2013 Doctor's Thesis

Simulation Analysis of Work-In-Process Inventory Control for Discrete Manufacturing Systems

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 INTRODUCTION

1.1 Research Background

Manufacturing is important for the development of human society from three aspects: technologically, economically, and historically. Technology can be defined as the application of science to provide society and its members with those things that are needed or desired. Economically, manufacturing is an important means by which a nation creates materials wealth. Historically, human cultures that were better at making things were more successful (Groover, 2007).

Manufacturing covers a myriad of inputs, processes, products, and capitals. As a field of study in modern context, manufacturing can be defined two ways, one technologic, and the other economic (Groover, 2007):

> *Technologically, manufacturing is application of physical and chemical processes to alter the geometry, properties, and/or appearance of a given starting materials or products; manufacturing also includes assembly of multiple parts to make products. The processes to accomplish manufacturing involve a combination of machinery, tools, power, and manual labor, as depicted in Figure 1.1(a).*
>
> *Economically, manufacturing is the transformation of materials into terms of greater value by means of one or more processing and/or assembly operations, as depicted in Figure 1.1(b).*

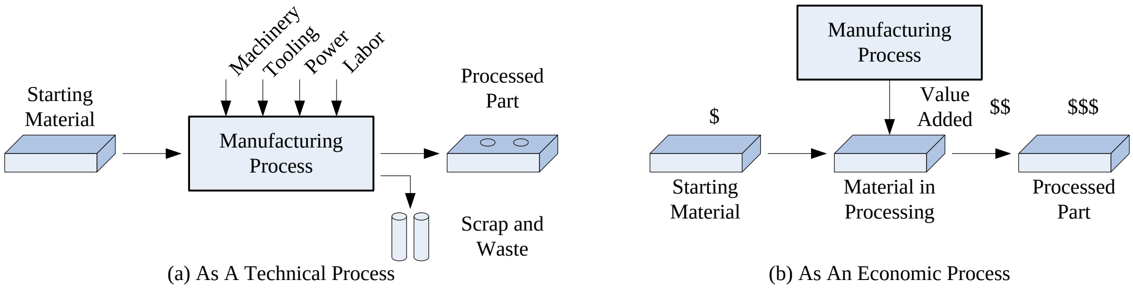


Figure 1.1: Two ways to define manufacturing

Therefore, generally, manufacturing is defined as the process of converting raw materials, components, or parts into finished goods in which the value of the materials and/or intermediate products is increased by changing the raw materials' shape or properties or by combining them with other materials.

Manufacturing is a system involving a high amount of complexity, which has grown with incredible speed and been stretching its boundaries in all directions in the past twenty year. This complexity results on the one hand from the fact that companies frequently have multiple locations in various countries and offer a large product variety associated with high manufacturing complexity. On the other hand, companies are increasingly embedded in complex global supply networks with a large number of actual or potential supplier and customers (Lang, 2010). Moreover, stiff global and domestic competition has allowed only the fittest companies to survive in recent years. Most successful manufacturing companies continually study and improve their manufacturing systems by applying various modern advanced manufacturing and management technologies.

Additionally, two of the main goals in operating a modern manufacturing enterprise are efficiency and benefit. The growth in modern manufacturing and management technologies have rendered the manufacturing environment such a complex place that some more comprehensive control approaches are needed to better compete in today's manufacturing industry. Therefore, in modern manufacturing environment, especially in the last two decades, advanced manufacturing management absorbed in rapid succession several new production management concepts, including manufacturing strategy, focused factory, Just-In-Time manufacturing, lean production, total quality management, agile manufacturing, flexible manufacturing system, concurrent engineering, supply chain management, and the list goes on. These considerable changes and development in manufacturing highlight the critical need for an efficient, authoritative reference tool for manufacturing management managers are now expected to think more broadly than their counterparts two to three decades age (Swamidass, 2000). Efficient advanced manufacturing management is the key to enhancing the productivity and economic effectiveness of manufacturing enterprises. Manufacturing management refers to all aspects of the product manufacturing process. Managing a manufacturing plant includes responsibility for the processes, from assembly design to packaging and transporting the finished product.

Inventory control as a core technology for advanced manufacturing management is an important activity to ensure the timely and inexpensive availability of materials, parts, components, subassemblies and finished goods (Swamidass, 2000). Manufacturing firms are engaged in an organized, formal effort to manage manufacturing resources and limit associated costs. Controlling and maintaining inventories of physical goods has always been an important issue for manufacturing enterprises that consume materials in their production processes. While in the past this field has often been treated as a subordinate, merely operational task, recent developments in the advanced manufacturing management have given rise to a strong demand for more profound methods for inventory management (Thomas, 2011).

Without effective inventory control and management, a manufacturing firm's inventory can become excessive, resulting in excessive cost to the firm. On the other hand, poor inventory control can result in either stockouts or overstocks of raw materials and components, which could halt productive activities Therefore, inventory control and management is concerned with achieving a balance between two competing objectives (Groover, 2007; Swamidass, 2000): 1) minimizing the cost of maintaining inventory and 2) ensuring the availability of materials, parts and components when needed for manufacturing. Consequently, an effective inventory control and management approach or system can save money and limited resources on these operations.

In the modern manufacturing environment, various types of inventory are encountered, and the categories of greatest interest in manufacturing management are generally three kinds of inventory: 1) Raw materials, and purchased parts and components; 2) Work-In-Process (WIP); 3) Finished goods in the factory or in the distribution system. Each type of inventory involves other action items and procedures that are unique to the specific inventory. All efforts to manage inventory of any type focus on adapting these essentials procedures to the specific circumstances of any inventory management strategy.

Return (profit) on capital employed is a key measure of a manufacturing company's financial health. Capital employed consists of several major elements, typically including fixed assets, accounts receivable less accounts payable, and raw material, finished goods, and WIP inventory. Of this amount, it is often found that inventories account for up to 85% of capital employed and 75% sales. Typically, in manufacturing factory, Work-In-Process inventory accounts for 50 to 75% of the total money tied up in inventory. This large amount of money must be managed wisely by manufacturing management using contemporary tools and techniques (Kivenko, 1981). Advanced manufacturing systems and management strategies are grounded in the belief that excess WIP inventory is a liability and should be minimized (Swamidass, 2000).

In the manufacturing system, Work-In-Process (WIP is called for short) is defined as follows (Kivenko, 1981):

> *Work-in-process as the inventory of materials, intermediate products and components is worked on or waiting for completion between operations in a factory.*

In practice, manufacturing managers use the WIP inventory level profile to control the material flow and simplify the production control (Lin et al., 2009). According to the characteristics and definition of WIP, the purpose of WIP is to give each stage of a production system some operational independence (Conway et al., 1988). Because of complexities and randomness of manufacturing system, WIP buffers set between two sequential workstations filter the unbalance of manufacturing cells having different production rates, prevent the propagation of the disturbances from the faulty manufacturing cells to the downstream cells (Faria et al., 2006), and increases capacity by reducing the frequency and severity of block and starvation (Yang and Posner, 2010).

However, in the manufacturing system, a high WIP inventory level leads to the following serious problems: 1) Having too much liquid capital caused by materials, components, or parts hold in the inventory (Kenneth 1992); 2) Decreasing market responsiveness of manufacturing systems and services (Tsourveloudis et al., 2000; Qiu, 2005); 3) Requiring more area and space for inventory layout and facility (Bertazzi, 2011); and 4) causing production imbalance (Zhao and Takakuwa, 2012). Additionally, the WIP level and the cycle time are convex increasing functions of the throughput (Lin and Lee, 2001). The inherent conflict in the determination of a proper WIP level is obvious when attempting to both maximize the throughput rate and minimize the cycle time (Lin et al., 2009).

Therefore, the increasing competition (Subramaniam, 2009), complexity and uncertainty in demand (Duffie et al., 2012) in the advanced modern manufacturing environment requires an appropriate control and management strategy for determining an optimal WIP inventory level that meets the tradeoff of maximizing the throughput rate and limited resource utilization rate and minimizing the cycle time and production cost. Successfully balancing these considerations is a critical factor in achieving management excellence for manufacturing systems.

Additionally, the idea of green manufacturing has become increasingly important to sustainable development that manufacturers minimize any negative environmental effects of their products and management process technology through determine the types of pollutants emitted, the solid and hazardous wastes generated, resources harvested and energy consumed (Swamidass, 2000; Kleindorfer et al., 2005). It reflects a new manufacturing paradigm that employs various green strategies (objectives and principles) and techniques (technology and innovations) to achieve greater eco-efficiency (Ahmed, 2011). Moreover, the environmental problems mentioned in this dissertation are not a generalized concept for the manufacturing environment but specifically consider green environment impacts and the eco-manufacturing concept for achieving negative emissions or wastes from manufacturing activities, reduced energy usage, zero pollutant emissions, waste recycling and other issues related to environmental protection and sustainable development.

In the manufacturing system, various WIP control methods can directly or indirectly affect the WIP inventory level. Especially in a multi-variety and small-batch production system, the appropriate determination of production lot-size for different part types at different production stages is a complex problem, which easily and directly causes serious WIP control problems (Azaron et al., 2009). A higher WIP inventory level leads to a higher scrap probability of overdue overstocks and more defective intermediate products or materials (Cordon, 1995). Because of inaccurate direct or indirect WIP inventory control methods, WIP overstocks of unnecessary materials and intermediate products are often produced, causing huge material waste, idle energy consumption idle processing and environmental maintenance wastes, and stock scraps, which all create a substantial environmental burden. These hidden environmental problems during the production process have yet to be fully recognized (Tang and Takakuwa, 2011 and 2012; Zhao, 2012; Zhao et al., 2013; Zhao, Ichimura and Takakuwa, 2013).

Therefore, considering sustainable development and green, managing and controlling the WIP inventory to improve environmental effectiveness by reducing negative environmental effects and burden are important issues for the modern manufacturing system.

In summary, determining an effective WIP inventory control strategy that limits and maintains an appropriate inventory level to achieve both production and environmental protection benefits associated with shorter cycle times, lower inventory cost, higher productivity, and better green performance is an important issue in modern manufacturing management research.

1.2 Problems Statement and Research Objectives

For modern environment-oriented manufacturing, to satisfy the requirements of the diversified demands of consumers, rapid responses to market needs and high core competitive advantages, many mechanical manufacturing enterprises have applied multi-variety and small-batch production mode (Lin and Lee, 2009). In this manufacturing system, substantial advanced automatic robot agent sets are used in the manufacturing cells to improve production performance (Groover, 2007). Additionally, WIP buffer spaces are widely adopted in the manufacturing system to reduce the fluctuations caused by the imbalances of systems or machine failures (Xia et al., 2013).

For the modern manufacturing industry, to accurately operate parts, use SMED (Single Minute Exchange of Die) technology to improve flexibility and reduce manufacturing costs (Monden, 2011), these manufacturing cells are designed as tightly coupled cells in which the part-arrival process is restricted by the limited WIP buffer space for part buffering between sequential workstations.

However, in these tightly coupled cells, the pre-workstation is easily blocked until this limited buffer space becomes available (Kelton et al., 2003). Therefore, these tightly coupled cells easily lead to many bottlenecks with high WIP levels and “block”/“starvation” frequency that affecting the system performance caused by many random events (Tao et al., 2008). Moreover, unreasonable WIP inventory control and management strategy for these coupled cells and entire system extends production cycle times, causes system instability and decreases productivity (Tsourveloudis et al., 2000).

On the other hand, WIP and other inventories are viewed by Japanese firms as wastes that should be eliminated (Groover, 2007). As illustrated in Section 1.1, overstocks of raw materials, intermediate products or components in WIP inventory systems cause huge material waste, idle energy consumption, idle processing and environmental maintenance wastes, creating a substantial environmental burden. Inaccurate production lot-size determination commonly leads to overstocks of WIP products and then creates negative environmental impacts.

In modern manufacturing, the main objective of manufacturing system activities is to maximize economic efficiency and ecological environmental benefits that not only obtain production profits but also contribute to the environmental harmony of a sustainable eco-society. Therefore, in this dissertation, two aspects of production capacity control and production environmental impact analysis are studied, with a focus on the integration of these two aspects. On the one hand, the goal of using of WIP inventories in production capacity control is mainly to eliminate system bottlenecks, reduce the production cycle time, and improve production capacity and balance by keeping WIP at a low level. However, the optimized control method for maintaining a low WIP inventory level cannot ensure better eco-manufacturing benefits and lower negative environmental impacts at the same time. On the other hand, the study of production environmental impact enables on analysis of negative environmental costs and burdens caused by an unreasonable WIP inventory level. However, a reasonable WIP inventory level that generates fewer negative environmental impacts cannot ensure that the corresponding control policy creates better production performance with short cycle times and without imbalances or system bottlenecks. Consequently, after researching these two different aspects of the WIP inventory control problem in detail in chapters 4, 5, and 6, the integration and tradeoff analysis of these two aspects are studied in chapter 7 using an effective control method to manage the WIP inventory at a lower and reasonable level to achieve both better productivity and environmental performance. Therefore, the final goals for this dissertation are as follows: production cycle time is reduced, system bottlenecks are eliminated, and the production operation capacity is improved while saving manufacturing resources and minimizing the negative environmental costs and burden by effectively controlling WIP inventory at a reasonable level.

To resolve these problems above and meet these final goals, the research presented in this dissertation has the following main objectives:

Objective 1: Identify the system bottlenecks caused by tightly coupled cells in a multi-variety and small-batch production system and propose reasonable control strategies to maintain the WIP and cycle time at a low level, while avoiding system imbalances and eliminating bottlenecks.

To achieve this main objective, two sub-objectives are studied.

Sub-objective 1-1: Analyze the effects of one tightly coupled bottleneck cell and of supervising the dynamic WIP inventory level changes of each workstation to the system's productivity and robustness.

Additionally, some specific performance evaluation indexes for *Sub-objective 1-1* are as follows: 1) reduce the average WIP inventory level in different production lines and the block/starvation frequency of the system by more than 50%; and 2) complete all orders in 3 days of delivery time.

Sub-objective 1-2: Study and improve the WIP inventory problems and system bottlenecks caused by multiple tightly coupled cells and enhance the system's performance, response and robustness.

Additionally, some specific performance evaluation indexes for *Sub-objective 1-2* are as follows: 1) the average WIP inventory level in different production lines is less than 300, and the block and starvation time are both over 50%; 2) the average value of the WIP inventory for tightly coupled production cells is similar to the value for uncoupled production cells; 3) all of the orders can be completed in 3 days of delivery time; and 4) the system response time when making a control policy to eliminate a disturbance is less than 1 second.

The control policy relative to the WIP inventory has considerable influence on the environment impacts of manufacturing. The level of WIP inventory determines the quantity of overstocks, which causes substantial wastes and environmental burdens.

Therefore, this research has the following second objective:

Objective 2: Analyze the environmental effects caused by the WIP inventory and propose a reasonable control policy to balance the economic and environmental benefits.

To achieve this main environmental objective, two sub-objectives are studied.

Sub-objective 2-1: Trace the large WIP inventories and other wastes caused by current inappropriate production lot-size determination and identify negative environmental impacts and corresponding changes.

Additionally, some specific performance evaluation indexes for *Sub-objective 2-1* are as follows: 1) obtain the definite scrap probability of WIP overstocks, the probability of defective products in WIP, the probability of processing residues or shavings and the frequency of the setup time; 2) in comparison with the conventional accounting method, identify definite negative products cost; and 3) find the tendency for a negative products cost for a unit part with changing production lot-size.

Sub-objective 2-2: calculate environmental waste hidden in the production processes and propose a corresponding control method to obtain an optimized negative environmental cost while improving production capacity.

Additionally, some specific performance evaluation indexes for Sub-objective 2-2 are as follows: 1) increase the positive products cost and the production capacity by more than 10% and decrease the negative products cost by more than 5%; 2) use the proposed control method to optimize the negative environmental cost; and 3) find a control priority.

Sub-objective 1-1 and *Sub-objective 1-2* are proposed to study the production capacity control problem. *Sub-objective 2-1* is proposed to study the environmental impact problem. To achieve these three sub-objectives, different control policies and perspectives of the WIP Inventory are considered and mastered. Moreover, *Sub-objective 2-2* is proposed to achieve both better production capacity and lower negative environment burden by performing an integration and tradeoff analysis of these two aspects.

Furthermore, the reasons for proposing these performance evaluation indexes for the different sub-objectives are as follows: first, according to Little's Law, reducing the WIP inventory level can reduce the lead-time; second, based on TOC, reducing system bottlenecks, such as "block/starvation", can improve several aspects of production system performance, including flexibility, balance capacity, robustness, stability, and randomized tolerance capability; third, according to inventory management theory, reducing the WIP inventory level not only releases more layout space for other production facilities but also releases liquid capital; fourth, according to the requirements of real production management, reducing the WIP inventory level and eliminating system bottlenecks can easily be monitored at the production line to control the production rhythm and save resources; and fifth, sustainable development of an eco-society requires green manufacturing processes and zero emissions. Environmental efficiency, such as the reduction of negative environmental impacts by more efficient WIP inventory control methods, is driven in large part by process and operational decisions that fall under the category of pollution prevention; finally, different specific figures required for performance evaluation indexes are determined based on the effectiveness of the control method, real production constraints and the possibility of realization and implementation.

1.3 Structure Overview

This dissertation is organized as follows:

The second chapter presents a general overview of the main issues and analytical approaches in WIP inventory control and illustrates three methods used in this dissertation, i.e., Fuzzy Control, Material Flow Cost Account and Simulation

Modelling.

The third chapter reviews the literature on WIP control and corresponding environmental impacts.

The fourth chapter analyzes a system bottleneck in a tightly coupled cell and proposes an optimized method, which is embedded in the discrete simulation model, to maintain the WIP inventory and cycle time at a low level by checking the inventory levels of distributed WIP buffers and dynamically adjusting the processing rate of each workstation.

The firth chapter uses a simulation to develop a hybrid control method and a corresponding centralized hybrid controller to resolve production problems in a multi-tightly-coupled-cells production system, while maintaining the rapid response ability to obtain a reasonable WIP control policy.

The sixth chapter presents a case study simulating a Pull production mode and back scheduling, traces and identifies substantial environmental burdens owing to large WIP inventories and wastes caused by inappropriate production lot-size determination, and use sensitivity analyses to present trends between production lot-size determination and negative environmental impacts by running several different simulation scenarios.

The seventh chapter integrates a centralized fuzzy control methodology and a new environmental accounting method to balance production and environmental performance, to increase production capacity by adjusting the processing rate according to the WIP inventory level, and to develop a simulation model that performs sensitivity analysis based on the control factors of the WIP inventory level and the negative manufacturing environmental cost ratio.

Finally, the eighth chapter presents the conclusion of this dissertation along with academic contribution, implementation of applied methods and suggestions for further research.

Figure 1.2 shows the structure of this dissertation and the relationship among chapters. In chapter one, the two problems and two corresponding main objectives with sub-objectives are proposed. In chapter 4 and chapter 5, problem 1 is resolved and objective 1 is achieved, as well as sub-objectives 1-1 and 1-2. Chapter 5 is expanded from chapter 4. Additionally, in chapter 6 and chapter 7, problem 2 is resolved and objective 2 is achieved, as well as sub-objectives 2-1 and 2-2. Chapter 7 is expanded from chapter 6. Furthermore, conclusions 1 and 2 are obtained by resolving the two problems and achieving the two main objectives. Further research aims 1 and 2 are expanded from problems 1 and 2, respectively.

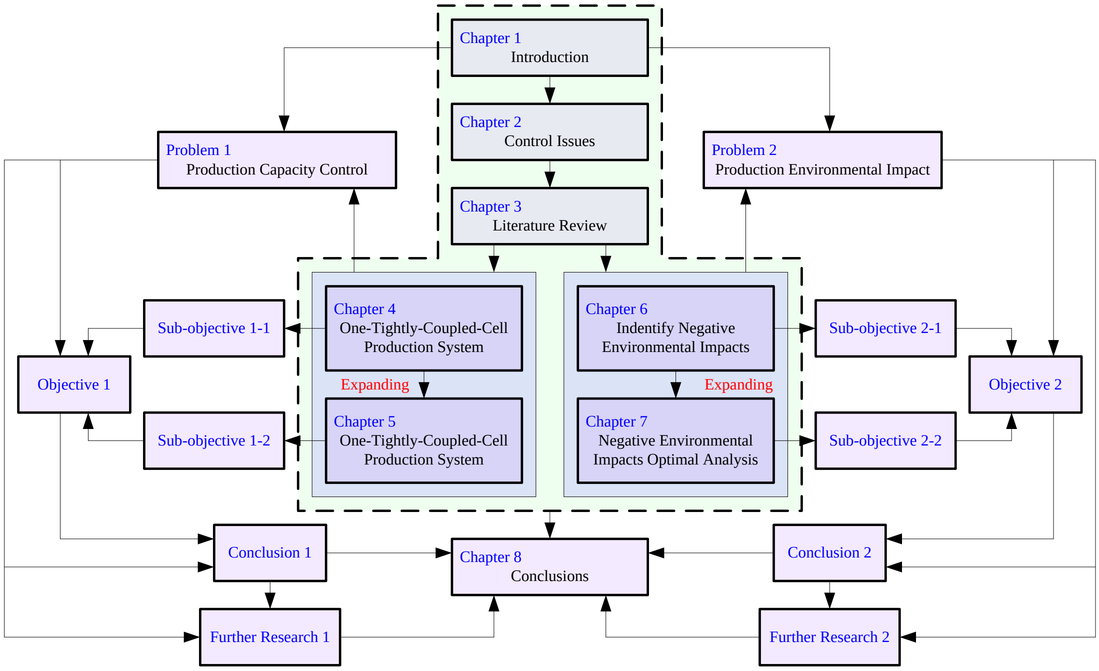


Figure 1.2: Overview of the structure of this dissertation

2 CONTROL ISSUES FOR WORK-IN-PROCESS INVENTORY

2.1 Introduction

From the days of Frederick Taylor, the Gilbreths, Hentry Gantt, and others early in this century and the "scientific management" they pioneered, much of the development of the production or manufacturing/operations management has been associated with the creation and refinement of tools and techniques for improving operations. The development of time and motion studies, scheduling charts and algorithms, inventory control models, statistical sampling, and a lot of other techniques, many very sophisticated, has been a triumph of a the discipline (Schmenner, 1990).

Moreover, in last two decades, although traditionally addressed by management science, operations research and industrial engineering, its complexity and importance have recently concentrated the efforts of different research communities, concerned with artificial intelligence, dynamic programming, queuing network theory, system simulation, large-scale systems, control theory, and other branches of engineering and computer science (Rovithakis, 2001). These advanced approaches from several research topics are used to solve current problems in management and improve manufacturing performance.

The research objective of this dissertation is optimizing the WIP inventory in a discrete multi-variety and small-batch production system. The tools that managers and scholars can wield in dealing with WIP inventory are frequently very different from the methods used to control other manufacturing and production issues (Schmenner, 1990). The reasons for this result are described as follows:

First, the WIP inventory level, operation processes and state variables of the production system change only at instantaneous, separated, discrete points on the time axis. Although this discrete specificity enables the use of a dynamic model, tracing the changing trends of state variables and identifying the relationships among production elements are complex elements in WIP control.

Second, multi-variety and small-batch production modes require high levels of automation and flexibility for the entire system operation to satisfy the diverse demands of consumers and rapidly respond to market needs. Variability in the variety and production lot-size of different parts/part families processed at different workstations causes frequent reset/setup (Feng et al., 2012) and substantial WIP buffers and inventory reserves, thus complicating the production schedule based on the WIP inventory level.

Third, a production system can be considered a collection of various service areas where jobs arrive at different rates and demand services with unequal processing times (Gupta and Kavusturucu, 2000). Moreover, system balance and stability are easily disturbed by stochastic factors such as unreliable machines, processing differentiation for part families, and disturbances from limited buffers in coupled cells. These random events lead to a high “block”/“starvation” frequency and substantial bottlenecks that restrict the optimization of WIP control.

Fourth, a manufacturing system is a collection of entities that function together for the benefit of the whole. When a change is made to any of the components, this change affects the other entities in the system. WIP inventory improvement should be designed as a systematic and comprehensive approach.

Fifth, green considerations from the concepts of sustainable development require the WIP inventory to be maintained at a lower level that produces fewer wastes and environmental burdens or costs. This eco-efficient manufacturing consideration integrates various WIP control methods for both production and environmental performances, increasing the complexity in WIP control.

Summarily, handling WIP inventory production and logistics often requires a high amount of complexity. Due to the nature of the system and the actual market environment, the management of production systems changes from pushed flow (based on stock filling) to pulled flow (based on customer requirements). The decision and control processes for WIP inventory move from a top-down approach based on responsible authority to a flexible approach based on the potential actor's personal interpretation (Habchi, 2000). Moreover, market competition is reducing production times, costs, product life cycles, negative environmental effects and enhancing quality. Furthermore, all production systems are submitted to external and internal random risks. Consequently, controlling WIP inventory is highly complex.

In recent years, managers and researchers have contemplated new ways of controlling WIP inventory level, shortening production cycle time, breaking existing production bottlenecks, strengthening productivity and improving the environmental effects of products and production processes. In this dissertation, to achieve the objectives and corresponding sub-objectives, control issues in WIP inventory are assessed and the three main approaches for these problems are reviewed in the next sections.

2.2 Control Issues in WIP Inventory

2.2.1 Finite WIP Buffer Capacity and Block

Given the increasing flexibility of manufacturing machines and assembly station it is rather frequent that more than one part type (multi-variety and small-batch) is produced on a single production line. Also, in automated systems, parts are operated by robot agent sets (Groover, 2007) and machines are normally connected by accumulating conveyors which act as finite capacity buffers (Colledani et al., 2005). In this manufacturing system, finite buffers are typically used and kept at small capacity to reduce storage space, WIP, production cycle time and disturbance of setup (Feng et al., 2012). In such a case, after finishing processing on a machine, a job either directly has to be processed on the next machine or it has to be stored in the buffer between the two machines. If the buffer is completely occupied, the job has to wait on its current machine and this machine is blocked for other jobs. This blocking will remain until at least a buffer unit becomes available (Grabowski et al., 1983; Smutnicki, 1998; Nowicki, 1999; Qian et al., 2009). Consequently, block and starvation result from variability in processing times and limited buffer space between sequential workstations (Blumenfeld, 1990).

Summarily, these manufacturing components involving the finite WIP buffer, sequential workstations and automatic robot agent sets form a tightly coupled cell, in which the part-arrival process is restricted by the limited space for part buffering between sequential workstations and the pre-workstation is easily blocked until this limited buffer space becomes available (Kelton et al., 2003). In this production cell, coupling is the relationship between sequential workstations, which reflects the degree of interconnection. Sequential workstations are less independent when there is a tighter relationship. Consequently, the tightness and coupling in this production cell reduce self-regulation and weaken the robustness and stability levels, with a heightened randomicity tolerance for stochastic factors. Figure 2.1 shows the production structure for this tightly coupled cell.

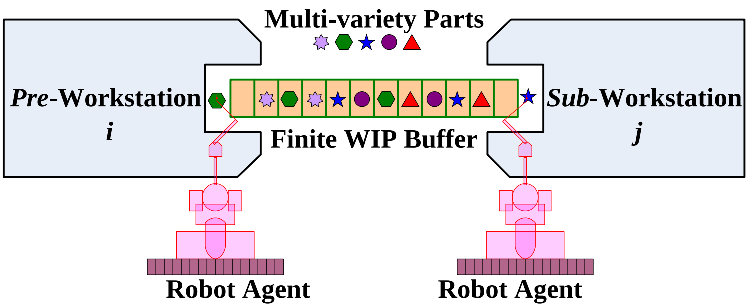


Figure 2.1: Production structure for a tightly coupled cell

In a production system with tightly coupled cells, blocking may occur because of the finiteness of buffers. Different types of blocking mechanisms have been considered in the literature (Perros, 1994): blocking-after-service (also referred to as type-1 blocking, transfer blocking, and manufacturing blocking), blocking-before-service (also referred to as type-2 blocking, service blocking, and communication blocking), and repetitive-service blocking (also referred to as type-3 blocking, and rejection blocking). In blocking-after-service, a server is blocked if the destination buffer of the customer is full after completion of the service of a customer. In blocking-before-service, the service of a customer is not allowed to start until there is room available in its destination buffer. In repetitive-service blocking, a customer attempts to join its destination buffer upon service completion. If this buffer is full, the customer receives another service and this is repeated until space becomes available in the destination buffer. A comparison of these types of blocking can be found in Onvural (1986) and Perros (1986 and 1994).

In this dissertation, the research objects are discrete manufacturing systems. In these systems, there exist many tightly coupled production cells. Additionally, based on analysis of the characteristics of the system structure and facilities, blocked tightly coupled cells are an example of type-1 blocking. In real production systems, these tightly coupled cells are located downstream of the production lines and include many fining processing machines that consume substantial processing time. Because these tightly coupled cells cannot be decoupled, these cells cause inventory overstocks in the upstream WIP buffers and also create a high block frequency for the pre-workstation and high starvation frequency for the sub-workstation. Consequently, these production cells generate substantial system bottlenecks.

Moreover, in these real systems, there exist many other system bottlenecks. However, these tightly coupled production cells are considered a research topic for the main system bottlenecks that must be eliminated as fast as possible. First, the inventory level in the upstream WIP buffer of these production cells is the highest for the entire production line; second, the block and starvation frequency is also the highest; third, due to longer stock time in the WIP buffer, the scrap quantity of WIP overstocks and defective products in the WIP are increased; fourth, maintenance costs for the intermediate product overstock in the WIP buffer are highest owing to the fining machining; and firth, the production cells are related to fining processes, which requires substantial processing time. Because intermediate product overstock in the WIP buffer cannot be processed in time, the production cycle time is extended. Consequently, these tightly coupled production cells are the weakest links in the entire production system and significantly decrease productivity and increase the production cycle time. Therefore, in this dissertation, these tightly coupled production cells are viewed as the main system bottlenecks.

2.2.2 Bottleneck Analysis

Having enough capacity in the short run is a constant headache, especially in job shop and batch flow production processes. Identifying where bottlenecks are or might occur and taking measures to overcome them are always on an operation manager's agenda. Production bottlenecks are generally considered to be temporary blockades to increased output; they can be thrown up anywhere along the course of a production process. In analyzing bottlenecks it is always helpful to trace the production process by using a process flow diagram and to assign what capacity numbers are available to each stage of the process. The process flow diagram becomes a planning aid for breaking significant, stationary bottlenecks. Still, judicious and systematic use of a process flow diagram can be a valuable tool in identifying the process elements and conditions that account for bottlenecks. Another useful tool in analyzing bottlenecks is an inventory buildup graph, a pictorial way of accounting for the rates at which inventories are either piled up or depleted (Schmenner, 1981).

However, in this dissertation, simulation modeling is applied to dynamically trace the production process and check the WIP inventory level by analyzing statistical data for the simulation. The workstation after the WIP buffer where inventory quickly piles up is considered the bottleneck.

Another method for bottleneck analysis in this dissertation is the Theory of Constraints (TOC), which is clearly defined by Eliahu M. Goldratt (1990).

In a multi-variety and small-batch production system with tightly coupled cells, tightly coupled cells cause system bottlenecks that limit the amount of products, lead to a high level of inventory upstream of the WIP, block the operation of the workstation in the cell, and control the throughput of the whole production system. Therefore, bottlenecks must be identified and removed to ensure the maximum possible utilization.

According to TOC, the Drum-Buffer-Rope mechanism is used to improve system bottlenecks. Bottlenecks are considered as constraint or drum that controls the pace of production; the rope is the material release mechanism that releases material to the first operation at a pace determined by the bottleneck. Material release is offset from the constraint schedule by a fixed amount of time, the buffer (Watson et al., 2007). Buffers are strategically placed upstream and downstream of tightly coupled cells to protect shipping dates and to prevent constraint processes from starvation because of limited materials. WIP inventory level in this buffer is controlled to both reduce disturbance and improve productivity. The arrangement in a typical DBR system is shown in Figure 2.2.

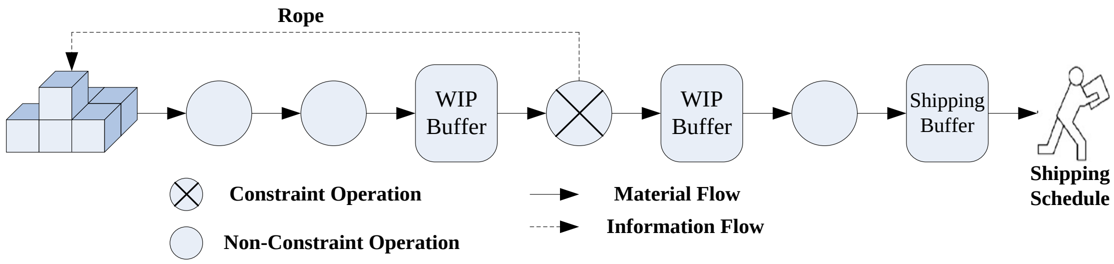


Figure 2.2: Typical drum-buffer-rope configurations (Watson et al., 2007)

2.2.3 CONWIP

CONWIP (CONstant Work-In-Process) production control system was introduced by Spearman et al., 1990) as an attempt to present a pull system more flexible than the current pull paradigm, the Kanban system. CONWIP is used to maintain constant the maximum amount of WIP by using cards that are attached to a job at the beginning of the system. As a pull system, CONWIP shares the advantages of push systems with respect to WIP control, while it is consider more robust, flexible and easier to implement than other pull systems. These are important characteristics for manufacturing companies that try to control inventory levels and at the same time, face uncertain and dynamic environments where Kanban does not perform well (Framinan, 2003).

In the production system in this dissertation, each tightly coupled cell is designed as a CONWIP control cell in which various operations and “block”/“starvation” situations can be easily monitored. The WIP inventory level of the tightly coupled cell is bounded and maintains a constant amount. In this control cell, work is started at the first station in a cell only when the WIP level for the cell has fallen below a specified level. Otherwise, work is pushed within the cell. In the CONWIP cell, production quantities are measured in terms of standard parts and are represented by the time a part spends in the slowest station in the cell (Bottleneck). The operator uses the “CONWIP Backlog” at the first station in the cell to determine which job to start next. This backlog is generated by attempting to group jobs sharing a common setup (at the bottleneck) while ensuring that all jobs finish on time (Spearman et al., 1992). Figure 2.3 shows the structure of the CONWIP cell.

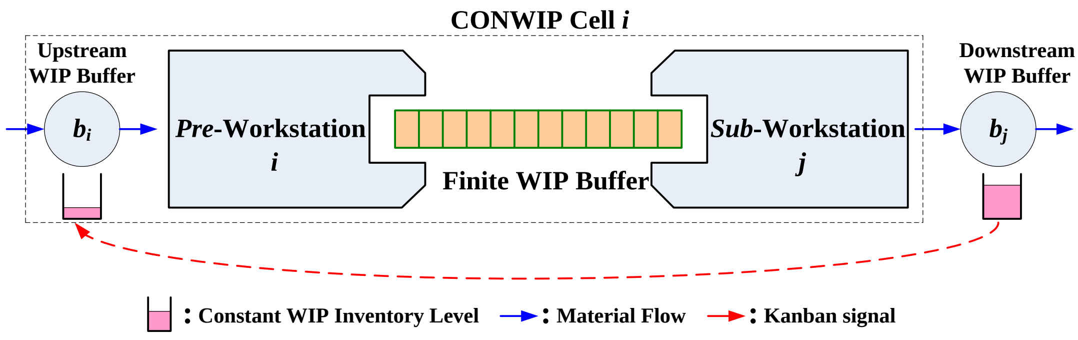


Figure 2.3: The structure of the CONWIP cell

2.2.4 Production Lot-Size Determination

The optimum production lot-size is the number of parts that must be produced to meet anticipated demand and minimize overall production cost (Kivenko, 1981). Additionally, in a multi-variety and small-batch production system, one of important requirements for minimizing WIP inventories is small production lot-size. It is examined the relationship between production lot-size and inventory in the famous Economic Order Quantity (EOQ) method (Groover, 2007). In the production line for a multi-stage production/inventory system, different lot-sizes are needed for different workstations. If the production system is scheduled based on an appropriate production lot-size determination strategy, the costs of the WIP inventory and total inventory can be reduced considerably (Drezner, 1984).

Moreover, in a multi-variety and small-batch production system, facing the continue change in demand quantity and part type, production lot-size also need be regulated accordingly. Additionally, in modern advanced manufacturing industry, a Pull production mode and inventory decision-making mechanism based on a corresponding back scheduling process are applied to make production plan and determinate production lot-size. However, because of inaccurate determination of production lot-size, huge WIP overstocks are produced, and an excess of energy, auxiliary fluids and operations are wasted. According to the requirements from the production design and the customers, overstocks lead to useless WIP stock, idle processing and environmental maintenance wastes. Moreover, WIP overstocks cause large amounts of scraps from overdue and defective intermediate products or materials. All of these wastes and scraps produce a substantial environment cost and burden.

The method for determining an appropriate production lot-size to maintain a reasonably low WIP inventory level is not studied herein because this topic is outside scope of this dissertation. However, a sensitivity analysis of production lot-size to maintain a low WIP inventory level and achieve both economic and environmental effectiveness is the focus of chapter 6. Additionally, the change in negative environmental impacts is studied. These achievements will provide production managers with effective and strategic knowledge and instructions for determining the appropriate production lot-size to maintain a low WIP inventory level, considering both economic and environmental benefits.

2.2.5 Pull/Push System

Production control systems can generally be subdivided into "push" and "pull" systems. In a push system, production is initiated by a central planning instance which makes use of forecasts for future demands. Production is initiated before the occurrence of demand; otherwise, the finished products cannot be delivered in time and are stocked to meet predicted demand. Therefore, the production lead times have to be known or approximated (Gstettner and Kuhn, 1996). In a pull system, production starts when demand actually occurs. The production is initiated by a decentralized control system that the order is used to trigger a pulling action from the end of the production line. When properly implemented, pull production system results in less WIP than push production system, which in turn reduces warehousing and investment costs (Swamidass, P. M., 2000).

In the aspect of WIP controlling, the advantages of pull system over push are: First, observability, WIP is directly observable, while capacity (with respect to which release rate must be set) is not; Second, efficiency, pull systems can achieve the same throughput rate as a push system with a smaller average WIP level; Third, variability, flow times are less variable in pull systems than in push systems because pull systems regulate the fluctuation of WIP level, while push systems do not; Fourth, robustness, pull systems are less sensitive to errors in WIP level than push systems are to errors in release rate (Hopp and Roof, 1998).

Moreover, the control policy of production system is classified as token-based, time-based, or surplus-based. In the surplus-based system, decisions are made on the basis of how far cumulative production is ahead of, or behind, cumulative demand. Hedging point, two-boundary and base stock policies are based on surplus and backlog (Gershwin, 2000). The main objective of this control policy is to produce smoothly while total demand is satisfied; it can also keeps WIP to be as low as possible and reduce surplus or backlog (Homayouni et al., 2009). In this control method the production is controlled to its maximum rate whenever inventory is below a critical level (hedging point) and set to zero whenever inventory is above that level (Bai and Gershwin, 1994).

In this dissertation, the entire production system is considered a surplus-based system in which the hedging point is a safety stock. The control policy is based on whether the real-time WIP level is higher or lower than the hedging point (safety stock). Additionally, different production system is analyzed, the control policy is different. For a production system with one tightly coupled cell, this cell is the main bottleneck for the entire system. According to the theory of constraints, this cell is viewed as the “drum”. The “Pull” mode is used for the production line that is upstream of the “drum”, and the “Push” mode is applied for the production line that is downstream of the “drum”. For a production system with multiple tightly coupled cells, this system is divided into multistage production cells, and a mixed Pull and Push mode is applied. Each tightly coupled cell is designed as a CONWIP control cell in which the Push mode is used to drive the parts process. Among multistage production cells, the Pull mode is used because of the merits of applying the JIT idea.

Regardless of the system control type and characteristics, according to the surplus-based system, largely due to the fact WIP is bounded, the mixed pull and push mode is the minimum inventory level system and creates shorter and less variable cycle times.

2.3 Fuzzy Control Method

Striving for a rationalistic, systematic, excellent optimized, and accurate operational solution or algorithm is the ultimate goal for the scholars. However, an actual production system is a black-box system that is synthetically restricted by various random factors. Accurately controlling these variable factors to achieve predetermined objectives is more difficult, and NP-hard problems are encountered frequently (Zhao and Takakuwa, 2012; Zhao and Takakuwa, 2013). Therefore, heuristic control policy has been gradually considered to achieve a satisfactory strategy that is not an exact solution (Bai and Gershwin, 1994; Tsourveloudis et al., 2000). Heuristics are rules of thumb for reasoning, simplifications, or educated guesses that reduce or limit the search for solutions in domains that are difficult and poorly understood.

Consequently, in this dissertation, a heuristic fuzzy control method is developed. The demonstrated advantages of this control method are computational simplicity and real-time and dynamic control/scheduling (Tsourveloudis et al, 2007). By applying this approach, disturbances from bottlenecks caused by tightly coupled cells can be avoided, and lower WIP inventory levels, shorter cycle times and higher productivity are achieved (Zhao and Takakuwa, 2012; Zhao and Takakuwa, 2013).

In fuzzy controllers, the control policy is described by linguistic IF-THEN rules with appropriate mathematical meaning (Driankov et al., 1993; Geering, 1998). The rule base of the line control module contains rules of the following form:

Rule 2.1 *IF* $\boldsymbol{A}$ *is* $\boldsymbol{X}$ *AND* $\boldsymbol{B}$ *is* $\boldsymbol{Y}$, *THEN* $\boldsymbol{c}$ *is* $\boldsymbol{Z}$

Here, $\boldsymbol{A}$ and $\boldsymbol{B}$ are the inputs for the fuzzy controller, and $\boldsymbol{c}$ is the output, respectively. $\boldsymbol{X}$, $\boldsymbol{Y}$, and $\boldsymbol{Z}$ are corresponding the linguistic variations, and are fuzzy sets with certain membership functions. The inference procedure for the fuzzy controller can be briefly described as follows. Let $\boldsymbol{a}^*$ and $\boldsymbol{b}^*$ be the numerical values of the input variables that are converted into two fuzzy sets, with membership functions denoted by $\boldsymbol{\mu}_X(\boldsymbol{a}^*)$ and $\boldsymbol{\mu}_Y(\boldsymbol{b}^*)$, respectively. These functions are compared with fuzzy sets $\boldsymbol{X}$ and $\boldsymbol{Y}$ and determine the output value of fuzzy set $\boldsymbol{Z}$.

Rule 2.2 *IF* $\boldsymbol{a_i}$ *is* $\boldsymbol{LX^{(k)}}$ *AND* $\boldsymbol{b_i}$ *is* $\boldsymbol{LY^{(k)}}$, *THEN* $\boldsymbol{c_i}$ *is* $\boldsymbol{LZ^{(k)}}$

Where, $\boldsymbol{k}$ is the rule number, $\boldsymbol{i}$ is the number of control elements, and $\boldsymbol{LX}$ and $\boldsymbol{LY}$ are linguistic values of $\boldsymbol{a}^*$ and $\boldsymbol{b}^*$, respectively, with the term set $\boldsymbol{X}$=$\boldsymbol{Y}$= {***PL*** (Positive Large), ***PS*** (Positive Small), ***O*** (Zero), ***NL*** (Negative Large), ***NS*** (Negative Small)}. The output $\boldsymbol{c}^*$ involves the linguistic value ***LZ***, which is also from the term set $\boldsymbol{R}$= {***PL***, ***PS***, ***O***, ***NL***, ***NS***}.

The mathematical meaning of the $\boldsymbol{k}$th rule can be provided as a fuzzy relation $\boldsymbol{F}^{(k)}$ on $\boldsymbol{X}\times\boldsymbol{Y}\times\boldsymbol{Z}$, which is represented in the membership function domain as:

$$\mu_{F^{(k)}}\left(a_i, b_i, c_i\right) = f_{\rightarrow}\left(\mu_{LX^{(k)}}\left(a_i\right), \mu_{LY^{(k)}}\left(b_i\right), \mu_{LZ^{(k)}}\left(c_i\right)\right) \tag{2.1}$$

where $f_{\rightarrow}= min$ for rules of the Mamdani type. The actual inputs can be represented as $\boldsymbol{a_i^*}$ and $\boldsymbol{b_i^*}$ with membership functions $\boldsymbol{\mu_X^*(a_i)}$ and $\boldsymbol{\mu_X^*(b_i)}$, respectively, and, $\boldsymbol{g}$ or $\boldsymbol{h}$ is the function of the correction factor. The membership functions of the conjunction of these two inputs, for *AND*=*min*, is:

$$\mu_{AND}^{*}\left(a_i, b_i, \alpha\right) = \left[g\left(\alpha\right) \times \mu_X^{*}\left(a_i\right)\right] \wedge \left[h\left(\alpha\right) \times \mu_Y^{*}\left(b_i\right)\right] \tag{2.2}$$

The output $\boldsymbol{c_i^*}$, is given by the following defuzzification formula:

$$c_i^* = \frac{\sum c_i \mu_Z^*\left(c_i\right)}{\sum \mu_Z^*\left(c_i\right)} \tag{2.3}$$

Where, $\boldsymbol{\mu_Z(c)}$ is the membership function of the aggregated output, which is computed by applying the *max-min* composition to the outcome of (2.1) and (2.2) as follows:

$$\mu_Z^*\left(r_i\right) = \max_{a_i, b_i, \alpha} \ min\left[\mu_{AND}^*\left(a_i, b_i, \alpha\right), \mu_{F^{(k)}}\left(a_i, b_i, \alpha, c_i\right)\right] \tag{2.4}$$

For the fuzzy logic controller, the reasonable division of input/output membership functions and the calculation of the defuzzification rule determine the performance of the overall control policy.

In this dissertation, an improved fuzzy control method is developed to maintain the WIP inventory and cycle time at low levels by supervising the dynamic changes in the WIP inventory and regulating the processing rate of each workstation with simple representations and linguistic IF-THEN rules.

2.4 Material Flow Cost Accounting

Material Flow Cost Accounting (called MFCA for short) is an environmental management accounting method that focuses on tracing waste, emissions and non-products and on helping to boost an organization’s economic and environmental performance. It is a system to measure the flow and stock of materials in the production process (raw materials and energy) in terms of physical and monetary units (Kokubu, 2008), and a tool of decision making by business executives and on-site managers.

The original concept of MFCA was developed in Germany in the late 1990s as an environmental protection accounting technique. Since around 2000, it has been adopted widely in Japan and modified for increased ease of use by dividing materials into raw materials and energy sources, as well as measuring them by processes for easier improvement plans. To standardize MFCA practices, a working group (WG) 8 of ISO technical committee ISO/TC 207 (Environmental management) is currently working on the development of ISO 14051, Environmental Management-MFCA-General Framework, targeted for publication early in 2011 (Kokubu, Tachikawa and Takakuwa, 2012).

MFCA has become recognized as a valuable management tool, balancing environmental and economic factors by reducing substantial waste costs. Figure 2.4 shows the concept of MFCA. It is also a management information system that traces all input materials flowing through production processes and measures output in finished products and waste. In MFCA, finished products and waste are respectively termed positive and negative products. In a processing-type production system, waste is generated in various steps of the production process. In particular, in the process of stocking and production, waste is substantially produced because materials and intermediate products that are overstocked as inventory may deteriorate in quality or be scrapped. Additionally, while materials or intermediate products are processed, residues or shavings may be generated. All of the wastes mentioned above are called “negative products” and lead to environmental burden. In MFCA, the idle processing, unnecessary energy and auxiliary material consumption caused during the waste generation are also called “negative products” and treated as environmental costs.

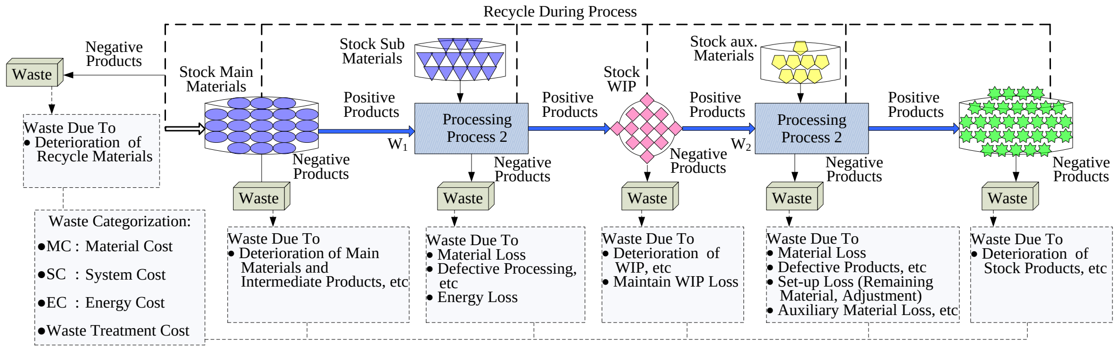


Figure 2.4: The concept of MFCA (Environmental Industries Office 2007)

The costs of both positive products and negative products are categorized into the following 4 groups (Environmental Industries Office 2010):

• MC: Material Costs (costs of materials including main materials for the initial process, sub materials added during midstream processes, and auxiliary materials such as detergents, solvents and catalysts);

• SC: System Costs (processing costs including labor, e.g., depreciation, overhead costs);

• EC: Energy Costs (electricity, fuel, utility and other energy costs);

• Waste Treatment Costs.

Many studies and practical applications have shown that by introducing MFCA, both economic and environmental performances are improved. However, cases of MFCA implementation and analysis for production lot-size determination in a multi-variety and small-batch production system are still scarce.

In this dissertation, MFCA is introduced to study the environmental impacts of the WIP control strategy by identifying overlooked wastes (owing to useless overstock) and environmental burdens hidden in the production processes.

2.5 Simulation

Scientists are always trying to find better solutions for optimum processes, methods and techniques. Unfortunately, theory and demonstration are long and time-consuming and experiment is not always possible. It is here that modeling and simulation are considered as a substitute for theory and experiment. Their goal is sometimes the search for the optimal solution, most of the time a better solution and sometimes the least bad solution. As an answer to these problems, modeling and simulation are becoming a widespread technique in all the phases of the production system life cycle: design, planning, manufacturing, control, real time monitoring, performance evaluation, optimization, etc (Habchi, 2000).

Additionally, the ever-increasing size and speed of computers has made simulation a more and more attractive means of obtaining some acceptable solutions to large-scale and/or complex problems, such as many queuing problems. The typical simulation model is a kind of mathematical “black box” that takes some initial inputs, processes them, usually over a number of periods of time, and spits out some outputs.

Simulation can help users by contributing in design, in management and in the decision-making of production systems. It is able to model all kinds of company processes: physical, informational and decisional. Simulation models can be built at all hierarchical (operational, tactical, strategic) and detailing levels (machine, cell, shop. . .) (Bakalem et al., 1995; Kindler, 2000). Moreover, the whole manufacturing system life cycle can be modelled and simulated (design, analysis, implementation, operation) (Habchi and Labrune, 1995).

Then, to design, organize and control current manufacturing systems, managers must take the following aspects into consideration (Habchi and Berchet, 2003): the diversity and heterogeneity of production flow, production space optimization, production process organization and management simplification. As manufacturing systems are by nature complex and analytic methods cannot be always applied, systemic analysis is then necessary to apply simulation. Basically, a production system is divided into three subsystems (Habchi, 2000): physical, informational and decisional. Nevertheless, as simulation models are based on information, two subsystems are only considered: operation and control (Figure 2.5).

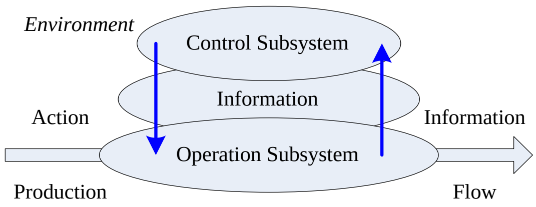


Figure 2.5: System analysis of a manufacturing system

The operation subsystem is considered as a combination of two types of physical objects: entities and resources. Entities represent products to be manufactured and resources are production means, and the flow of entities on resources describes the manufacturing process. On the other hand, the control subsystem is considered as a set of decision-makers able to act on the manufacturing process if it is necessary using control rules, management procedures and so on. Both the manufacturing and control processes together form a firm's production process.

Although there are different types of simulation model, the focus of this dissertation is on *discrete-event simulation* that is characterized by discrete, dynamic, and stochastic. In such an approach, the flow of *entities* that move through the system must be modeled. In the perspective of a manufacturing system, materials, components, intermediate products and finished products are the major entities. Entities process various characteristic - *attributes* such as types of materials and products, processing size. The entities flow through the system while using a series of *resources*, such as machines, workers, WIP buffer. A simulation model is therefore a computer program which represents the logic of the system i.e. entities arrive with various attributes and wait for resources, next processed by resources, finally release the entity. Moreover, this program keeps a track of *performance measures* such as machine utilization, products production cycle time, product throughput, WIP inventory level in the buffer, block/starvation frequency, and other useful statistics. Sine real world simulation models are rather large, and since the amount of data stored and manipulated is so vast, the runs are usually conducted with the aid of a computer.

Figure 2.6 is a schematic of simulation study. The iterative nature of the process is indicated by the system under study becoming the altered system which then becomes the system under study and the cycle repeats. In a simulation study, human decision making is required at all stages, namely, model development, experiment design, output analysis, conclusion formulation, and making decisions to alter the system under study. The only stage where human intervention is not required is the running of the simulations, which most simulation software packages perform efficiently. The steps involved in developing a simulation model, designing a simulation experiment, and performing simulation analysis are (Maria, 1997):

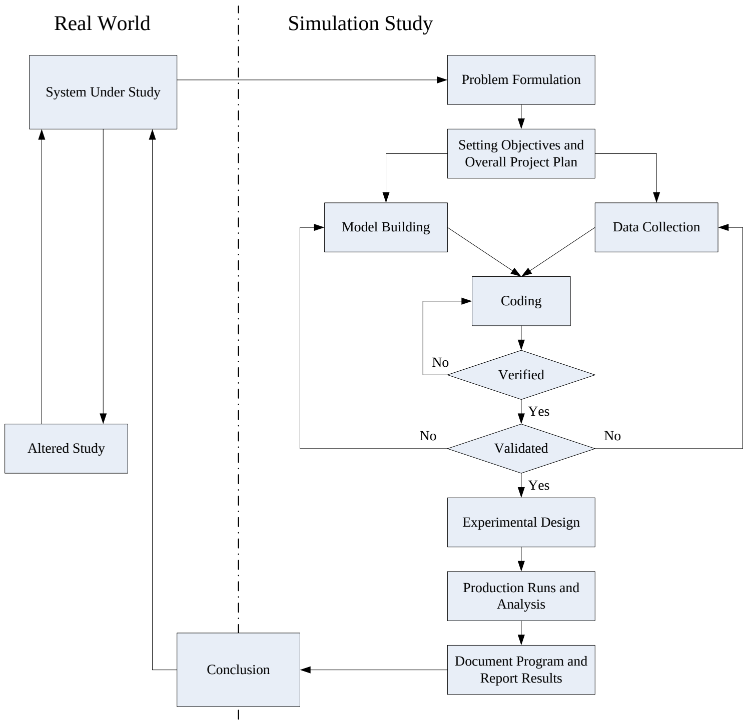


Figure 2.6: Simulation study schematic

[Step 1] Problem Formulation

Analysis begins by gathering information about the problem. In a multi-variety and small-batch production system with tightly coupled cells, this information may include a high level of WIP inventory, the frequency of blockage caused by bottlenecks, the production cycle time and serious environmental burden. Although not shown in Figure 2.6, there are occasions where the problem must be reformulated as the study progresses.

[Step 2] Setting of objectives and overall project plan

In this step, the proposal for the study is prepared. The objectives indicate the questions that are to be answered by the simulation study. The project plan should indicate the required time, cost, resources, stages in the investigation, and output at each stage. The overall objective of the study is defined and performance measures are identified.

[Step 3] Model building

The real-world system is modeled according to mathematical and logical relationships and the structure of the system. In a manufacturing workshop, the basic model of orders, machines and WIP buffers are constructed. The demand plan and machine schedules are then added. Next, complex routines based on the indentified sequences are added. The construction of the model system is most likely as much an art as a science (Banks et al, 2001).

[Step 4] Data collection

After identifying the process, the analyst collects data indicating the processing time for different part types and the random workstation failure frequency. In this step, the analyst collects real system data. The data collection involves input variables (arriving time, processing time, travel time between stations, WIP buffer capacity), the performance of the existing system (productivity, production cycle time, and environmental costs), and entities of randomness in the system (the percentage of each part type). Data collection and model building proceed simultaneously as the analyst builds the model while collecting data. In a real-world simulation study, collecting and evaluating input data is very time consuming and difficult. As the complexity of the model changes, the required data may also change.

[Step 5] Coding

This step translates the conceptual model developed in Step 3 into a computer program. Using sophisticated software, the analyst can make choices according to the model's requirements. In this dissertation, the *Arena Simulation Platform* is used for coding.

[Step 6] Verification

After the development of the model, the analyst must check whether the model works correctly. Throughout the verification process, the analyst tries to find and remove errors in the model's logic. For example, using the trace facility of Arena, the analyst can find and remove unintentional errors in the logic of the model.

[Step 7] Validation

This step determines whether the conceptual model is an accurate representation of the real system. For this purpose, the analyst compares the model's performance with the performance of the real system. In this dissertation, by increasing the quantity of each part family in one batch and fixing the other system parameters, the "block" and "starvation" frequency of the model system is checked to determine if these parameters have increased or decreased compared with those of the real-world system. Furthermore, the inventory level of each production line is monitored for changes when adjusting the mixing ratio of the parts family. Moreover, the extreme cases are tested by using a constant processing time for any of the parts in the workstation and eliminating machine failure. The average inventory level for the station processing only one type of part is investigated to determine if it is close to 1. All of these tests are validated to determine whether the original simulation model behaves the same as the real system. In such a case, the statistical significance should measure within the confidence interval.

[Step 8] Experimental Design

In this step, analysts work with issues such as how long to run the model (sample size or number of replications), manner of initialization (terminating simulation system or steady-state simulation system), and what statistical tests are valid for the data. In this dissertation, the production system is developed as a steady-state simulation system with a warming running time.

[Step 9] Production runs and analysis

This step involves running the models and carrying out analyses of the performance metrics. Usually, simulation models are used to compare a large number of alternatives and select a few recommended alternatives for further analysis. To reduce the WIP level, production cycle time and environmental burden, several alternatives are considered, such as regulating the processing rate of the workstation, changing the production control policy, and optimizing the production lot-size determination strategy.

[Step 10] Document the program and report results

Documentation is necessary for future modifications of the model. The results of all analyses should be reported to review alternative criteria and formulations.

The simulation cannot use a deterministic single value when inputs vary (e.g., parts or order arrival) and service times are uncertain (e.g., processing time of different part type). Modeling the process of a workshop or production cell is enormously complex due to inherent variability, resulting from changing demand, varying mix ratio of part types and machine failure.

The use of simulation techniques is further signifying the complexity of manufacturing system. Simulation is relatively easy compared to analytical techniques. The benefits available to analysis and improvement of the manufacturing system through computer simulation have been described by many authors (Leitch, 2001; Lin and Lee, 2001; Subramaniam et al., 2009).

3 LITERATURE REVIEW

3.1 Introduction

In manufacturing systems, random occurrences, such as market demand change, part type transformation, and machine failure, cause disturbances to production. To reduce the impact of the disturbances, WIP buffers are implemented between machines to give each stage of a production system some operational independence (Conway, 1988; Ma and Koren, 2004). However, the introduction of WIP buffers raises the level of WIP inventory, and, in turn, WIP increases the operating complexity and serious production problems: First, too much inventory causes excessive holding costs, while too little inventory causes shortage and intermittent flow of materials (Hwang and Koh, 1992); Second, the WIP and the cycle time are convex increasing functions of the throughput (Lin and Lee, 2001). Though an infinite WIP level maximizes the throughput which cannot exceed the capacity of the bottleneck workstation (Buzacott, 1971), finite WIP level restrict the throughput; Third, different WIP levels can influence the negative environmental burden (Zhao, 2012; Zhao et al., 2013; Tang and Takakuwa, 2011 and 2012).

Therefore, in many manufacturing facilities, the minimization of WIP inventory level is considered as one of the most important performance measures for production efficiency (Sipper and Shapira, 1989). By reducing the mean WIP subject to throughput requirements, many benefits can be achieved, such as reduced working capital requirements, lower storage requirements and associated costs, improved product quality, improved customer service, the maintenance of flexibility (Wang and Prabhu, 2006), and a pleasant ecological environment.

Additionally, traditional manufacturing management systems assume that production environments are deterministic; however, dependent and stochastic (variable) events such as order arrival frequency, machine failure, production lot-size determination and processing times are present in all production environments.

Variability in production is one of the largest factors that negatively impacts both production and environmental performance. Variability can induce dynamic and unexpected conditions, disrupting production objectives and obscuring the means to achieve these objectives (González, 2009). Consequently, natural randomness, uncertainty and dynamics complicate the management of WIP inventory for achieving an optimized and reasonable control policy. Moreover, during the production process, changing and adjusting for various stochastic factors related to WIP makes production management and control more complicated.

In the past two decades, many scholars have researched these problems of WIP control policy using unreliable production systems and focusing on various aspects of these systems. These efforts aim to resolve different research objects or problems in the production system, such as production cost minimization (Yang and Liou, 1998), the elimination of system bottlenecks (Hu et al., 2010), material flow control mechanisms (Sepehri and Nahavandi, 2007), production scheduling optimization (Yang and Posner, 2010), optimal production lot-size determination strategy (Nirmal and Tapan, 2006), base stock policy (Liberopoulos and Dallery, 2002), stock area (Bertazzi, 2011) or buffer capacity allocation optimization (Papadopoulos and Vidalis, 2001), production lot-size determination (Hong and Hayya, 1997), quality control (Cordon, 1995), worker training (Bokhorst, 2011), negative environmental effects (Tang and Takakuwa, 2011 and 2012) and other topics related to WIP control. From the perspective of research methods, queuing theory (Nye et al., 2001), heuristic algorithms (Ryan and Vorasayan, 2005), simulation methods (Toshniwal, 2011), modeling analysis methods (Jodlbauer, 2003), and system structure control strategy (Hu et al., 2010) have been applied.

In this dissertation, the case of a discrete multi-variety and small-batch production system with tightly coupled cells is studied. Based on the system operation characteristics, research objectives and control issues presented in chapter 2, this literature review focuses on two topics. First, the literature describing the aspects of system control and modeling strategy are discussed, which involves five parts: queue modeling, finite WIP buffer control, CONWIP control, production lot-size determination and environmental eco-control. Second, the literature concerning optimization methods, specifically heuristic algorithms, fuzzy control methods and simulations, is considered. These two research areas comprise the literature reviewed in the following sections.

3.2 Literature Review on System Control and Modeling Strategy

3.2.1 Queue Modeling

A *queueing system* is one in which entities (like customers, parts, or messages) arrive, get served either at a single station or at several stations in turn, might have to wait in one or more queues for service or process, and then may leave (if they do leave the system is called open, but if they never leave and just keep circulating around within the system it's called closed) (Kelton et al., 2011). According to the definition above, in the production system, the operation mechanism of the parts, components or intermediate products that temporarily are stored in the WIP buffer and waiting for process is viewed as a queueing system. Many analysis technologies and methods from queuing theory are applied in WIP control research. Consequently, many researchers use or improve basic queuing theory to solve WIP control problems and achieved substantial successes.

Hopp and Spearman (1991) modeled the production system as a closed queuing network and developed an approximate regenerative model for estimating throughput and average cycle time as a function of WIP level.

Rao (1992) explained how queuing theory (waiting line analysis) can play an important role in understanding the relationship between WIP inventories, lead times and queues that built up in typical manufacturing setups such as flow lines and job shops.

Srinivasan and Bozer (1992) provided insight based on well-known analytical results in queuing theory and discussed certain properties of the workstations and the handling systems that affect WIP levels.

Lin and Lee (2001) proposed a queuing network-based algorithm to determine the total standard WIP level so that the fixed-WIP release control policy can be applied to determine the total standard WIP level. The simulation results indicated that the total standard WIP level achieved a target throughput rate while keeping the corresponding cycle time relatively low.

Based on queuing theory, Nye et al. (2001) developed a new model to estimate WIP levels as a function of the decision variables, batch size and setup time.

Ryan and Choobineh (2003) modeled the job shop as a single chain multiple class closed queuing network and identified the minimum total WIP that was guaranteed to yield throughput near the maximum possible for the specified product mix and set individual WIP levels by multiplying the optimal WIP mix proportions by the minimum total WIP. Ryan and Vorasayan (2005) modeled the production system as a multiple-chain multiple-class closed queuing network by simultaneously evaluating the system performance and minimizing the total WIP to achieve specified throughput targets.

Samaddar and Hill (2007) used a queuing model of a two product cyclic production to show that the reduction in setup time influenced WIP, leading to better or worse results.

3.2.2 Finite WIP Buffer Control

Given the increasing flexibility of manufacturing machines it is rather frequent that more than one part type is produced on a single production line. In the manufacturing of these products, finite buffers are typically used and kept at small capacity to reduce storage space, WIP, and production cycle time (Colledani et al., 2005; Feng, 2012). Previous studies in manufacturing and operations research indicate that planning appropriate decision tools based on production line models (or service line models or queueing network models) with finite buffers is of great economic importance (Chang and Gershwin, 2010). However, because of the finiteness of buffers, the performance of the system as measured by its production rate (which is called 'the throughput' or 'the capacity' in queueing theory) is seriously degraded due to the so-called 'blocking phenomenon' (Tcha et al., 1992). Consequently, to optimize the performance of such systems, many researchers have considered the design, planning, scheduling, allocation, and production performance problems of finite WIP buffers.

Moreover, tightly coupled production cells are a typical finite WIP buffer control research issue. Previous literature reviews of finite WIP buffer control provide useful suggestions for research on tightly coupled cells.

Blumenfeld (1990) developed an analytical formula for throughput of a serial production line with variable processing times and finite buffer capacity, taking into account the effects of blocking and starving.

Lee et al. (1998) have presented a new approximate algorithm for analyzing an arbitrary configuration of open queueing networks with finite buffers. The new algorithm was very general in that it can analyze all the classes of models considered by the previous studies under blocking-after-service mechanism. This new algorithm held promise as a useful tool in the analysis of arbitrary configuration of open queueing networks with finite buffers.

Gupta and Kavusturucu (2000) considered a production system with finite buffers and arbitrary topology where service time was subject to interruptions in one of three ways, viz. machine breakdown, machine vacations or *N*-policy. They develop a unified approximation methodology to calculate the throughput of the system using queueing networks together with decomposition, isolation and expansion techniques. The results showed that the performance of the approximation methodology was consistent, robust and produces excellent results in a variety of experimental conditions.

Colledani et al. (2005) presented an approximate analytical method for the performance evaluation of a production line with finite buffer capacity, multiple failure modes and multiple part types. They presented a solution to a class of problems where flexible machines took different parts to process from distinct dedicated input buffers and deposited produced parts into distinct dedicated output buffers with finite capacity.

Jang (2007) investigated multi-stage production systems with finite buffers, constant processing rates, and unreliable machines without setups.

Dasci and Karakul (2008) considered both finite buffers and sequence-dependent setup times. An iterative method was proposed to approximate system performance, and this method has been shown to be fast and accurate.

Kock et al. (2008) proposed an Effective Process Time (EPT) approach for the building of aggregate models to represent multi-server tandem queues with finite buffers. The approach was illustrated in an industrial case study using both simulation and analytical queuing approximations as aggregate models. The mean and variance of a measured EPT distribution quantified the effective workstation capacity and variability, respectively, which can be used for bottleneck analysis.

Chang and Gershwin (2010) have discussed the analytical modeling and exact analysis of production lines with two unreliable batch machines and a finite buffer when the machines may have different batch sizes. Various performance measures of interest such as production rate, mean size of batches served in each machine, machine efficiencies, probabilities of blocking and starvation, and expected in-process inventory were presented.

Bierbooms et al. (2012) developed an approximative method to analyze production lines with fluid flow and exponentially distributed breakdown and repair times caused by a finite buffer between each pair of servers. An iterative method was constructed that efficiently and accurately estimates performance characteristics such as throughput and means total buffer content. The proposed method performed well on a large test set, including long and imbalanced production lines. For production lines with imbalance in mean downtimes, it was shown that a more refined modeling of the servers in each subsystem leads to significantly better performance.

3.2.3 CONWIP Control

CONWIP (CONstant Work-In-Process) production control system was introduced as an attempt to present a pull system more flexible than the current pull paradigm, the

Kanban system (Framinan et al., 2003). The development of CONWIP control has highlighted the benefits of control policies that pull work into the facility in response to demand while limiting inventory (Ryan et al., 2000). The key point of CONWIP is that it does not limit the single station's WIP or its buffer size, but the total WIP in the system (Framinan et al., 2001). Since the introduction of the CONWIP production control system more than two decades ago, this system has received a great deal of attention from practitioners and researchers. Also, the CONWIP control method is used to improve the operation of tightly coupled production cells and maintain the WIP at a low level in this dissertation.

Gstettner and Kuhn (1996) described and classified different pull production systems. The production control systems Kanban and CONWIP were analyzed with respect to production rate and average WIP. These authors examined single product flow lines with exponential service time distributions and unlimited demand at the final buffer.

Ryan et al. (2000) extended the concept of CONWIP control to a job shop setting, in which multiple products with distinct routings competed for the same set of resources. A throughput target was derived for each product type in a closed queuing network and provided a simple heuristic to find a minimum total WIP that would achieve an operating throughput close to the target throughput.

Framinan et al. (2001) addressed the backlog sequencing problem in a flow-shop controlled by a CONWIP production control system, with the objective of minimizing the makespan. They characterized the problem and analyzed its similarities to and differences from the unconstrained permutation flow-shop problem. Regarding simpler and faster heuristics, the proposed dispatching rule outperformed those methods commonly used for the unconstrained permutation flow-shop problem.

Takahashi and Nakamura (2002) compared a reactive Kanban system to a reactive CONWIP system under conditions of unstable changes in demand using simulation experiments. In the reactive CONWIP system, the total of the mean WIP inventories becomes much more than or nearly equal to that in the traditional CONWIP system without controlling buffer size under the strongly correlated or the weakly correlated processing times, respectively. Based on the results, it can be claimed that, in the proposed systems, the reactive Kanban system is more effective to react to unstable changes in demand than the reactive CONWIP system.

Takahashi et al. (2005) studied the performance of kanban, CONWIP and synchronized CONWIP in complex supply chains and different lead times. The authors presented mathematical models for investigating the parameters affecting superiority. The results obtained from the study showed superiority of synchronized CONWIP in eliminating inventory at other stations at the expense of increasing inventory at the assembly station.

Framinan and Schuster (2006) proposed a procedure for dynamically controlling the number of cards in a CONWIP system. The proposed procedure was tested under various production environments and was shown to be competitive compared to fixing the number of cards or card setting.

Cao and Chen (2005) presented a CONWIP-based fabrication and assembly system. The model determined the optimal parts assignment, production sequence and lot sizes simultaneously.

Different models are presented in the literature to allocate Kanban systems to product types to equitably minimize lost sales (Ryan and Vorasayan, 2005), determine inventory levels (Ryan and Choobineh, 2003), investigate an assembly station with input from multiple fabrication lines (Rao and Suri, 2000), study CONWIP-based production lines with multiple bottlenecks (Dar-El et al. 1999), set WIP levels with statistical throughput control in CONWIP production lines (Hopp and Roof, 1998), evaluate artificial intelligence heuristics for flexible Kanban systems (Lee, 2007), and use parallel algorithmic setting of the WIP levels in multiple CONWIP systems (Wang and Prabhu, 2006).

3.2.4 Production Lot-Size Determination

In a production system, different strategies to determine production lot-size can change in response to different WIP inventory levels and inventory costs. Overstocks or stockouts of the WIP inventory disrupt the production stability and balance. Overdue overstocks and defective intermediate products or materials lead to a higher scrap probability and substantial negative production costs. Therefore, to achieve a reasonable production lot-size, scholars have studied many useful control or optimization methods.

Joglekar and Lee (1993) provided an exact formulation of the relevant costs which, when minimized, give the true optimal lot size. They also proposed approximate formulas for determining the relevant total costs and the optimal lot size in face of sudden obsolescence.

Hoquea and Kingsmanb (1995) presented a new heuristic solution procedure for the constant production lot-size model for the production of a single product requiring processing through a fixed sequence of manufacturing stages.

Gutiérrez et al. (2003) addressed the dynamic lot size problem with storage capacity and demonstrated the superiority of their new algorithm to the existing procedure.

Kämpf and Köchel (2006) used simulation optimization with a genetic algorithm as an optimizer to identify the optimal production lot-size.

Nirmal and Tapan (2006) have developed a multi-item finite production lot size model with reworking of imperfect quality items. Multi-objective geometric programming was used to develop a multi-item finite production lot-size model.

Chiu (2008) demonstrated that solutions for lot size and the optimal production-inventory cost of an imperfect EMQ model can be derived without derivatives.

Azaron et al. (2009) developed a polynomial algorithm for obtaining dynamic economic lot sizes in a single product multiperiod production system with the objective of minimizing total production and inventory costs over T periods.

3.2.5 Environmental Eco-Control

The definition of sustainability which is generally adopted is: "meeting the needs of the present generation without compromising the ability of future generations to meet their own needs" (World Commission on the Environment and Development, 1987). With this definition all eco-friendly approaches, methodologies and researches to preserve environmental conditions and resources through wastes reduction, prevention or recycling can be categorized under sustainability (Deif, 2011). Consequently, sustainability is a concept and a paradigm that is implemented and interpreted differently in a manufacturing system. Moreover, the manufacturing management approach should remember the impact of production or the production the environment and resources and include these impacts in overall efficiency planning and control. In resent researche, scholars considered manufacturing environmental impacts in both environmental management approaches and environmental strategy, which are called eco-control method.

Deif (2011) presented a system model for the new green manufacturing paradigm. The model captured various planning activities to migrate from a less green into a greener and more eco-efficient manufacturing. The various planning stages were accompanied by the required control metrics as well as various green tools in an open mixed architecture. The system model was demonstrated by an industrial case study. The proposed model was a comprehensive qualitative answer to the question of how to design and/or improve green manufacturing systems as well as a roadmap for future quantitative research to better evaluate this new paradigm.

Rothenberg et al. (2001) examined the relationship between lean manufacturing practices and environmental performance as measured in terms of air emissions and resource use. They drawn on two unique surveys of 31 automobile assembly plants in North America and Japan and their survey results and interviews suggested that lean management and reduction of air emissions of volatile organic compounds were associated negatively. They used survey results to describe some mechanisms by which all three aspects of lean management (buffer minimization, work systems, and human resource management) may be related to environmental management practices and performance.

To explore the link between lean production practices and environmental performance, King and Lenox (2001) conducted an empirical analysis of the environmental performance of 17,499 U.S. manufacturing establishments during the time period 1991-1996. They found that those establishments that adopted the quality management standard ISO 9000 were more likely to adopt the environmental management standard ISO 14000. They also found strong evidence that lean production, as measured by ISO 9000 adoption and low chemical inventories, was complementary to waste and pollution reduction.

Sroufe (2003) reported empirical insights into EMS practices based on the largest EMS survey of manufacturing firms in the United States. The objective of his study was to determine the relationship between environmental management systems and perceived operations performance, while considering direct and indirect effects of various environmental practices.

Melnyk et al. (2001) introduced a new tool that integrated environmental concerns into the material planning activities and identified the waste streams generated in both quantitative and financial terms.

Tang and Takakuwa (2011 and 2012) used a simulation-based Material Flow Cost Accounting analysis to reduce negative environmental impacts caused by overstocks in manufacturing systems.

Ibrahim (2012) discussed environmentally benign and sustainable (green) methods for hydrogen production and categorized these methods based on the driving sources and applications.

3.3 Literature Review of Optimization Methods

3.3.1 Heuristic Algorithm

Modern problems tend to be very intricate and relate to analysis of large data sets. Even if an exact algorithm can be developed its time or space complexity may turn out unacceptable. But in reality it is often sufficient to find an approximate or partial solution. Such admission extends the set of techniques to cope with the problem. Consequently, the heuristic algorithms that find approximate solutions but have acceptable time and space complexity play indispensable role (Kokash, 2008).

In the manufacturing system, due to the production complexity and randomness, it is not easy to obtain an exact algorithm for production control. Therefore, for the research field of WIP control, the solutions based on heuristic algorithms applied to achieve a reasonable control and management policy are also focused on by many scholars. Additionally, in this dissertation, a relative heuristic algorithm using the fuzzy method is applied to control WIP inventory in this dissertation.

Abdolazim and Mcginnis (1990) developed a general heuristic procedure to determine an assignment of machines with a limited input/output WIP buffer to locations on a straight track such that the total distance that the material handling vehicle travels loaded was minimized.

Kim (1994) introduced a heuristic approaches and an LP formulation, along with extensive computational experience that showed reasonable model accuracy and modest memory requirements, to resolve the problem of translating WIP inventory into a schedule of completed product in order to calculate net demand and net resource capacities.

Based on three classes of activities—operations, failures and repairs, and starvation and blockage—Bai and Gershwin (1995) developed a real-time heuristic algorithm for scheduling single-part-type production lines with WIP inventory buffers to keep the actual production close to the demand, the WIP inventory level low, and the cycle time short.

Zozom et al. (2003) developed a heuristic algorithm that used an efficient, detailed shop-floor scheduling model to aim at solving the problem of releasing jobs to the factory floor while meeting delivery dates and minimizing the WIP inventory. This heuristic approach was tractable for industrial-sized problems and provided solutions close to a calculated lower bound for WIP.

Kim et al. (2008) suggested a heuristic approach using linear relaxation and its adjustment to control the fabrication line by maintaining the target WIP level as close as possible for the purpose of short cycle time and by minimizing the setup time loss for maximal throughput.

Yang (2009) considered two new machine flow shop-scheduling problems with the objective of minimizing the total WIP cost. A known simple heuristic was introduced, and the worst-case upper bounds on relative errors were identified. They established the complexity of several problems with different types of job restrictions and weighted cost characteristics.

Jula and Kones (2012) proposed a two-step mixed-integer programming model and a new network-based heuristic algorithm to resolve the problem of selecting and scheduling several jobs on a single machine to sustain the desired dynamic WIP profile. The primary objective of these approaches was to maximize the total defined score for jobs while satisfying production targets. The secondary objective was to minimize the maximum completion time of all selected jobs. The effectiveness, efficiency, and robustness of the proposed algorithms were analyzed and compared with two existing approaches over a wide range of simulated scenarios.

3.3.2 Fuzzy Control

Many industrial production systems generate typical processes of large-scale, time-varying and stochastic manufacturing systems. They involve different kinds of operation, operate in an uncertain and unpredictable environment and manufacture a high-volume and medium variety of products. These features seriously limit the effectiveness of the conventional modelling and control approaches. As a result, since an exact analytical control design cannot be determined in realistic manufacturing conditions, intelligent methods using heuristic algorithm seem to be a very effective tool to develop control strategies for these systems where complete mathematical models are not available (Tamani et al., 2009).

For the intelligent methods, fuzzy logic has been successfully applied in many industrial systems, both for inference and control. This technique has found its place in control industry not only because of its efficiency with rapid control action and lower building costs, but also due to its elegant yet common sense methodology that mimics human thinking most realistically for both simple and complex systems as demonstrated in (Jamshidi, M., 1997). Moreover, the fuzzy control approach has been implemented to improve the performance of different control architectures in production systems (Michels, 2006).

Researchers have studied the applicability of fuzzy logic in various areas of production management such as solving routing problems (Chan et al., 1997), process and quality monitoring (Pacella et al., 2004), general and specialized production planning (Wang et al., 1999), balancing multiple-part-type conflicts (Tamani et al., 2011), controlling production-inventory systems (Suhail and Khan, 2009), optimizing order release mechanism (Tedford and Lowe, 2003), and managing the WIP (Chen, 2012). Some researchers have used fuzzy control in combination with other artificial intelligence techniques: Dadone and Vanlandingham (1997) addressed the short-term control of flexible manufacturing systems and proposed a fuzzy scheduler based on evolutionary programming techniques; Pacella et al. (2004) presented a fuzzy adaptive resonance theory neural system for manufacturing quality monitoring; Tsourveloudis (2010) developed optimized fuzzy controllers through extensive use of evolutionary algorithms (EAs) to control the production rate and reduce WIP within the production system; and Homayouni et al. (2009) used a genetic fuzzy logic control (GFLC) methodology to develop two production control architectures. Fuzzy systems have also been used as classifiers for monitoring and maintenance tasks (Devillez et al., 2004).

In addition, the heuristic fuzzy method for controlling WIP was used in production systems by Tsourveloudis et al., and their research achievements and applications provided useful suggestions for this dissertation.

Tsourveloudis et al. (2000) considered the single and multiple part type production lines and networks with finite WIP buffers and unreliable machines. Three fuzzy control modules, namely, line, assembly, and disassembly controller, were developed. The objective was to keep the WIP inventory and cycle time at low levels, along with high machine utilization and throughput. After a series of simulation runs, it had been observed that the proposed approach outranked other control policies in keeping the WIP inventory low.

Ioannidis et al. (2004) used a supervisory controller to tune a set of lower level distributed fuzzy control modules that reduce WIP and synchronize the production system’s operation. Extensive simulation results showed that the supervisory controller, when compared with the single-level distributed fuzzy controllers, reduced WIP and cycle time while keeping backlog to acceptable levels.

Tsourveloudis et al. (2006) considered multiple-part-type production lines, and viewed the overall production control system as a surplus-based system. A set of distributed single-level fuzzy controllers was used to reduce WIP and synchronize production system’s operation. The overall control objective was to keep the WIP and cycle time as low as possible and, at the same time, satisfy demand, avoid overloading of the production system and synchronize the production system operation to eliminate machine starvation or blocking.

Tsourveloudis et al. (2007) presented an evolutionary algorithm (EA) strategy for the optimization of generic WIP scheduling fuzzy controllers. The EA strategy was used to tune a set of fuzzy control modules that are used for distributed and supervisory WIP scheduling. The proposed EA strategy was compared with known heuristically tuned distributed and supervised fuzzy control approaches. Extensive simulation results showed that the EA strategy significantly improved the system's performance.

3.3.3 Simulation

Simulation can model non-linear and stochastic problems and allow examination of the likely behavior of a proposed manufacturing system under selected conditions. It can take into account many details and constraints in evaluating the performance of a system (Yang, 2007). Moreover, because of the complexity of real systems and the numerous disturbances and fluctuations that are present in a practical environment (Jodlbauer, 2008), some authors have tried to use computer simulations to study the WIP control problem with key logistical figures.

Hopp and Roof (1998) simulated and demonstrated the effectiveness of statistical throughput control under a variety of conditions, including single and multiple products, simple flow lines, routings with shared resources and assembly systems.

Leitch (2001) used a simulation approach to examine the effect of stochasticity, capacity, and lead-time on WIP and throughput in a pull production environment. In this dynamic simulation environment, production variation, capacity, and lead-time were found to be significant cost drivers in terms of their effect on WIP inventory and throughput.

Yang et al. (2007) addressed an evolutionary-simulation optimization approach by solving a multi-constant WIP (multi-CONWIP) pull strategy problem. The proposed methodology was effective and robust for the proposed problem.

Toshniwal et al. (2011) obtained results using discrete-event simulations and applied these results to assess the control-theoretic approach, providing evidence that fidelity varies depending upon factors such as the WIP level and the magnitude of capacity adjustments.

Duffie et al. (2012) used the results obtained from discrete event simulations in Arena, which is driven by industrial data, to illustrate the dynamic behavior of WIP regulation in an autonomous work system with the goal of maintaining desired fundamental dynamic behavior.

Dennis (2012) used a dynamic system simulation approach to suggest that WIP variability increases when changes in anchoring for capacity adjustment were based on downstream information rather than upstream information.

4 SIMULATION-BASED DISTRIBUTED FUZZY CONTROL FOR WIP IN A ONE-TIGHTLY-COUPLED-CELL PRODUCTION SYSTEM

4.1 Introduction

For modern environment-oriented manufacturing, many mechanical manufacturing enterprises have applied multi-variety and small-batch production systems with coupled cells, represented by robot agent sets to improve flexibility and precision. This production mode satisfies the diversified demands of consumers and rapid responses to market needs. In this advanced production system, WIP buffers are set among workstations. They are used to balance production rhythm and guarantee production lines stability by avoiding "block"/"starvation" caused by many random events (Tao et al., 2008; Tsourveloudis, 2010; Luca, 2011). However, a high WIP inventory level leads to the following serious problems: 1) having too much liquid capital without any profit (Kenneth, 1992); 2) increasing production cycle time and decreasing market responsiveness (Tsourveloudis et al., 2000); 3) requiring more space for layout; and 4) causing production imbalance. A control policy for reducing WIP, which is associated with shorter cycle times and higher productivity, is thus an important and urgent issue in modern production research.

During the production process, changing and adjusting for various stochastic factors related to WIP complicate production management. Many scholars have recently researched these WIP control policy problems in unreliable production systems, which are illustrated in Chapter 3. These studies mainly focused on WIP minimization or optimization by improving production scheduling or adjusting production capacity based on certain system structure hypotheses. However, research on multi-variety and small-batch discrete production systems considering major production uncertainty factors and control policies for WIP by analyzing dynamic inventory level changes is rare, especially research identifying bottlenecks caused by tightly coupled cells to design a WIP control policy.

Most current studies on production research have also performed minimal work on heuristic control policy because accurate analytical solutions are not easily attainable (Gershwin, 2000). This chapter thus developed a distributed heuristic fuzzy control method for a multi-variety and small-batch production system with one tightly coupled cell. A corresponding simulation model applying this optimized control approach was constructed, which considers specific major random factors and system bottlenecks. The control objective involves keeping WIP inventory and cycle time at low levels while improving productivity by dynamically regulating the processing rate according to inventory-level changes of distributed WIP buffers between workstations. Consequently, this chapter is also studied to achieve the *Sub-objective 1-1*.

4.2 Approach

4.2.1 Approach Review

The case study in this chapter is considered as a surplus-based system. The production rate for each workstation is adjusted by investigating whether the real-time WIP inventory level is higher or lower than a hedging point. An actual production system is a black-box system that is synthetically restricted by various random factors. Accurately controlling these variable factors to achieve predetermined objectives is more difficult, and NP-hard problems are frequently encountered. A heuristic control policy has thus been gradually considered to achieve a satisfactory strategy that is not an exact solution (Gershwin, 2000). Consequently, this chapter develops a heuristic fuzzy control method. Applying this approach can avoid disturbances from bottlenecks caused by a tightly coupled cell and achieve lower WIP inventory levels, shorter cycle time and higher productivity.

The fuzzy control method has been applied in production systems by Tamani et al., resulting in successful heuristic fuzzy production control applications for WIP (Tsourveloudis et al., 2000; Tamani et al., 2009; Tsourveloudis, 2010; Tamani et al., 2011). Additionally, their research achievements and successful applications provide many suggestions and references. For easier analysis, their study cases are simulated by viewing the production system as a continuous system while only considering two random factors: machine failure/repair probability and demand change. However, the most realistic mechanical manufacturing system is a classic discrete system. This is especially apparent in a multi-variety and small-batch production system because various stochastic factors cause random WIP changes and reduce system performance. A bottleneck in a system with high "block"/"starvation" frequency can also disturb the whole discrete system. Based on the studies of Tamani et al., this study case is considered as a discrete system with more uncertain factors, and provides a closer representation of the actual production system. This chapter also further improves the distributed fuzzy control method by increasing two correction factors, which can easily and quickly control the system's performance, compared to the methods used by Tamani et al..

4.2.2 Fuzzy Control Method

An appropriate control policy for a production system can satisfy multiple conflicting criteria and adapt to dynamic and stochastic constraints. A fuzzy logic controller uses a mathematical structure and method to control the production operation with some simple control principle representations using IF-THEN rules. This chapter applied a two-dimensional (double-input and simple-output) fuzzy logic controller with two correction factors. For on-site supervisors, the easiest way to adopt a control strategy that regulates processing rates is to investigate the relative and absolute error values in WIP inventory levels for each distributed workstation in each check time interval. According to a surplus-based system, the relative error value is the difference between the actual WIP value and a hedging point. The absolute error value refers to the difference between successive WIP values. These relative and absolute error values constitute the double input for the fuzzy logic controller, and the processing rate is the simple output. For the two correction factors, the first factor is set to quickly eliminate errors when the actual WIP inventory levels drastically depart from the hedging point, and the second factor maintains stability when the actual WIP inventory level is near the hedging point. The other main inputs affecting the system output are dynamic and stochastic factors, which can cause discrete WIP level and system performance changes. Figure 4.1 shows a two-dimensional fuzzy logic structure with two correction factors.

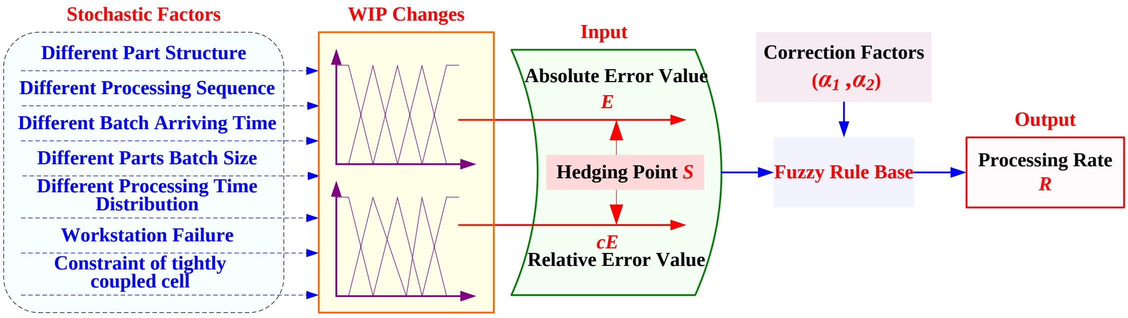


Figure 4.1: A double-input and simple-output fuzzy logic structure with two correction factors

For the double-input and simple-output fuzzy logic controller in this work, the rule base for the control model contains rules with the following form:

Rule 4.1 *IF **E** is **X** AND **cE** is **Y**, THEN **R** is **Z***

Here, ***E*** and ***cE*** are the inputs' relative and absolute WIP error values, respectively. ***R*** is the output or processing rate. These inputs and output are divided into five corresponding linguistic variations sets: ***X***=***Y***=***Z***={***PL*** (Positive Large), ***PS*** (Positive Small), ***O*** (Zero), ***NL*** (Negative Large), ***NS*** (Negative Small)} (Zhao, 2012).

The correction factors, α_1 and α_2, are real numbers between 0 and 1, with $\alpha_1 < \alpha_2$. The analytical expression for the fuzzy controller is corrected thus:

Rule 4.2 *IF **E*** $\in$ { ***PL***, ***PS*** }, *THEN* ***R***= -[$\alpha_1 \times E+(1-\alpha_1)\times EC$]

*ELSEIF **E*** $\in$ {***NL***, ***NS***}, *THEN* ***R***= - [$\alpha_2 \times E+(1-\alpha_2)\times$EC]

The outputs of the activated rules are aggregated to form the value of the overall control output with two correction factors, which are then defuzzified into a crisp number ***Z***.

In this Chapter, the processing time for each workstation is regulated based on a processing speed change rate $\boldsymbol{r_i}$, which is the fuzzy controller output and can be calculated by defuzzification. A VBA module in the simulation model operates this calculation, as illustrated in Section 4.4.

4.3 Case Study

4.3.1 Basic Description of the Case Study

This chapter considers a case of a certain multi-variety and small-batch discrete production system with one tightly coupled cell. This system is located in an engine component manufacturing workshop of a Japanese company. Figure 4.2 show the layout and main workflow for this manufacturing workshop.

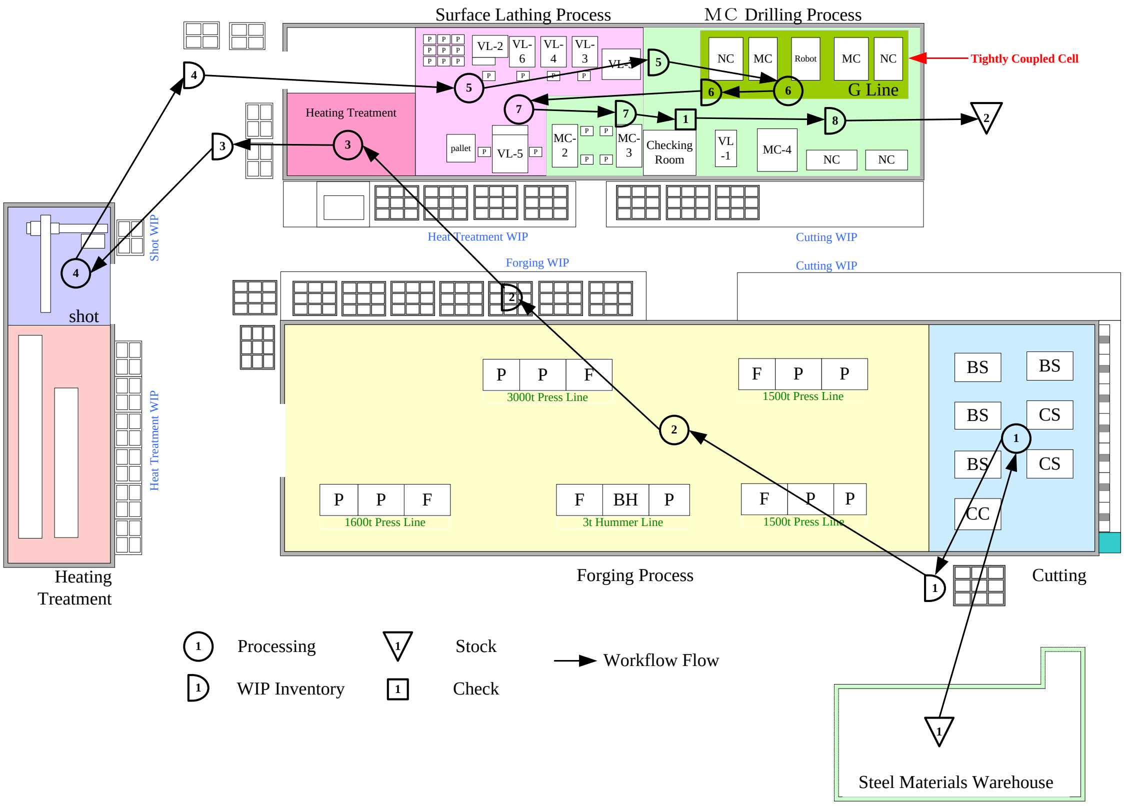


Figure 4.2: The layout and main workflow of manufacturing workshop

Considering the system characteristics and ensuring the current workflow structure, Figure 4.3 shows a simplified layout model for this production system in details. This production system mainly comprises 21 workstations and three main part families (Part Type A, B, and C), which are processed by different production lines that can use the same machines, according to their technology groups. Each part batch that enters the system includes three types of parts in random proportions. The WIP buffers are used to balance the machining capabilities, improve production stationarity, and meet the processing demands for the diversified part types. The processing capacity of each independent process in a workstation is handled by a machining center that can be controlled by regulating processing time. According to the part family characteristics, each workstation completes the processing task for various parts in a corresponding part family, either in whole or part. The processing time for each part on each workstation is different.

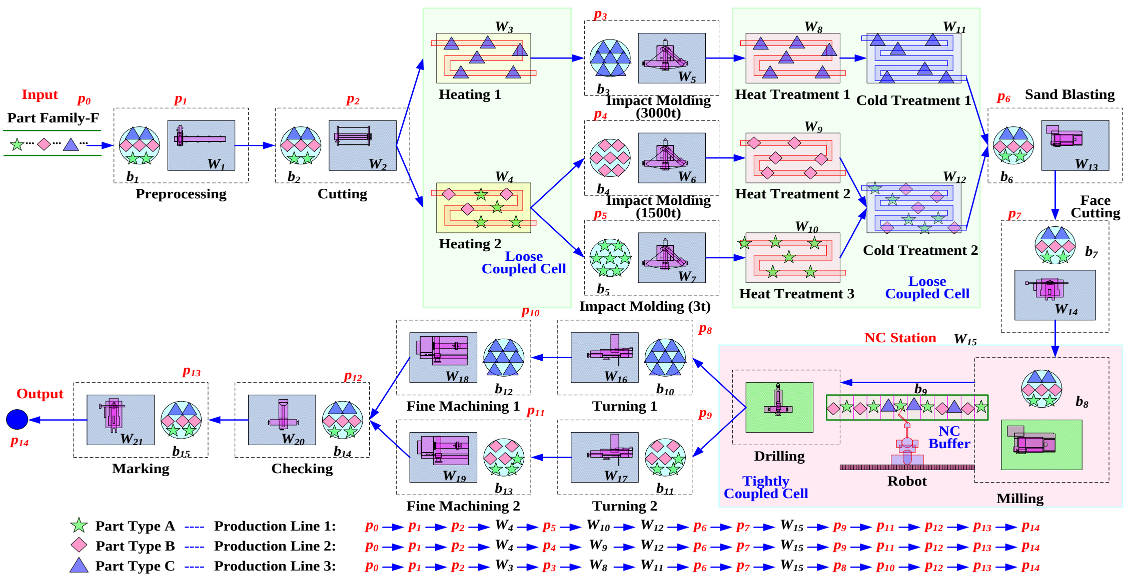


Figure 4.3: Multi-variety and small-batch production systems with one tightly coupled cell

Furthermore, there are three coupled cells: two cells are loose coupled cells with machines that act like conveyors and can do continuous processing; the remaining cell is a tightly coupled cell in the NC station, in which a robot agent is used to accurately transfer parts between two fine machines. The buffer space is limited to 12. In this cell, the milling machine is easily blocked until limited buffer space becomes available.

4.3.2 Original Simulation Construction and Validation

In this chapter, a simulation model is constructed for analyzing the case study, called the AS-IS model. By running the simulation, the capacity of the limited buffer in the tightly coupled cell can be easily adjusted, and the bottlenecks can be identified clearly. The AS-IS simulation model comprises four sub-models, shown in Figure 4.4. The Parts Order Arriving sub-model is designed to simulate part family orders arriving, randomly create part batch quantities, and determine the production line. The Parts Orders Processing sub-model is designed to process parts on the corresponding workstations. The Parts Order Leaving sub-model is designed to ensure that all parts in a batch are completed and develop statistics for the parts leaving. The Order Cycle Time Calculation sub-model creates WIP change statistics for workstation and processing cycle time for each part order. The main simulation running parameters are set as shown in Table 4.4.

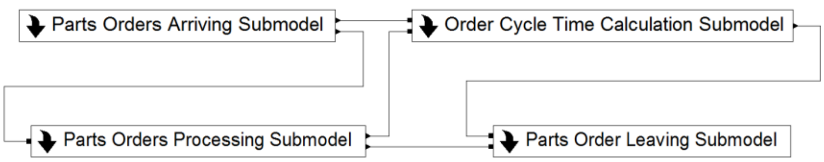


Figure 4.4: AS-IS simulation model

After the simulation model has been generated, validation of the model is necessary. The correlative validation data were compared to the existing data statistics from the real system, shown in Table 4.1. As shown in Table 4.1, each data point from the AS-IS model is close to that of the real system. All of the difference ratios are below 10%. In the AS-IS simulation model, when quantity of each part family in one batch is increased respectively and other system parameters are fixed, the “block” frequency of the tightly coupled cells is also increased and the “starvation” frequency is decreased. This is consistent with the real system. Furthermore, when the mixing ratio of these three parts family is adjusted, the inventory level of each production line was changed. When the mixing ratio of one parts family was higher, the WIP level was accordingly increased. Additionally, when extreme cases are tested by setting the same constant processing time for any parts on a workstation and eliminating machine failure, the average WIP level for a workstation processing only one type part was close to 1. Consequently, all of these tests are validated, confirming that the AS-IS simulation model behaves in the same manner as the real system.

Table 4.1: The validation data compared AS-IS simulation model with the real system

(Unit/Quantity)	Real system			AS-IS Simulation Model			Change Ratio %		
	Average	Half Width	Standard Deviations	Average	Half Width	Standard Deviations	Average	Half Width	Standard Deviations
Production Line 1 WIP	516.06	16.76	47.33	574.17	21.32	39.15	11.26 %	27.21 %	17.28 %
Production Line 2 WIP	605.62	26.59	69.12	664.01	30.37	72.43	9.64 %	14.22 %	4.79 %
Production Line 3 WIP	666.62	29.26	87.85	615.29	25.83	79.55	7.7 %	11.72 %	9.45 %
Cycle Time Unit/min	$X \sim N$ (μ=5220, σ^2=2700)			$X \sim N$ (μ=4972, σ^2=2561)			4.75 %	/	5.15 %
Tightly Coupled Cell	Block Frequency		Starvation Frequency	Block Frequency		Starvation Frequency	Decline Ratio %	Block Frequency	Starvation Frequency
	5.88 %		0.69 %	4.97 %		0.57 %		15.47 %	17.39 %

4.3.3 Current Production Problems from AS-IS Simulation Results

After running AS-IS model, Table 4.2 provides the simulation results for the latest two months of production data. The largest average WIP inventory level is over 80, and the standard deviations (SDs) are large. The system’s ability to resist disturbance is affected by various random factors and is low. WIP control in this production system remains a serious issue. From Table 4.2, due to the large SD, the Takt time is unbalanced when comparing production lines. In the tightly coupled cell, the “block” frequency of the milling machine exceeds 5%, but the “starvation” frequency of the drilling machine is not zero and is instead approximately 0.7%. The SD of each downstream WIP level in this cell is larger than the upstream WIP. This suggests that this cell has a large effect on disturbances in the entire system and is the main bottleneck for the whole production system.

Table 4.2: AS-IS simulation results

	Average Takt Time *Unit/min*	Standard Deviations	Average WIP Level *Unit/Quantity*	Standard Deviations	Tightly Coupled Cell	
Production Line 1	**14.89**	**1.72**	**516.06**	**47.33**	**Block Frequency of Milling**	**5.88 %**
Production Line 2	**10.62**	**2.04**	**605.62**	**69.12**		
Production Line 3	**7.43**	**2.09**	**666.62**	**87.85**	**Starvation Frequency of Drilling**	**0.69 %**

WIP Inventory	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}
Average Level *Unit/Quantity*	**92.9**	**260**	**84.4**	**55.8**	**197**	**212**	**60.5**	**201**	**52.9**	**88.8**	**83.9**	**142**	**68.7**	**104**
Standard Deviations	**31.2**	**103**	**34.7**	**21.2**	**67.4**	**86.7**	**23.8**	**133**	**38.9**	**53.6**	**57.1**	**91.9**	**53.1**	**71.7**

Based on data from these two months, the cycle time for each part family batch obeys a normal distribution ($\boldsymbol{X \sim N}$ ($\boldsymbol{\mu}$=5220, $\boldsymbol{\sigma}^2$=2700)). Approximately 19.31% of the batches are completed within two days, while half of the batches are completed in three days or more. Most orders thus cannot meet the delivery time of three days. Figure 4.5 presents the details for this distribution.

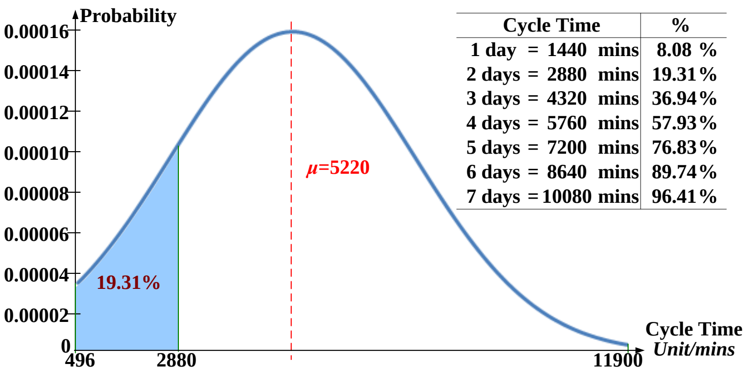


Figure 4.5: Probability distribution of cycle time for the AS-IS model

Analysis and data from the AS-IS model suggest that the WIP inventory level of each workstation is high, the cycle time is long, and the tightly coupled cell seriously restricts productivity.

4.4 Optimized Simulation (TO-BE Simulation Model)

4.4.1 Optimized Approach–A Distributed Fuzzy Control Controller

In order to resolve the current production problems, a Fuzzy Control sub-model developed into AS-IS simulation mode, and is the core for the optimized simulation. It is designed to calculate changing WIP values from the Parts Orders Processing sub-model and make a control policy to regulate processing time for each workstation using a distributed fuzzy control methodology. This optimized simulation is called TO-BE Model, which is shown in Figure 4.6.

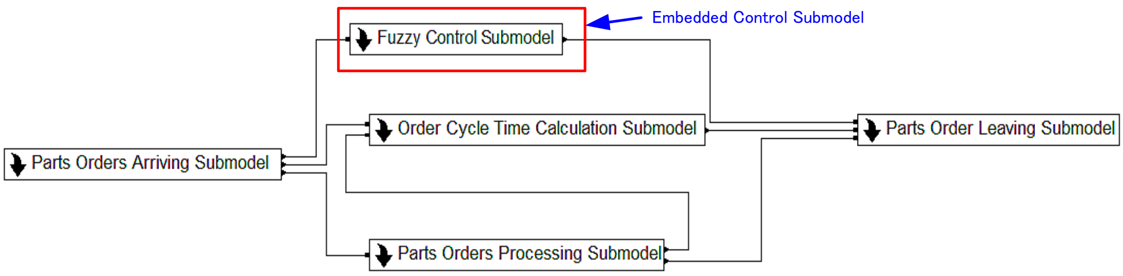


Figure 4.6: TO-BE Simulation Model

The Fuzzy Control sub-model embeds and uses a two-dimensional fuzzy controller with two correction factors to make an optimized control policy to regulate processing time for each distributed workstation. Because of system's stochastic changes caused by various random factors, the inventory level changes at workstations differ from one another over time. According to the distributed workstation locations in a real production system, a corresponding distributed fuzzy controller developed for each workstation simplifies making the corresponding control policy.

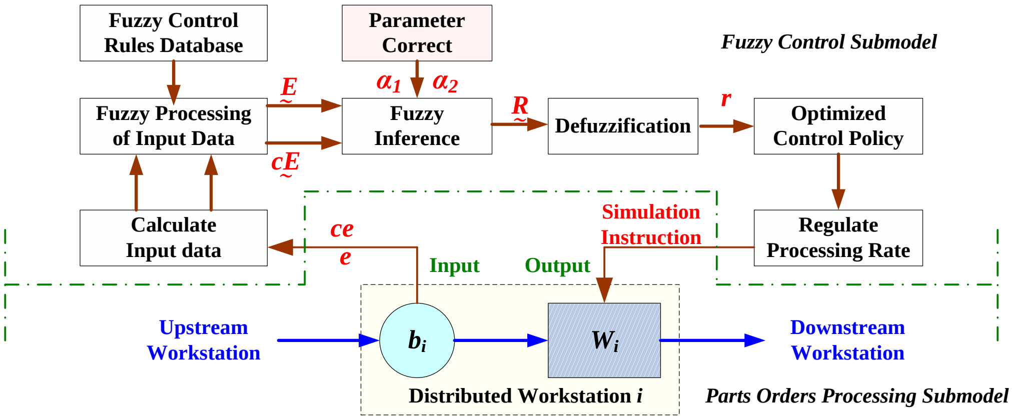


Figure 4.7: A distributed fuzzy controller

As Figure 4.7 shows, for each distributed workstation in the Parts Orders Processing sub-model, its relative and absolute WIP error values (***e*** and ***ce***) are collected and input into the corresponding fuzzy controller in the Fuzzy Control sub-model. In this controller, the output ***r*** is computed using fuzzy processing, parameter correction, fuzzy rules selection, fuzzy inference, and defuzzification. By consulting this output, a simulation instruction based on an optimized control policy is made to regulate the processing time of a corresponding workstation.

In the Fuzzy Control sub-model, a VBA module operates these calculation steps during the simulation running at each check time interval. After the optimized fuzzy calculation, a control instruction is sent to the Parts Orders Processing sub-model. The process time for the corresponding workstation is regulated by $\boldsymbol{p_i}$. The main steps in this optimized approach are designed as follows.

[Step 1] Perform Fuzzification and Define Fuzzy Sets Universe

The relative and absolute WIP error values (***e*** and ***ce***) of each distributed workstation are input into the Fuzzy Control sub-model. The fuzzy controller converts inputs into fuzzy sets, and a quantizer ***k*** is used with $\boldsymbol{k_e} = \boldsymbol{k_{ce}} = 1/5$. After fuzzification, for ***e***, three cases exist.

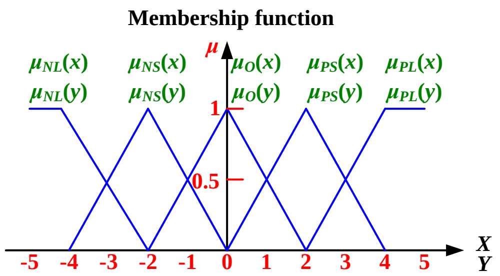
1) If $\boldsymbol{e \times k_e} \in \boldsymbol{X}$, and $\boldsymbol{-4 < e \times k_e < 4}$, it should be rounded off.

2) If $\boldsymbol{e \times k_e} \notin \boldsymbol{X}$, and $\boldsymbol{e \times k_e \leq -4}$, it should be quantized as **-4**.

3) If $e \times k_e \notin X$, and $e \times k_e \geq 4$, it should be **4**.

[Step 2] Design Linguistic Fuzzy Sets and Fuzzy Rules

This paper denotes the linguistic fuzzy sets as $X=Y=\{PL, PS, O, NL, NS\}$, $\alpha_1=1/2$, $\alpha_2=3/4$. Using Rules 4.1-4.2, the membership function and variable assignment of inputs and the output are obtained. Membership function is a generalization of each corrected input in classical sets and represents the attribution ratio as a fuzzy set for input. After fuzzification, fuzzy rules should be made for the control policy. Figure 4.8 shows the results of this step.



Fuzzy control rules

R (E \ EC)	NL	NS	O	PS	PL
NL	PL	PL	PL	PS	PS
NS	PL	PS	O	O	NS
O	PS	O	O	O	NS
PS	PS	O	O	NS	NL
PL	NS	NS	NL	NL	NL

Figure 4.8: Membership function and fuzzy control rules

[Step 3] Defuzzification

The corrected inputs can be represented as e_i and ce_i, with membership functions $\mu_X^*(e_i)$ and $\mu_X^*(ce_i)$, respectively. The membership functions of the conjunction of these two inputs, for *AND=min*, is:

$$\mu_{AND}^*(e_i, ce_i) = \mu_X^*(e_i) \wedge \mu_Y^*(ce_i) \tag{4.1}$$

The following defuzzification formula gives the processing rate r_i^*, which is the control degree after each WIP checking time interval:

$$r_i = \frac{\sum r_i \mu_Z^*(r_i)}{\sum \mu_Z^*(r_i)} \tag{4.2}$$

[Step 4] Calculate the Processing Time

Based on step 3, after setting quantizer k_r, the processing time p_i for workstation i

can be designed as the following function and regulated by $\boldsymbol{p_i}$:

$$p_i = p_d \times (1 - r_i \times k_r) \tag{4.3}$$

where, $\boldsymbol{p_d}$ means the processing time created by the normal processing time distribution. After Step 3, $\boldsymbol{r_i}$ has positive and negative values as shown in Table 4.3. ($\boldsymbol{r_i \times k_r}$) denotes the regulation value for processing time $\boldsymbol{p_d}$. The process time for workstation $\boldsymbol{i}$ is regulated by (1- $\boldsymbol{r_i \times k_r}$) of the original processing time.

Table 4.3: Variable ***r*** Assignment of Fuzzy Control Rules

r / e \ ec	-4	-3	-2	-1	0	1	2	3	4
-4	4	4	4	3	3	3	3	2	2
-3	3	3	3	3	2	2	2	2	1
-2	3	3	2	2	1	1	0	-1	-1
-1	3	2	2	1	1	0	-1	-1	-2
0	2	2	1	1	0	-1	-1	-2	-2
1	2	1	1	0	-1	-1	-2	-2	-3
2	1	1	0	-1	-1	-2	-2	-3	-3
3	-1	-2	-2	-2	-2	-3	-3	-3	-3
4	-2	-2	-3	-3	-3	-3	-4	-4	-4

4.4.2 Optimized Simulation Control Logic

For the entire simulation system, dynamic testing and control of changing WIP inventory levels is the primary objective for determining a solution. However, upstream and downstream WIP buffers exist for each workstation, and the controller must select the first buffer to determine. As analyzed, the tightly coupled cell in this production system is the main bottleneck. According to the theory of constraints, this cell is viewed as the “drum” for the whole production system. The “pull” mode is thus used for the production line upstream of the “drum”, and the “Push” mode is applied for the production line downstream of the “drum”. Each upstream workstation of the NC station should check the downstream WIP buffer, and each downstream workstation of the NC station should check the upstream WIP buffer. This paper integrates the "Pull"/"Push" mode and the fuzzy controller into a simulation model for controlling WIP. Figure 4.9 shows the simulation control logic.

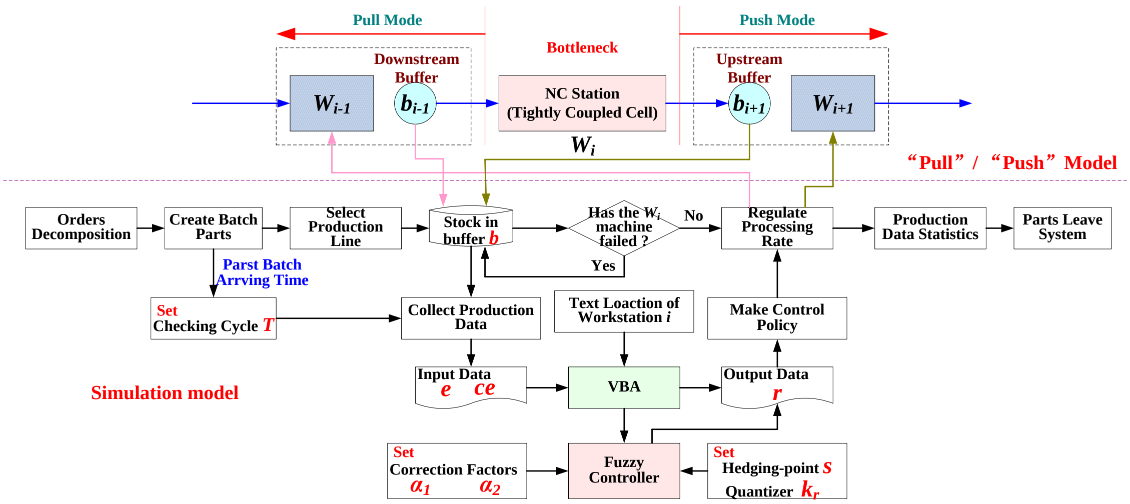


Figure 4.9: Simulation control logic using the optimized fuzzy control approach

When a workstation is in the upstream line of the NC station, its downstream WIP change value is input into the corresponding distributed fuzzy controller for calculation. If the relative and absolute WIP error values are both low, the fuzzy controller makes the control policy that the productivity of this workstation should be increased. The processing time is thus reduced by simulation instruction. By doing this, the "starvation" frequency of the milling machine is reduced, and the production lines are steadier and more balanced. The NC station "pulls" the upstream line, and production performance is optimized. For a workstation downstream of the NC station, based on the same WIP value, the control policy made by the fuzzy controller is contrary to the upstream NC station line. Different outputs are made in the VBA module by distinguishing workstation location and converting the positive/negative output r_i values.

4.4.3 Running the Optimized Simulation Model (TO-BE Model)

This Chapter uses the Arena simulation platform to build the simulation model. To ensure simulation randomness similar to the real system with the various stochastic factors described in Figure 4.1, random distribution data and main parameters are set, as shown in Table 4.4.

Table 4.4: Simulation data and parameters

Parts Processing Time *Unit/min*	Production Line 1	Production Line 2	Production Line 3	Machine Failure Up Time	Machine Failure Down Time
Preprocessing (W_1)	TRIA(3.8,4,4.2)	TRIA(2.8,3,3.2)	TRIA(1.8,2,2.2)	EXPO(720)	EXPO(30)
Cutting Station (W_2)	TRIA(3.9,4.1,4.3)	TRIA(2.9,3.1,3.3)	TRIA(1.9,2.1,2.3)	EXPO(720)	EXPO(30)
3000t Impact Molding (W_5)	TRIA(9.1,11.6,14.1)			EXPO(720)	EXPO(30)
1500t Impact Molding (W_6)		TRIA(7.3,9.3,11.3)		EXPO(720)	EXPO(30)
3t Impact Molding (W_7)			TRIA(6,8,10)	EXPO(720)	EXPO(30)
Sand Blasting (W_{13})	TRIA(4.1,4.3,4.5)	TRIA(3.1,3.3,3.5)	TRIA(2.1,2.3,2.5)	EXPO(720)	EXPO(30)
Face Cutting (W_{14})	TRIA(4.3,4.5,4.7)	TRIA(3.1,3.3,3.5)	TRIA(2.1,2.3,2.5)	EXPO(720)	EXPO(30)
Turning 1 (W_{16})	TRIA(9.6,12.6,15.6)			EXPO(720)	EXPO(30)
Turning 2 (W_{17})		TRIA(4.6,4.8,5)	TRIA(4.3,4.5,4.7)	EXPO(720)	EXPO(30)
Fine Machining 1 (W_{18})	TRIA(11.7,13.2,14.7)			EXPO(720)	EXPO(30)
Fine Machining 2 (W_{19})		TRIA(4.8,5,5.2)	TRIA(4.3,4.5,4.7)	EXPO(720)	EXPO(30)
Checking (W_{21})	TRIA(3.1,4.3,4.5)	TRIA(3.8,4,4.2)	TRIA(2.8,3,3.2)	EXPO(720)	EXPO(15)
Marking (W_{22})	TRIA(4.3,4.5,4.7)	TRIA(3.1,3.5,3.7)	TRIA(3.1,3.3,3.5)	EXPO(720)	EXPO(15)
Tightly Coupled Cell					
NC Station-Drilling (W_{15})	TRIA(4.1,4.3,4.5)	TRIA(3.1,3.3,3.5)	TRIA(2.1,2.3,2.5)	EXPO(1200)	EXPO(20)
NC Station-Milling (W_{15})	TRIA(4.3,4.5,4.7)	TRIA(3.3,3.5,3.7)	TRIA(2.3,2.5,2.7)	EXPO(1200)	EXPO(20)

Loose Coupled Cell	Run Speed	Unit Size	Length
Heating 1 (W_3)	0.72 m/min	0.9 m	7.2 m
Heating 2 (W_4)	0.90 m/min	0.6 m	7.2 m
Heat Treatment (W_8)	0.75 m/min	0.9 m	4.5 m
Heat Treatment (W_9)	0.90 m/min	0.6 m	5.4 m
Heat Treatment (W_{10})	0.90 m/min	0.6 m	5.4 m
Cold Treatment (W_{11})	0.90 m/min	0.9 m	3.6 m
Cold Treatment (W_{12})	0.90 m/min	0.6 m	5.4 m
Parts Family Batch Data			
Parts Type Proportion	DISC(0.27,1,0.61,2,1)		
Parts Batch Arriving Time Unit/min	TRIA(360,420,480)		
Each Parts Batch Quantity Unit/Quantiy	AINT(TRIA(124,138,152))		
Fuzzy Control Parameters			
Hedging-Point s	30	T	24 Hours
k_e=k_{ce}	1/5	α_1	1/2
k_r	1/10	α_2	3/4

The simulation duration is set to two months to match the AS-IS model. To avoid the impact of data deviation on simulation system performance due to the initial status, a steady-state simulation is appropriate for this study. According to the statistical analysis for output inventory level data based on the original simulation model, the effects of the artificial initial conditions have worn off after 5000 minutes. The warm-up period is thus selected as 5000 minutes. Twenty replications are performed to obtain good statistical analysis features and a narrower 95% prediction interval. To reduce output variance affected by random number generation, a common random number method is applied so that all simulations running in the same input have the same random situation.

4.4.4 Simulation Results from TO-BE Model

In this section, the average WIP inventory level of each distributed workstation and cycle time are dynamically calculated with the TO-BE model. Simulation results show that the largest WIP average inventory level for each workstation is under 60. Figure 4.10 shows that the SD is also largely reduced. Although the WIP for the preprocessing workstation is increased by 17 over the AS-IS model, the SD is reduced, which means system stability is effectively controlled.

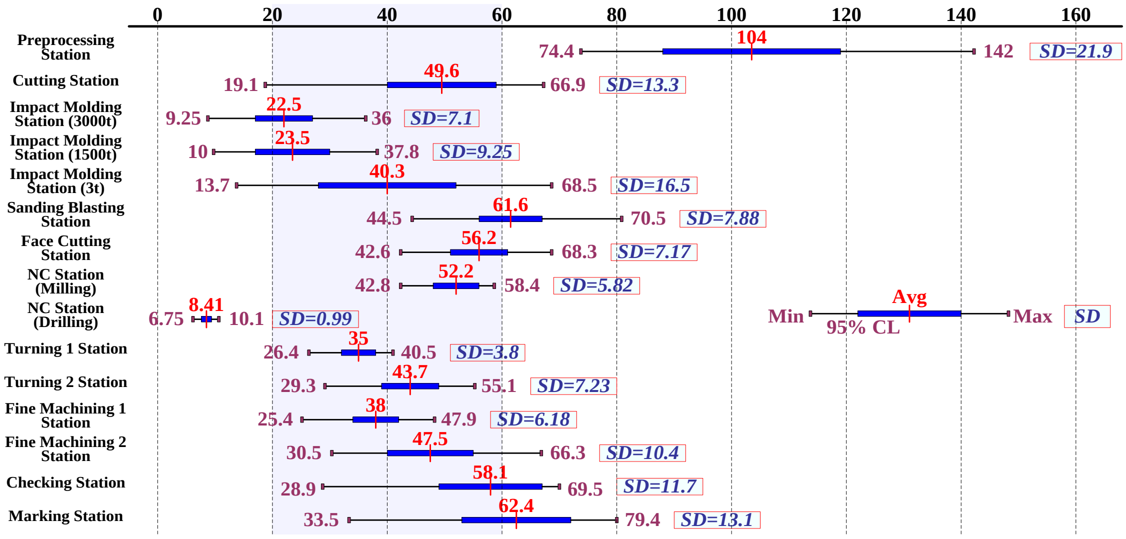


Figure 4.10: Statistical data of the WIP inventory for the TO-BE Model by simulation

Figure 4.11 provides the cycle time for the TO-BE Model, which follows a normal distribution (***X~N*** (***μ***=558, ***σ***^{2}=87)). Approximately 97.81% of the batch parts can be completed before two days, and 100% of the batches are completed before three days. The delivery date is thus reduced and met.

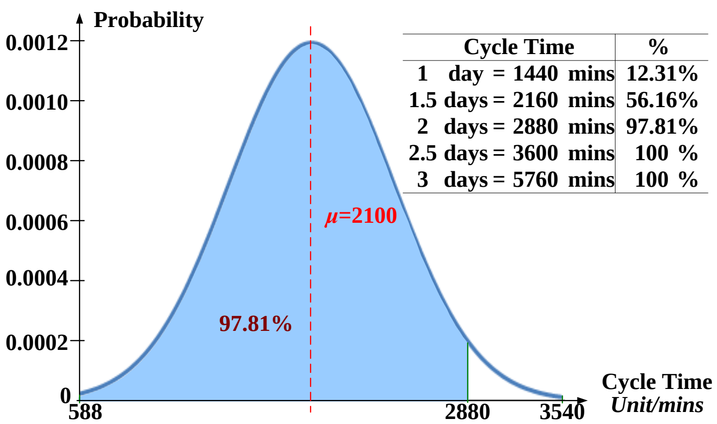


Figure 4.11: Probability distribution of cycle time for the TO-BE model

4.4.5 Comparison and Remarks

Table 4.5 compares the AS-IS and TO-BE models. In the TO-BE model, the average WIP inventory level of each production line has been reduced by over 60%. The width of the 95% confidence interval and the SD for the TO-BE model are narrower and smaller than those for the AS-IS model, respectively. The cycle time distribution SD for the TO-BE model is considerably smaller than that for the AS-IS model. These results show that the TO-BE model has higher stability, a stronger capacity for resisting disturbance, and greater flexibility than the AS-IS model. Furthermore, the cycle time of the TO-BE model is shortened and the delivery day requirement is satisfied for almost all part batches. Conversely, for the bottleneck tightly coupled cell in the TO-BE model, simulation results show that the "block" frequency for milling is below 1%, and the "starvation" frequency for drilling is approximately 0.1%; effects due to the bottleneck are thus essentially eliminated.

Table 4.5: Comparison of the AS-IS and TO-BE models

(Unit/Quantity)	AS-IS Model			TO-BE Model			Decline Ratio %		
	Average	Half Width	Standard Deviations	Average	Half Width	Standard Deviations	Average	Half Width	Standard Deviations
Production Line 1 WIP	516.06	16.76	47.33	202.16	6.3	18.11	60.83 %	62.41 %	61.74 %
Production Line 2 WIP	605.62	26.59	69.12	202.81	7.34	26.70	66.51 %	72.40 %	61.37 %
Production Line 3 WIP	666.62	29.26	87.85	232.01	8.41	28.05	65.20 %	71.26 %	68.07 %
Cycle Time Unit/min	$X \sim N$ (μ=5220, σ^2=2700)			$X \sim N$ (μ=2100, σ^2=387)			59.61 %	/	85.67 %
Tightly Coupled Cell	Block Frequency		Starvation Frequency	Block Frequency		Starvation Frequency	Decline Ratio %	Block Frequency	Starvation Frequency
	5.88 %		0.69 %	0.71 %		0.103 %		87.93 %	85.07 %

The TO-BE model using the optimized approach is developed based on the major parameters in Table 4.4. According to Figure 4.1, stochastic factors affect production system stability and the WIP changes. In this surplus-based system, the hedging point $\boldsymbol{s}$, check time interval $\boldsymbol{T}$, quantizer $\boldsymbol{k_r}$, and correction factors $\boldsymbol{\alpha_1}/\boldsymbol{\alpha_2}$, can greatly disturb the production system. The setting of $\boldsymbol{s}$ thus determines the descent speed of the WIP inventory level, system balance, and selection of other fuzzy control variables.

Table 4.6: Robustness analysis of WIP and cycle time with variations in ***s***

s (*Unit/Quantity*)	Production Line 1 Average WIP		Production Line 2 Average WIP		Production Line 3 Average WIP		Average Cycle Time μ (*Unit/min*)		σ^2	
5	347.79	72.03% ↑	438.73	126.33% ↑	500.56	115.75% ↑	3885	85.00% ↑	1623	319.38% ↑
10	317.68	57.14% ↑	394.47	94.50% ↑	450.23	94.06% ↑	3544	68.76% ↑	1431	269.77% ↑
15	299.55	48.17% ↑	364.31	79.68% ↑	413.61	78.27% ↑	3319	58.05% ↑	1245	221.71% ↑
20	211.37	4.56 % ↑	238.40	17.54% ↑	271.86	17.18% ↑	2331	11.00% ↑	527	36.18% ↑
25	204.68	1.25 % ↑	218.59	7.78 % ↑	249.70	7.62 % ↑	2195	4.52 % ↑	432	11.63% ↑
30	*202.16 MIN*	0 % —	202.81	0 % —	232.01	0 % —	2100	0 % —	*387 MIN*	0 % —
35	206.21	2.00 % ↑	195.69	3.51 % ↓	224.39	3.28 % ↓	*2065 MIN*	1.67 % ↓	395	2.07 % ↑
40	213.09	5.41 % ↑	*193.41 MIN*	4.63 % ↓	*221.74 MIN*	4.43 % ↓	2071	1.38 % ↓	412	6.46 % ↑
45	222.16	9.89 % ↑	194.92	3.89 % ↓	222.82	3.96 % ↓	2104	1.90 % ↑	443	14.47% ↑
50	232.26	14.89% ↑	197.33	2.70 % ↓	225.56	2.78 % ↓	2147	2.24 % ↑	479	23.77% ↑
55	242.01	19.71% ↑	229.51	13.17% ↑	295.41	27.33% ↑	2195	4.52 % ↑	513	32.56% ↑

By running several different simulation scenarios, Table 4.6 shows the average WIP inventory values of each production line and cycle time with variations in ***s***. When ***s*** is lower than 15, resulting from a narrow span of WIP control, the absolute error value ***ce*** is also reduced and the correction factors $\boldsymbol{\alpha_2}$ does not work properly. This causes a higher WIP level that cannot be reduced quickly, and the results are not satisfactory and largely depart from ***s***=30. When ***s*** is larger than 45, conversely, resulting from a wider span of WIP control, the relative error value ***e*** is small and the correction factor $\boldsymbol{\alpha_1}$ does not work properly. This results in WIP levels close to ***s*** not being reduced while higher WIP levels can be reduced quickly; these results are thus slightly higher than ***s***=30. The results for ***s***=40 are generally better than those for ***s***=30. For changes in ***s*** ranging from 25 to 45, the results maintain their stability. This work shows that the optimized model (TO-BE model) has higher robustness and stability levels with a heightened randomicity tolerance capability for stochastic factors. Similarly, other major factors affecting the system reduce sensitivity to control effects. The optimized fuzzy control method thus performs strongly.

4.5 Conclusions

This Chapter, aiming to resolve problems in a multi-variety and small-batch production system with one tightly coupled cell, has developed a distributed fuzzy controller. It is used to maintain the WIP inventory and cycle times at a low level by checking the inventory levels of distributed WIP buffers and dynamically adjusting the processing rate of each workstation. According to the surplus-based system, using correction factors makes the dynamic real-time WIP inventory level changes close to the hedging point and maintains system stability. The advantage of this two-dimensional fuzzy controller is that it can provide a supervisor group with a control policy based on simple representations and linguistic IF-THEN rules. A VBA module operates all fuzzy calculations for each distributed workstation in the simulation model. By analyzing a system bottleneck tightly coupled cell, a proposed optimized method, which integrates a “Pull”/“Push” mode and fuzzy method, is embedded into the discrete simulation model by fixing specific major stochastic factors. An AS-IS model joined with a TO-BE model provides remarkable control ability for WIP and enhanced cycle time. Noticeable performance improvements and robustness are achieved with this model. This fuzzy control policy thus represents a successful approach to reduce WIP and shorten cycle time for this modern production system. Consequently, it is also demonstrated that the *Sub-objective 1-1* proposed in Chapter 1 is achieved.

5 SIMULATION-BASED HYBRID CONTROL RESEARCH ON WIP IN A MULTI-TIGHTLY-COUPLED-CELLS PRODUCTION SYSTEM

5.1 Introduction

For the modern manufacturing industry, many enterprises that are qualified as having high automation levels and are equipped with robot agent sets have applied this advanced production mode with multiple tightly coupled cells. This mode can accurately operate parts, use SMED (Single Minute Exchange of Die) technology to improve flexibility and reduce manufacturing costs (Monden, 2011). These improvements satisfy the diverse demands of consumers and rapid responses to market needs. However, ineffective control of multiple tightly coupled cells easily lead to high WIP levels and “block”/“starvation” frequency, which is caused by many random events (Tao et al., 2008). Moreover, unreasonable WIP management extends production cycle times, decreases market responsiveness and causes system instability (Tsourveloudis et al., 2000). Therefore, a reasonable WIP control method in a multi-tightly-coupled-cells production system, which is associated with a lower WIP inventory level and better production performance, is an important and urgent issue in modern production research.

Many studies have recently investigated WIP control policy problems, which is illustrated in Chapter 3. However, few studies have focused on developing simulation models to analyze WIP level changes and identifying system bottlenecks caused by unreasonable control of multiple tightly coupled cells to design a WIP control method.

This study expands on a previous study in Chapter 4 on WIP control for a discrete production system with one tightly coupled cell. Although the production system still applies the heuristic control policy, its characteristics are changed, and the corresponding optimized method is improved. The control objective involves keeping the WIP inventory at low levels for the entire system while eliminating bottlenecks caused by ineffective control of tightly coupled cells by dynamically the regulating processing rate of distributed workstations (Zhao and Takakuwa, 2013). Consequently, this Chapter is also studied to achieve the *Sub-objective 1-2*.

5.2 Approach

5.2.1 Approach Review

The case study in this Chapter is also considered to be a surplus-based system, and a control policy is made based on whether the real-time WIP level is higher or lower than a hedging point (safety stock). Additionally, the entire production system is divided into multistage production cells for control. The system's merits are to monitor the change in WIP level for the entire system and to master dynamic parts processing in a cell. This system is viewed as a network of cells, workstations and buffers that is restricted by various random factors. A heuristic control policy has been considered gradually to achieve a satisfactory strategy (Gershwin, 2000). Consequently, this study develops a heuristic hybrid control method. Applying this approach can avoid disturbances from bottlenecks caused by ineffective control while achieving lower WIP levels and better production performance.

Most real production systems are classic discrete systems in which various stochastic factors cause WIP random changes and lower system performance. Bottlenecks in a system with a high "block"/"starvation" frequency can also disturb system stability. Additionally, the fuzzy method that Tamani et al. (Tamani et al., 2009; Tamani et al., 2011) applied is not qualified as a rapid response ability to obtain a satisfactory WIP control policy. Based on the studies of Tamani et al., this case study is considered to be a discrete system with more uncertain factors. The present study also improves the fuzzy control method that was used in a previous study in Chapter 4, which can more effectively enhance a system's performance in a hybrid mode.

5.2.2 Hybrid Control Method

The present study improves the fuzzy control method that was used in a previous study in Chapter 4. The controller used in this method is a hybrid controller (dual-mode) that integrates a switching control mode and a fuzzy control mode with a self-correction factor. The advantages of this controller are that it satisfies multiple conflicting criteria and has a better convergence to obtain a reasonable level of control that rapidly maintains the system stability. The inputs for this hybrid controller are the relative and absolute error values in the WIP levels for each distributed workstation. According to a surplus-based system, the relative error value is the difference between the actual WIP value and the safety stock. The absolute error value refers to the difference between successive WIP values. These two inputs are seriously affected by dynamic and stochastic factors, which can cause discrete WIP level and system performance changes. Figure 5.1 shows the logic structure of this hybrid controller. The functions and rules bases are as follows:

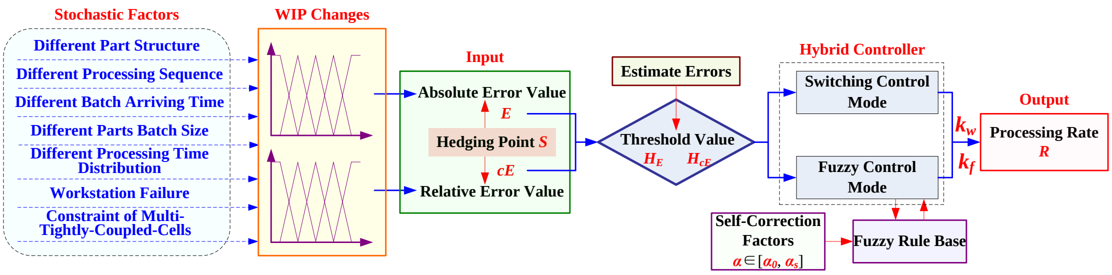


Figure 5.1: The logic structure of a hybrid controller

1) Switching control mode: When the relative or absolute error values are higher than a certain threshold value, the switching control mode is triggered to take an urgent control policy to rapidly reduce the WIP inventory to a relatively low level.

2) Fuzzy control mode: When both error values are lower than the threshold value, the fuzzy control mode is triggered. If the errors are relatively higher, the mode will quickly respond to eliminate the errors; if the errors are moderate, then the mode will avoid over-control and maintain system stability; if the errors are relatively lower, then the mode will eliminate errors, avoid over-control and maintain a steady state. These policies are taken based on fuzzy rules by applying a corresponding self-correction

factor.

For this hybrid controller, a control policy is described using linguistic IF-THEN rules. Unlike the general fuzzy controller, it is a dual IF-THEN rule for dual-mode with the following form:

Rule 5.1 ***IF*** [Switching Control Mode]

$\boldsymbol{E} \geq \boldsymbol{H_E}$ *OR* $\boldsymbol{cE} \geq \boldsymbol{H_{cE}}$, *THEN* $\boldsymbol{R}$ *is* $\boldsymbol{Z_W}$

ELSEIF [Fuzzy Control Mode]

IF $\boldsymbol{E}$ *is* $\boldsymbol{X}$ *AND* $\boldsymbol{cE}$ *is* $\boldsymbol{Y}$, *THEN* $\boldsymbol{R}$ *is* $\boldsymbol{Z_F}$

Here, $\boldsymbol{E}$ and $\boldsymbol{cE}$ are the inputs' relative and absolute WIP error values, respectively. $\boldsymbol{H_E}$ and $\boldsymbol{H_{cE}}$ are the threshold values for two errors. $\boldsymbol{R}$ is the output or processing rate. For the switching control mode, the output policy is determined as $\boldsymbol{Z_W}$ = (Over Large). For the fuzzy control mode, the inputs and output are divided into five corresponding linguistic variations sets: $\boldsymbol{X}=\boldsymbol{Y}=\boldsymbol{Z_F}$={***PL*** (Positive Large), ***PS*** (Positive Small), ***O*** (Zero), ***NL*** (Negative Large), ***NS*** (Negative Small)}.

In the fuzzy control mode, the self-correction factor, $\boldsymbol{\alpha} \in [\boldsymbol{\alpha_0}, \boldsymbol{\alpha_s}]$, is a real number between 0 and 1, with $\boldsymbol{\alpha_0} < \boldsymbol{\alpha_s}$. The analytical expression for the fuzzy controller is corrected as follows:

Rule 5.2 $\boldsymbol{R} = -[\, \boldsymbol{\alpha} \times \boldsymbol{E} + (1-\boldsymbol{\alpha}) \times \boldsymbol{EC} \,]$

$$\boldsymbol{\alpha} = \frac{1}{N} \times (\boldsymbol{\alpha_s} - \boldsymbol{\alpha_0}) \times |\, \boldsymbol{E} \,| + \boldsymbol{\alpha_0}$$

Here, $\boldsymbol{\alpha}$ is self-corrected by changing the absolute value of $\boldsymbol{E}$. It presents that the control policy has different requirements for $\boldsymbol{\alpha}$ in different states. The outputs of the activated rules are aggregated to form the value of the overall control output with $\boldsymbol{\alpha}$, which are then defuzzified into a crisp number, $\boldsymbol{Z_F}$.

The processing time for each distributed workstation $\boldsymbol{i}$ is regulated by $(1-\boldsymbol{r_i}\times\boldsymbol{k})$ of the original processing time, which is the hybrid controller output and can be calculated by a VBA module in the simulation model, as illustrated in Section 4, where, $\boldsymbol{k}=\{\boldsymbol{k_f}, \boldsymbol{k_w}\}$is a quantizer, and $(\boldsymbol{r_i}\times\boldsymbol{k})$ denotes the regulation value for the processing time.

5.3 Case Study

5.3.1 Case Description

The present study considers a case of a multi-variety and small-batch discrete production system with multiple tightly coupled cells. This system is located in a variator component manufacturing workshop of a Japanese company. Figure 5.2 show the layout and main workflow for this manufacturing workshop.

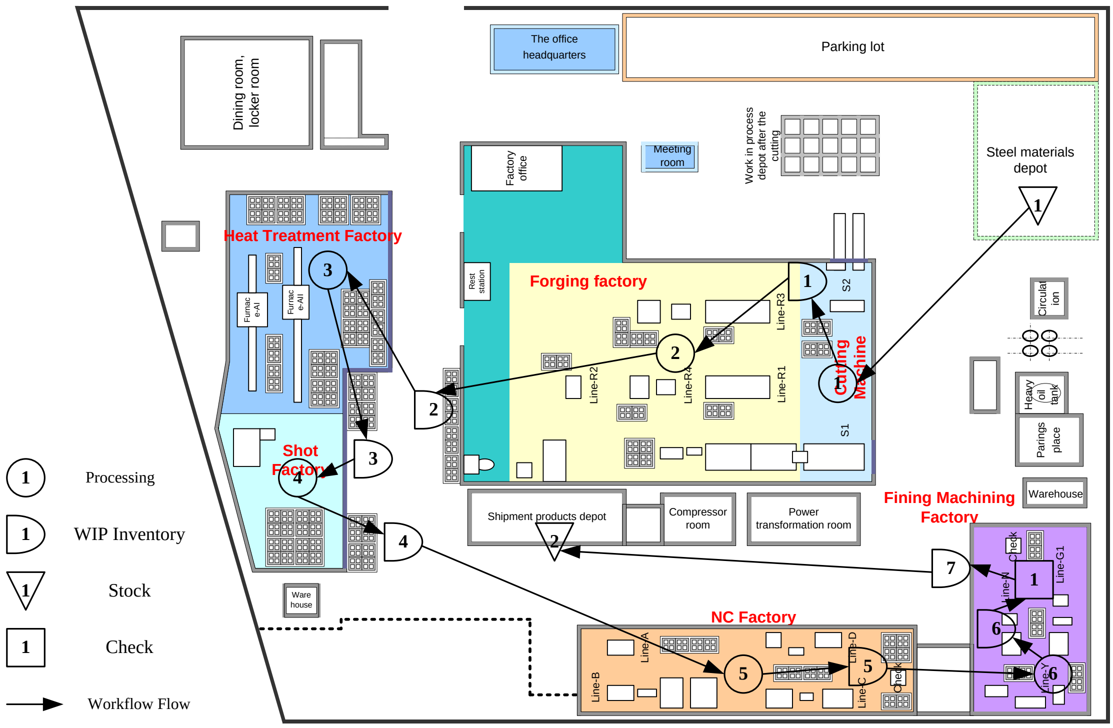


Figure 5.2: The layout and main workflow of manufacturing workshop

This production system applies robot agent sets in a tightly coupled cell, and has a high level of automation. Figure 5.3 shows a simplified structure for this system in details. It mainly comprises 6 tightly coupled cells and 3 main production lines sharing some same machines or production cells. Each part order that enters the system includes three types in random proportions. In each tightly coupled cell, two robot agents are used to accurately operate parts between two fine workstations, and the buffer space is limited to 12. For other uncoupled cells, the WIP buffers with unlimited space are used to balance workstation capabilities, improve system stability, and meet the processing demands for diversified part types. Additionally, there are two loosely coupled cells with machines that act like conveyors and can perform continuous processing.

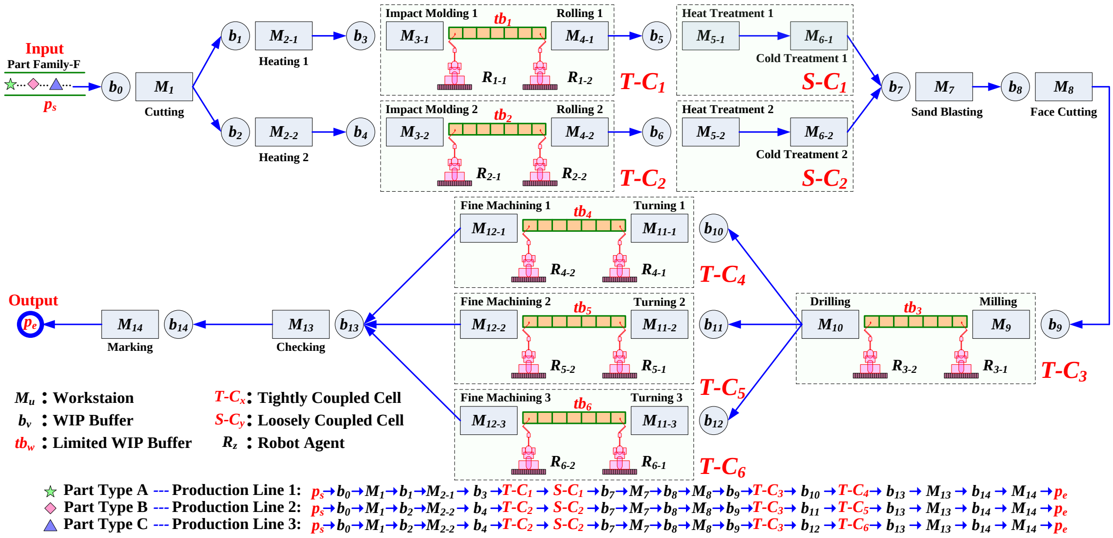


Figure 5.3: A simplified structure model for a multi-tightly-coupled-cells production system

5.3.2 Original Simulation Model (AS-IS Model)

5.3.2.1 Simulation Model Construction

This study mainly analyzes changes in the WIP level to obtain an optimized control policy for reducing the WIP inventory level of the entire system. Based on the characteristics and structure of the real system, an original simulation model is constructed, called AS-IS model. By running the simulation, the capacity of the limited buffer in tightly coupled cells can be easily adjusted, and the bottlenecks can be identified clearly. Furthermore, the production performance of the entire system can be monitored. The AS-IS model can be used to analyze current problems for this production system. The present study uses the Arena simulation platform to build this AS-IS model comprising five sub-models, shown in Figure 5.4. The Order Arriving sub-model is designed to simulate part order arriving. The Orders Operation sub-model is used to randomly create part quantities in an order, and determine the production line. The Parts Processing sub-model is constructed to process parts on the corresponding production line. The Data Statistics sub-model creates WIP level change statistics and other performance statistics. The Parts Completion sub-model is designed to ensure that all parts in an order are completed.

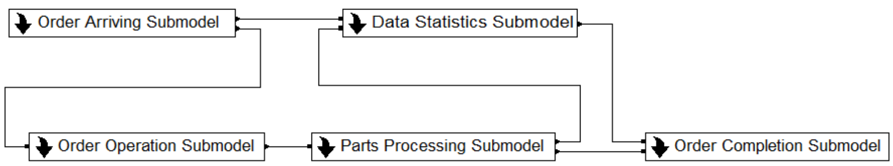


Figure 5.4: Original simulation model (AS-IS model)

Statistical analysis data from the latest two months of real production are used as input parameters. To run the simulation, a steady-state simulation is appropriate. The warm-up period is selected as 5000 minutes, 20 replications are performed, and a common random number method is applied. To ensure simulation randomness similar to the real system with the stochastic factors described in Figure 5.1, the random distribution data and main parameters are set in the AS-IS model, shown in Table 5.1.

Table 5.1: Main simulation data and parameters

Tightly Coupled Cell		Parts Processing Time *Unit/min*			Workstaion Failure	
		Production Line 1	Production Line 2	Production Line 3	Up Time	Down Time
T-C$_1$	Impact Molding 1 (M_{3-1})	TRIA(9.1,11.7,15.1)			EXPO(1000)	EXPO(30)
	Rolling 1 (M_{4-1})	TRIA(9.7,12.5,15.9)			EXPO(1200)	EXPO(25)
T-C$_2$	Impact Molding 2 (M_{3-2})		TRIA(3.0,4.2,5.4)	TRIA(3.2,4.3,5.2)	EXPO(1000)	EXPO(30)
	Rolling 2 (M_{4-2})		TRIA(3.2,4.5,5.7)	TRIA(3.1,4.4,5.8)	EXPO(1200)	EXPO(25)
T-C$_3$	Milling (M_9)	TRIA(2.7,3.2,4.1)	TRIA(2.8,3.1,4.2)	TRIA(2.6,3.0,4.3)	EXPO(1000)	EXPO(30)
	Drilling (M_{10})	TRIA(2.9,3.4,4.2)	TRIA(3.0,3.4,4.1)	TRIA(3.1,3.2,4.5)	EXPO(1200)	EXPO(25)
T-C$_4$	Turning 1 (M_{11-1})	TRIA(14.3,14.7,15.2)			EXPO(1000)	EXPO(30)
	Fine Machining 1 (M_{12-1})	TRIA(14.6,15.1,15.5)			EXPO(1200)	EXPO(25)
T-C$_5$	Turning 2 (M_{11-2})		TRIA(9.9,10.5,11.2)		EXPO(1000)	EXPO(30)
	Fine Machining 2 (M_{12-2})		TRIA(10.1,10.7,11.3)		EXPO(1200)	EXPO(25)
T-C$_6$	Turning 2 (M_{11-2})			TRIA(9.3,10.0,10.7)	EXPO(1000)	EXPO(30)
	Fine Machining 3 (M_{12-3})			TRIA(9.5,10.3,10.8)	EXPO(1200)	EXPO(25)

Loosely Coupled Cell		Run Speed *Unit m/min*	Unit Size *Unit m*	Length *Unit m*
S-C$_1$	Heat Treatment 1 (M_{5-1})	0.72	0.9	7.2
	Cold Treatment 1 (M_{6-1})	0.64	0.9	5.4
S-C$_2$	Heat Treatment 2 (M_{5-2})	0.96	0.9	7.2
	Cold Treatment 2 (M_{6-2})	0.72	0.9	5.4

Other Uncoupled Workstaion Failure		*Unit/min* Up Time	Down Time
Cutting	(M_1)	EXPO(2000)	EXPO(10)
Others	(M_{2-1},M_{2-2}) (M_7,M_8) (M_{13},M_{14})	EXPO(750)	EXPO(20)

Parts Order Data	
Parts Type Proportion	DISC(0.28,1,0.63,2,1,3)
Parts Order Arriving Time *Unit/min*	TRIA(320,450,480)
Each Order Parts Quantity *Unit/Quantiy*	AINT(TRIA(126,142,160))

5.3.2.2 Simulation Validation

After the simulation model has been generated, validation of the model is necessary. The correlative validation data were compared to the existing data statistics from the real system, shown in Table 5.2. As shown in Table 5.2, each data point from the AS-IS model is close to that of the real system. All of the difference ratios are below 10%. Moreover, in the AS-IS model, when the part quantity of each order is respectively increased, the "block" frequency of the tightly coupled cells is also increased and the "starvation" frequency is decreased. These results are consistent with those of the real system. Additionally, when extreme cases are tested by setting the same constant processing time for any parts on a workstation and eliminating machine failure, the average WIP level for a workstation processing only one type part was close to 1. Consequently, all of these tests are validated, confirming that the AS-IS simulation model behaves in the same manner as the real system.

Table 5.2: Validation data comparing the AS-IS model with the real system

(*Unit/Quantity*)		AS-IS Model (Simulation System)		Existing Data Statistics (Real System)		Difference Ratio %	
		Avg	*SD*	*Avg*	*SD*	*Avg*	*SD*
WIP	Production Line 1	733	401	785	434	6.62 %	7.60 %
	Production Line 2	659	344	710	372	7.18 %	7.53 %
	Production Line 3	804	409	876	446	8.22 %	8.30 %
(*Unit/%*)		*BF*	*SF*	*BF*	*SF*	*BF*	*SF*
Tightly Coupled Cells	$T\text{-}C_1$	5.41 %	1.78 %	5.67 %	1.91 %	4.59 %	6.81 %
	$T\text{-}C_2$	5.93 %	2.54 %	6.11 %	2.72 %	2.95 %	6.62 %
	$T\text{-}C_3$	5.05 %	3.30 %	5.36 %	3.59 %	5.78 %	8.08 %
	$T\text{-}C_4$	4.47 %	2.98 %	4.81 %	3.22 %	7.07 %	7.45 %
	$T\text{-}C_5$	5.02 %	2.62 %	5.35 %	2.79 %	6.17 %	6.09 %
	$T\text{-}C_6$	4.34 %	2.27 %	4.70 %	2.43 %	7.66 %	6.58 %

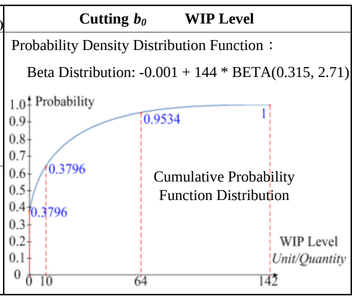
Notes * *Avg*: Average Value *SD*: Standard Deviations *BF*: "Block" Frequency *SF* : "Starvation" Frequency

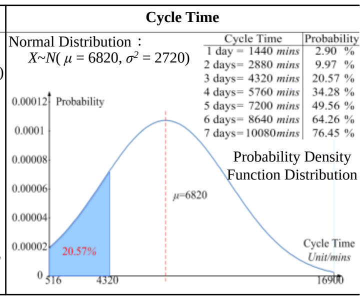
5.3.2.3 Simulation Results from the AS-IS Model

After the simulation, the results of the AS-IS model are shown in Table 5.3. The average WIP level for each workstation is over 100, and the standard deviation is large. The values of the tightly coupled cells are almost as large as those of uncoupled cells. Additionally, the probability distribution of WIP in Cutting, which is the first workstation in the system, shows that most orders can completely enter production before the next order arrives. However, only 20.57% of orders presented from the normal distribution of cycle time are completed within the delivery time of 3 days.

Table 5.3: Simulation results of the AS-IS model

WIP Level (*Unit/Quantity*)			**Avg** (Average Value)	**SD** (Standard Deviations)
Tightly Coupled Cells	$T\text{-}C_1$	b_3	225	143
	$T\text{-}C_2$	b_4	317	179
	$T\text{-}C_3$	b_9	243	152
	$T\text{-}C_4$	b_{10}	198	131
	$T\text{-}C_5$	b_{11}	177	124
	$T\text{-}C_6$	b_{12}	272	156
Uncoupled Cells	Heating 1	b_1	154	71.5
	Heating 2	b_2	153	78.9
	Sand Blasting	b_7	142	70.5
	Face Cutting	b_8	100	46.6
	Checking	b_{13}	121	84.4
	Marking	b_{14}	19.7	13.1





Additionally, the sensitivity analysis results, obtained by adjusting the limited buffer spaces of tightly coupled cells, shown in Figure 5.5. Increasing the limited spaces of the WIP buffer improves the production ability of tightly coupled cells. The WIP levels of b_7 and b_{13}, located downstream of tightly coupled cells, are increased gradually. However, the WIP levels of b_3, b_4 and b_9, located upstream of tightly coupled cells, are decreased. Moreover, the inventory level changes of b_{10}, b_{11} or b_{12}, located between two sequential tightly coupled cells, are almost smooth because the improved productivity of these two cells is offset.

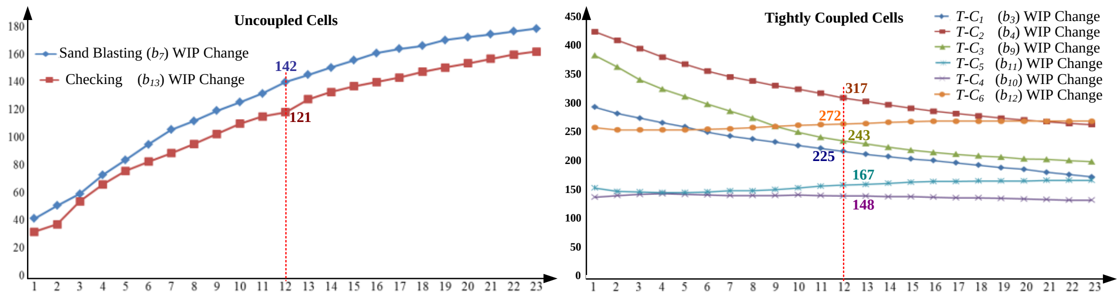


Figure 5.5: WIP level changes by adjusting the limited buffer spaces of tightly coupled cells

Consequently, the simulation results analysis suggests that ineffective control of tightly coupled cells cause higher WIP levels and longer cycle times. Thus, tightly coupled cells are system bottlenecks and seriously restrict production capacity.

5.4 Optimized Control

5.4.1 Description of the Optimized Control Method

In this study, to resolve the problems caused by unreasonable control of tightly coupled cells, a hybrid control method integrating the Pull and Push mode is applied. First, the entire system is divided into multistage production cells. Each tightly coupled cell is a CONWIP control cell in which the Push mode is used to drive the parts process. In this cell, various operations and "block"/"starvation" situations can be monitored easily. Second, for the entire system, among multistage CONWIP cells, the Pull mode is used because of the merits of applying the JIT idea. By constantly checking the upstream buffers of production cells, the changes in WIP level are mastered, and bottlenecks are identified. Following system global regulation, a corresponding reasonable control policy is taken. The logic for this optimized control method is shown in Figure 5.6.

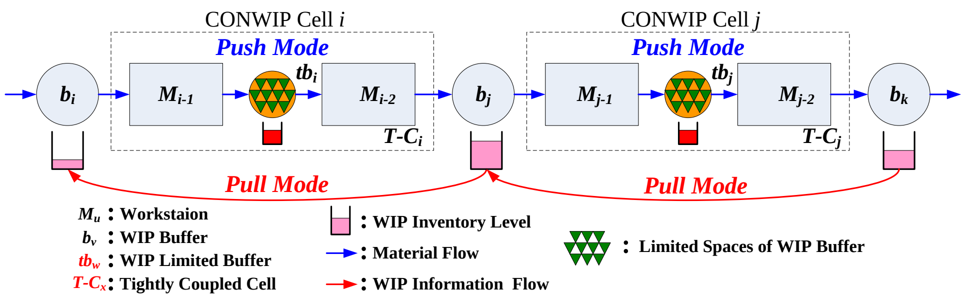


Figure 5.6: A hybrid control method for the multi-tightly-coupled-cells production system

5.4.2 The Centralized Hybrid Controller

To execute the optimized control idea, a corresponding controller is developed that integrates a switching control mode and a fuzzy control mode with a self-correction factor. This controller is used to monitor the WIP level and make a reasonable control policy to reduce the WIP level and eliminate system bottlenecks. In this study, the hybrid controller is designed to be centralized, as shown in Figure 5.7. It has the advantage that WIP changes in distributed cells are monitored, so a global optimized policy can be made easily. For distributed workstations, the relative and absolute WIP error values (***e*** and ***ce***) are inputs into the centralized hybrid controller. After checking based on the threshold value ($\boldsymbol{H_{ce}}$ and $\boldsymbol{H_e}$), the corresponding control mode is selected. For the Fuzzy control mode, based on **Rules 5.1 and 5.2,** fuzzy calculation steps are processed in the same manner as in a previous study in Chapter 4. Regardless of the control mode selected, the global performance of the system is considered and the output ***r*** is adjusted. Then, an optimized control policy is used to regulate the processing time for each distributed workstation.

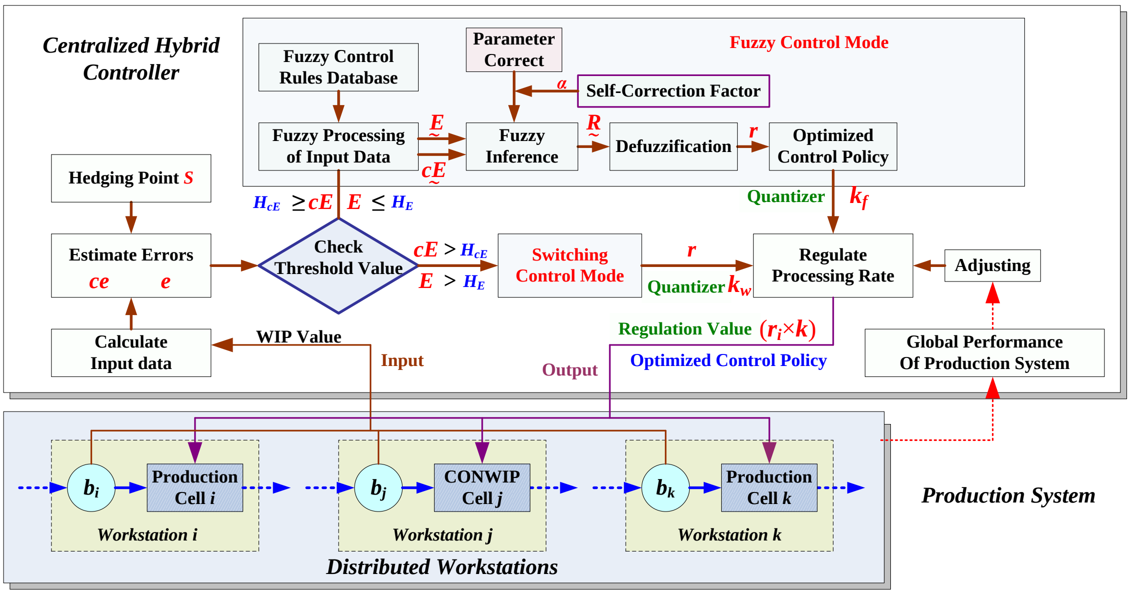


Figure 5.7: The centralized hybrid controller for distributed workstations

5.4.3 Simulation for Optimized Control Method

5.4.3.1 Constructing the TO-BE Model

A centralized control sub-model, executing the optimized control method and hybrid controller, is added into the AS-IS model, which is now called the TO-BE model. In this sub-model, a VBA module operates all calculation and control steps at each checking time interval. As analyzed, because of ineffective control, tightly coupled cells are considered as system bottlenecks. Controlling the WIP level of these cells is the primary objective for optimization. After the VBA module calculation, the hybrid controller makes an optimized control policy to regulate the processing time for each distributed workstation. The corresponding control instruction needs to be adjusted by considering the global performance of the production system and then sent to the Parts Processing sub-model for execution. Figure 5.8 shows the main control parameters and corresponding simulation logic for the centralized control sub-model.

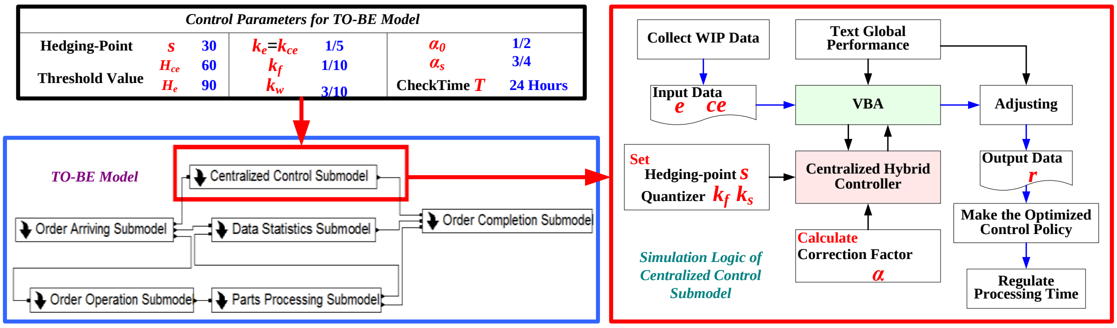


Figure 5.8: Simulation for optimized control method (TO-BE model)

5.4.3.2 Simulation Results from the TO-BE Model

In the TO-BE model, the average WIP level of the production system is dynamically monitored and calculated. As shown in Table 5.4, the average WIP level of each production line and each production cell are dramatically reduced. The standard deviations are also decreased, which means that the system stability is effectively enhanced. Furthermore, by a paired-t comparison of the means difference between the AS-IS model and the TO-BE model, there is a statistically significant difference for most of data points except for the Marking station. The average difference and confidence interval are both negative. These results demonstrate that the optimized control approach used in the TO-BE model shows better performance.

Table 5.4: Simulation results of the WIP inventory level from the TO-BE model

WIP Level (*Unit/Quantity*)			*Avg* (Average Value)	*SD* (Standard Deviations)
	Production Line 1		252	36
	Production Line 2		211	30
	Production Line 3		233	34
Tightly Coupled Cells	$T\text{-}C_1$	b_3	29.8	9.04
	$T\text{-}C_2$	b_4	30.5	11.3
	$T\text{-}C_3$	b_9	52.3	19
	$T\text{-}C_4$	b_{10}	59.1	14.9
	$T\text{-}C_5$	b_{11}	38.6	15.4
	$T\text{-}C_6$	b_{12}	42.9	14.9
Uncoupled Cells	Heating 1	b_1	30.7	9
	Heating 2	b_2	28	10.2
	Sand Blasting	b_7	47.5	18.6
	Face Cutting	b_8	52.3	19.9
	Checking	b_{13}	71	24.8
	Marking	b_{14}	24.1	8.6

Paired-t Comparison of Means Difference between the AS-IS model and the TO-BE model

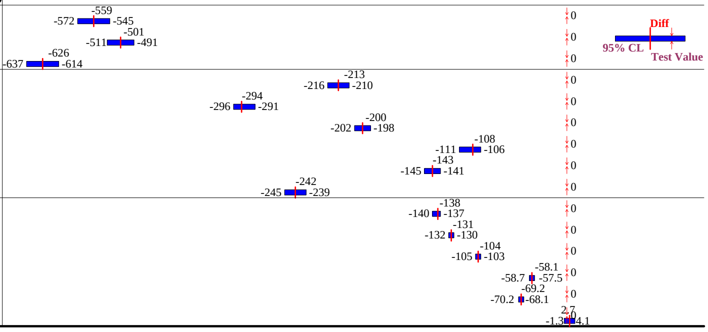


Figure 5.9 provides the “block” and “starvation” times comparison between the AS-IS model and the TO-BE model. In the TO-BE model, the “block” time of each tightly coupled cell is reduced to less than 1000 minutes, and the “starvation” time is reduced to less than 500 minutes. Compared to the AS-IS model, the ranges of decreased values are both over 65%. These results mean that system bottlenecks are essentially eliminated.

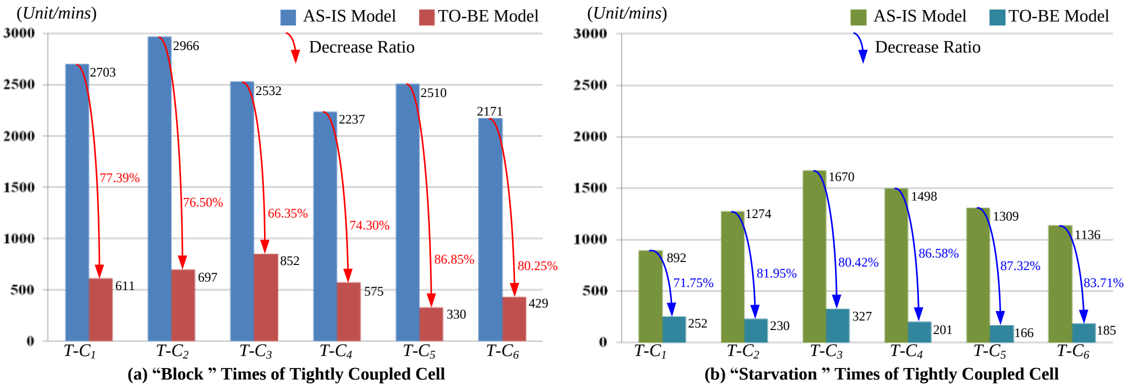


Figure 5.9: “Block” and “Starvation” times comparison between the AS-IS model and the TO-BE model

Figure 5.10 shows the cycle time for the TO-BE model, which obeys a normal distribution ($\boldsymbol{X \sim N}$ ($\boldsymbol{\mu}$=2350, $\boldsymbol{\sigma}^2$=516)). Approximately 84.73% of the part orders can be completed in less than 2 days, and 100% of the orders are completed in less than 3 days. The delivery date is thus reduced and met.

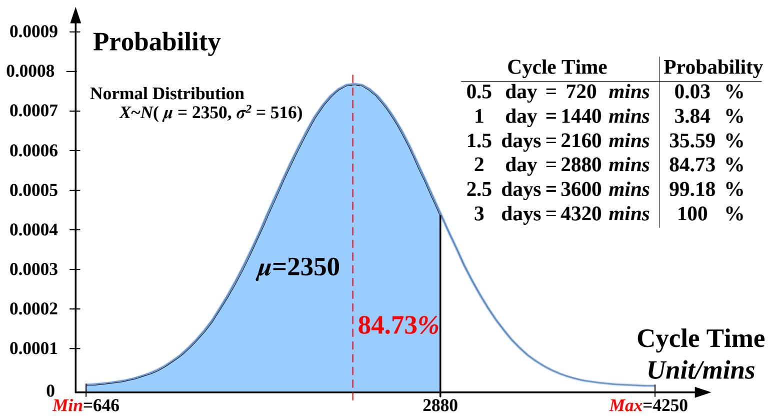


Figure 5.10: Probability distribution of cycle time for the TO-BE model

These results show that the TO-BE model has a higher stability, stronger capacity for resisting disturbance, and greater flexibility than the AS-IS model. The optimized control method is also demonstrated to have greater effectiveness in eliminating bottlenecks and improving the production capacity.

5.4.3.3 Remarks

In a previous study in Chapter 4, a fuzzy control method was used and demonstrated to have good performance. However, under the same case and production data as in the present study, the simulation model using the fuzzy method as applied in the previous study (OM model) presented a worse performance than the simulation model using the improved optimized control method applied in the present study (NM model). As shown in Figure 5.11, the average value and SD of the WIP level in the OM model are both larger than those of the NM model. Moreover, the system response time of the OM model to make a control policy is longer than that of the NM model. Therefore, the optimized control method improved in the present study has an improved efficiency in reducing the WIP level and maintaining the system stability rapidly.

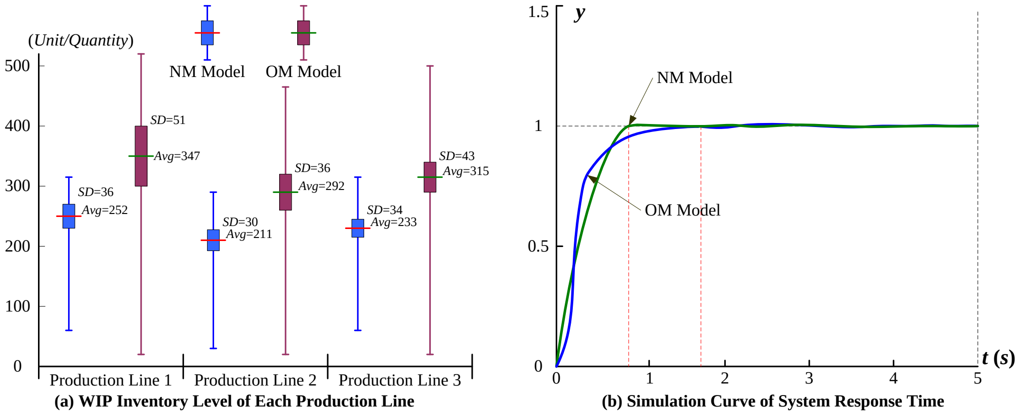


Figure 5.11: Comparison between the OM model and the NM model

By running several different simulation scenarios, Figure 5.12 shows the completion probability of part orders in 1, 2 and 3 days with variations in the Hedging Point ***s*** (safety stock). By increasing ***s*** gradually, the completion probability decreases in different curves. This decreasing trend obeys Little's Law. However, regardless of the change in ***s***, over 95% of part orders meet the delivery time of 3 days. This result indicates that the optimized method (TO-BE model) has greater robustness and stability with an increased randomicity tolerance capability for stochastic factors. The results thus mean that the optimized method used in the present study is strong and performs better than the previous method.

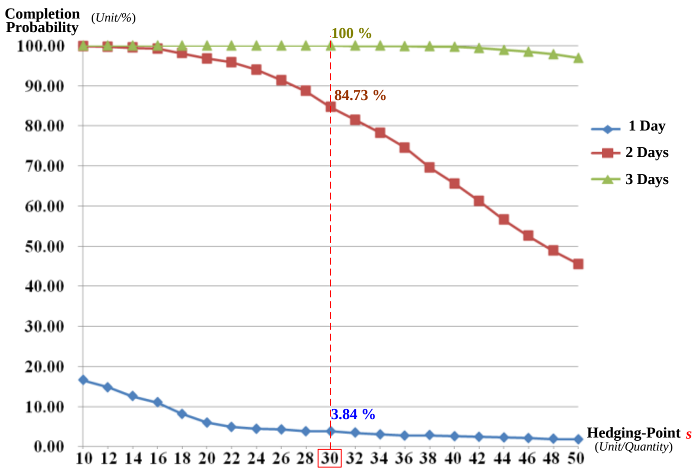


Figure 5.12: Completion probability of part order with changing Hedging Point ***s***

5.5 Conclusions

The present study, aiming to resolve production problems in a multi-tightly-coupled-cells production system, has developed a hybrid control method and a corresponding centralized hybrid controller. These tools are used to eliminate system bottlenecks and maintain the WIP level and cycle times at low levels by checking the inventory levels of WIP buffers and dynamically adjusting the processing rate of distributed workstations. To effectively resolve current problems caused by unreasonable control of tightly coupled cells in this case, by analyzing the system characteristics, the proposed optimized approach is designed as a hybrid control method with a mixed Pull and Push mode, which divides the system into multistage CONWIP cells and other production cells. It applies the JIT operation ideology and easily monitors the dynamic parts process in a production cell. To execute this optimized control idea, the corresponding centralized hybrid controller is developed, which consists of two parts: a switching control mode and a fuzzy control mode with a self-correction factor. According to the surplus-based system, this hybrid controller makes the dynamic real-time WIP level changes close to the hedging point and maintains the system stability. The merit is that this system utilizes the superiority of fuzzy control, satisfies multiple conflicting criteria, and has a rapid response ability to obtain a reasonable control policy. In the TO-BE simulation model, a VBA module operates all calculation processes for the optimized method. Compared with the AS-IS model, the simulation results presents that the TO-BE model provides a remarkable control ability to reduce WIP and cycle times. As illustrated in the previous sections, the present study improved the method used in a previous study in Chapter 4. By comparing the NM and OM models, noticeable performance improvements, rapid response and robustness are achieved with the optimized control method proposed in the present study. This approach thus more successfully improves production capacity, reduces

WIP inventory and shortens cycle times for a modern production system. Consequently, it is also demonstrated that the *Sub-objective 1-2* proposed in Chapter 1 is achieved.

6 MFCA-BASED WIP SIMULATION ANALYSIS FOR ENVIRONMENTAL IMPACTS

6.1 Introduction

6.1.1 Environment-oriented Research in Production System

In a multi-variety and small-batch production system, because of inaccurate determination of production lot-size, overstocks of WIP products are often produced, causing huge material waste, idle energy consumption and stock scraps, which create substantial environmental burden (Zhao, 2012). Therefore, analyzing and determining an appropriate production lot-size to maintain an reasonable low WIP inventory level while achieving both economic and environmental effectiveness are an important issue in the production research field that urgently needs to be solved. Consequently, this chapter is also studied to achieve the *Sub-objective 2-1*.

In this chapter, MFCA is introduced to study the environmental impacts of production lot-size determination through structuring simulation models in a multi-variety and small-batch production system. By applying MFCA, significant invisible wastes (called “negative products” in MFCA) caused by inaccurate determinations of production lot-size are identified. These wastes, or negative products, generate large environmental burdens owing to substantial useless WIP overstocks and idle processing (Zhao, Ichimura and Takakuwa, 2013).

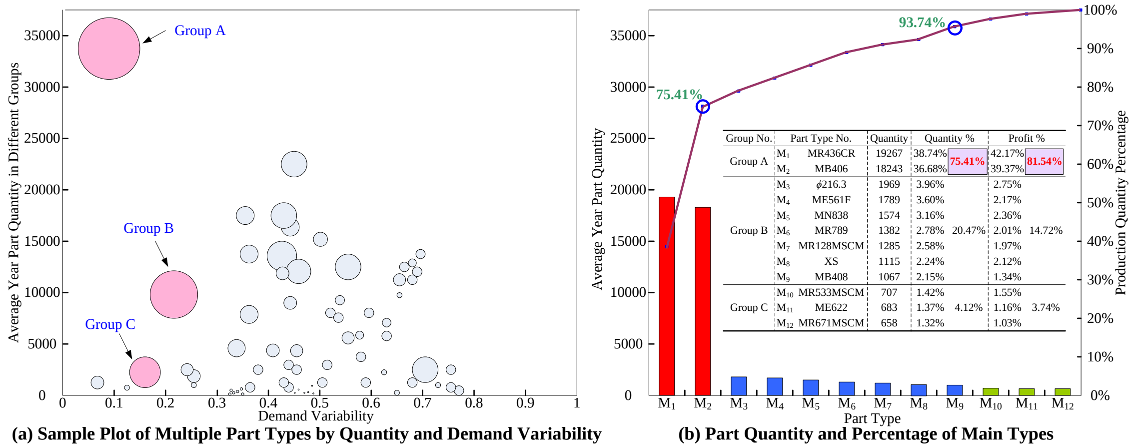
6.1.2 Research Phases in this chapter

In section 2, a case study of a multi-variety and small-batch production system is described. Based on a Pull production mode and inventory decision-making mechanism, a corresponding back scheduling process for system operation is analyzed by building an original simulation model called the AS-IS model. Using the simulation results, the current production states and WIP inventory problems caused by inapposite production lot-size are presented. In section 3, a new simulation model using the concept of MFCA is constructed, called the AS-IS-NC model. By comparing the two simulation models, the corresponding negative environmental burdens hidden in the production processes are shown. After running several different simulation scenarios and sensitivity analyses, an impact mechanism for the negative environmental costs caused by production lot-size changes is explained.

6.2 Case Study

6.2.1 Case Description

This chapter considers a case of a certain multi-variety and small-batch production system, which is located in a precision component manufacturing workshop of a Japanese company (The layout and main workflow are the same as Figure 5.2). To satisfy diverse demands from different customers, hundreds of part types are produced, and corresponding production lines are designed. As Figure 6.1 (a) shows, the part types are divided into tens of groups owing to changes in the market needs. Parts in groups A, B and C have large production quantity and lower demand variability compared to other groups. The economic benefit and productivity of these part types is crucial to the entire system. Figure 6.1 (b) shows that parts in group A occupy over 75% of production and 80% of profits. Consequently, in this chapter, part types M_1 (MR436CR) and M_2 (MB406), composing group A, are selected as the research object. The study of the environmental problems for these part types will also provide some suggestions for the other part types.



Group No.	Part Type No.		Quantity	Quantity %		Profit %	
Group A	M_1	MR436CR	19267	38.74%	75.41%	42.17%	81.54%
	M_2	MB406	18243	36.68%		39.37%	
Group B	M_3	ϕ216.3	1969	3.96%	20.47%	2.75%	14.72%
	M_4	ME561F	1789	3.60%		2.17%	
	M_5	MN838	1574	3.16%		2.36%	
	M_6	MR789	1382	2.78%		2.01%	
	M_7	MR128MSCM	1285	2.58%		1.97%	
	M_8	XS	1115	2.24%		2.12%	
	M_9	MB408	1067	2.15%		1.34%	
Group C	M_{10}	MR533MSCM	707	1.42%	4.12%	1.55%	3.74%
	M_{11}	ME622	683	1.37%		1.16%	
	M_{12}	MR671MSCM	658	1.32%		1.03%	

(a) Sample Plot of Multiple Part Types by Quantity and Demand Variability **(b) Part Quantity and Percentage of Main Types**

Figure 6.1: Some relative statistical data on multiple part types from the current production

Figure 6.2 shows the current production line logical structure for part types M_1 and M_2, which mainly comprises seven workstations sharing the same production line. To adapt to the requirements of part type diversification and rapid responses to market needs, different small production lot-sizes for M_1 and M_2 are adopted for each workstation, denoted as M_x-PL_y. In the Heat-Treatment Station and Shot-Blasting Station, processing begins only when a number of parts equal to the preestablished production lot-size have all arrived. For the other stations, however, the parts are processed one by one.

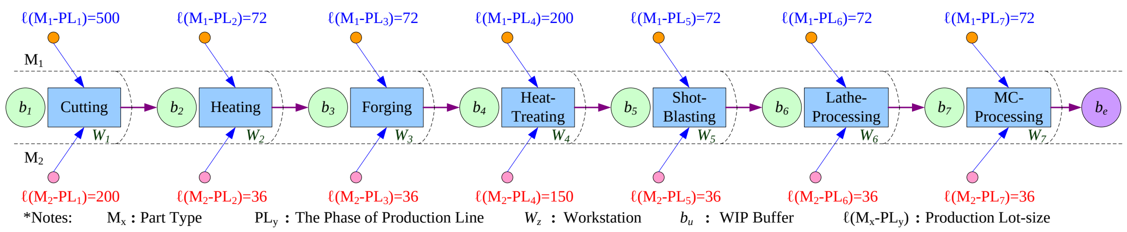


Figure 6.2: Production line logical structure for part types M_1 and M_2

This production system is operated in Pull mode based on an inventory level decision-making mechanism. For one part type, when the order is arriving, the managers will first check the finished product inventory ($\boldsymbol{b_e}$) to determine whether the stock is large enough to provide the quantity ordered. If the order can be fulfilled, a corresponding quantity of parts will be delivered to the customer. If the order cannot be filled, the upstream WIP inventory ($\boldsymbol{b_7}$) of the last workstation ($\boldsymbol{W_7}$) will be checked. In addition, for the last workstation $\boldsymbol{W_7}$, a certain quantity of intermediate products of multiple production lot-sizes from b_7 will be processed to meet the shortage of b_e. This approach is called a back scheduling for the production system operation. All of the checking work and production will thus be stopped until a certain upstream WIP inventory level ($\boldsymbol{b_i}$) of a certain workstation ($\boldsymbol{W_i}$) can fulfill the shortage of a certain downstream WIP inventory level ($\boldsymbol{b_j}$) for workstation ($\boldsymbol{W_j}$) production. Moreover, safety stock $\boldsymbol{s}$ is considered, and each WIP inventory level should be larger than $\boldsymbol{s}$ after determining the production quantity for the downstream workstation. Considering the design requirements of the production line and setup-time reduction, the production quantity for each workstation is multiple production lot-sizes. Figure 5.3 shows the logic for this Pull production mode.

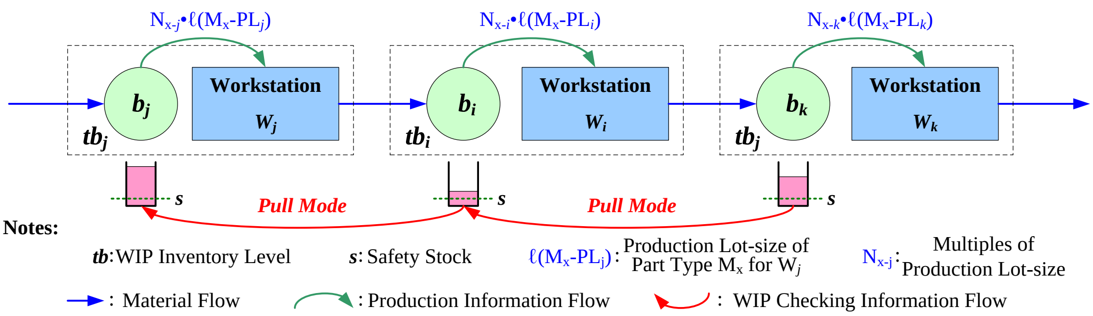


Figure 6.3: The logic of the Pull production mode based on an inventory level rule

6.2.2 Original Simulation Model (AS-IS Model)

6.2.2.1 Simulation Model Construction

Based on the characteristics and structure of the real production system, an original simulation model is constructed to analyze the current production problems, called the

AS-IS model. By running the simulation, the Pull mode and the determination process of the production lot-size for each part type in different workstations can be clearly understood. Furthermore, this AS-IS model facilitates introducing MFCA to the production system to identify hidden environmental problems effectively over a long running time. This study uses the Arena simulation platform to develop this AS-IS model comprising four parts, shown in Figure 6.4.

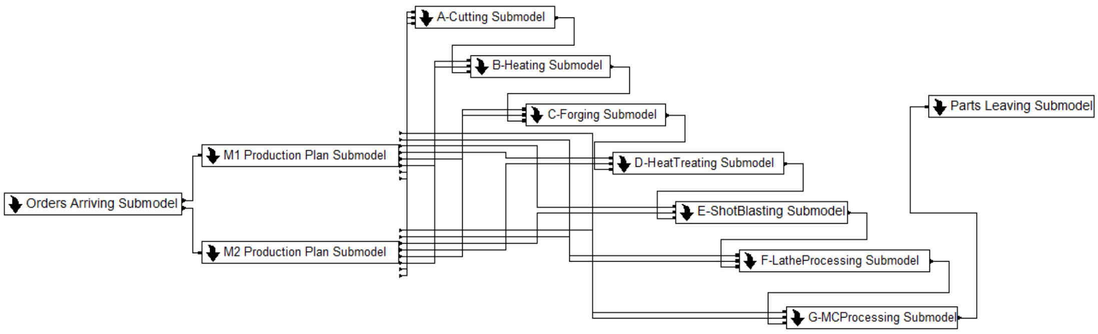


Figure 6.4: AS-IS simulation model

Figure 6.5 shows the main simulation logic for the AS-IS Model. The first part is the Order Arriving submodel, designed to simulate the arrive of orders, and randomly create the production quantities needed by each order. The second part is the M_1/M_2 Production Plan submodel, designed to create a production plan and production lot-size determination for each workstation according to the Pull mode, based on an inventory level decision-making rule. The third part includes seven processing submodels, designed to implement the production plan on the corresponding workstations. The last part is the Parts Leaving submodel, which is used to develop the necessary statistics to analyze production system performance.

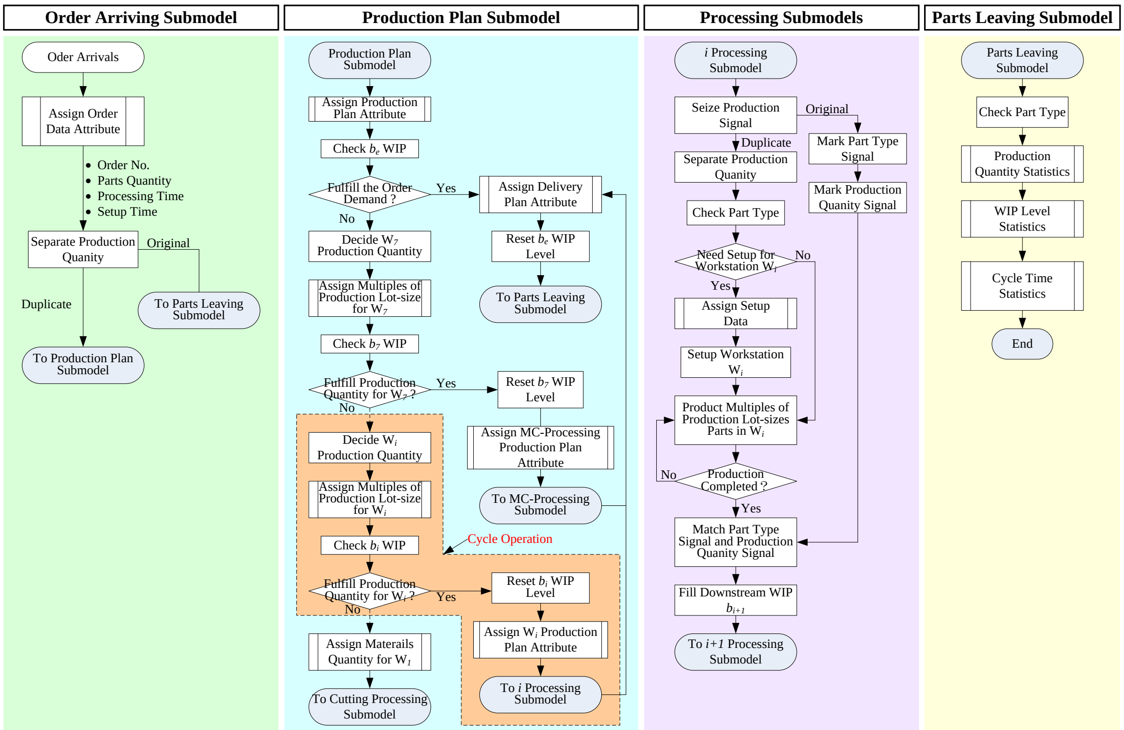


Figure 6.5: The main simulation logic of the AS-IS model based on back scheduling

Statistical analysis data from the latest year of real production is used as input parameters. To run the simulation, a steady-state simulation is appropriate. The warm-up period is selected as 5000 minutes, 20 replications are performed, and a common random number method is applied. To ensure simulation randomness similar to the real system, the random distribution data and main parameters are set in the AS-IS model, shown in Table 6.1.

Table 6.1: Main simulation data and parameters

Parts Processing Time *Unit/Min*		M_1	M_2	Defective Products Rate M_1	Defective Products Rate M_2	Processing Waste Rate M_1	Processing Waste Rate M_2	Safety Stock ***s*** M_1	Safety Stock ***s*** M_2
A	Cutting	TRIA(0.03,0.04,0.05)	TRIA(0.60,0.66,0.70)	0	0	0.059	0.055	150	50
B	Heating	TRIA(0.50,0.55,0.58)	TRIA(0.75,0.80,0.83)	0	0	0	0	20	10
C	Forging	TRIA(0.23,0.25,0.28)	TRIA(0.63,0.71,0.75)	0	0	0.091	0.071	20	10
D	Heat-Treating	1440	1440	0	0	0	0	50	30
E	Shot-Blasting	TRIA(7.5,8.01,8.43)	TRIA(9.50,10.12,10.76)	0	0	0.0002	0.0002	20	10
F	Lathe-Processing	TRIA(0.92,1.05,1.67)	TRIA(5.87,6.33,7.01)	0.03	0.03	0.174	0.149	20	10
G	MC-Processing	TRIA(2.25,2.92,3.41)	TRIA(15.12,17.06,19.63)	0.05	0.05	0.118	0.221	20	10

Part Order Data	Order Arriving Interval *Unit/Min*	Part Quantity *Unit/Quantity*	Part Weight *Unit/kg*
M_1	UNIF(2880,4320)	DISC(0.33,144,0.67,180,1,216)	11.37
M_2	UNIF(1440,2880)	DISC(0.3,36,0.7,60,1,108)	22.81

6.2.2.2 Simulation Validation

After the simulation model has been generated, validation of the model is necessary. The correlative validation data were compared to the existing data statistics from the real system, shown in Table 6.2. As shown in Table 6.2, each data point from the AS-IS model is close to that of the real system. All of the difference ratios are below 10%. Additionally, when extreme cases are tested by fixing the processing time, the order arrival interval and the quantity of parts in one order, the inventory level for each WIP buffer presents a regular cyclical change, and each average value is almost constant. This tentative hypothesis is consistent with the peculiarity of the Pull mode. Consequently, all of these tests are validated, confirming that the AS-IS simulation model behaves in the same manner as the real system.

Table 6.2: Validation data comparing the AS-IS model with the real system (the latest 3 months of data)

Workstations		AS-IS Model (Simulation System)				Existing Data Statisitic (Real System)				Difference Ratio			
		Effective Processing Time *Unit/Hours*		Output *Unit/Quanity*		Effective Processing Time *Unit/Hours*		Output *Unit/Quanity*		Effective Processing Time *Unit/%*		Output *Unit/%*	
		M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2
A	Cutting	507	451	4214	4045	553	477	4620	4423	8.32	5.45	8.79	8.55
B	Heating	513	441	4113	4126	542	482	4515	4327	5.35	8.92	8.90	4.65
C	Forging	531	433	4305	4174	573	476	4734	4485	7.33	9.03	9.06	6.93
D	Heat-Treating	487	397	4016	3711	519	431	4363	3972	6.17	6.03	7.95	6.57
E	Shot-Blasting	515	423	4257	4118	569	456	4698	4475	9.03	7.24	9.39	7.98
F	Lathe-Processing	527	440	4249	4195	554	473	4579	4413	4.87	6.98	7.21	4.94
G	MC-Processing	504	435	4178	4065	538	465	4451	4356	6.32	6.45	6.13	6.68

6.2.2.3 Simulation Results from the AS-IS Model

The WIP inventory levels for each workstation, based on running the AS-IS simulation model, are shown in Figure 6.6. Because of the higher production lot-size for M_1, the WIP inventory value is larger than for M_2. Based on the same reason above for the Cutting and Heat-Treating workstations compared with the others, the inventory values of their downstream WIP b_1 and b_5 are also larger. Additionally, each WIP average value is much larger than the respective safety stock. To meet demand rapidly, increasing production lot-size can satisfy downstream workstation production in time, but will cause WIP overstocks. Additional WIP stocks also generate substantial scrap and waste to burden the environment.

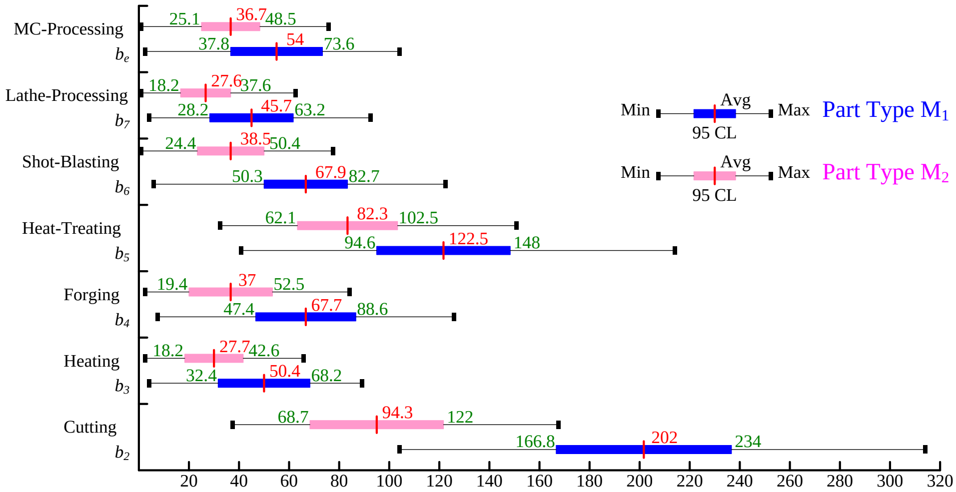


Figure 6.6: WIP inventory level of simulation results from the AS-IS model

From the data in Table 6.3, the average value of each WIP inventory time exceeds 3 days (4320 minutes). A longer inventory time leads to a higher scrap probability of overdue overstocks and more defective intermediate products or materials. Huge amounts of scrapped waste, residues and shavings cause both financial profits and environmental burden.

Table 6.3: Simulation results of the AS-IS model

			WIP Inventory Time Distribution Normal Distribution $X \sim N(\mu, \sigma^2)$ (*Unit/Min*)				Scrap Probability of Overstock (*Unit/%*)		Scrap Probability of Defective Products in WIP		Processing Residues or Shavings Probability		Frequency of Setup Time	
			M_1		M_2		M_1	M_2	M_1	M_2	M_1	M_2	M_1	M_2
			μ	σ^2	μ	σ^2	>10080 *Mins*	>14400 *Mins*	(*Unit/%*)	(*Unit/%*)	(*Unit/ % /kg*)	(*Unit/ % /kg*)	(*Unit/ %*)	(*Unit/ %*)
A	Cutting	b_2	6087	2753	7729	4396	7.35	6.46	0.75	0.53	0.037	0.024	13.13	12.04
B	Heating	b_3	5723	2658	7536	4014	5.06	4.36	0.84	0.67	0	0	27.65	25.13
C	Forging	b_4	5269	2447	7230	3731	2.46	2.73	0.32	0.19	0.072	0.065	28.96	30.74
D	Heat-Treating	b_5	6804	3094	8452	5757	14.48	15.08	1.46	1.15	0	0	14.67	11.56
E	Shot-Blasting	b_6	5070	2985	6784	4415	4.66	4.23	0.91	0.78	0.0002	0.0002	31.46	37.28
F	Lathe-Processing	b_7	4865	2831	6152	4278	3.27	2.69	2.27	1.88	0.141	0.128	37.51	35.97
G	MC-Processing	b_e	4591	2712	5720	σ^2	2.15	1.05	2.89	2.50	0.105	0.193	32.73	38.85

Facing the production lot-size in this case study, WIP overstocks, scraps and wastes are obviously created, but their costs are usually ignored in conventional cost accounting. Hidden environmental problems during the production process are not realized clearly. Consequently, the concept of MFCA should be used to reconstruct the model and to visualize the hidden wastes impacting the environment by automatically identifying positive products and negative products. Moreover, based on MFCA technology, the impact of the regulation of production lot-size on the negative environmental costs needs to be analyzed.

6.3 Simulation Analysis for the AS-IS-NC model Introducing MFCA

6.3.1 Construction of the AS-IS-NC Model Using the Concept of MFCA

To apply the concept of MFCA, the actual wastes generated during the production process need to be further understood. Because of the current unreasonable production lot-size, huge WIP overstocks are produced, and an excess of energy, auxiliary fluids and operations are wasted. According to the requirements from the production design and the customers, overstocks lead to useless WIP stock, idle processing and environmental maintenance wastes. Moreover, WIP overstocks cause large amounts of scraps from overdue and defective intermediate products or materials. All of these wastes and scraps produce a substantial environment cost and burden.

In this chapter, the AS-IS model is reconstructed to introduce the concept of MFCA by embedding a Monitor submodel, which is called the AS-IS-NC Model. All of the production operations are monitored, and all of the material flows are traced by the Monitor submodel. They are also divided into positive products and negative products, and the costs are calculated, as shown in Table 6.4.

Table 6.4: Cost categorizations based on MFCA

	Positive Products Cost	Negative Products Cost
MC	• Material Cost • Auxiliary Fluids Cost	• Material Waste Cost • Material Scraps Cost • Auxiliary Fluids Waste Cost • Environment Maintenance Cost
SC	• Processing Cost • Labour Cost • Management Cost • Workstation Setup/Reset Cost	• Idle Processing Waste Cost • Idle Labour Waste Cost • Idle Management Waste Cost • Idle Workstation Setup/Reset Waste Cost • Inventory Maintenance Cost
EC	• Energy Cost	• Energy Waste Cost

6.3.2 Simulation Results from the AS-IS-NC Model Using the Concept of MFCA

The results of running the AS-IS-NC simulation model are compared with the results of the AS-IS model in Table 6.5. It can be observed that using MFCA can uncover invisible costs in the production processes; in particular, the negative products cost referring to environmental impacts become visible. For each unit part in the AS-IS-NC model, the negative products cost of M_1 makes up 36.65% of the total cost, and the negative products cost of M_2 makes up 30.64% of the total cost. By simulation tracing and analysis, the source of these negative products cost is found to be WIP overstocks caused by the inapposite production-lot size. Because the negative products cost is invalid for this production case, these high percentages mean that the determination strategy for the production lot-size needs to be analyzed and improved to reduce the environmental burden by maintaining a low WIP inventory level.

Table 6.5: Cost results of unit part comparing the AS-IS-NC model and the AS-IS model

(*Unit*/JPY ￥)

AS-IS-NC Simulation Model						AS-IS Simulation Model				
MFCA		M_1		M_2		**Conventional Cost Accounting**	M_1		M_2	
		Avg(1)	*SD*(2)	*Avg*	*SD*		*Avg*	*SD*	*Avg*	*SD*
Positive Products Cost	MC	1129.61	14.45	2240.19	31.71	**Materials Cost**	2009.77	14.45	3658.36	31.71
	SC	1251.24	18.50	2717.67	39.95					
	EC	152.77	2.22	411.87	4.82					
	TPC(3)	2533.62	32.17	5369.73	49.55					
Negative Products Cost	MC	78.16	11.76	1318.17	20.90	**Process Cost**	1989.43	20.93	4083.71	43.28
	SC	669.23	17.00	971.21	27.76					
	EC	16.19	0.07	82.96	0.41					
	TNC(4)	1465.58	20.69	2372.34	25.78					
Total Cost		3999.2	41.88	7742.07	59.14	Total Cost	3999.2	27.66	7742.07	68.47
TNC-P(5)		**36.65%**		**30.64%**						

Notes: (1): *Avg = Average Value* (2): *SD = Standard Deviation* (3): TPC = Total Positive Products Cost (4): TPC = Total Negative Products Cost (5): TNC-P = Negative Products Cost / Total Cost

6.3.3 Sensitivity Analysis for Production Lot-size Determination

Different production lot-size will produce different WIP inventory level for different production stage. In this chapter, a sensitivity analysis is used to analyze the changes in the negative products cost as a result of regulating the production lot-size. Additionally, in this case study, the production lot-size for the Cutting and Heat-Treating stations is set as a fixed value due to the current production schedule and technological design. The production lot-size for the other stations can be regulated by running several different simulation scenarios. To reduce the reciprocal effects, the production lot-size of M_1 and M_2 in each workstation is regulated to the same value.

From Figure 6.7, it can be observed that the negative products cost of a unit part is changed. With increasing production lot-size, four similar curve sections for each part type are obtained. Therefore, the negative products cost for each section is changed in almost the same manner. The cycle value of the production lot-size is approximately 60, and each cycle range in the Figure 6.7 is the same for both part types. This situation disobeys the mass production mode that increasing the production lot-size can generally reduce costs. First, corresponding to the parts quantity distribution for the current order demand of each part type, there exists a relative appropriate production lot-size radix with the lowest WIP inventory level and negative products cost. Second, based on this radix, multiple production lot-sizes produce the appropriate value with similar lowest WIP inventory level and negative products cost; Third, through simulation monitoring and tracing, corresponding to each production lot-size point in each cycle changing region, the overstocks left in the WIP inventory and the useless idle processing are similar; Fourth, inapposite production lot-size generates substantial WIP scraps and wastes, increasing the negative products and environmental costs that are invisible during the production process and are easily ignored by the conventional cost accounting method; Fifth, huge increasing negative environmental costs will offset the costs saved by mass production mode that only consider production cost, but ignore environmental costs; Final, the data in this Figure 6.7 comes from simulation. But, in the real production system, the similar change curve for different part types in different processes will be changed due to various random production factors, and the corresponding cycle value will be increased or declined.

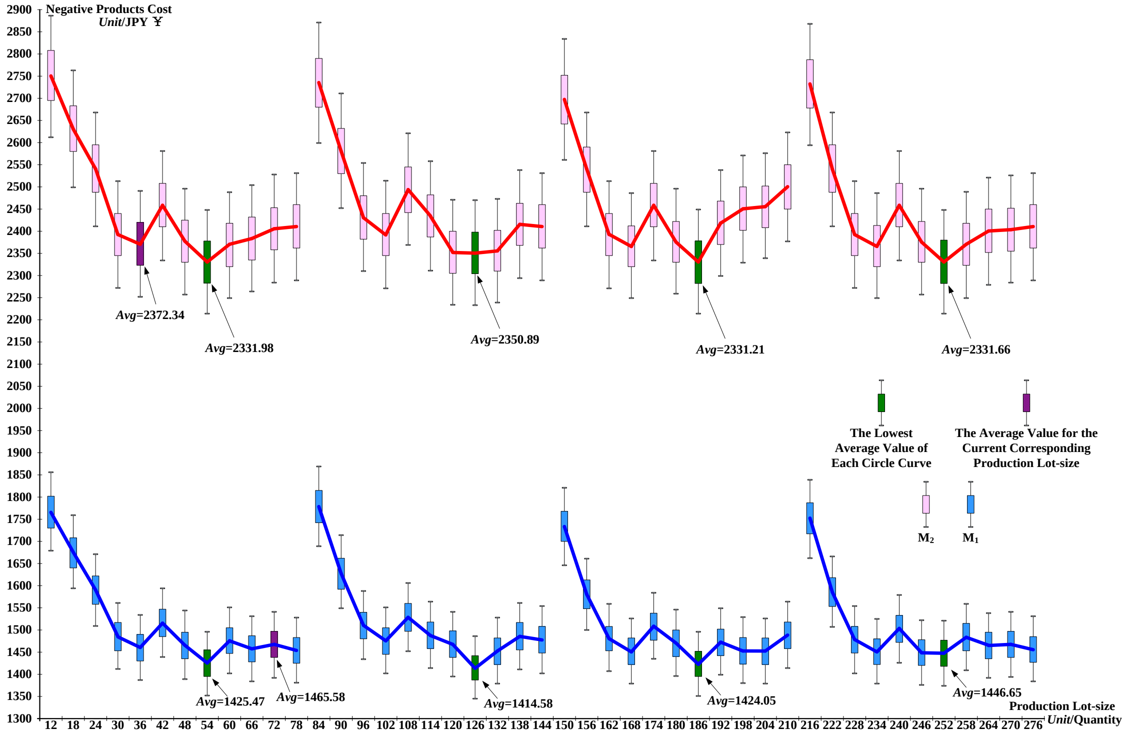


Figure 6.7: Negative products cost of a unit part by regulating production lot-size

From Figure 6.8, for the total cost, the negative products cost percentage of the unit part is also changed in a cyclical manner with changing production lot-size. The cycle value is similar to the one found in Figure 6.7 at approximately 60. However, in contrast to Figure 6.7, the lowest points of the production lot-sizes and cycle range of M_1 are not the same as for M_2. Moreover, comparing these two figures, the production lot-size value corresponding to the lowest point is not coincident. This result means that for a unit part, regulating the production lot-sizes to obtain the lowest WIP level and negative products cost percentage may not produce the lowest negative products cost overall.

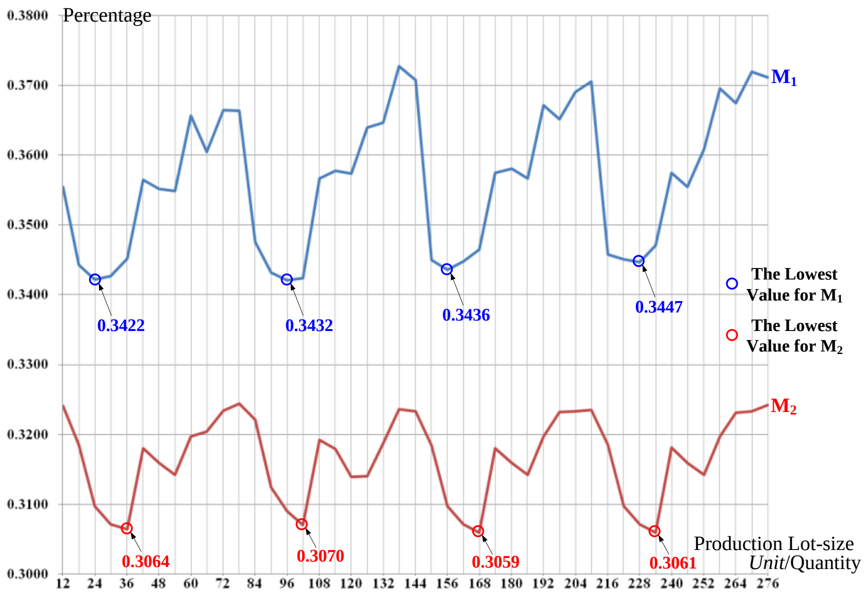


Figure 6.8: Negative products cost percentage of a unit part by regulating production lot-size

These two figures indicate that the determination strategy for the production lot-size has significant impacts on the control of WIP inventory, the negative products cost and environmental burden. Additionally, these impacts present a regular change. It is not demonstrated that blindly increasing or reducing the production lot-size can improve the control of WIP inventory while achieving economic profits and environmental performance. Therefore, such analysis can motivate managers to find the hidden negative products costs and regular change to identify an appropriate production lot-size to maintain a low WIP level, then enhance material productivity and significantly reduce the negative environmental impacts.

6.4 Conclusions

In this chapter, an AS-IS model is constructed to simulate the Pull production mode and back scheduling for a case study of a multi-variety and small-batch production system. By analyzing the simulation data from running the AS-IS model, substantial WIP overstocks and idle processing are traced in the production system owing to the current unreasonable production lot-size determination. Moreover, overdue WIP overstocks and defective WIP intermediate products are scrapped in abundance, causing a huge environmental burden that is ignored in conventional cost accounting. However, the effectiveness of a new environmental accounting method called MFCA is confirmed through the construction of an AS-IS-NC simulation model introducing the MFCA concepts. Based on MFCA, the abandonment of the dead WIP stocks, useless materials and idle processing are reflected as the generation of negative products cost in terms of monetary units, which are invisible during production. Additionally, as analyzed in section 6.3.1 and 6.3.2, after comparing the AS-IS-NC model and the AS-IS model, substantial WIP inventory level, huge negative products cost and environmental cost caused by the current production lot-size determination policy are identified. Moreover, through running several different simulation scenarios, two sensitivity analyses are obtained to analyze the changes in the negative products cost as a result of regulating the production lot-size. After observing the characteristics of similar cycle curves with gradually regulating the production lot-size, two regular changes in negative products cost and the corresponding percentages for the unit part are presented. These change trends provide production managers with effective and strategic knowledge or instructions for determining appropriate production lot-size to maintain a low WIP inventory level and for considering both economic and environmental benefits. Consequently, it is also demonstrated that the *Sub-objective 2-1* proposed in Chapter 1 is achieved.

7 SIMULATION-BASED NEGATIVE ENVIRONMENTAL COST OPTIMAL ANALYSIS FOR WIP

7.1 Introduction

Achieving zero emission from production activities is forming a common view around the world. However, in the current manufacturing mode, because of the complex nature and randomicity of WIP control, high WIP inventory level can not only affect productivity, but also cause environmental cost as a result of inaccurate WIP control level, especially negative products cost such as raw material waste cost, energy waste cost, and idle processing cost and so on. Therefore, that how to control the WIP inventory level to improve the production capacity as well as to achieve green manufacturing effects is the important issue to be solved urgently in production research field. In order to achieve environmental sustainability, many researches mainly focused on green resources, green energy, green products and studied a macroscopic structure for entire green production process, which is reviewed in Chapter 2. However, they seldom attach importance to environmental effect by studying dynamic or stochastic change of production process in details, and also rarely emphasize the control of WIP inventory level which can cause environmental cost.

In this Chapter, therefore, a discrete simulation model for a certain pretreatment workshop is developed, and the real-time change of WIP inventory level is dynamically tracked by monitoring the model running. In contrast to the traditional production research approaches, a centralized fuzzy control methodology is applied to manage WIP inventory level and its environmental cost is calculated by MFCA. In addition, the sensitivity of WIP to the green environmental performance is also analyzed. From the standpoint of MFCA, a change law of negative product costs ratio with the changing of WIP inventory level is indicated. Furthermore, an optimized control approach of WIP inventory level is proposed to achieve both green environmental consideration and production capacity, which is studied to achieve the *Sub-objective 2-2*.

7.2 Basic Description of The Case Study

Group-Production Cell (Called GPC for short) is a specialized cellular production organization. It uses group technology to process part families with multi-variety and small-batch in an appropriate region of workshop with corresponding manufacturing facilities performing similar processes (Gajendra and Divakar, 2000). In this production mode, in order to meet the processing demands for parts diversification, some WIP buffers are used to balance machining capability. So, the management and control for WIP in GPC is an important issue.

In this Chapter, a certain GPC in CD Shipyard's pretreatment workshop is studied for the case. In this GPC, it mainly comprises eight workstations that occupy a partial area of this workshop. Each independent processing in a workstation is handled by three machines or workers. According to the characteristics of part family, each workstation completes the processing task of various parts in a corresponding part family either in whole or in part. The processing time of each part on each workstation is different. In this case, three main part families (F_1, F_2, and F_3) are chosen. Each part family is processed by different and independent production line. In the last workstation, each different part from these three part families is matched to be a set of component. Thinking of GPC's characteristics and ensuring its current logical structure, a simplified layout model for this GPC is show in Figure 7.1.

Three processing sequences of Part Family-F:

F=$\{F_1,F_2,F_3|F_1=([b_1,W_1]\rightarrow[b_2,W_2]\rightarrow[b_4,W_4]\rightarrow[b_8,W_8]),F_1=([b_1,W_1]\rightarrow[b_3,W_3]\rightarrow[b_5,W_5]\rightarrow[b_7,W_7]\rightarrow[b_8,W_8]), F_1=([b_1,W_1]\rightarrow[b_3,W_3]\rightarrow[b_6,W_6]\rightarrow[b_7,W_7]\rightarrow[b_8,W_8])\}$.

All the parts in three Part Family-F are randomly mixed to form a parts batch.

WIP buffers B= $\{b_1, b_2, b_3, b_4, b_5, b_6, b_7, b_8\}$, each WIP buffer has a certain capacity, but not an accurate inventory level.

Workstations: $W = \{W_1, W_2, W_3, W_4, W_5, W_6, W_7, W_8\}$. Each workstation has a set of machines. Workers can reset machines to adjust production rate by manager's centralized examination on upstream WIP inventory level.

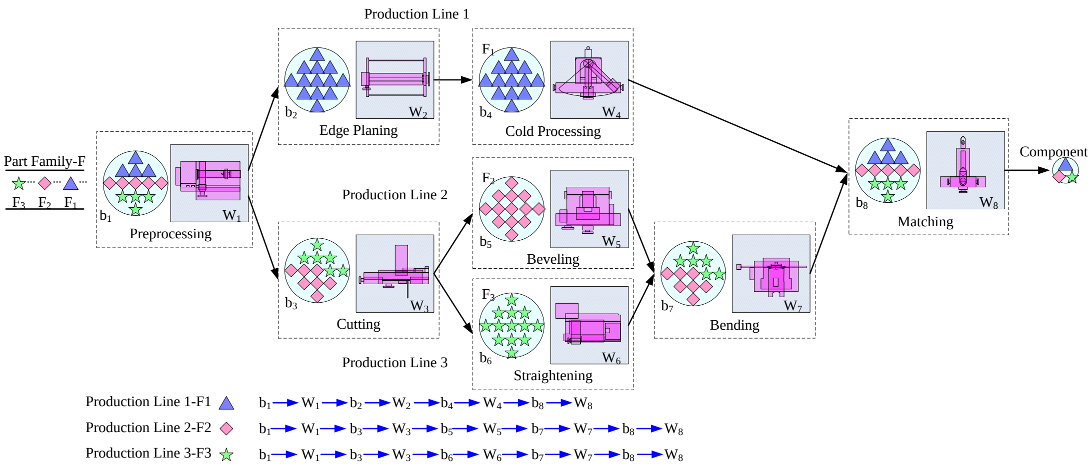


Figure 7.1: A simplified layout model for GPC

From Figure 7.2, according to the actual production data, the Takt time of each workstation for the same production line is unbalanced and processing load is not consistent. These fluctuations of Takt time are mainly caused by different parts structures, the processing compatibility of machines for different parts and processing stability of machine. In order to reduce these fluctuations, a certain amount of WIP buffers are set in the upstream of the stations. However, though this setting improves the production stationarity, accurate control of WIP is still a serious problem. For instance, firstly, the current inventory level of WIP is very high. It still exits some cases that some upstream workstation is stopped optionally to reduce parts' input for downstream WIP. Secondly, too many parts in WIP buffers consume plenty of material cost, idle processing cost, and maintenance cost. Thirdly, processing these parts need lots of unnecessary electric energy and also cause raw material waste or auxiliary detergents waste. So, the production capacity and environmental cost need to be improved urgently.

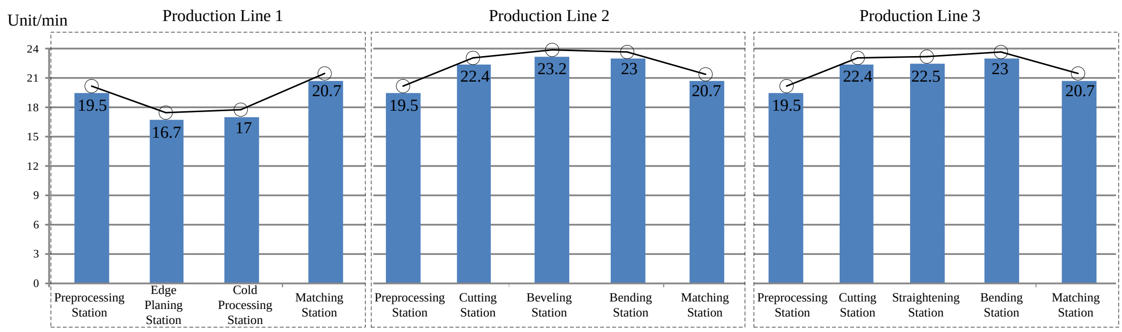


Figure 7.2: The Takt time of each workstation

7.3 Approach Analysis

In this Chapter, research object is a typical discrete production system, and its specific characteristics are illustrated in the Section 7.2. In order to resolve the current problems, firstly, a centralized fuzzy control methodology is used to simulate actual control manners for WIP by operators on site. It is also applied to adjust production rate for workstation by examining inventory level of upstream WIP. The processing rhythm of production lines can be balanced and stability can be ensured. Secondly, MFCA is used to calculate some main production costs, specially, including unnoticed environmental costs that are hided under the production processes. Thirdly, a simulation model integrated with two approaches above is developed. And then, the simulation data is used to analyze sensitivity of WIP to environmental effect. Fourthly, an optimal solution is proposed. And a comparison is made to verify whether the production capacity and environmental cost is improved or not.

7.3.1 A Centralized Fuzzy Control Methodology

In the actual production workshop, operators on site cannot control the WIP inventory level in the form of an accurate quantity, but randomly adjust the production capacity in the manner of a random distribution by examining the inventory level of WIP buffer. This random distribution makes the production process more stochastic and also make system model more complex, but can describe the real situation clearly. Furthermore, a production system is usually viewed as a network of workstations and WIP buffers. The differences of items' structure in the part family make the processing time of machine be random, and also lead volatility disturbing the production stationarity. For the operators in the workstation, the easy way to balance the production line is to control WIP inventory level by examining the phenomena such as starvation/blocking that may occur in the upstream WIP buffer. On the other hand, in practice, a centralized control for WIP can be easily applied to manage WIP inventory level and also can avoid adverse impact caused by operators' separated adjustment. Therefore, in this Chapter, in view of actual conditions, a centralized control method of WIP inventory level is only taken account into and it is embedded into the computer simulation to research the production system. However, actually, stochastic of WIP control make it more difficult to simulate and control actual production.

Fortunately, a fuzzy control methodology can easily resolve this problem, and keep the WIP inventory at a reasonable level (Tsourveloudis et al., 2000; Zhao, 2011). So, in this Chapter, a fuzzy controller is set to simulate real control. In Figure 7.3, wave shape curve shows the change of WIP inventory level with time. $F(X)$ and $g(y)$ is stochastic distribution functions of WIP control, and denote the highest and lowest threshold value of WIP inventory level. X_{min}, X_{max} ,y_{min}, y_{max} respectively obey these functions. If deviating from these threshold values that are assumed to be a certain distribution of random, the production ratio of downstream workstation will be adjusted to balance the production line. And these random distributions in the simulation model present a fuzzy control methodology, and this control is centralized.

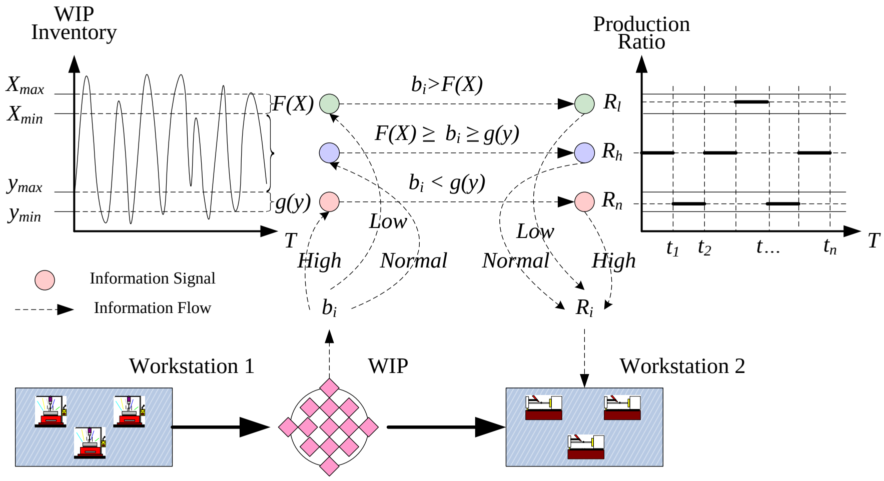


Figure 7.3: A fuzzy controller for WIP inventory level

In fuzzy controller, the control policy is described by linguistic IF-THEN rules with appropriate mathematical meaning ([3] Driankov et al., 1994).The rule base of the control model contains rules of the following form (Zhao, 2011):

$$\text{IF } b_i \text{ is } BL^{(n)}$$

$$\text{THEN } r_i \text{ is } PR^{(n)}$$

Where n is the rule number (n=*1*, *2*, *3*), i is the number of workstation, BL is a linguistic value of the variable of WIP inventory level b (Upstream WIP of the workstation) with term set B= {*Low*, *Normal*, *High*}. The production speed r takes linguistic values of PR from the term set R= {*Low*, *Normal*, *High*}. The actual rulebase is presented in Table 7.1.

Table 7.1: Linguistic IF-THEN rules for fuzzy controller

RULE	IF BL_i		THEN R_i	
1	$b_i < g(y)$	*Low*	R_l	*Low*
2	$F(X) \geq b_i \geq g(y)$	*Normal*	R_n	*Normal*
3	$b_i > F(X)$	*High*	R_h	*High*

This centralized fuzzy control methodology can not only simulate the actual stochastic control for WIP by operators on site, but also can adjust production ratio by examining inventory level of upstream WIP.

7.3.2 MFCA

In this Chapter, the author adds the MFCA method into the simulation system to dynamically calculate environmental costs throughout all the processes with the change of WIP inventory level. According to rules of MFCA, the product cost is divided into positive and negative products cost for calculation in terms of monetary unit. Comparing with the other account methods, MFCA makes negative products and some loss visible for each process. This visibility testifies that the change of WIP inventory level can not only make an influence on productivity, but also environmental cost.

7.3.3 Simulation Analysis

Aiming to resolve current problems in GPC, the centralized fuzzy control methodology is used to control change of WIP inventory level, and MFCA is adopted to calculate environmental cost. In this Chapter, one WIP managers group is set up to exam the WIP level in the manner of centralized management at regular intervals. The criterion of WIP inventory capacity is assumed to be a certain random distribution $F(X)$ and $g(y)$. After finding some WIP inventory level is high than $F(X)$ or lower than $g(y)$, the downstream workstation's production ratio will be adjusted. During the processing, MFCA is used to calculate positive and negative products cost. The simulation logic is shown in Figure 7.4.

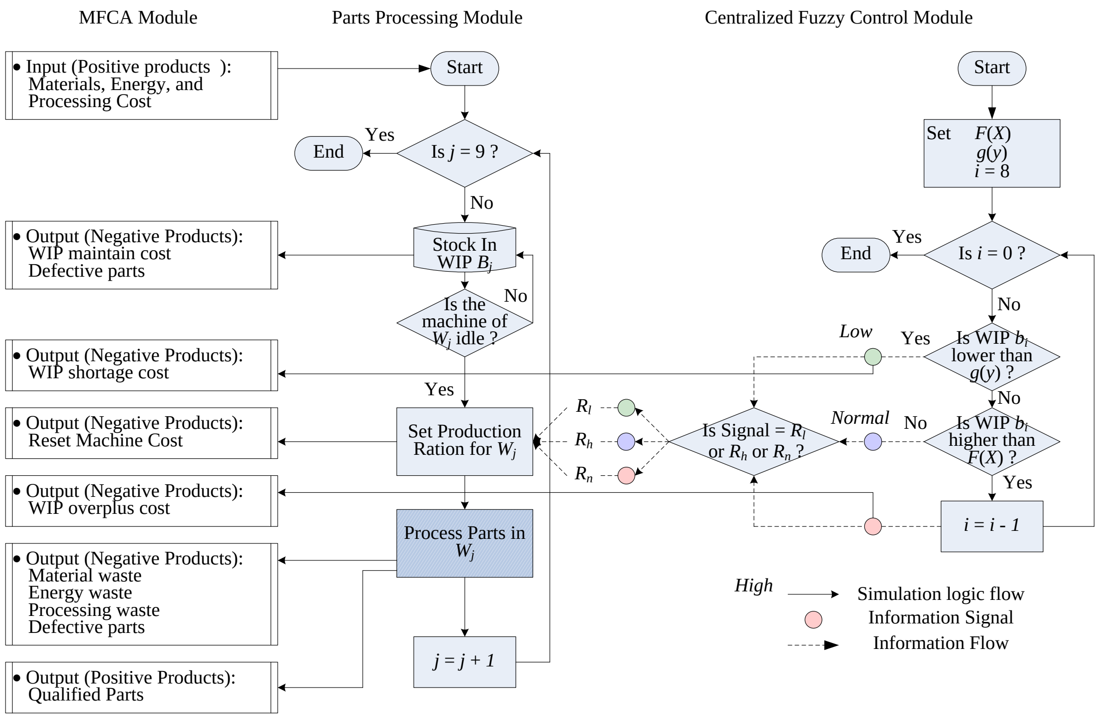


Figure 7.4: The simulation logic

Seen as the Figure 7.4, system simulation model is composed by fuzzy control logic module MFCA module, and Parts processing module. Fuzzy Control logic module monitor the change of WIP inventory level at a certain examining time in the manner of centralized control, and decide to adjust production speed. Parts processing module operate the production system. MFCA module calculates all the manufacturing costs including environmental cost.

After collations and sorting out, main data is embedded into the simulation model. All the parts in different part family enter this system at a random distribution. Each WIP buffer is set in upstream of the each workstation, and each a group of five parts in a WIP buffer is placed in a pallet. In order to avoid “block” or “starvation”, a certain WIP inventory level is set. The lowest and highest level of fuzzy control both obeys uniform distribution, i.e. $F(X)$ =UNIF (X_{min}, X_{max}), $g(y)$ = UNIF (y_{min}, y_{max}). The difference between min value and max value of uniform distribution is 5 that are equal to the pallet capacity. According to the fuzzy control signal, the number of machines in a workstation is reset to adjust production speed. Processing time all obeys random distribution. Because of the relative heaviness of each steel part, it is transferred to downstream workstation by the fork truck.

In this Chapter, Arena simulation platform is used to build simulation model, and simulation running is based on practical production data of a month. Each workday has 24 hours and CD shipyard uses three-shift workday system because of prosperous shipbuilding business at present in China. So, the simulation running-length is 43200 minutes. In order to avoid the impact of data deviation on simulation system performance due to initial status, steady-state simulation is appropriate and warm-up period is 5000 minutes. Additionally, in order to make simulation more stochastic and independent and to get a narrower 95% prediction interval, number of replication is set by 20.

7.3.4 Environmental Cost Calculation

One object of this Chapter is to show the sensitivity of negative products cost to change of WIP inventory level. Due to the adjustment of production speed, positive products inputs inevitable change a lot. It is difficult to set a fixed criterion to evaluate negative products cost in a fixed input. Thus, a negative products cost ratio is adopted in this Chapter that the ratio is the value of negative products cost divided by positive products input. And, the lower the ratio is, the better control efficiency of WIP inventory level is, and the higher production capacity is. To calculate this ratio, first step is to collect the positive products input, and then calculating negative products cost is the second step. All the cost is in form of monetary units.

[Step 1] Calculate the Positive Products Cost

Positive products input are composed by three parts: material cost, processing cost, and energy cost.

$$TPC = Mc + Pc + Ec \tag{7.1}$$

Where,

TPC: total positive products input cost. *Mc*: material cost, *Pc*: process cost, *Ec*: energy cost.

[Step 2] Calculating Negative Products Cost

Negative products Cost are composed by eight parts by maintain cost of WIP inventory, cost of lower than safe WIP level $g(y)$, cost of higher than safe WIP level $F(X)$, cost of resetting machine set, cost of part weight waste, cost of part processing waste, cost of part energy waste, cost of defective part.

$$TNC = MIc + LMIc + HMIc + RMc + WWc + PWc + EWc + DPc \tag{7.2}$$

Where,

TNC: total negative products cost. *MIc*: maintain cost of WIP inventory, *LMIc*: cost of lower than safe WIP level $g(y)$, *HMIc*: cost of higher than safe WIP level $F(X)$, *RMc*: cost of resetting machine set, *WWc*: cost of part weight waste, *PWc*: cost of part process waste, *EWc*: cost of part energy waste, *DPc*: cost of defective part.

Based on step 1 and step 2 above, according to MFCA, all kinds of cost are shown in Table 7.2.

Table 7.2: Cost Categorization Based on MFCA

		Input	Output	
Positive Products Cost	MC	*Mc*	/	*TPC*
	SC	*Pc*	/	
	EC	*Ec*	/	
Negative Products Cost	MC	/	*WWc*	*TNC*
	SC	/	*Mic, LMIc, HMIc, RMc, PWc, DPc*	
	EC	/	*EWc*	

These negative products cost can be calculated easily by simulation system.

[Step 3] Calculating Negative Products Cost Ratio

$$R = \frac{TNC}{TPC} \tag{7.3}$$

Where,

R: negative product cost ratio

According to the centralized fuzzy control method and simulation requirement about time, *R* can be seen as a function of the variables *t*, *y* and *X*. So, *R* is denoted as *R* (*t*, *g*(*y*), *F*(*X*)). The change of WIP inventory level is related to these variables closely.

7.4 Data Analysis

7.4.1 Sensitivity Analysis

Some factors such as the differences in worker qualification and practical technique can affect the production performances. But, in this Chapter, in order to study the efficiency of fuzzy control method, only three related variables, *t* (examination time of WIP inventory level), *g*(*y*) (the lowest fuzzy control threshold value of WIP), and *F*(*X*) (the highest fuzzy control threshold value of WIP) are considered. Alteration of these variables can change the *R*. It also can be seen that *R* is not a continuous derivatived function, and its partial differential equation of first order for *t*, *g*(*y*) or *F*(*X*) cannot be gotten. So, sensitivity analysis can show the impact degree of random variable *t*, *g*(*y*) and *F*(*X*). The other factors are not considered.

$$\left|\Delta R_{(\Delta t)}\right| = \left|R(t) - R(t \pm \Delta t)\right| \tag{7.4}$$

$$\left|\Delta R_{(\Delta y)}\right| = \left|R\left[g(y)\right] - R\left[g(y \pm \Delta y)\right]\right| \tag{7.5}$$

$$\left|\Delta R_{(\Delta X)}\right| = \left|R\left[F(X)\right] - R\left[F(X \pm \Delta X)\right]\right| \tag{7.6}$$

$\Delta R_{(\Delta t)}$, $\Delta R_{(\Delta y)}$, $\Delta R_{(\Delta X)}$ denote that changing value of *R* with the minimal change of *t*, *g*(*y*) or *F*(*X*) and the other two fixed variables. If ΔR is more obvious relatively, it indicates that sensitivity degree is high, but low. For an example, starting with the lowest y_{min}, *y* increases progressively to the highest y_{max} by a small fixed increment Δy. In the interval (y_{min}, y_{max}), each $\Delta R_{(\Delta y)}$ is calculated with each Δy increase. Among these $\Delta R_{(\Delta y)}$, we can get a lowest *R* and can also the highest sensitive degree in a certain *y*. If the increment change of these $\Delta R_{(\Delta y)}$ is so little, it can be seen that highest sensitive is not obvious, i.e. the control of *g*(*y*) cannot improve *R* effectively. The other two variables *t* and F(*X*) *is* the same as *g*(*y*).

In this study, the change of WIP is mainly affected by three factors. The sensitivity analysis regarding with these factors is made based on the simulation data. In order to accurately analyze the sensitivity, one factor is studied and the others must keep steady.

From simulation data, it can be seen that average WIP level is about 50, and *t* should start with the 3^{th} hour. And, in the practice, the lowest threshold value of $g(y)$ must be 5 at least, which is equal to the quantity of a pallet. So, the sensitivity analysis about examining time *t* must keep the other two factors the $g(y)$ =UNIF (5, 10), and F(X) =UNIF (50, 55) be steady.

In Figure 7.5, the red line shows the *R* change of each *t* point which changes from the 4^{th} hour to 30^{th} hour, and each *R* is the value which subtracts the t=3^{th} value. The blue line shows the change of $\Delta R_{(\Delta t)}$ based on each fine increment Δt (Δt=1hour). Seeing the blue line, the change of $\Delta R_{(\Delta t)}$ is uneven. Before t=8, $\Delta R_{(\Delta t)}$ <0, it denotes that *R* gradually becomes lower and amplitude of variation is large. It means that sensitivity degree is high before t=8. After t=8, ΔR >0 mostly, it denotes that *R* gradually becomes larger, and the zigzag change means sensitivity degree is not high. When t=8, ΔR=0, it means the R is the lowest value. These change is also can be testified from red line. So, it shows that control of *t* should be close to 8, and the change speed of *R* before t=8 is larger than after t=8 in the same fine increment Δt.

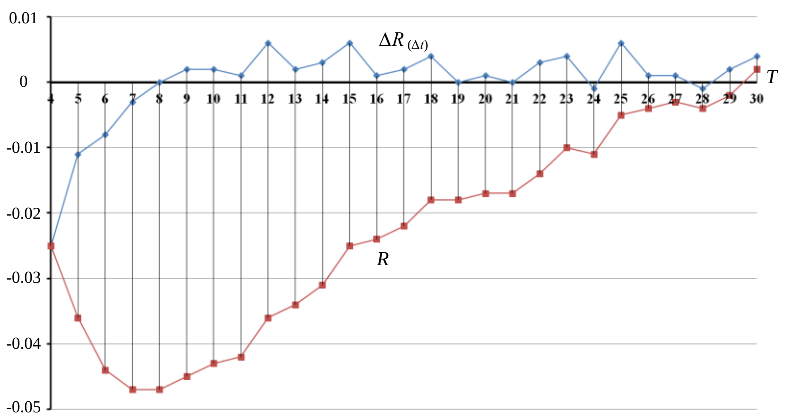


Figure 7.5: Sensitivity analysis about examining time ***t***

For the sensitivity analysis about $g(y)$ in Figure 7.6, we keep t=8, Δy=5 and study the changes from $F(X)$ = UNIF (115,120) to UNIF (50, 55). Seeing Fig.8, all the curves show that with the decrease of $g(y)$ value, the change of curve became gently. And based on the same $F(X)$, $\Delta R_{(\Delta y)}$ of the same $g(y)$ point became larger with increase of g(y).and the lowest R occurs in curve $g(y)$ = UNIF (5,10). It shows that sensitivity degree became larger with increase of g(y) value. So, it means that we should keep the g(y) lower.

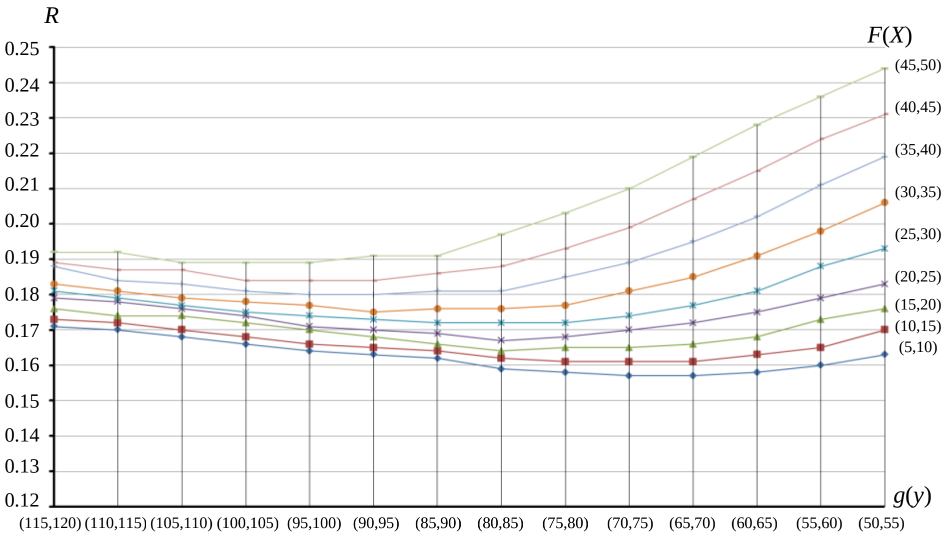


Figure 7.6: Sensitivity analysis about $g(y)$

Figure 7.7 shows the sensitivity analysis about $F(X)$, keeping the t=8, ΔX=5 and study the changes from $g(y)$ = UNIF (5, 10) to UNIF (55, 60). It is can be seen that the lowest point of all the curves correspond to $g(y)$ = UNIF (5, 10). With the increase of $g(y)$, the lower $F(X)$, the higher R is. It also shows that sensitivity degree became larger with decrease of $F(X)$.

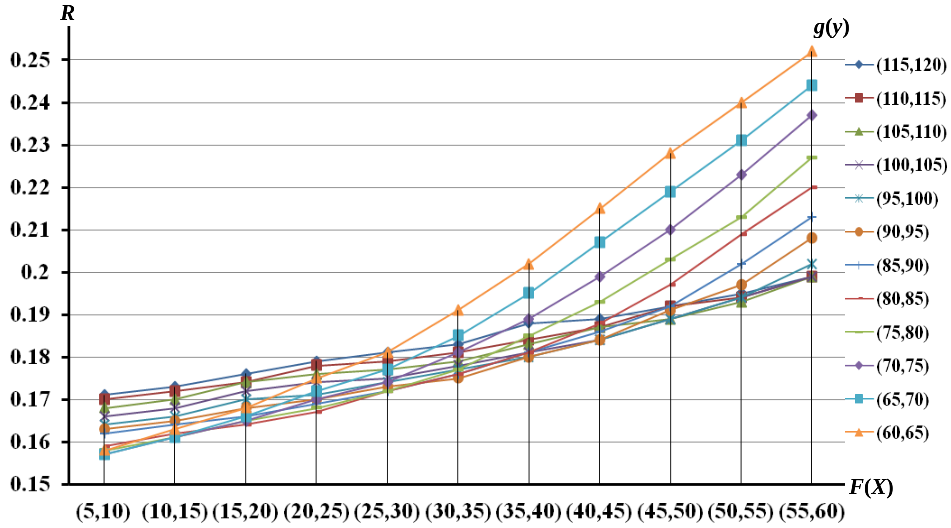


Figure 7.7: Sensitivity analysis about $F(X)$

By analyzing sensitivity, we can clearly see that the how these factors affect the R, and also can know the effect degree. And, in the practice, the managers can control R with changing these factors, master which factor can bring about larger changes, and predict the change trend. At the same time, the workers can reasonably adjust the WIP inventory level of upstream to improve R by resetting production speed, and know the change amplitude of R by adjusting the WIP. Additionally, analyzing sensitivity can provide an effective and fast search route for optimization analysis.

7.4.2 Sensitivity Analysis about Optimization

Optimization analysis can get an optimal t, g(y) and F(X) to achieve the lowest R. The manager and worker can use this optimal solution to manage WIP control as a base. Optquest is a software package embedded in the Arena. It applies Tabu Search and Scatter Search to get the optimal solution. In this Chapter, the author uses this Optquest to find the optimal control of WIP with considering change law of sensitivity analysis about three factors, which can limit down the search scope. And, according to the expressions in section 7.3.4., optimal R and constraint conditions can be presented in Optquest as follows:

$$min\ R = min\frac{TNC}{TPC} \tag{7.7}$$

$$s.t.\quad \begin{aligned} & y_{max} = y_{min} + 5 \\ & X_{max} = X_{min} + 5 \\ & y_{max} < X_{min} \\ & t = 3,4,5,...,30 \end{aligned}$$

After searching, an optimal solution is achieved: t =7 hour, $g(y)$ = UNIF (5, 10), $F(X)$ = UNIF (55, 60), and then R= 0.158. In the same way, the sensitivity analysis about optimal solution also can also be got, seen as Figure 7.8.

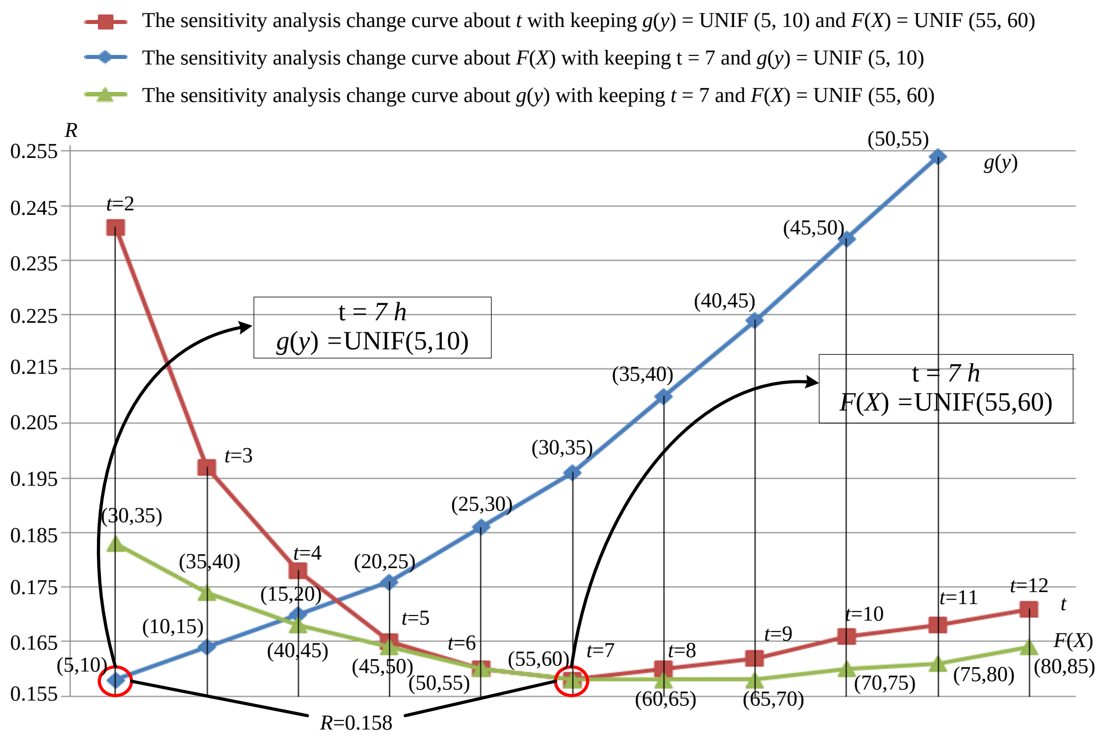


Figure 7.8: Sensitivity analysis about optimal solution

The point drawn by red circle is the optimal value R =0.158 about three curves. The '■' curve denotes the sensitivity analysis about t with keeping $g(y)$ = UNIF (5, 10) and $F(X)$ = UNIF (55, 60). With increasing t gradually, the '■' curve shows a sag change. The '▲' curve denotes the sensitivity analysis about $g(y)$ with keeping t = 7 and $F(X)$ =

UNIF (55, 60). With increasing *g*(*y*) gradually, the '▲' curve shows a sag and a ascend change. The '♦' curve denotes the sensitivity analysis about *F*(*X*) with keeping *g*(*y*) = UNIF (5, 10) and t = 7. With increasing *F(X)* gradually, the '♦' curve shows a sag change. For these curves, the optimal value is the lowest point, and the green curve is most flat, i.e. the sensitivity about *F*(*X*) is lowest. Additionally, the curvation of blue curve is the biggest, i.e. the sensitivity about *g*(*y*) is the highest. So, from Figure 7.8, we can consider that the control about *g*(*y*) is more effective than other two factors. And, for the managers or workers, in the same situation, the control priority about these three factors is: firstly, *g*(*y*); secondly, *t*; finally, *F*(*X*).

7.4.3 Comparison

After sensitivity and optimization analysis, comparison with, original model (AS-IS-1) with using MFCA partially, model applying MFCA (AS-IS-2) with using MFCA completely and optimal model with using MFCA completely, these three models can be got. By this comparison, that how the production capacity and environmental performance be improved can be seen clearly in Table 7.3.

Table 7.3: Comparison based on output data

(Unit / CNY ¥)

		AS-IS-1 Model	AS-IS-2 Model	Optimal Model
Positive Products Cost	MC	3304215.65	3267720.31	3567972.28
	SC	265691.12	240773.04	400084.87
	EC	137953.71	129730.18	140409.32
	Total	3707860.48	3638223.53	4108466.47
Negative Products Cost	MC	432109.83	468605.17	505864.96
	SC	342976.47	367894.55	256389.12
	EC	/	8223.53	9071.32
	Total	775086.3	844723.25	771325.4
Negative Cost Ratio	*R*	0.1729	0.1884	0.158
Production Capacity	*C*	10666	10666	11968

From Table 7.3, traditional accounting method about AS-IS-1 model show that *R*=0.1729, and the production capacity of positive products number is 10666. After using MFCA, it shows that *R* is changed to 0.1884. So MFCA are easier to find problem that many negative products cost is hided, and the amount of difference in cost is up to ¥70,000. After improvement adopting MFCA and fuzzy centralized control methodology, *R* is down to 0.158, and capacity is up to 11968. Comparing with AS-IS-2 model, it can be seen that, in the same work time, cost of positive products increases 12.93%, capacity increases 12.21%, but cost of negative products decrease 8.69%. So, the effect of improvement is very obvious.

7.5 Conclusions

In this Chapter, the centralized fuzzy control methodology is used to control the change of WIP inventory level, and MFCA is adopted to calculate system environmental cost by adjusting production capacity. According to comparison results in section 7.4.3, it is easily seen that the centralized fuzzy control methodology can exactly simulate WIP control by on-site operators. Also, it can adjust production ratio according to the WIP inventory level to balance production line and increase production capacity. For the MFCA, this method can be used to calculate environmental cost hiding in the production processes by the simulation for each process. Additionally, through sensitivity analysis with regard to three factors, t, $g(y)$ and $F(X)$, it can be found that the fine increment or decrement change of each factor can lead a relative big change of *R*. And, the sensitivity analysis can also make a fast search route to get the optimal solution by Optquest software package. These change laws of sensitivity analysis as well as the optimal solution give the managers and worker on-site an easy and effective control method of WIP inventory level to achieve a good performance considering production capacity and environmental cost. Comparing with three models (AS-IS-1 model, AS-IS-2 model and optimal model), a conclusion is made that the methods for controlling WIP applied in this Chapter really improve the production capacity as well as reduce green manufacturing cost that it is a scientific issue proposed in section 7.1 and have achieved the *Sub-objective 2-2* .

8 CONCLUSIONS

8.1 Conclusions

Under the modern discrete manufacturing mode, the multi-variety and small-batch production system satisfies the requirements of the diversified demands of consumers, rapid responses to market needs and high core competitive advantages. Especially, in this production system, tightly coupled cells are widely applied to improve production flexibility and precision and reduce manufacturing costs. However, the complexities and randomness of manufacturing system can lead to the ineffective control of multiple tightly coupled cells, resulting in high WIP levels and a high “block”/“starvation” frequency. Moreover, unreasonable WIP management extends production cycle times, decreases market responsiveness and causes system instability. Additionally, green production and reduced environmental impacts have been increasingly considered part of sustainable development practices. However, in the current manufacturing mode, because of the complex nature and randomicity of WIP inventory control, high WIP levels can not only affect productivity but also cause environmental costs as a result of inefficient WIP control. Owing to high WIP levels, overstocks of unnecessary materials and intermediate products are often produced, causing huge material waste, idle energy consumption, idle processing cost and stock scraps, which have substantial negative environmental burdens. Two aspects above of production capacity control and production environmental impact analysis are emphasized. Specifically, important issues in developing a WIP control strategy are achieving a lower WIP inventory level, higher productivity and better environment-oriented eco-efficiency performance. To overcome the urgent control issue, these eight chapters are structured to study the corresponding problems in detail.

In chapter one, based on previous research on the current discrete manufacturing system and inventory management, two control problems regarding WIP inventory are presented. This dissertation aims to resolve the production capacity control and production environmental impact problems of WIP inventory control, and a final goal, two main objectives and corresponding sub-objectives are proposed. Additionally, the structure of this dissertation is overviewed.

In chapter two, for different WIP inventory control problems, five corresponding control issues are overviewed, and the three control methods applied in this dissertation are illustrated.

In chapter three, the literature on WIP control issues, methods and applications are reviewed.

In chapter four, a discrete manufacturing system with one tightly coupled production cell is analyzed to resolve the production capacity control problem in WIP inventory and to achieve *sub-objective 1-1*. In this chapter, based on a simulation, a distributed fuzzy controller is developed to keep the WIP inventory and the cycle time at low levels while improving production performance.

In chapter five, a more complicated discrete manufacturing system with multiple tightly coupled production cells is studied to resolve the production capacity control problem in WIP inventory and to *achieve sub-objective 1-2*. A centralized hybrid controller is developed using simulation method to eliminate system bottlenecks and maintain the WIP inventory and the cycle time at low levels as well to increase the robustness and response capacity to increase the system stability. Additionally, this chapter extended the complexity of the manufacturing system and improved the control method studied in chapter four.

In chapter six, a Pull production mode is developed for two types of parts, and the corresponding back scheduling for the WIP inventory control system is simulated to analyze the production environmental impact problem related to the WIP inventory and to achieve *sub-objective 2-1*. Based on MFCA, substantial environmental costs and burdens caused by large WIP inventories and wastes are traced and identified. Moreover, sensitivity analyses are used to present regular changes between production lot-size determination and negative environmental impacts for on-site managers.

In chapter seven, based on simulation, a centralized fuzzy control methodology integrating MFCA is built to study the integration of and perform tradeoff analysis for the two WIP control problems. An optimal method with sensitivity analysis for three main factors is proposed to achieve *sub-objective 2-2*, with both better production capacity and less negative environment burden.

In chapter eight, the conclusions from different chapters and research objectives for different WIP control problems, academic contribution of this dissertation, and the implementation steps for the methods proposed in this dissertation and some suggestions for further research are illustrated.

For the main objectives and corresponding sub-objectives proposed in chapter one and studied in chapters four through seven, two general conclusions are obtained and explained in the following sub-sections. Furthermore, a conclusion about contribution of this dissertation to the academic is also proposed as follows.

8.1.1 Conclusion One

The subsequent statements are important points for the objective and two sub-objectives.

Objective 1:

1) Identify system bottlenecks caused by tightly coupled cells.

2) Propose a reasonable control policy for WIP inventory and cycle.

3) Avoid system imbalances and eliminate bottlenecks.

To achieve the research goals for main objective one, the following sub-objectives are applied.

Sub-objective 1-1:

1) Analyze system performance caused by one tightly coupled bottleneck cell.

2) Improve the system's productivity and robustness.

In chapter four, the followings are performed to achieve this sub-objective:

1) A multi-variety and small-batch production system with a tightly coupled cell is examined. Using production data analysis, various random factors and constraints in a system with a tightly coupled bottleneck cell causing higher WIP inventory levels and longer cycle times are analyzed.

2) A two-dimensional distributed fuzzy controller with two correction factors has been developed to resolve WIP problems. This heuristic approach is used to supervise the dynamic WIP inventory level changes and regulate the processing rate of each workstation with simple representations and linguistic IF-THEN rules.

3) Based on consideration of certain major stochastic factors, a simulation model is explored with a control objective to maintain the WIP and cycle time at a low level. Simulation results show that this optimized control policy avoids system imbalances and eliminates bottlenecks. By comparison, the proposed approach significantly improves the system's performance and robustness.

4) The specific performance indexes proposed in *Sub-objective 1-1* are achieved: (1) Table 4.5 shows that the decrease in the average value of the WIP inventory in different production lines is over 60%, and Table 4.5 shows that the "block" frequency is below 1%, the "starvation" frequency is approximately 0.1% and the two decrease are both greater than 85%; (2) Table 4.5 shows that the decrease in the production cycle time is over 50%, and Figure 4.11 shows that 97.81% of orders can be completed in 2 days and 100% orders can be completed in 3 days of delivery time; and (3) Table 4.6 shows that values of s ranging from 25 to 45 maintain system stability, including that the optimized model has higher robustness, improved stability levels and heightened randomicity tolerance for stochastic factors.

Sub-objective 1-2:

1) Eliminate serious system bottlenecks caused by multiple tightly coupled cells.

2) Enhance the system's performance, response time and robustness.

In chapter five, the followings are performed to achieve this sub-objective:

1) Through an analysis of an AS-IS simulation model, ineffective control of multiple tightly coupled production cells causing serious system bottlenecks, higher WIP inventory levels and longer cycle times are analyzed.

2) Aiming to resolve current WIP problems, a hybrid control method and a corresponding centralized hybrid controller are developed. This optimized method is used to monitor the changes in WIP and improve WIP control by integrating the Pull and Push modes.

3) In a TO-BE simulation model, the centralized hybrid controller is embedded to execute the optimized control idea. The model is explored with a control objective to maintain the WIP inventory and cycle times at low levels by dynamically regulating the processing rate of distributed workstations. The simulation results demonstrate that this optimized method avoids system instability and eliminates bottlenecks. By comparison, the proposed approach significantly improves the system’s performance, rapid response and robustness.

4) The specific performance indexes proposed in *Sub-objective 1-2* are achieved: (1) Table 5.4 shows that the average value of the WIP inventory in different production lines declined to approximately 250, and the average values of WIP inventory for tightly coupled production cells and the value for uncoupled production cells are almost the same and are both less than 60; (2) Figure 5.9 shows that block/starvation times are both reduced by over 70%; (3) Figure 5.9 shows that 84.73% of orders can be completed in 2 days and 100% orders can be completed in 3 days of delivery time; and (4) Figure 5.11 shows that the average value and SD of the WIP level in the NM model are both shorter than those of the OM model, and the difference in the average value is over 50. Moreover, the system response time of the OM model to make a control policy is longer than that of the NM model; the specific response time is reduced to less than 0.5 seconds, and the difference in response time between the two models is over 1 second.

After *sub-objective 1-1* and *1-2* are studied in chapters four and five, respectively, main *Objective 1* and corresponding *Conclusion 1* are achieved

Conclusion 1: *The optimized fuzzy control method integrating a "Pull"/"Push" mode provides remarkable control over the WIP inventory and enhanced cycle times in a multi-variety and small-batch production system with tightly coupled cells. This approach was also more successful in eliminating system bottlenecks and improving production capacity for a modern discrete manufacturing system.*

8.1.2 Conclusion Two

Objective 2:

1) Analyze the environmental effects caused by WIP inventory.

2) Propose a reasonable control policy to balance economic and environmental benefits.

To achieve these research points in main objective two, the following sub-objectives are formulated:

Sub-objective 2-1:

1) Trace the WIP caused by inappropriate production lot-size determination.

2) Identify negative environmental impacts and corresponding changes.

In chapter six, the following are performed to achieve this sub-objective:

1) Inappropriate production lot-size determination can generate substantial scrapped overdue WIP stocks and idle processing, which lead to serious negative environmental burdens. By simulating the Pull mode and back scheduling of a multi-variety and small-batch production system, large WIP overstocks and other wastes caused by current production lot-size determination are traced.

2) For comparison with the conventional cost accounting used in the original simulation model, a new environmental management accounting method, Material Flow

Cost Accounting (MFCA), is introduced to identify negative products cost related to environmental impacts hidden in the production processes.

3) After sensitivity analysis by gradually regulating the production lot-size, two regular changes in the negative products cost and the corresponding percentages in the total cost are observed. These change trends indicate that a reasonable determination strategy for production lot-size can maintain a low WIP inventory level and improve both economic and environmental performances.

4) The specific performance indexes proposed in *Sub-objective 2-1* are achieved: (1) Table 6.3 shows that for different workstations, the scrap probability of WIP overstocks, the probability of defective products in the WIP, the probability of processing residues or shavings and the frequency of setup time are obtained; (2) Table 6.5 shows that for each unit part, the negative products costs of M_1 and M_2 both make up over 30% of the total cost, separately; and (3) Figure 6.7 and 6.8 show that the negative products cost of the unit part and the corresponding percentages change in a cyclical manner with changing production lot-size.

Sub-objective 2-2:

1) Calculate environmental waste hidden in the production processes.

2) Propose an optimal method for minimizing the negative environmental cost while improving production capacity.

In chapter seven, the following are performed to achieve this sub-objective:

1) In order to dynamically analyze and control changes of WIP inventory level, a centralized fuzzy control method is proposed. Additionally, a new environmental management accounting method, Material Flow Cost Accounting (MFCA), is adopted to find and calculate environmental waste hiding in the production processes.

2) A simulation model integrated with fuzzy control method and MFCA above is constructed. Based on the simulation data, sensitivity analysis between control factors of WIP inventory level and negative product costs ratio is made.

3) To achieve a reasonable productivity as well as green environmental performance for this case, a corresponding optimized solving measure is put forward by means of OptQuest in the Arena simulation system. Through studying, the proposed control approach of WIP reduced the green environmental cost, and improved production capacity.

4) The specific performance indexes proposed in *Sub-objective 2-2* are achieved: (1) Table 7.3 shows that the cost of positive products is increased by 12.93%, capacity is increased by 12.21%, and the cost of negative products is reduced by 8.69%; (2) Figure 7.8 shows that the control method integrating the fuzzy controller and MFCA can obtain an optimal negative product ratio, and the specific value is reduced to 0.158; (3) the sensitivity analyses in figures 7.5, 7.6, 7.7 and 7.8 show that the control priorities for these three factors are as follows:: first, $g(y)$ (the lowest fuzzy control threshold value of WIP); second, t (examination time of WIP inventory level); and final, $F(X)$ (the highest fuzzy control threshold value of WIP).

After studying *sub-objectives 2-1* and *2-2* in chapters four and five, respectively, main *Objective 2* and corresponding *Conclusion 2* are achieved:

Conclusion 2: *The new environmental management accounting method-MFCA identified the abandonment of the dead WIP stocks, useless materials and idle processing as the generation of negative products cost in terms of monetary units, which were invisible during production. The integration of the fuzzy control method with MFCA provides the managers and workers on-site an easy and effective control method for the WIP inventory level to achieve good performance considering the criteria of production capacity and negative environmental impacts.*

8.1.3 Conclusion Three

In this dissertation, three academic contributions are obtained.

First, fuzzy control method is applied to study a classic discrete system and various stochastic factors are considered. However, in previous studies, the continuous system mode and only two random factors (machine failure/repair probability and demand change) are focused on. This dissertation thus expands the application field of fuzzy control in the production research, and also improves system complexity.

Second, a simulation method integrating hybrid control mode is structured to analyze the tightly coupled production cell. It can provide some new method to consider finite WIP buffer control and CONWIP management.

Third, in a multi-variety and small-batch production system, the environmental effect of WIP management is considered. MFCA method related to environmental protection has been developed to improve economic efficiency while reducing environmental burden. This study opens up a new vision angle for the WIP control.

8.2 Implementation

8.2.1 Implementation of Fuzzy Control

In this dissertation, fuzzy control methods are applied in chapters 4, 5 and 7 to maintain the WIP inventory and cycle time at low levels while improving the system performance. A corresponding fuzzy controller is developed in a different chapter because: the fuzzy control method is a heuristic method with some simple control principle representations using IF-THEN rules, rather than other optimal methods that require complicated mathematical methods to analyze and deduce an algorithm for the real system. The implementation of fuzzy control for the real system is very important. This dissertation is a summary of one part of a current research project in Metal Worker Toa & Arai Company, Ltd. The improved approach has not been implemented. However, according to recent work from the team, four steps to apply this fuzzy control method for this project can be taken.

First, fuzzy control is not an accuracy control method. The inputs are the relative and absolute error values in the WIP inventory levels. The output is the processing rate for the workstation. According to the fuzzy rules and calculation steps, the inputs and output are classified as ranges. Consequently, a look-up table for inputs for fuzzy calculation can be designed. Additionally, a look-up table for control policy according to the corresponding output can also be developed (Table 8.1 shows a simple look-up table integrating one input and one output).

Table 8.1: A simple look-up table integrating one input and one output for fuzzy control

	Input: WIP Inventory Level l		
	Low ($l < s^{(1)}$)	Normal ($s \le l \le S^{(2)}$)	High ($l > S$)
Output: Processing Speed p	High $p \bullet (1+r^{(3)})$	Normal p	Low $p \bullet (1-r)$

Notes:
$s^{(1)}$, $S^{(2)}$ is upper bound and lower bound respectively, and obey inventory control model (s, S)
$r^{(3)}$ is processing control rate

Second, an ERP system is used at this company. At the beginning of the WIP checking cycle, managers can obtain the WIP level value from this information system. The workers at each workstation can collect WIP level data from the corresponding buffers. Consequently, the production managers can easily correct these two data, accurately check the inventory level and master changes in this inventory level. Then, after using the two look-up tables and inputting the value of the inventory level, the managers can easily determine the optimal control policy for each distributed workstation.

Third, the workers should be trained to understand the managers' instruction bills and accurately regulate the workstation.

Finally, before implementation, a plan and a schedule should be developed in detail. During the implementation, many problems in the real production system will be met. Our research team will discuss these problems with workers and managers and then propose reasonable solutions.

8.2.2 Implementation for MFCA

In the MFCA guide (Environmental Industries Office, 2007), the implementation steps for MFCA are described in table 8.2 below. Additionally, the cases in which MFCA has been successfully applied in companies or enterprises have provided numerous suggestions and references for implementation (Environmental Industries Office, 2010).

Table 8.2: Steps for MFCA implementation

Basic Steps		Examination & Operation Items
1	Preparation	Determine targeted products, lines and processes.
		Perform rough analysis of targeted processes and determine quantity centers (theoretical processes in MFCA calculation).
		Determine models and periods to analyze.
		Determine materials to analyze and the methods of collecting their quantity data (measurement & calculation).
2	Data collection & compilation	Collect and compile the data of material types, their input & waste quantities in each process.
		Collect and compile the data of system (processing) cost and energy cost.
		Determine the allocation rules for system and energy costs.
		Collect and compile the data of machine operating status for each process (optional).
3	MFCA calculation	Establish an MFCA calculation model and input the required data.
		Confirm and analyze the MFCA calculation results (negative product costs and their causes by process).
4	Identifying improvement requirements	Identify and list requirements for improvement, including material loss & cost reduction.
5	Formulating improvement plans	Examine the extents and possibilities of material loss reduction.
		Calculate and assess the cost cut effect through material loss reduction (MFCA calculation).
		Determine priorities of improvements and formulate improvement plans.
6	Implementing improvements	Implement improvements.
7	Evaluating improvement effects	Identify the quantities of input and wasted materials following the improvement, and recalculate MFCA.
		Calculate the overall costs and negative product costs following the improvement, and evaluate the improvement effects.

The key in these steps lies in collecting and compiling the data of input and wasted material quantities in each process. Although it is desirable to measure such quantities on-site, the survey may take too much time if you make all the measurements on an on-site basis. You may accept estimates from theoretical values or calculated figures as long as they have tolerable accuracy. Inappropriate measurements may make it unable to identify losses. Examine what data should be usable considering that the required calculation accuracy depends on your objective of implementing MFCA. You must also note that on-site input management is often based on the numbers and other units of materials, not on quantities in kilograms. In such cases, you shall convert the on-site data of input and waste quantities into kilograms. You will also have to establish an

MFCA calculation model to perform the required operations using the on-site management data as parameters.

In this dissertation, the WIP inventory level is studied to reduce negative environmental burdens. The implementation of MFCA on this aspect should focus on the following points:

First, an appropriate production line and part types should be determined for easy analysis. Additionally, products should be divided into positive and negative products in each process. The categories of negative products should be classified and identified. Furthermore, system cost (SC) and energy cost (EC) should be allocated to positive and negative product costs, in accordance with the proportion of positive and negative product quantities.

Second, for WIP inventory, the ERP system or on-site managers should monitor the dynamic inventory level and inventory time. Moreover, the scrap probability of WIP overstocks, the scrap probability of defective products in the WIP, the probability of processing residues or shavings, the setup time, the usage quantity of auxiliary fluids, the protection liquid for the WIP inventory and other related green environmental materials needed should be determined.

Third, other production data related to green manufacturing and environmental protection should be collected.

Fourth, the unit of quantity centers should be given appropriately. Quantity centers are theoretical units in the MFCA calculation. Theoretically, regarding all loss-causing points as quantity centers is desired.

Finally, with the application of MFCA, reasonable improvement policies (such as the fuzzy control method applied in chapter 7) should be considered. Additionally, the implementation of MFCA is a process of fine management and continuous improvement.

8.3 Suggestions for Future Research

8.3.1 Fuzzy Control in Managing the WIP Inventory

In the discrete manufacturing system, the control method for the WIP inventory is restricted by various random factors. Accurately controlling these variable factors to achieve predetermined objectives is more difficult.

For the production system, the selection of the safety stock ***s*** and checking time ***T*** are the crucial factors that determine the cumulative WIP level before regulating production, system balance, and selection of other fuzzy control variables. Although Section 4.4.5 (Comparison and Remarks) in Chapter 4 simply discussed robustness analysis of the WIP and cycle time with variations in safety stock ***s***, the mechanism describing how these factors affect production balance and robustness has not been studied yet. The optimized selection of and determination strategies for safety stock ***s*** and checking time ***T*** should be investigated in future research. Furthermore, the impacts on the fuzzy control parameters coming from different selections of the safety stock ***s*** and checking time ***T*** will be considered in the future.

On the other hand, for the fuzzy control method, the improvement of the control mode, the selection of the control parameters and the partition of the fuzzy membership function are important for WIP inventory control. Different parameters will produce different performances for production control. Though section 4.3.3 (Remarks) in chapter 5 illustrated that an optimized control for the fuzzy mode has improved efficiency in reducing the WIP level and maintaining the system stability, the reasonable determination of other control parameters has not been discussed. Homayouni et al. (Homayouni et al., 2009; Suhail and Khan, 2009) illustrated that different values will produce a large effect on the control performance of fuzzy logic. Tedford et al. (Tedford and Lowe, 2003; Tsourveloudis, 2007) presented the advantages of an intelligent algorithm for identifying optimal fuzzy control parameters. Based on these achievements and suggestions, a simulation method integrating intelligent algorithm will be applied to study reasonable control parameters in the future research.

Additionally, the implementation of the fuzzy control method is also an important research issue. An optimized and reasonable fuzzy controller or method from theory cannot always be implemented effectively in practice due to many random constraint factors in the real production system. The complexity of the system, randomness of production and knowledge or technology of the managers or workers influences on the implementation scale and precision of the fuzzy control method. Therefore, implementation for fuzzy control will be considered in the future.

8.3.2 Environmental Consideration Issue on WIP Inventory

Chapter 6 discusses the overstocks of WIP produced by the inaccurate determination of the production lot-size, thus creating substantial environmental burden. In the multi-variety and small-batch production system, there exist many operation activities that directly or indirectly impact the WIP inventory level and environmental performance. In future research, the determination of delivery time and the dynamic order decomposition mechanism will be studied to provide a reasonable decision-making policy for environmental considerations.

In this dissertation, MFCA was applied to identify and calculate invisible wastes and negative environmental costs. Although MFCA is an effective environment evaluation method for discovering problems, this approach cannot be used to resolve problems. Therefore, improving the integration of MFCA with other appropriate optimal methods will be considered in future studies.

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