules.

5.2 Due-Date Objective SBLE Application

Many dynamic manufacturing requirements in mass customization may affect the customer's satisfaction and one of the targets is to meet the customer's due date requirement. We consider due date assignment is also an important production performance index for large product manufacturer in this section. The goal of this due-date oriented SBLE is to provide manufacturers better schedule decision support, so they may improve throughput while satisfying the due date requirement from their customers.

The performance measures are listed as follows: mean flow time, standard deviation of flow time, total tardy jobs, total tardiness, and standard deviation of total tardiness. In this present study, three scenarios are used to assign due dates of jobs as follows: tight time allowance to due date, moderate time allowance to due date, and long time allowance to due date. Time allowance to due date describes the time period between the completion of a job and its delivery date agreed by both manufacturers and customers. Tight time allowance to due date indicates shorter time period to delivery, moderate time allowance indicates average time period to delivery, and long time allowance to due date indicates longer time period to delivery than average. Seven scheduling rules considering learning effect are performed to give jobs in the queue priority to enter the production line as follows: First Come First Served (FCFS_LE), shortest processing time (SPT_LE), earliest due date (EDD_LE), a throughput oriented SBLE (SBLE), a due-date objective SBLE with FCFS as alternative scheduling rule (SBLE_DD), a due-date objective SBLE with SPT as alternative scheduling rule (SBLE_SPT), and a due-date objective SBLE with EDD as alternative scheduling rule (SBLE_EDD). Therefore, there are a total of twenty one circumstances in this simulation case study as shown in Table 5.1. The objective of this experimentation is to investigate the impact of due date assignment to

production performance of the mass customized large product assembly line and evaluate the capability of the proposed SBLE considering due date assignment objective.

Table 5.1 Experimental conditions

| Factors | Levels |
|---------------------------|---|
| Due date scenarios | <ol style="list-style-type: none"> 1. Tight time allowance to due date 2. Moderate time allowance to due date 3. Long time allowance to due date |
| Scheduling rules | <ol style="list-style-type: none"> 1. First Come First Served considering learning effect (FCFS_LE) 2. Shortest processing time considering learning effect (SPT_LE) 3. Earliest due date considering learning effect (EDD_LE) 4. Shifting bottleneck procedure considering learning effect with throughput objective (SBLE) 5. Shifting bottleneck procedure considering learning effect and due date assignment with FCFS as alternative scheduling rule (SBLE_DD) 6. Shifting bottleneck procedure considering learning effect and due date assignment with SPT as alternative scheduling rule (SBLE_SPT) 7. Shifting bottleneck procedure considering learning effect and due date assignment with EDD as alternative scheduling rule (SBLE_EDD) |

Initially, each job's due date has to be pre-assigned by the scheduler who could be manufacturers or customers in a practical case before a job arrives to the production system. The equation 4.4: $d_i = t_{i0} + U_d(l_d, u_d)$ is used to generate random due date with specified lower and upper limit (l_d and u_d) to represent different due date scenarios. In section 5.1, it was found that for this case study mean flow time of FCFS_LE is 24419 minutes and mean flow time of SBLE is 22827 minutes. Therefore, it will be reasonable to make lower limit in due date equation no less than 24419 minutes, otherwise, the completion time of each order will exceed its due date definitely.

5.2.1 Hypothesis one

Three due date levels are assumed with the fixed 30000 minutes lower limit and specified upper limits to generate a random duration from the time a job is completed to its due date. Three kinds of due date assignment situations are listed as follows to represent the tight time allowance, moderate time allowance, and long time allowance to due date:

1. Tight time allowance to due date : $(l_d, u_d) = (30000, 50000)$
2. Moderate time allowance to due date : $(l_d, u_d) = (30000, 100000)$
3. Long time allowance to due date : $(l_d, u_d) = (30000, 150000)$

Figure 5.7 shows the simulation results for mean flow time and standard deviation of flow time resulting from the three due date scenarios with seven scheduling rules. First of all, note that the mean flow time and standard deviation of flow time resulting from FCFS_LE, SPT_LE, SBLE are not influenced significantly by different due date scenarios. The SBLE rule provides overall the best performance which gives lowest mean flow time among all scheduling rules when due date assignment is considered as a more important production performance index as shown in Figure 5.7 (a). SBLE_SPT gives a second best performance with average mean flow time 23100 minutes under three due date scenarios. Other scheduling rules provide proximate performance with average mean flow time between 24500 to 25000 minutes. However, SBLE and SBLE_SPT perform the worst in mean flow time with an average of 2291 and 2198 minutes respectively. The EDD_LE rule provides an average standard deviation of flow time of 1623 minutes which is the lowest standard deviation of mean flow in Figure 5.7 (b). Other scheduling rules' standard deviation of flow time is found to be between 1700 to 1900 minutes. Besides, scheduling by SBLE_DD shows a notable trend that mean flow time goes smaller and standard deviation of flow time goes larger when the time from receive order to committed due date is

longer. It is concluded that SBLE provides the best result of mean flow time and SBLE_SPT can provide a second best mean flow time compared to other scheduling rules in this case.

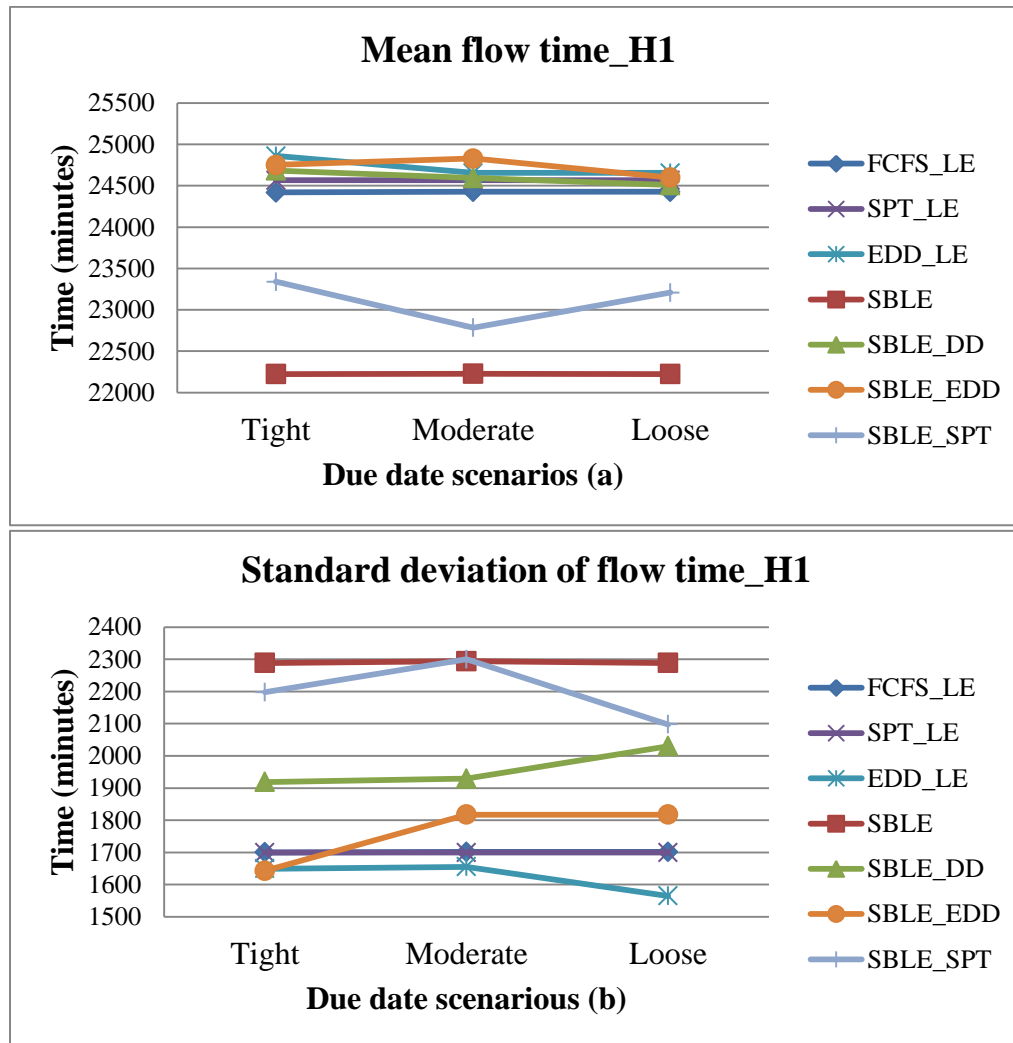


Figure 5.7 Hypothesis one: (a) Mean flow time and (b) Standard deviation of flow time

Figure 5.8 presents simulation results of total tardiness, standard deviation of total tardiness, and total tardy jobs generated by seven proposed scheduling rules in three due date assignment circumstances. It can be found that all seven scheduling rules have a significant decreasing trend and have lower total tardiness and fewer tardy jobs when the time to committed

due date is longer in Figure 5.8 (a) and (c). This describes that due date scenarios could be an important influence to total tardiness and tardy jobs in the scheduling problem. On the other hand, different due date scenarios do not have a major impact on the standard deviation of total tardiness for all scheduling rules in this case study as shown in Figure 5.8 (b). In Figure 5.8 (a), SBLE provides a lowest total tardiness and SBLE_SPT scheduling rule provides similar better performance compared to other scheduling rules. Therefore, both SBLE and SBLE_SPT are viable scheduling rules to improve the performance of total tardiness when manufacturers aim to minimize total tardiness.

Consider the other performance measure: standard deviation of total tardiness. SBLE not only provides the best results of total tardiness but also provides the best standard deviation of total tardiness with 0.124 million minutes as shown in Figure 5.8 (b). SPT_LE and SBLE_SPT have worse performance of standard deviation of total tardiness of 0.319 and 0.233 million minutes respectively compared to other scheduling rules. Other scheduling rules give comparable results of standard deviation of total tardiness between 0.14 and 0.15 million minutes. Note that most of scheduling rules have increasing trend on standard deviation of total tardiness when the due date scenario has longer time to committed due date except that EDD_LE has a decreasing trend. Since the smaller standard deviation of tardiness implies better due date prediction capability, manufacturers will prefer to have smaller standard deviation of total tardiness to make better scheduling decisions to meet customers' due date assignment. Therefore, it shows that SBLE scheduling rule has better capability to improve this performance measure.

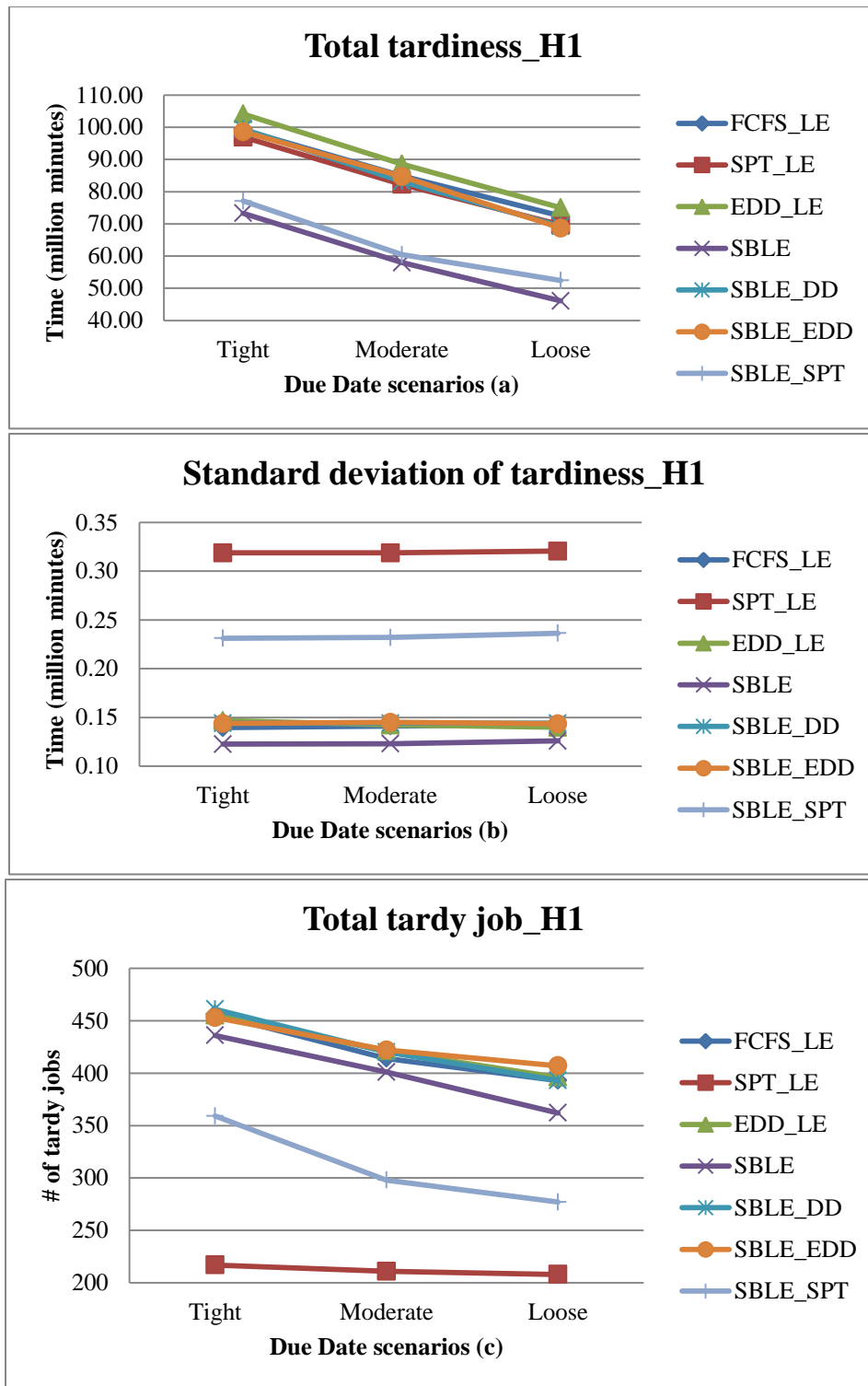


Figure 5.8 Hypothesis one: (a) Total tardiness, (b) Standard deviation of total tardiness, and (c) Total tardy jobs

In Figure 5.8 (c), SPT_LE unexpectedly provides the lowest amount of total tardy jobs and SBLE_SPT provides the second best amount of total tardy jobs in all three due date scenarios. Besides, it is noticed that due date scenario is not the major impact to the result of total tardy jobs for SPT_LE and the reason SPT_LE has relatively slow decreasing tardy jobs is because jobs are sequenced according to jobs with shortest processing time in the queue. As long as the job has the shortest processing time in the queue, it has the priority to enter the production line even if it is the latest job. This also indicates why SPT_LE has the largest standard deviation of total tardiness. However, all other scheduling rules have significant decreasing trend on total tardy jobs when the time to the due date is larger. In conclusion, SPT_LE could be a better scheduling rule for manufacturers in this case when their goal is to minimize the total number to tardy jobs. The next step is to discuss the use of different due date scenario levels setting and investigate the impact of due date scenario to these production performance measures.

5.2.2 Hypothesis two

The result of the previous hypothesis one indicates that SBLE provide the best result of mean flow time and SBLE_SPT can provide a second best mean flow time compare to other scheduling rules in this case. SBLE and SBLE_SPT can provide better performance of total tardiness when manufacturers aim to minimize total tardiness and SBLE scheduling rule has better capability to improve standard deviation of total tardiness. Finally, SPT_LE could be a better scheduling rule to minimize the total number to tardy jobs in this case study. In hypothesis two, three due date scenario levels are defined with the same upper limit (150000 minutes) and different lower limits to represent three kinds of due date assignment conditions to evaluate the impact of these due date scenarios setting to production performance measures as listed below:

1. Tight time allowance to due date : $(l_d, u_d) = (30000, 150000)$
2. Moderate time allowance to due date : $(l_d, u_d) = (50000, 150000)$
3. Long time allowance to due date : $(l_d, u_d) = (100000, 150000)$

It can be observed that due date scenario does not have significant influence on the result of mean flow time and standard deviation of flow time for scheduling by FCFS_LE, SPT_LE, and SBLE. The SBLE rule still provides overall the best performance which gives lowest mean flow time among all scheduling rules in Figure 5.9 (a). SBLE_SPT gives a second best performance with average mean flow time 24566 minutes under three due date scenarios. The rest of scheduling rules provide similar performance with average mean flow time between 24000 to 25000 minutes. SBLE_DD and SBLE_EDD have significant improvement in mean flow time when the time to due date is long compared to the result in hypothesis one.

SBLE performs the worst for mean flow time of 2289 minutes and EDD_LE scheduling rule provides the best standard deviation of flow time of 1564 minutes at tight time to due date scenario in Figure 5.9 (b). However, SBLE_SPT becomes the worst mean flow time of 2635 minutes and both FCFS_LE and SPT_LE scheduling rules provide equally good standard deviation of flow time at long time allowance to due date scenario. The standard deviation of flow time of the rest of the scheduling rules is found to be between 1700 to 1900 minutes. Similarly, SBLE provides the best result of mean flow time and SBLE_SPT can provide a second best mean flow time as the result of mean flow time in hypothesis one.

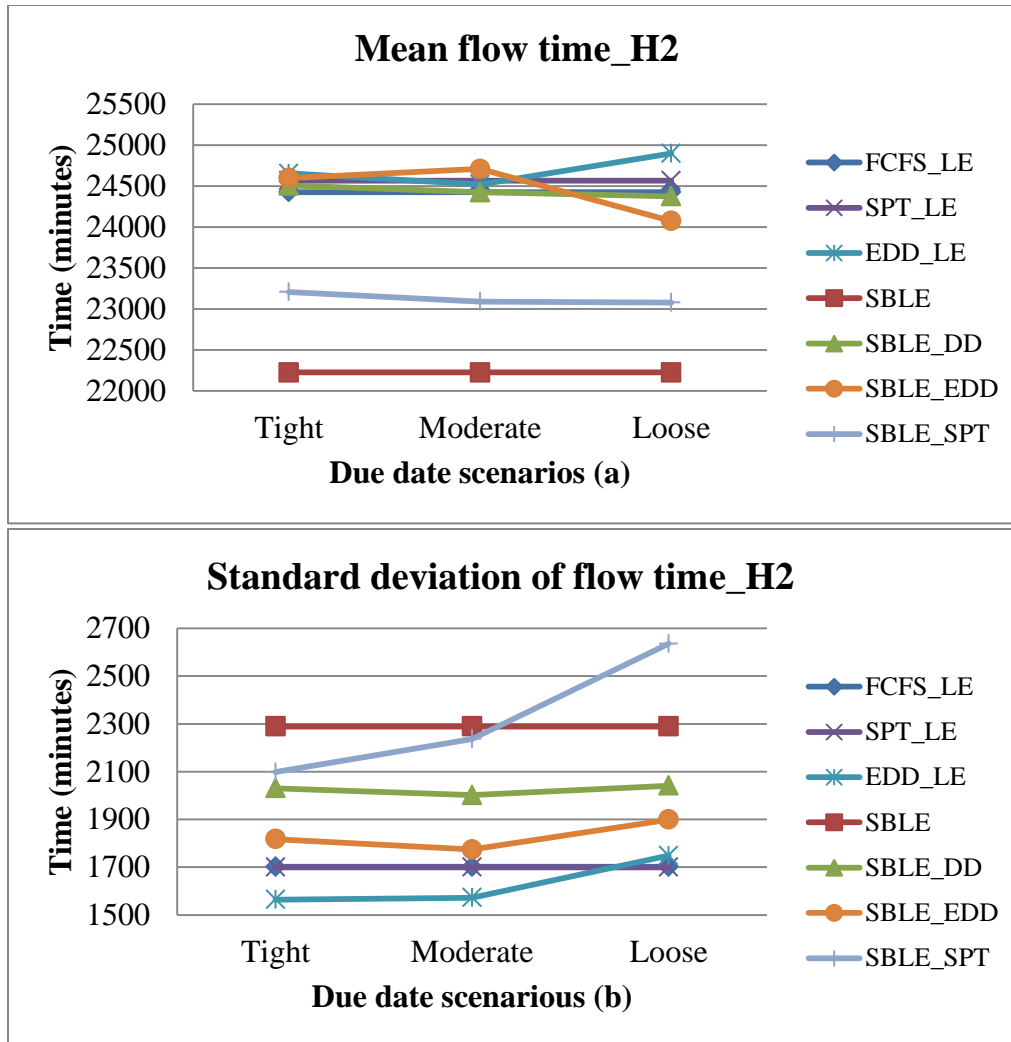


Figure 5.9 Hypothesis two : (a) Mean flow time and (b) Standard deviation of flow time

Figure 5.10 presents simulation results of total tardiness, standard deviation of total tardiness, and total tardy jobs for hypothesis two. Similar to hypothesis one, all seven scheduling rules have a significant decreasing trend and have lower total tardiness and fewer tardy jobs when the time to committed due date is longer in Figure 5.10 (a) and (c). Besides, due date scenario does not have major impact to the standard deviation of total tardiness for all scheduling rules in Figure 5.10 (b). In Figure 5.10 (a), SBLE provides a lowest total tardiness and SBLE_SPT scheduling rule provides close performance to SBLE. Therefore, both SBLE and

SBLE_SPT are feasible scheduling rules to improve the performance of total tardiness when manufacturers try to minimize total tardiness in hypothesis two.

In Figure 5.10 (b), it shows that SBLE provides the best standard deviation of total tardiness with 0.125 million minutes. SPT_LE provides the worst performance of standard deviation of total tardiness of 0.319 and SBLE_SPT the second worst performance 0.233 million minutes compared to the other scheduling rules. The rest of the scheduling rules also have similar results of standard deviation of total tardiness to each other with between 0.14 and 0.15 million minutes. Therefore, it can be concluded that SBLE scheduling rule has better capability to improve standard deviation of total tardiness in hypothesis two.

SPT_LE again provides the lowest amount of total tardy jobs in Figure 5.10 (c) and SBLE_SPT provides the second best amount of total tardy jobs during short and medium time to due date scenarios. However, the total number of tardy jobs of SBLE_SPT is close to the amount of total tardy jobs of SPT_LE at long time to due date scenario. Besides, it can be seen that due date scenario is not the major impact to the result of total tardy jobs for SPT_LE and the reason is described in section 5.2.1. All other scheduling rules have significant decreasing trend on total tardy jobs when the time to the due date is larger. In conclusion, SPT_LE could be a better scheduling rule for manufacturers in this case when their goal is to minimize the total number of tardy jobs and has shorter due date assignment. SBLE_SPT will have the similar performance as SPT_LE when due date assignment is long enough

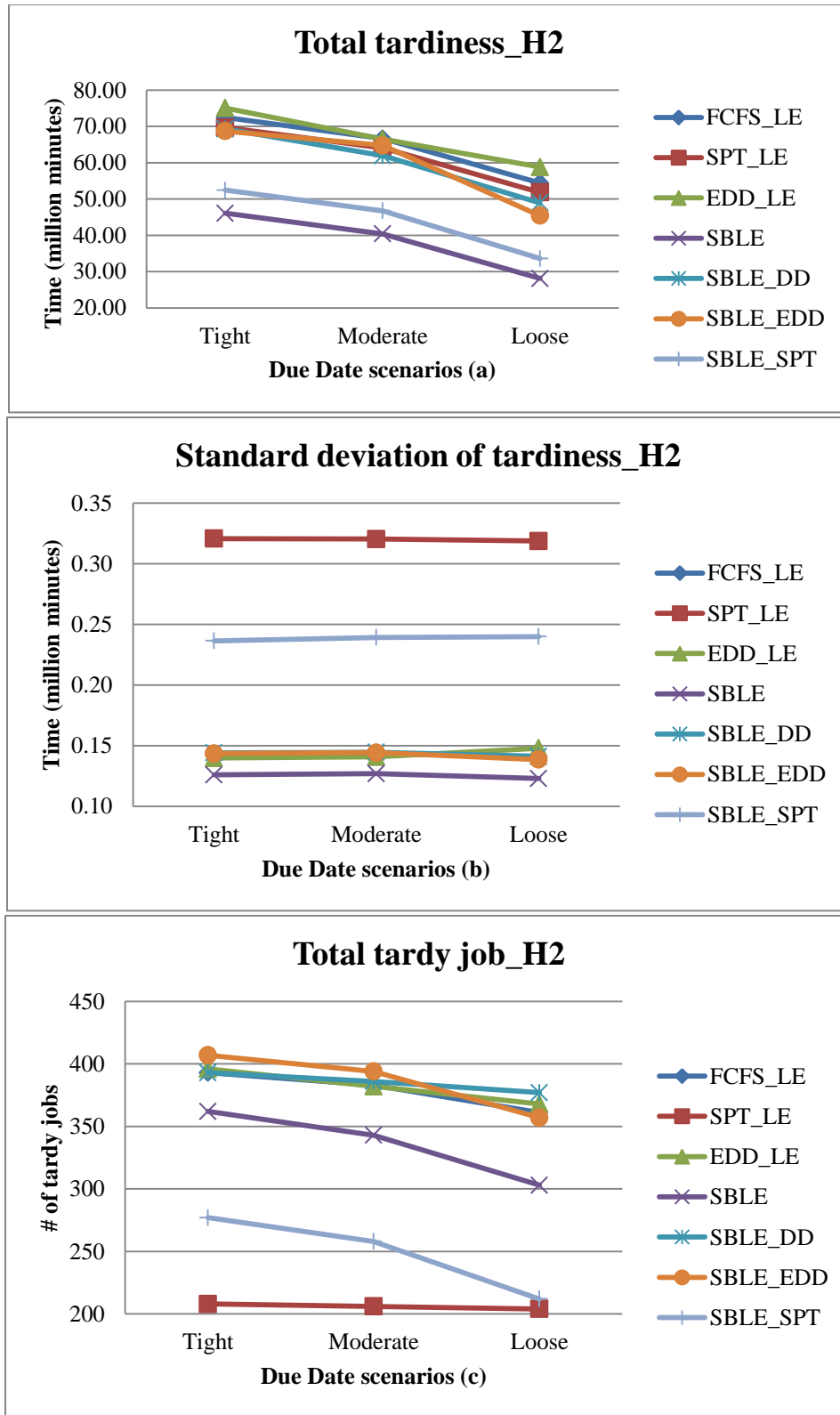


Figure 5.10 Hypothesis two: (a) Total tardiness, (b) Standard deviation of total tardiness, and (c) Total tardy jobs

This section presents several scheduling procedures considering learning effect and due date assignment under mass customized large scale production environment. A simulation model also is developed to demonstrate this proposed scheduling rule and analyze the results according to a simulated wind turbine assembly line example. Table 5.2 indicates that both SBLE and SBLE_SPT work better than other scheduling rules for the result of mean flow time in two hypotheses, however, they also provide worse standard deviation of flow time compare to other scheduling rules. In Table 5.3, SBLE and SBLE_SPT have nearly the same performance for total tardiness but SBLE provides the best performance for standard deviation of total tardiness. SPT_LE scheduling rule works the best to minimize the total tardy jobs among all scheduling rules but has extremely large standard deviation of tardiness. It can be concluded that SBLE could be a better scheduling rule to improve the performance of mean flow time, total tardiness and standard deviation of total tardiness.

Table 5.2 A summary of mean flow time and standard deviation of flow time

| Rank | Mean flow time | | | | | | Standard deviation of flow time | | | | | |
|----------|----------------|--------|------|--------------|--------|------|---------------------------------|--------|------|--------------|--------|------|
| | Hypothesis 1 | | | Hypothesis 2 | | | Hypothesis 1 | | | Hypothesis 2 | | |
| | Short | Medium | High | Short | Medium | High | Short | Medium | High | Short | Medium | High |
| FCFS_LE | 3 | 3 | 3 | 3 | 4 | 5 | 4 | 3 | 3 | 3 | 3 | 2 |
| SPT_LE | 4 | 4 | 5 | 5 | 6 | 6 | 3 | 2 | 2 | 2 | 2 | 1 |
| EDD_LE | 7 | 6 | 7 | 7 | 5 | 7 | 2 | 1 | 1 | 1 | 1 | 3 |
| SBLE_TH | 1 | 1 | 1 | 1 | 1 | 1 | 7 | 6 | 7 | 7 | 7 | 6 |
| SBLE_SPT | 2 | 2 | 2 | 2 | 2 | 2 | 6 | 7 | 6 | 6 | 6 | 7 |
| SBLE_DD | 5 | 5 | 4 | 4 | 3 | 4 | 5 | 5 | 5 | 5 | 5 | 5 |
| SBLE_EDD | 6 | 7 | 6 | 6 | 7 | 3 | 1 | 4 | 4 | 4 | 4 | 4 |

Table 5.3 A summary of total tardiness, standard deviation of total tardiness, and tardy jobs

| Rank | Total tardiness | | | | | | Standard deviation of total tardiness | | | | | | Tardy jobs | | | | | |
|----------|-----------------|--------|------|--------------|--------|------|---------------------------------------|--------|------|--------------|--------|------|--------------|--------|------|--------------|--------|------|
| | Hypothesis 1 | | | Hypothesis 2 | | | Hypothesis 1 | | | Hypothesis 2 | | | Hypothesis 1 | | | Hypothesis 2 | | |
| | Short | Medium | High | Short | Medium | High | Short | Medium | High | Short | Medium | High | Short | Medium | High | Short | Medium | High |
| FCFS_LE | 5 | 6 | 6 | 6 | 7 | 6 | 2 | 2 | 3 | 3 | 3 | 3 | 6 | 4 | 5 | 5 | 5 | 5 |
| SPT_LE | 3 | 3 | 5 | 5 | 4 | 5 | 7 | 7 | 7 | 7 | 7 | 7 | 1 | 1 | 1 | 1 | 1 | 1 |
| EDD_LE | 7 | 7 | 7 | 7 | 6 | 7 | 5 | 3 | 2 | 2 | 2 | 5 | 5 | 6 | 6 | 6 | 4 | 6 |
| SBLE_TH | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 3 | 3 | 3 | 3 | 3 | 3 |
| SBLE_SPT | 2 | 2 | 2 | 2 | 2 | 2 | 6 | 6 | 6 | 6 | 6 | 6 | 2 | 2 | 2 | 2 | 2 | 2 |
| SBLE_DD | 6 | 4 | 4 | 4 | 3 | 4 | 4 | 4 | 5 | 5 | 5 | 4 | 7 | 5 | 5 | 5 | 6 | 7 |
| SBLE_EDD | 4 | 5 | 3 | 3 | 5 | 3 | 3 | 5 | 4 | 4 | 4 | 2 | 4 | 7 | 7 | 7 | 7 | 4 |

5.3 Tradeoff in Flow time, Tardiness, and Production variance

The manufacturing industry generally involves many operations on several machines and requires many decisions to perform the production or service. There have been several classical scheduling theories for the deterministic problem of scheduling a fixed number of jobs on a given set of machines to improve the production performance such as minimizing flow time, minimizing tardiness. The tradeoff involved in different criteria to provide useful insight to a decision maker is always a crucial problem because a solution that is optimal for a certain criterion could be a poor candidate for others (Chen et al., 2006, Lee et al., 2004). Hence, more than one criterion consideration in scheduling problems is a practical course of research in real life application. Many researchers have pointed out that flow time or makespan and tardiness are the most important performance measures among scheduling objectives considered in industrial applications (Jain and Meeran, 1999, Biskup, 1999, Mosheiov, 2001a). Basically, minimizing flow time is also equivalent to minimizing the cycle time, which implies maximizing the throughput and therefore minimizing costs by Little's law, while minimizing the tardiness reduces the penalties from late job delivery and improves customer's satisfaction. Since the importance of these objectives may vary in different areas of application, two situations are considered in this section: the evaluation of a weighted linear combination of total flow time and total tardiness, and a revenue opportunity function considering price per unit and penalty cost.

5.3.1 A linear combination objective

Firstly, the evaluation of linear combination of weighted total flow time and weighted total tardiness generated by different scheduling rules with five levels of due date scenarios is discussed in this section. The lower value of linear combination of weighted total flow time and total tardiness represents better production performance in this case study. Five scenarios are used to assign due dates of jobs as follows: tight time allowance to due date, tight-moderate time allowance to due date, moderate time allowance to due date, moderate-long time allowance to due date, and long time allowance to due date. Seven scheduling rules considering learning effect are performed to give jobs in the queue priority to enter the production line as in the previous section: First Come First Served (FCFS_LE), shortest processing time (SPT_LE), earliest due date (EDD_LE), a throughput oriented SBLE (SBLE), a due-date objective SBLE with FCFS as alternative scheduling rule (SBLE_DD), a due-date objective SBLE with SPT as alternative scheduling rule (SBLE_SPT), and a due-date objective SBLE with EDD as alternative scheduling rule (SBLE_EDD). A problem formulation to describe the sum of total flow time and total tardiness is below:

$$y = \alpha T_{total}(S) + (1 - \alpha) F_{total}(S) \quad (5.1)$$

where α is the given weight, F_{total} denotes the total flow time, T_{total} denotes the total tardiness and S is the scheduling rules performed in this case. Four different weights ($\alpha = 0.2, 0.4, 0.6, 0.8$) are used to evaluate the impact of the parameter on the performance measure y of linear combination of weighted total flow time and weighted total tardiness resulting from the proposed scheduling rules. An issue for the decision maker is that he has to decide the weight of total tardiness in a long term production perspective. The smaller weight α considered for total tardiness indicates that due date assignment has lower priority in this long term production

project. The objective is to evaluate the impact of different weights α to the performance of sum of weighted total flow time and total tardiness.

Table 5.4 Results of sum of weighted total flow time and weighted total tardiness

| Tight time allowance | | | | | | | |
|----------------------|---------|--------|--------|-------|----------|---------|----------|
| α | FCFS_LE | SPT_LE | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| 0.2 | 29.60 | 29.22 | 30.77 | 23.55 | 24.75 | 29.77 | 29.62 |
| 0.4 | 47.00 | 46.15 | 49.12 | 35.99 | 37.84 | 47.20 | 46.86 |
| 0.6 | 64.39 | 63.09 | 67.46 | 48.43 | 50.93 | 64.63 | 64.11 |
| 0.8 | 81.78 | 80.02 | 85.81 | 60.87 | 64.01 | 82.07 | 81.35 |

| Tight-moderate time allowance | | | | | | | |
|-------------------------------|---------|--------|--------|-------|----------|---------|----------|
| α | FCFS_LE | SPT_LE | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| 0.2 | 26.76 | 26.28 | 27.58 | 20.48 | 21.20 | 26.48 | 26.87 |
| 0.4 | 41.30 | 40.28 | 42.83 | 29.86 | 31.01 | 40.66 | 41.33 |
| 0.6 | 55.85 | 54.28 | 58.08 | 39.23 | 40.83 | 54.84 | 55.79 |
| 0.8 | 70.39 | 68.28 | 73.33 | 48.60 | 50.64 | 69.02 | 70.25 |

| Moderate time allowance | | | | | | | |
|-------------------------|---------|--------|--------|-------|----------|---------|----------|
| α | FCFS_LE | SPT_LE | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| 0.2 | 24.26 | 23.77 | 24.87 | 18.11 | 19.77 | 23.66 | 23.58 |
| 0.4 | 36.30 | 35.25 | 37.42 | 25.11 | 27.94 | 35.07 | 34.86 |
| 0.6 | 48.35 | 46.74 | 49.97 | 32.10 | 36.11 | 46.48 | 46.14 |
| 0.8 | 60.40 | 58.22 | 62.51 | 39.10 | 44.28 | 57.89 | 57.42 |

| Moderate-long time allowance | | | | | | | |
|------------------------------|---------|--------|--------|-------|----------|---------|----------|
| α | FCFS_LE | SPT_LE | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| 0.2 | 23.10 | 22.64 | 23.10 | 16.97 | 18.59 | 22.16 | 22.84 |
| 0.4 | 33.98 | 32.99 | 33.94 | 22.83 | 25.63 | 32.10 | 33.32 |
| 0.6 | 44.86 | 43.34 | 44.79 | 28.69 | 32.68 | 42.04 | 43.80 |
| 0.8 | 55.75 | 53.70 | 55.63 | 34.55 | 39.72 | 51.99 | 54.28 |

| Long time allowance | | | | | | | |
|---------------------|---------|--------|--------|-------|----------|---------|----------|
| α | FCFS_LE | SPT_LE | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| 0.2 | 20.66 | 20.19 | 21.72 | 14.51 | 15.95 | 19.54 | 18.72 |
| 0.4 | 29.10 | 28.10 | 30.98 | 17.92 | 20.36 | 26.89 | 25.39 |
| 0.6 | 37.54 | 36.01 | 40.25 | 21.32 | 24.77 | 34.24 | 32.07 |
| 0.8 | 45.98 | 43.92 | 49.52 | 24.72 | 29.18 | 41.60 | 38.75 |

As given in summary Table 5.4, the larger given weight α is, the higher the value y is for all seven scheduling rules with a significant increasing trend of y when weight α is increasing. This indicates that a linear combination of total flow time and total tardiness could have better performance when a scheduling decision maker defines that due date assignment has lower priority in this long term production project. However, this is highly dependent on a firm's marketing strategy and the larger weight α just indicates that the company tends to satisfy customers due date assignment instead of a throughput oriented strategy. In addition to the weight α , different due date scenarios do have a meaningful impact on the performance value y for all seven scheduling rules. It can be found that overall performance measure y has significantly higher value when manufacturers have tighter due date allowance.

Besides, it is noticed that SBLE provides the best performance value y and SBLE_SPT has nearly the same good performance in all different due date scenarios compared to other scheduling rules as shown in Figure 5.11. The given weight α has greater influence on the performance value y when manufacturer have a tighter due date allowance. It can be observed that the slope of each result in Figure 5.11 (a) the tight time allowance is steeper than the slope of each result in Figure 5.11 (b) the long time allowance. This section provides insights into the scheduling rules with due date weight α and due date scenarios consideration. It can be conclude that both SBLE and SBLE_SPT could be suitable scheduling rule options to provide better performance value y of linear combination of weighted total flow time and total tardiness in every due date scenario. Therefore, manufacturers may have more scheduling decision information support to result in better performance of value y when they are faced with different due date requirements from their customers and know how to decide weight α .

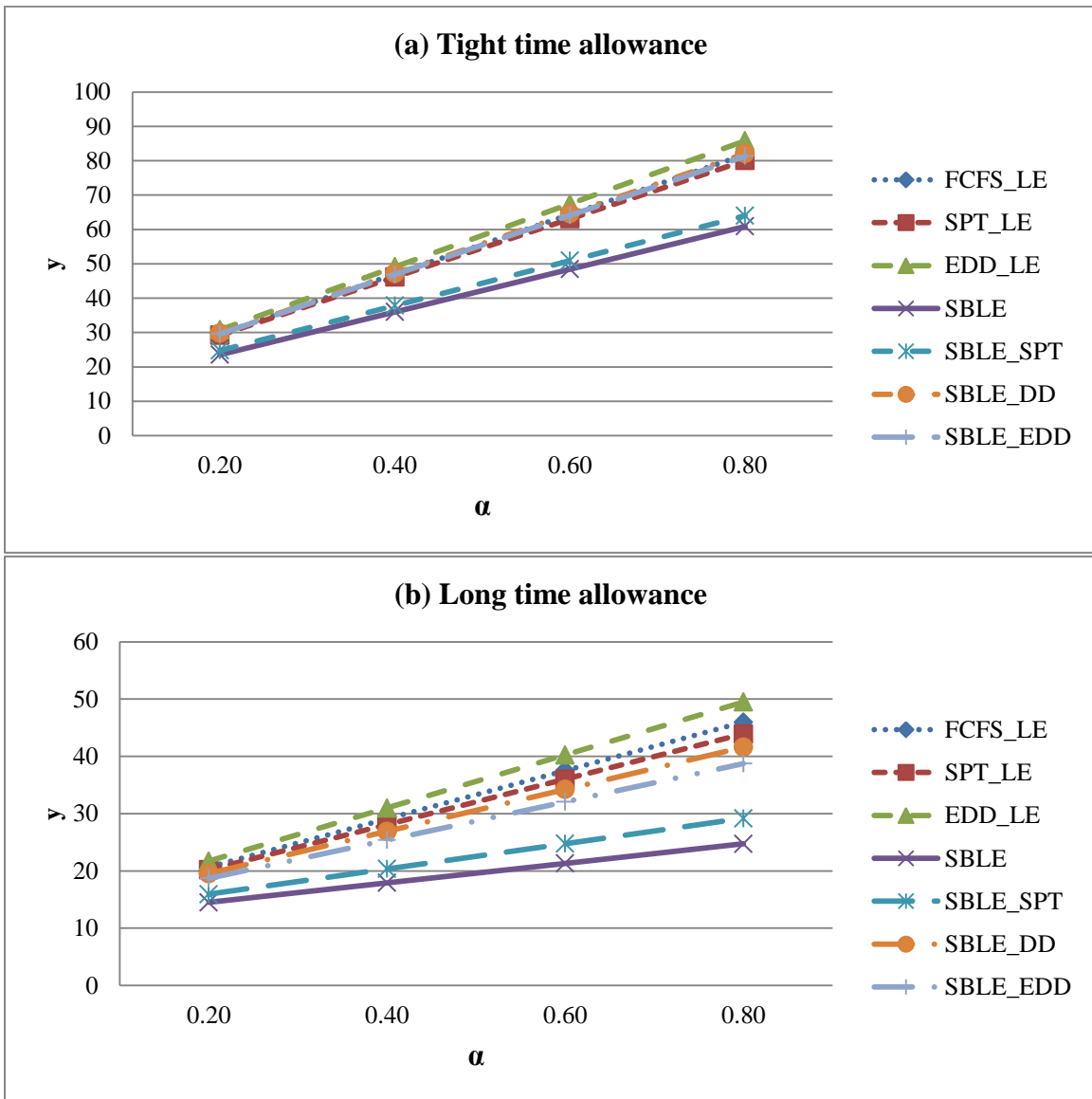


Figure 5.11 Result of performance measure y

5.3.2 Revenue oriented objective

Manufacturers usually consider increasing throughput when they encounter the situation with a rising demand for their services and resource utilization nears its maximum, threatening profit opportunities when late delivery penalty increases. The impact of late delivery penalty cost on the performance of total revenue is analyzed when schedule sequence decisions are made by SBLE scheduling rules and different due date scenarios. The delay of a completion of a large product normally results adding expenses for both owner and contractor. These costs may be not only associated with the actual extension of production time for completing the product for manufacturers but also related impacts on the potential revenue opportunity during delayed period for owner. Typically, these additional costs will be litigated or arbitrated by owner as a delay claim and will be vary depending on the contract and the relationship between the owner and the contractor (Goetz and Scott, 1977). Aircraft industry involves in late delivery penalty a lot due to limited production volume. For example, Boeing faces huge penalties for late delivery of planes such as the 787 Dreamliner in 2012 and Airbus was also reportedly facing a £156 million fine for late delivery of its A380 superjumbo in 2009 (Ratnam and Schlangenstein, 2010, Sundaram and Tomesco, 2012, Post, 2009). The average price of a Boeing 787 Dreamliner is \$250 million (<http://www.boeing.com/boeing/commercial/prices/>) and the estimation of penalty payments to 787 buyers may reach about \$5 billion for 847 orders from 2008 through July 2010. Therefore, the estimate of late penalty cost could be \$5,000 per day for any late Boeing 787 Dreamliner delivery.

In the wind turbine industry, the costs for a commercial scale wind turbine will vary depending on the number of orders, the location to install the project, and other factors and the price range could be from about \$1.3 million to \$2.2 million per MW (Megawatt). Most of the

commercial scale wind turbines can provide from 1 MW to 5 MW in different sizes for various purposes and locations. Therefore, it is assumed that the average price of a wind turbine costs \$2 million and the estimate of late penalty cost roughly \$500 per day as a baseline for a commercial wind turbine. A problem formulation to describe the total revenue in our case study is below:

$$z = cY_{total}(S) - pT_{total}(S) \quad (5.2)$$

where c is the average price of a commercial wind turbine which is assumed \$2 million per unit, T_{total} denotes the total tardiness in days, Y_{total} denotes total expected yield with a baseline average flow time from FCFS_LE, S is the scheduling rule performed in this case, and p is the late penalty cost. Four late penalty cost ($p = \$500, \$1000, \$2500, \5000) are used to evaluate the impact of the parameter on the performance of total revenue resulting from different scheduling rules and due date scenarios.

The results are presented in Table 5.5. Assuming that negotiation between manufacturers and buyers for late delivery penalty is fair, the late delivery penalty is fixed for all jobs once the contract is agreed by both parties. Clearly, the larger late penalty c results in the lower total revenue z for all seven scheduling rules in different due date scenarios. Furthermore, late penalty c has more significant influence to total revenue when the time allowance to due date is tighter as shown in Figure 5.12. An observation in Figure 5.12 (a), the total revenue of SBLE drops from \$1060 million to \$717 million when the penalty cost increases from \$500 to \$5000 under tight time allowance to due date, while, the total revenue of SBLE declines from \$1085 million to \$953 million when the penalty cost increases from \$500 to \$5000 under long time allowance to due date in Figure 5.12 (b).

Table 5.5 Results of total revenue (\$Million)

| Late penalty | FCFS_LE | SPT_LE | Tight time allowance | | | | |
|--------------|---------|--------|-------------------------------|---------|----------|---------|----------|
| | | | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| \$500 | 948.62 | 943.77 | 928.33 | 1060.93 | 1006.38 | 937.76 | 935.50 |
| \$1,000 | 896.96 | 893.27 | 874.08 | 1022.75 | 966.23 | 885.94 | 884.15 |
| \$2,500 | 742.00 | 741.77 | 711.34 | 908.20 | 845.77 | 730.48 | 730.09 |
| \$5,000 | 483.72 | 489.27 | 440.11 | 717.28 | 645.00 | 471.37 | 473.33 |
| Late penalty | FCFS_LE | SPT_LE | Tight-moderate time allowance | | | | |
| | | | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| \$500 | 955.76 | 951.42 | 944.55 | 1068.73 | 1040.53 | 949.84 | 939.62 |
| \$1,000 | 911.52 | 908.56 | 898.42 | 1038.54 | 1009.05 | 906.51 | 895.50 |
| \$2,500 | 778.80 | 780.01 | 760.02 | 947.96 | 914.60 | 776.50 | 763.14 |
| \$5,000 | 557.61 | 565.75 | 529.34 | 797.00 | 757.19 | 559.81 | 542.54 |
| Late penalty | FCFS_LE | SPT_LE | Moderate time allowance | | | | |
| | | | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| \$500 | 962.27 | 957.96 | 951.65 | 1075.10 | 1025.16 | 960.59 | 957.22 |
| \$1,000 | 924.54 | 921.65 | 912.55 | 1051.09 | 997.85 | 924.49 | 921.44 |
| \$2,500 | 811.35 | 812.73 | 795.28 | 979.07 | 915.90 | 816.22 | 814.10 |
| \$5,000 | 622.70 | 631.20 | 599.81 | 859.02 | 779.32 | 635.75 | 635.21 |
| Late penalty | FCFS_LE | SPT_LE | Moderate-long time allowance | | | | |
| | | | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| \$500 | 965.30 | 960.91 | 961.58 | 1078.07 | 1033.54 | 967.80 | 954.76 |
| \$1,000 | 930.59 | 927.55 | 926.96 | 1057.02 | 1009.18 | 935.54 | 921.03 |
| \$2,500 | 826.48 | 827.46 | 823.09 | 993.89 | 936.11 | 838.77 | 819.84 |
| \$5,000 | 652.96 | 660.66 | 649.99 | 888.68 | 814.33 | 677.49 | 651.19 |
| Late penalty | FCFS_LE | SPT_LE | Long time allowance | | | | |
| | | | EDD_LE | SBLE | SBLE_SPT | SBLE_DD | SBLE_EDD |
| \$500 | 971.65 | 967.27 | 950.40 | 1084.46 | 1040.88 | 976.55 | 990.92 |
| \$1,000 | 943.31 | 940.28 | 919.78 | 1069.81 | 1023.39 | 951.06 | 967.26 |
| \$2,500 | 858.26 | 859.30 | 827.93 | 1025.87 | 970.90 | 874.57 | 896.27 |
| \$5,000 | 716.53 | 724.34 | 674.85 | 952.62 | 883.42 | 747.10 | 777.97 |

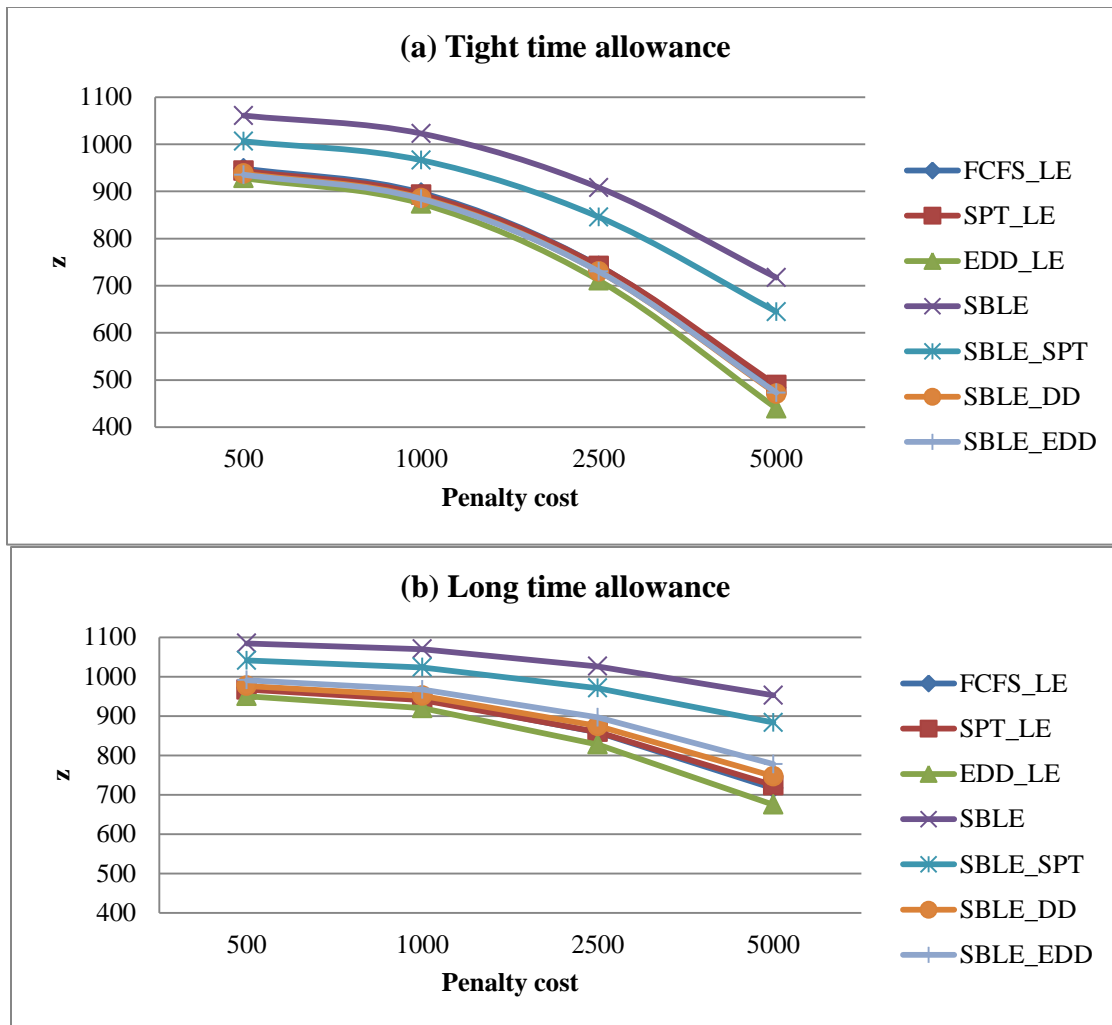


Figure 5.12 Result of total revenue

Total revenue z decreases when the late delivery penalty increases among all seven scheduling rules and due date scenarios. However, SBLE still provides the highest total revenue z compare to all scheduling rules under different due date scenarios. SBLE_SPT provides the second best performance of total revenue and have nearly the same result as SBLE. It is concluded that both SBLE and SBLE_SPT still have capability to provide better result of total revenue z with different late delivery penalty. Therefore, manufacturers may have to be more careful to negotiate the amount of late delivery penalty with their customer in order to maximize

their total revenue opportunity in a long term strategy especially when the time allowance to due date is shorter.

5.3.3 The impact of scheduling rules to production variance

In a real production, manufacturers not only aim to improve production performance measures, e.g., throughput and tardiness but also prefer lower production variability in order to make a stable and smooth production (Hopp and Spearman, 2011). A mass customized large product assembly industry also try to provide to simplify the product offering and reduces part variety by standardizing components so as to reduce manufacturing and inventory costs and variability while satisfying the individual needs of customers. Chao and Graves (1998) provided empirical recommendations to Boeing to improve their production performance from reducing flow times and eliminating system variance. This implies that lower standard deviation is desired and is another important production performance measure in a scheduling problem.

Figure 5.13 shows simulation modeling results of relationship between mean flow time and standard deviation of flow time based on seven scheduling rules which are discussed in the previous section under tight time allowance to due date circumstances. Each dot represents the estimated mean and variance of flow time for each examined scheduling rule. As the conclusion in section 5.3.1 and 5.3.2, both SBLE and SBLE_SPT provide better results in linear combination of weighted total flow time and total tardiness objective and total revenue objective. However, it can be found that both SBLE and SBLE_SPT have much higher standard deviation of flow time compare to other scheduling rules. In order to discover the reason why SBLE and SBLE_SPT have higher standard deviation of flow time, all examined scheduling rules are distinguished into two groups according to similar mean flow time and standard deviation as

following listed: (1) SBLE and SBLE_SPT and (2) FCFS_LE, SPT_LE, EDD_LE, SBLE_DD, and SBLE_EDD.

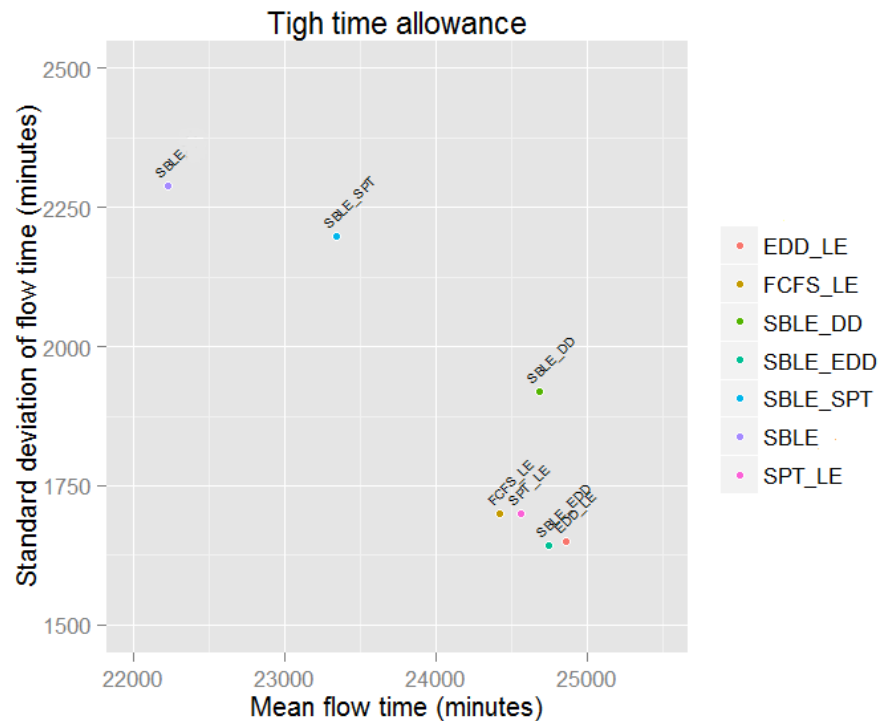


Figure 5.13 Mean-Variance relationship of flow time

Figure 5.14 shows the simulation result of flow time for each job/observation resulting from seven scheduling rules. Schedule observation denotes the suggested schedule sequence generated by simulation model with different scheduling rules. Most jobs' total flow time in group 2 is between 20000 minutes and 30000 minutes except first 10 jobs which are still in the warm-up period in Figure 5.14 (b). On the other hand, total flow time of each job resulted from group 1 (SBLE and SBLE_SPT) are between 16000 minutes to 30000 minutes as given in Figure 5.14 (a). Lower total flow time for job generated from SBLE as well as SBLE_SPT is caused by the utilization of learning effect and then reduces the processing time in each work station because operators become more experienced when operating the same process repetitively.

Furthermore, it can be noticed that SBLE_SPT provides better total flow time performance before schedule observation 200 compare to group 2, however, the total flow time of each job are similar to group 2 which is between 20000 minutes and 30000 minutes after schedule observation 200.

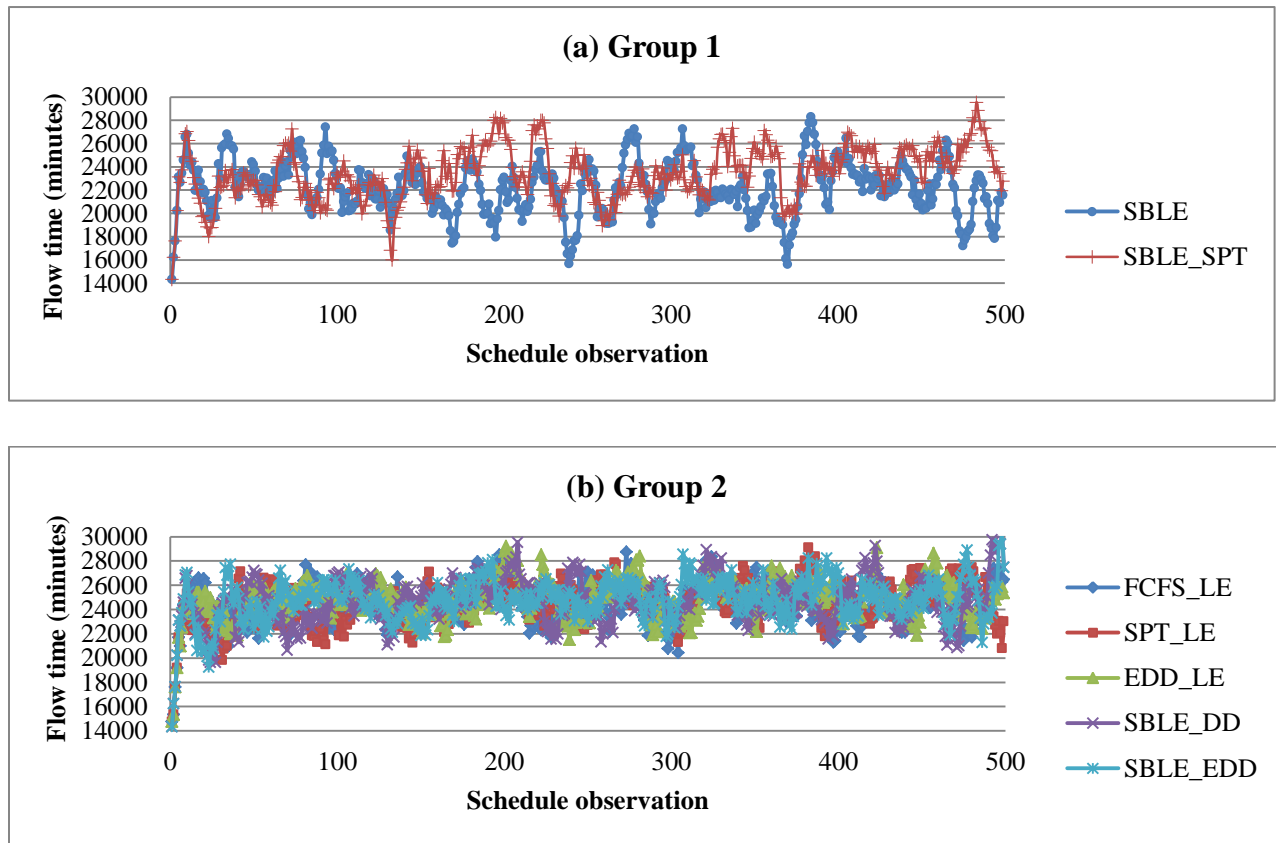


Figure 5.14 Flow time trend for group 1 and group 2

Figure 5.15 gives simulation modeling results of relationship between mean tardiness and standard deviation of tardiness based on seven scheduling rules which are presented in this section under tight time allowance to due date circumstances. Clearly, SPT_LE will not be an appropriate candidate for tardiness oriented scheduling problem due to highest mean tardiness and highest standard deviation of tardiness. SBLE_SPT has the second lowest mean tardiness,

however, it also results the second worst standard deviation of tardiness. SBLE provides the best result for both mean tardiness and standard deviation of tardiness which are 104 days and 82 days respectively. Other scheduling rules, i.e. FCFS_LE, EDD_LE, SBLE_DD, and SBLE_EDD, have approximately the same mean tardiness and standard deviation of tardiness in this case study.

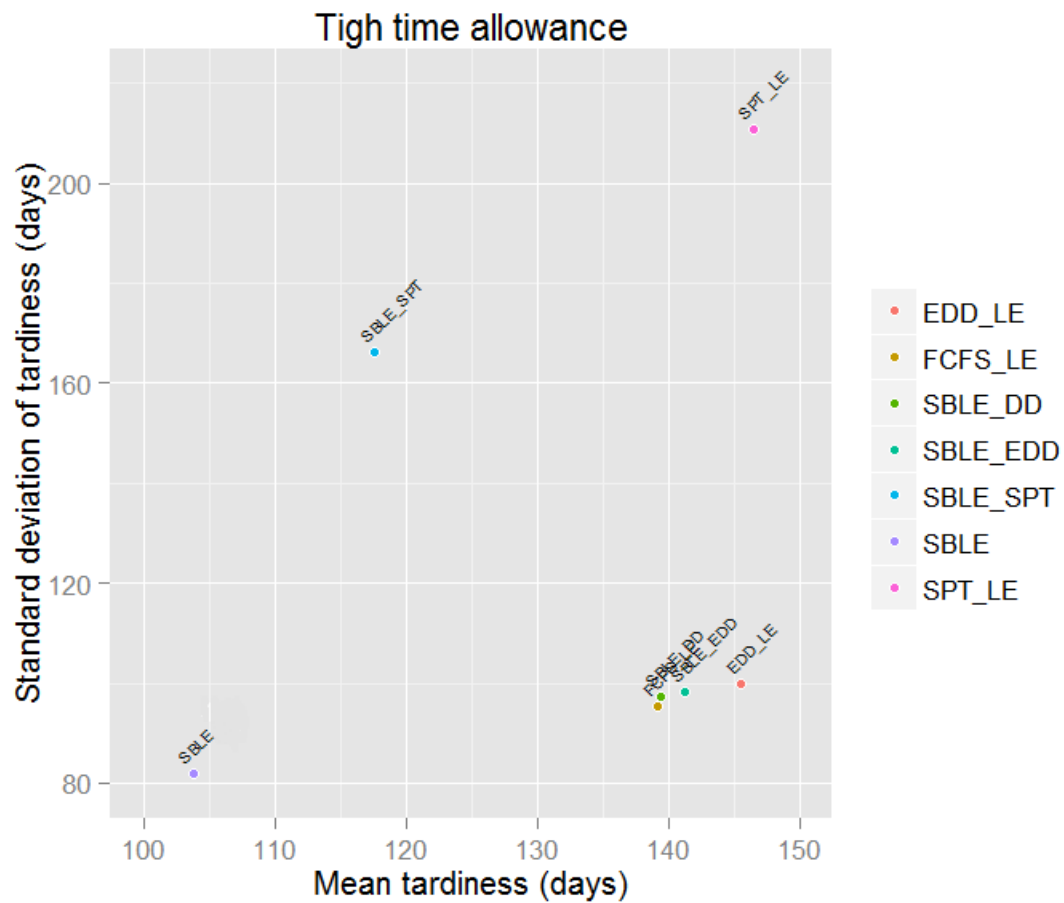


Figure 5.15 Mean-Variance relationship of tardiness

With the proposed scheduling model considering Shifting Bottleneck procedure and learning effect, overall production performance has been improved compared to traditional

scheduling dispatching rules, i.e. FCFS, SPT, and EDD. Through the conclusion from section 5.1 to 5.3, simulation model and data analysis have been provided to prove both SBLE and SBLE_SPT have capability to improve production performance, i.e. mean flow time, total tardiness, and expected revenue opportunity, in a mass customized large product assembly line. Although both SBLE and SBLE_SPT have worse results of standard deviation of flow time compared to other scheduling rules, SBLE surprisingly provides the best result on standard deviation of tardiness in this case study.

Based on the results achieved, it can be concluded that the proposed scheduling model considering Shifting Bottleneck procedure and learning effect (SBLE) could be the most suitable scheduling rule under mass customized large product assembly line environment. Even though SBLE results the worst standard deviation of flow time (2289 minutes in tight time allowance to due date scenario), it could be not the most significant problem for the large product industry because the standard deviation of flow time is comparatively small considering mean flow time (22223 minutes in tight time allowance to due date scenario). Consequently, large product manufacturers could be able to make better scheduling decisions to satisfy customers' requirement while improving production performance by understanding the final predicted performance measures from proposed SBLE scheduling rule.

Chapter 6 Conclusion

6.1 Overview of Main Contributions

In this dissertation, a scheduling problem considering Shifting Bottleneck procedure and learning effect (SBLE) in mass customized large product assembly line environment is studied to fill the major research gap between learning effect literature and bottleneck based heuristics. The SBLE model provides the framework of the manufacturing scheduling problem to predict important production performance measures, i.e., flow time, tardiness, production variance to support manufacturers in making better scheduling sequence decisions. Through the presentation of a simulation model carried out in a wind turbine assembly line, the impact of the proposed scheduling model is successfully tested and evaluated on this industrial dataset. Encouraging results are obtained in terms of predicting production performance measures of a complex large product assembly line. The research results in the following original contributions:

- The introduction of the research opportunities considering learning effect and Shifting Bottleneck procedure in a mass customization environment (Chapter 1 & 2)
- The SBLE framework (Chapter 3)
- The results of the FCFS model considering learning effect (FCFS_LE) showed this method produces a clear decrease in mean flow time compared to traditional FCFS rule (Chapter 3)
- A mathematical presentation approach of the SBLE model was developed (Chapter 4)
- An evaluation of due date oriented SBLE model with three levels of due date allowance scenarios based on several production performance measures, i.e., mean flow time, standard deviation of flow time, total tardy jobs, total tardiness and standard deviation of total tardiness (Chapter 5)

- An extension of the SBLE model based on a linear combination of the weighted total flow time and weighted total tardiness objective function and the revenue oriented objective (Chapter 5)
- Recommendations for the use of scheduling rules based on this research under different objectives (Chapter 5)

6.2 Summary of Research Findings and Conclusions

6.2.1 Mass customized large product assembly industry

This research focuses on large product assembly industries which are known to produce or assemble large scale products such as commercial airplanes, ships, and wind turbines. A large product assembly line often consists of a group of structured organizations to produce a family of complex and customized products in a certain geographic region. There are several crucial characteristics among these industries and the nature of a large scale production system is influenced by its products. The most common characteristics of a large scale production system are long cycle time, low total throughput and limited buffer space and inventory. Long cycle time leads to the limited total production volume in the large scale product manufacturing industry which means total throughput, the average output of a production process per unit time, is limited. In addition to particular production characteristics, in the recent decades, customers who are willing to buy mass customized large product often have very specific requirements. While large product manufacturing enterprises are also increasingly striving to satisfy the individual needs of customers by providing customized products in this highly competitive market, mass customization (MC) therefore is considered as an important strategy in this study.

Mass customization can be described as an ability to support manufacturing companies to meet the very specific requirements of the customer, while simultaneously approaching the operational efficiency of mass production. In the present day, many companies are able to offer options that enable customers to design their own individual products to meet particular

requirements. Several researchers have provided approaches to investigate and practice mass customization applications from the perspective of operations. However, implementing the concept of mass customization into the production system still comes with some drawbacks as it increases both the complexity and the difficulty of the production process compared to mass production. The drawbacks of mass customization also strongly affect large product assembly line which is a heavily manually based assembly process since workers need to frequently adapt to new processes and cannot reach maximum operational efficiency. Forcing workers to constantly adapt to new processes creates a production scenario that could potentially benefit from the implementation of learning curve (LC) modeling to mass customization environment to improve the production performance of large product assembly line.

Learning effect is a phenomenon where people improve operational efficiency when they do the same task repeatedly (Wright, 1936). In 1913, Henry Ford first implemented assembly line technique, called mass production, at its Highland Park Assembly Plant to reduce chassis build time from 14 hours per car to just 1.5 hours. Mass production can simply reach steady production and operational efficiency by scheduling a series of standardized processes consecutively. Learning effect played an important role in this standardized mass production line because workers can earn experience rapidly by processing the same tasks repeatedly and then improving their production performance. Furthermore, learning curve provides a more reliable prediction of processing time required for workers on each work station. However, in a mass customization environment, processing time is not easy to be reduced because workers need to frequently adapt to new processes and cannot obtain learning experience efficiently. Despite the challenges of the learning effect in mass customization environments, the learning effect is still considered in this study because today's large product assembly industry remains a heavily

manually based manufacturing process. Therefore, there are still research opportunities to improve production performance by utilizing learning effect as shown in the literature review (Chapter 2).

In order to achieve mass customization at near mass production efficiency, eliminating the bottleneck is one of the key manufacturing tactics. Most manufacturing systems' performance is constrained by one or more bottlenecks and the critical bottleneck may shift from one work station to another. The development of the SBLE provides a systematic way to allocate the same tasks consecutively to reduce processing time on the critical bottleneck stage and further improve the whole production performance in mass customized large product assembly line for the first time.

6.2.2 The SBLE model

Manufacturing involves many operations on many machines and effective management requires many decisions. There have been numerous classical scheduling theories for the deterministic problem of scheduling a fixed number of jobs on a given set of machines to improve the production performance. The processing time of each job for operators on each station is assumed to be fixed in traditional scheduling rules such as First come first served (FCFS), Shortest processing time (SPT), and Earliest due date (EDD). Unlike classical scheduling theories, the SBLE does not assume a fixed processing time. The processing time will decrease owing to learning effect when the same tasks are scheduled on the same station consecutively in this research.

The developed wind turbine nacelles assembly case study can be used to study research gaps in the current knowledge, to study trends in the data and to verify the recommendations that result from the simulation model carried out in this research. The application of SBLE is

demonstrated on this case study including a total of 500 jobs with continuous arrival time. Assumptions are provided in section 3.3.1 and the dataset is preprocessed to make it ready for applying to the simulation model. The schedule decision using FCFS dispatching rule considering learning effect (FCFS_LE) demonstrated 6.4% reduction of mean flow time in this nacelles assembly line case study compared to the results from FCFS alone. Given the fact that is compared two scheduling rules in section 3.3, it is first verified that scheduling rule considering learning effect can provide more reliable flow time based on a better prediction of processing time used by workers on each work station where learning curve takes place.

Shifting Bottleneck procedure considering learning effect (SBLE) is developed as a scheduling rule, inspired by single machine scheduling with learning consideration (Biskup, 1999) and learning effects in mass customization process (Lu et al., 2009). It is a tool to provide large product manufacturers better scheduling decision support for not only satisfying their customer's demand, but also improving the performance of the production system. In section 4.3, a step by step guide is given on how to assign job priority to enter the production line by using SBLE. The proposed SBLE scheduling rule strongly depends on the identification of a major system bottleneck and a decision tree example is provided in Figure 4.6. This helps identify the major bottleneck in this mass customized large product assembly environment. One of the particular features of SBLE is that it can use the simulation model to predict system performance measures. The simulation model of the wind turbine nacelles assembly was used to predict mean flow time, standard deviation of flow time, total tardy jobs, total tardiness and standard deviation of total tardiness.

In section 5.1, mean flow time and standard deviation of flow time are assumed as the most important performance measures in the wind turbine case study. Since most throughput

oriented applications can be solved according the shortest processing time (SPT) rule (Biskup, 2008), four scheduling rules are examined for scheduling jobs to enter production line as follows: FCFS, FCFS_LE, SPT, and SBLE. It is shown that the results obtained with the SBLE model give a better mean flow time than when using existing scheduling rules. However, it is important to note that SBLE scheduling rule did not provide the best standard deviation of flow time. Therefore, SBLE could be better suited to this wind turbine case study when manufacturers are only aiming to minimize mean flow time or maximize system throughput.

Due date assignment is then introduced as another important production performance measure for large product manufacturer in section 5.2. Many dynamic manufacturing requirements in mass customization may affect the customer's satisfaction and one of the targets is to meet the customer's due date requirement. Three due date scenarios are considered to represent different situations as follows: tight time allowance to due date, moderate time allowance to due date, and long time allowance to due date. As given in table 5.1, seven scheduling rules considering learning effect are used to assign jobs in the queue priority to enter the production line. It is shown that both SBLE and SBLE_SPT provide better results of mean flow time but they also provide worse standard deviation of flow time compared to other scheduling rules. It is also noted that SBLE and SBLE_SPT perform equally well for total tardiness; however, SBLE gives the best results for standard deviation of total tardiness as provided in table 5.2 and 5.3.

The discussion of tradeoff between throughput objective and due date assignment is given in section 5.3. The tradeoff involved in different criteria to provide useful insight to a decision maker is always a crucial problem because a solution that is optimal for a certain criterion could be a poor candidate for others (Chen et al., 2006, Lee et al., 2004). More than one

criterion consideration in scheduling problems is a practical course of research in real life application. Two criteria are considered to evaluate the performance of proposed SBLE scheduling rules: (1) a linear combination of weighted total flow time and weighted total tardiness, and (2) a revenue opportunity function considering price per unit and lateness penalty cost. First, it is noticed that both SBLE and SBLE_SPT have better performance value of sum of weighted total flow time and weighted total tardiness (y) in all different due date scenarios based on the weighted linear combination objective. It is recommended that SBLE or SBLE_SPT are better scheduling rules to result in a better performance value y when they are faced with different due date requirements from their customers and know how to decide weight α , where α is the given weight on total tardiness. In revenue objective criterion, the influence of late penalty cost on revenue function is provided and total revenue z decreases when the late delivery penalty increases among all seven scheduling rules. It is shown that SBLE still provides the highest total revenue z in every due date scenario.

From the conclusion in section 5.1 to 5.3, the results from simulation model and data analysis indicated that both SBLE and SBLE_SPT have capability to improve production performance, i.e. mean flow time, total tardiness, and expected revenue opportunity. Although SBLE results in the worst performance standard deviation of flow time, it might not be the major concern for the large product industry with a relatively small standard deviation (mean flow time = 22223 minutes, s.d. = 2289 minutes). Therefore, when comparing the results of all scheduling rules, it is clear that using SBLE on mass customized large product assembly line is to be preferred.

The goal of this research is to test alternative scheduling heuristics and one of the key findings of the research is the proposed SBLE scheduling rule which can be used for predicting

production performance measures. Making more accurate prediction helps to improve due date assignment performance measures which move towards better customer satisfaction. In addition, the SBLE model not only helps manufacturers in understanding the impact of critical bottlenecks on the final performance measures, but also helps to understand the influence of learning effect on scheduling sequence decision. It is also worth mentioning that this SBLE methodology is applicable in other large product assembly industries where they are faced with large variety of individual requirements from customers.

6.3 Limitations and Future Research Opportunities

Although the Shifting Bottleneck procedure and learning effect (SBLE) model is representative of mass customized large product assembly industry, it is recognized that the conclusion is limited to assumptions which are considered in this research. In particular, inventory shortage is never considered in the model, transportation between workstations is neglected, skill level of each operator is assumed the same, and there are no further investment options such as adding equipment or hiring operators to increase resource capacity. The SBLE model does have limitations and it is important to understand these limitations to present future research opportunities. Therefore, it is recommended that the following research be considered:

- **Inventory**

When developing the scheduling problem for the Shifting Bottleneck procedure and learning effect (SBLE) model, it was assumed that there is no lack of inventory which may not be practical in most real manufacturing cases. Without this assumption, schedulers will not be able to literally follow SBLE scheduling rule to assign job priority to enter the production line. Inventory happens because

of a mismatch of demand and supply. Manufacturers would not need to prepare any raw materials or component inventories if they can receive raw materials or components from their suppliers in a just-in-time environment. Since it is impossible for suppliers to provide raw materials to their customers at exactly the time when they are needed from the production system in real life, all manufacturers definitely hold certain amounts of inventory. It also has been known that higher inventory level is not a favorable circumstance in the production system because it leads to higher cost, more non-value added storage space, and management problems. Moreover, in the mass customization environment, forecasting future demand for a large volume of raw material and reorder point will be a challenge for manufacturers. Therefore, the presence of interactions between inventory level and scheduling problem will have another significant impact to the SBLE model which is not covered in this research and will need to be investigated further.

- Transportation

While applying the SBLE model to the complex wind turbine nacelles assembly line, it is assumed that transportation time between each station was ignored. However, this assumption might not be practical especially in the large product assembly industry which is still a heavily manually based assembly manufacturing process. Operators might need to use several moving tools, i.e., cranes, lift trucks, or hand pallet truck to process and assemble those large components. It is impossible for operators to continue their tasks without using

those tools. Under such circumstances, moving tools availability could become an important factor to identify the real bottleneck in the production system and scheduler will not be able to utilize the characteristics of SBLE model to improve the bottleneck efficiently. Additional studies of the usage of moving tools on this mass customized large product assembly industry are recommended to investigate the impact of moving tools availability effect on the identification of major bottleneck and production performance measures.

- Operators

In the SBLE model, the processing time on each task is assumed highly dependent on operator's experiences and skills because this is a complex and heavily manually based assembly manufacturing process. Each operator is assumed to have the same skill level in the beginning of production and also will only gain experience from performing exactly the same task sequentially. For example, an operator does not gain experience for assembling a 5MW generator if he is assembling a 4MW generator. This might not be realistic and operators could learn and gain skill by processing similar tasks even though tasks are different. Therefore, the influence of operator skills and the use of different learning curve on the scheduling decision and production performance measures could be further study opportunities.

- Investment on resources

The development of SBLE model is also under the assumption that manufacturers aim to improve the production performance without spending additional funds to invest in equipment or hiring more operators. However, in real life, it is typical to see that manufacturers consider increasing plant capacity when they are faced with a rising demand for their services or resource utilization nears its maximum. An issue for manufacturers is that they traditionally had to shoulder the immediate cost of resources expansion while today's investment might fail to materialize in a long term project due to uncertainty parameters such as interest rate, depreciation, corporation taxes, demand, possibly the item price, and late delivery penalty cost. Hence, there is a need to characterize investment variables and find out the key factors driving the optimal strategy in SBLE model from manufacturer's perspective.

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Appendix A: Source Data for the Nacelles Assembly Line Case Study

| MODULE | STEP | SAP SubOp. | Denomination |
|----------|------|------------|--|
| A | | | Main Frame assembly |
| SAP 0010 | A01 | 0101 | Assembly of the yaw system |
| SAP 0010 | A02 | 0102 | Main Frame part assembly before turning over |
| SAP 0010 | A03 | 0103 | Assembly of the Auxiliary elements and yaw gear |
| SAP 0010 | A04 | 0104 | Yaw test |
| SAP 0010 | A05 | 0105 | BF Hydraulic unit and Columns assembly |
| SAP 0010 | A06 | 0106 | Hydraulic assembly of the rotary joint brake |
| B | | | Rear Frame assembly |
| SAP 0020 | B01 | 0201 | Rear beam preparation |
| SAP 0020 | B02 | 0202 | Assembly of rotor cables and aluminum plate |
| SAP 0020 | B03 | 0203 | Assembly of the rear beam floor |
| SAP 0020 | B04 | 0204 | Assembly of the support and sand filling in the rear frame |
| SAP 0020 | B05 | 0205 | Cable routing in the rear beam |
| SAP 0020 | B06 | 0206 | Assembly of the column on the rear beam |
| SAP 0020 | B07 | 0207 | Assembly of Trafo wall and floor on the rear beam |
| C | | | Phase 1 |
| SAP 0030 | C01 | 0301 | Rear-Main Frame assembly |
| SAP 0030 | C02 | 0302 | Top control unit assembly |
| SAP 0030 | C03 | 0303 | beam assemblies |
| SAP 0030 | C04 | 0304 | Connection of cables in top cabinet |
| SAP 0030 | C05 | 0305 | Assembly of wall bridge and plate for cable tray |
| SAP 0030 | C06 | 0306 | Cable routing and connection in main frame |
| SAP 0030 | C07 | 0307 | Cable routing in Trafo wall and final operations |
| SAP 0030 | C08 | 0308 | Prepare Transport support and union nacelle with bottom |
| D | | | Phase 2 |
| SAP 0040 | D01 | 0401 | Shaft-Gearbox union assembly |
| SAP 0040 | D02 | 0402 | Trafo assembly |
| SAP 0040 | D03 | 0403 | Assembly of generator |
| SAP 0040 | D04 | 0404 | Cable routing of stage 2 |
| SAP 0040 | D05 | 0405 | Final test |
| SAP 0040 | D06 | 0406 | Operation after final test |
| SAP 0040 | D07 | 0407 | Connection of the Trafo cable in top |
| SAP 0040 | D08 | 0408 | Assembly stator cables of the generator |
| SAP 0040 | D09 | 0409 | Cabin assembly |
| SAP 0040 | D10 | 0410 | Assemblies inside the cabin |
| F | | | Trafo preassembly |
| SAP 0050 | F01 | 0501 | Trafo preassembly |

| | | | |
|-----------------|-----|------|--|
| SAP 0050 | F02 | 0502 | Preassembly of cables to support Trafo |
| G | | | Hydraulic group part assembly |
| SAP 0060 | G01 | 0601 | Hydraulic group part-assembly |
| E | | | Preassembly of main shaft/gear box |
| MAIN SHAFT 0010 | E01 | 0010 | Preassembly main shaft |
| GEARBOX 0010 | E02 | 0102 | Preassembly gear box |
| GEARBOX 0010 | E03 | 0103 | Rotating union and right arm assembly |
| GEARBOX 0010 | E04 | 0104 | G8X gear box by-pass assembly |
| GEARBOX 0010 | E05 | 0105 | Main shaft/Gear box union |
| GEARBOX 0010 | E06 | 0106 | Main shaft/Gear box final test |
| H | | | Oil-coolers preassembly |
| OIL-COLLER 0010 | H01 | 0010 | Oil-coolers preassembly |

| MODULE | #1 | #2 | #3 | #4 | #5 | #6 | #7 | #8 | #9 | #10 | #11 | #12 | #13 | #14 | #15 |
|----------|------|------|------|------|------|------|------|------|------|------|-------|------|------|------|-------|
| A | | | | | | | | | | | | | | | |
| SAP 0010 | 22.8 | 6.8 | 12.5 | 18.5 | 22.7 | 44.3 | 40.6 | 22.7 | 28.9 | 23.6 | 22.5 | 23.5 | 31.4 | 20.6 | 24.9 |
| SAP 0010 | 22.1 | 13.1 | 15.7 | 4 | 19.5 | 19.3 | 17.5 | 15.1 | 8.3 | 17.2 | 15.5 | 8.1 | 11.1 | 9.2 | 15.6 |
| SAP 0010 | 5.7 | 14.9 | 15.5 | 8.1 | 9.3 | 7.1 | 7.2 | 7.7 | 12.4 | 7.5 | 2.5 | 4.1 | 4 | 3 | 2.3 |
| SAP 0010 | 6.5 | N/A | 3.4 | N/A | 3.1 | 1.2 | 1.1 | 1.9 | 1.8 | 1 | 2.5 | 2 | 2 | 3.5 | N/A |
| SAP 0010 | 2.3 | 2 | 8.5 | 3.2 | 8.6 | 6.5 | 3.3 | 4.5 | 3.1 | 5.2 | 4.3 | 2.6 | 11.3 | 10.6 | 2.4 |
| SAP 0010 | 1.5 | 8.7 | 5.4 | 8.5 | 1.1 | 12.9 | 4.1 | N/A | 1.5 | 7.4 | 12.3 | 11.1 | 6.9 | 4.3 | 4.5 |
| B | | | | | | | | | | | | | | | |
| SAP 0020 | 4.4 | 0.1 | 15.1 | 7.7 | N/A | 9.3 | 0.7 | 3.7 | 3.3 | 4.8 | 1.3 | 4 | 3.8 | 6.3 | 3.3 |
| SAP 0020 | N/A | 0.7 | 0.3 | N/A | N/A | 2.6 | 1.2 | 1.5 | 0.8 | N/A | 1.6 | 1 | 2.6 | 1 | 1 |
| SAP 0020 | 2.6 | 3.3 | N/A | N/A | N/A | 1 | 3.3 | N/A | 2.3 | 2 | N/A | 2 | 3 | 3.8 | 1.4 |
| SAP 0020 | 1.3 | 0.7 | 0.8 | N/A | N/A | 7.3 | 1 | 3.8 | 0.7 | 1.5 | 1 | 3.1 | 5.6 | 8.7 | 2 |
| SAP 0020 | N/A | N/A | N/A | N/A | 1 | 6.3 | 1.2 | 4 | 1.3 | N/A | 1 | 2.2 | 1.8 | N/A | 3.2 |
| SAP 0020 | 1.1 | 0.5 | 1.7 | 3 | N/A | 0.4 | 2 | 0.2 | 0.5 | N/A | 1.3 | | 1 | N/A | N/A |
| SAP 0020 | 6.6 | 4 | 3.2 | 3 | 4.3 | 2.3 | 6.3 | 7.4 | 8.9 | 6.1 | 1.7 | 4.6 | 1 | 3.2 | 1 |
| C | | | | | | | | | | | | | | | |
| SAP 0030 | 6.2 | 4.7 | 2.8 | 2.8 | 3.6 | 3.4 | 5.1 | 4.5 | 2 | 2.5 | 5.4 | 7.4 | 1.2 | 0.5 | 2.5 |
| SAP 0030 | 3.2 | 14.7 | 13.4 | 16.1 | 5 | 9.5 | 3.7 | 15.8 | 8.4 | 16.8 | 8.9 | 9.2 | 5.2 | 10.7 | 13.45 |
| SAP 0030 | 4.2 | 12.5 | 8.9 | 14.6 | 11.4 | 9.4 | 9.1 | 8.4 | 6.6 | 8.5 | 5.7 | 1.7 | 3.2 | 2.9 | 4.6 |
| SAP 0030 | 14.5 | 17.7 | 21.1 | 12.2 | 22 | 18 | 19 | 5.6 | 20.4 | 17.1 | 11.7 | 15.8 | 7.5 | 5.1 | 19.45 |
| SAP 0030 | 10.2 | 22.1 | 6.5 | 22.8 | 16.9 | 7.9 | 8.5 | 7.8 | 9.8 | 4.6 | 7.8 | 5 | | 0.8 | 9.75 |
| SAP 0030 | 9.5 | 21.2 | 7.5 | 24.7 | 18.9 | 10.4 | 30.6 | 21.2 | 18.6 | 15.5 | 26.1 | 22.5 | 10.9 | 17.8 | 29 |
| SAP 0030 | 8.6 | 7.1 | 13.2 | 6.7 | 8.4 | 2 | 10.3 | 16.1 | 1.1 | 13 | N/A | 1.8 | 3.9 | 2.5 | 6.4 |
| SAP 0030 | 1.3 | N/A | 1.2 | 5 | 2.2 | 5.8 | 6.8 | 3 | 5 | N/A | N/A | N/A | N/A | N/A | N/A |
| D | | | | | | | | | | | | | | | |
| SAP 0040 | 18.2 | 19.3 | 25.9 | 15.8 | 7.2 | 14.4 | 27.9 | 16.5 | 9.1 | 16.9 | 17.85 | 5.5 | 8.9 | 7.9 | 12.9 |

