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藉多動態庫存管理設計閉迴路運籌

Closed-Loop Logistics Based on Dynamic Multi-Buffer Management

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摘要

傳統的供應鏈中，通常補貨模式是由推式管理的方式來運作，搭配預測，來盡量滿足客戶需求。然而需求的預測十分不精準，在原物料、商品種類過多的情況下，不適當的庫存管理和生產活動必將造成公司的損失，並且侵蝕其獲利水準。

本研究以動態庫存管理 (Dynamic Buffer Management, DBM)為基礎，發展成多動態多庫存管理 (Dynamic Multi-Buffer Management, DMBM)，以 ABC 存貨分析對不同的貨物和原物料分別管理，並給予不同的服務水準以及調整變數，再利用帝國競爭演算法求得最佳的管理變數，並搭配拉格朗日鬆弛法輔以偽梯度法 (Lagrangian Relaxation with Surrogate Sub-Gradient Method)，讓生產到存貨都獲得最佳控制。

希望能推廣 DBM，讓企業了解 DBM 能有助於不同產業公司應對市場需求的變動，並且避免產生大量損失，提升公司應變能力，提高獲利能力。

關鍵詞： 動態庫存管理、 拉格朗日鬆弛法、推式生產

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Abstract

Forecasting and push system are implemented to help enterprises do the replenishment in traditional supply chain. However, the forecasting is not always accurate. Once the market trend turns down, company has to face the fact of much higher inventory which can significantly affect to profit margin. The more types of products and material the company has, the more difficult to manage.

Based on the Dynamic Buffer Management (DBM), this paper tries to study another way study of Demand-Pull way, Dynamic Multi-Buffer Management (DMBM), to help enterprise to manage multi-products. With ABC classification to manage different type of products and material, Imperialist Competition Algorithm (ICA) is used to find factors of service level and adjustment factors for DMBM. Moreover, Lagrangian Relaxation with Surrogate Sub-Gradient Method is used to make inventory management and manufacturing system coordinated.

The proposed method has been used in a company, and the result is satisfactory.

Keywords: Dynamic Buffer Management, Lagrangian Relaxation with Surrogate Sub-Gradient Method, Demand-Pull.

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Nomenclature

DDMRP

ADU = average daily usage

$ASRLT$ = sum of unprotected flow of lead-time

LT = lead-time factor

VAR = variability factor

PAF = planned adjustment factor

ABC classification

y_{ij} = Measurement of the i th item under the j th criteria

Si = score of the i th item

S’ = Si ’s in descending order

LR with surrogate –gradient method

B_i = beginning time of part i

C_i = completion time of part i

c_{ij} = completion time of operation (i, j)

D_i = due date of part i

E_i = earliness of part i, which is $\max(0, D_i - C_i)$

T_i = lateness of part i, which is $\max(0, C_i - D_i)$

m_{ij} = machine type selected to process operation (i, j)

$M_{h\tau}$ = number of available machine type h at time τ

O_h = set of operation that can be performed on machine type h

t_{ijh} = processing time of operation (i, j) on machine type h

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w_i = lateness weight of part i

β_i = earliness weight of part i

δ_{ijh} = operation index over time for machine of type h with $\delta_{ijh}(\tau)=1$, if operation (i, j) is performed on a machine of type h at time τ. Otherwise $\delta_{ijh}(\tau)=0$. In other word, $\delta_{ijh}(\tau)=1$ for $m_{ij}=h$ and $c_{ij}-t_{ijh}\le\tau\le c_{ij}$, and else $\delta_{ijh}(\tau)=0$

J_{IP} = integer programming problem in considered

x = an $n\times 1$ decision variable with $n=\sum_{i=1}^{I} n_i$

Z = the set of integers.

$L(\lambda)$ = Lagrangian dual problem of J_{IP}

λ = a vector of Lagrangian multipliers.

$\tilde{L}(\lambda, x)$ = surrogate dual problem of J_{IP}

$\tilde{g}(x)$ = $Ax- l$

λ^0 = λ at initialized iteration

x^0 = x minimized the $\tilde{L}(\lambda^0, x)$

L^* = $L(\lambda^*)$, the optimal objective of the Lagrangian dual problem.

$\tilde{L}^k$ = $\tilde{L}(\lambda^k, x^k)$, which is the objective of surrogate dual at the kth iteration.

s^k = $\beta\left(L^*-\tilde{L}^k\right)/\left\|\tilde{g}^k\right\|^2$, which is the sub-gradient term

L^U = $\left(1+w/\theta^{\rho}\right)\times\tilde{L}^{[k]}$, which is an estimation of L^*

$\tilde{L}^{[k]}$ = the best surrogate dual to iteration $k-1$.

w = a parameter which is chosen within [0.1, 1.0].

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ρ = a parameter which is chosen within [1.1, 1.5].

θ = adaptively adjusted by the formula below.

$$\theta = \begin{cases} \max(1, \theta - 1), & if \quad \tilde{L}^k > \tilde{L}^{[k]} \\ \theta + 1, & otherwise \end{cases}$$

ε_1 = tolerance of change in λ at each iteration

ε_2 = tolerance of change in x at each iteration

DMBM

TDD = throughput-dollar-day

IDD = inventory-dollar-day

LT = average lead time

variation factor = coefficient of variation

ADU = $(\sum_{t=1}^{t+length} demand_t) / length$

Re = quantity of material

TIL = target inventory level

IL = recent inventory level

W_{IDD} = weight for *IDD*

W_{TDD} = weight for *TDD*

dem_t = quantity of customer’s demands so far.

length = time started from $t = 1$ till now.

ICA

country = an array of variable values to be optimized

N_{pop} = number of colonies

N_{imp} = number of imperialists

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N_{col} = countries which is a colony and be assigned to an empire

C_n = $c_n - \max_i\{c_i\}$

c_n = cost of nth imperialist

C_n = cost of nth imperialist be normalized cost

P_n = The normalized power of each imperialist

x = distance each colony move $x \sim U(0, \beta \times d)$

β = a number larger than 1

d = distance between the colony and imperialist

θ = direction of the movement. $\theta \sim U(-\gamma, \gamma)$

γ = an adjustment factor that makes the deviation from original direction.

TC_n = $\cos t(imperialist_n) + \delta \times mean(\cos t(colonies\ \ of\ \ empire_n))$

δ = a positive number and it is lower than 1

SL_{PA} = service level of product of type A

SL_{PB} = service level of product of type B

SL_{PC} = service level of product of type C

SL_{MA} = service level of material of type A

SL_{MB} = service level of material of type B

SL_{MC} = service level of material of type C

α_{PA} = adjustment factor of product of type A

α_{PB} = adjustment factor of product of type B

α_{PC} = adjustment factor of product of type C

α_{MA} = adjustment factor of material of type A

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α_{MB} = adjustment factor of material of type B

α_{MC} = adjustment factor of material of type C

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Chapter 1 Introduction

1.1 Motivation

From ancient times to the present, there are always problems, inventory management and scheduling, among manufacturing enterprises.

Successful inventory management creates a purchasing plan to ensure that items are available when they are needed and it keeps track of existing inventory and its use.

In order to do so, the manufacturer determines the quantity of products and inventory by using a strategy of push supply chain based on the vendor’s forecast. However, the vendor’s forecast is always higher than the actual customer’s demand and the push supply chain brings the bullwhip effect, so the enterprise cannot get real time information and must hold a high inventory. A company's inventory is one of its major assets and represents an investment that is tied up until the item is sold or used in the production. It also costs money to store, track and insure inventory. Inventories that are mismanaged can create significant financial problems for a business, whether the mismanagement results in an extra inventory or an inventory shortage.

Good scheduling plans brings advantages like:

1. More predictable lead times based on accurate, real-time evaluation of your jobs
2. More optimized use of available resources, including material constraints, work center uptime and labor capacity
3. Lower inventory levels and minimized production costs as materials are only ordered when they are needed
4. Demand driven, more reliable on-time delivery for increased customer service
5. Notifications and exception messages for increased business activity

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monitoring and proactive decision making

However, most of inventories and scheduling are mismanaged by human decision. Along with the development of techniques, research combined with computer science can be used in solving inventory management problems and scheduling problems. To optimize the quantity of inventory and scheduling plan, a closed-loop logistics (CLL) is considered. It is a closed-loop control system, also known as a feedback control system. Closed-loop systems are designed to automatically achieve and maintain the desired output condition by comparing it with the actual condition.

There are two CLLs in the system. First part is about dynamic buffer management (DBM). This part is about the demand-driven material requirement planning (DDMRP). There has been an increasing interest in pull strategy because push strategy causes high inventory. Pull supply chain is extended to the concept of DDMRP, which means that the manufacturer no longer produces products in terms of the forecast but produces products owing to the actual demand from customer. Moreover, in actual situations for enterprise, a long lead-time is an urgent problem that should be solved for the manufacturer. Therefore, the manufacturer starts to set many buffers for different product so that the manufacturer can disperse the inventory. This strategy is applied from DDMRP which we call dynamic buffer management (DBM). The biggest advantage of DBM is cutting down the lead-time.

However, DBM is set for finished goods. Additionally, classifications of inventory can help inventory manager to determine control policies to apply on the different inventory. In this study, DBM is extended into dynamic multi buffer management (DMBM) which is set for multiple products and material management. ABC analysis is used to manage inventory more efficiently.

Second part is about scheduling which is a function of MRP. Scheduling is the

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process of arranging, controlling and optimizing work and workloads in a production process or manufacturing process. The purpose of scheduling is to minimize the production time and costs, by telling a production facility when to make, with which staff, and on which equipment. Production scheduling aims to maximize the efficiency of the operation and reduce costs. This study will focus on how to lower the inventory and satisfy customer's demand. Moreover, after scheduling, manufacturer will know the consumption of materials. This can make inventory management become more efficient.

This study will do a simulation of inventory management and scheduling plan in C#. For inventory management, this study will get the optimization of adjustment factors and service levels while penetration happened in DMBM by ABC analysis and 2.4 imperialist competitive algorithm (ICA). For scheduling plan, this study will do job shop scheduling by Lagrangian relaxation with surrogate sub-gradient method.

1.2 Literature Reviews

There are two main factors that make inventory is hard to manage. One is bullwhip effect and the other is loss of real information.

The bullwhip effect is one of the most significant causes of high inventory. Sheu [1] proposed that the bullwhip effect is due to three related phenomena. One of the three is delayed information transferring. Sheu also proposed that a shortage of logistics control techniques still exists coordinating demand information for solving problems caused by the bullwhip effect.

The loss of real information is another cause of the manufacturer maintaining too much stock. Closs, Goldsby and Clinton [2] mentioned that information is a logistics resource and information technology is a competitive weapon if the manufacturer can

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control and handle actual information. Both Lee, Ho and Lau [3] and Keskilammi, Sydanheimo and Kivikoski [4] used radio frequency identification (RFID) to enhance the responsiveness of the logistics flow. That can increase the capability and reduce the cost.

Today inventories are used as a buffer to even out variations and handle uncertainty by many manufacturers. With a volatile market creating stochastic demands and a production process working best under economies of scale, the inventory can be seen as a way to balance these conflicting goals. A low response time to the customers and an effective usage of the production apparatus is often very hard to combine without an inventory. With this in mind, inventory management can be seen as managing the conflicting goal between supply, i.e. procurement and production, and demand.

Even though there usually are inventories both before and after the production, it is often the procurement on the component side that is under consideration in inventory management theory. One reason for this is that the production planning philosophy often overrides the inventory decision made in the finished goods inventories. In a push environment, where the work is scheduled based on demand, the inventory levels are direct consequences of the order releases and quantities, while they are ideally fixed and pre-calculated in a pull environment where the work is authorized through the status of the system.

The literature on inventory management is vast, reaching from introductory textbooks in operations research and management science to purpose-made journals, and the use of operations research models and decision support systems (DSS) within inventory management is wide spread in industry. The number of software providers that offer DSS for inventory management is large and growing, and the large enterprise resource planning system providers all have inventory management as an integrated part

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of their systems. A general inventory management framework is presented in Hillier et al. [5]. It comprises the following four steps:

1. Formulate a mathematical model describing the behavior of the inventory system.
2. Seek an optimal inventory policy with respect to this model.
3. Use a computerized information processing system to maintain a record of the current inventory levels.
4. Using this record of current inventory levels, apply the optimal inventory policy to signal when and how much to replenish inventory.

Even though all four steps are important and for the whole system to work, it is mainly in step 1 and 2 that operations research expertise is needed. Ranging from tailor-made and very sophisticated systems to off-the-shelf products, some of the systems are based on relatively basic operations research theory, while others include advanced methods and algorithms. Our experience is that very few users in industry are familiar with the underlying assumptions and methods in the inventory management DSS implemented in their organization. The road to these systems and models started in the early twentieth century with the derivation of the economic order quantity, the production lot size model, and the newsboy problem. These models have since then been extended with among other things; multiple products, multiple tiers, defective items and discrete times between shipments. For a clear and precise description of inventory management, the reader is referred to D. R. Anderson et al [6].

The cost structures and supervision of the inventory are very well developed in most systems, and functions for handling for example contracts, discounts, alternative parts, and so on are easily managed. The same can be said about the integration between inventory management and production, especially in make-to-stock environments.

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Material requirement planning (MRP) is a computer-based inventory management system and it is well-known for assisting production managers. Most of the information about the number of the quantity is decided according to the consequence of MRP. However, MRP is used successfully only in the early days because the forecast accuracy gets lower due to the variety of demand. Plenert [7] proposed that, in the case of MRP, MRP lost the optimization without considering the real demand, so that the inventory cost is tremendously higher than just in time (JIT). Herer and Masin [8] also proposed the viscous cycle of MRP, which is illustrated in Figure 1-1. D. A. Smith and C. Smith [9] indicated that MRP does not facilitate the material's availability and merely does manufacturing planning without considering the materials.

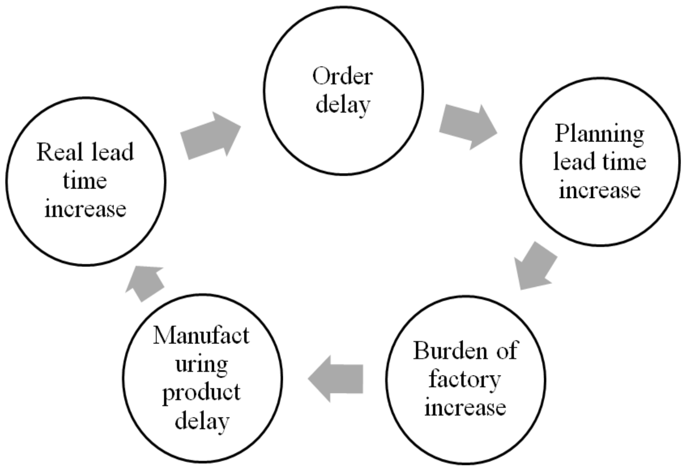

Figure 1-1　The vicious cycle of MRP

Due to the disadvantages of the push supply chain and MRP, manufacturer tends to use pull supply chain and manufacture products according to the actual demands of the customer. In 2011, Ptak and Smith [10] introduce a new type of MRP called Demand Driven Material Requirement Planning (DDMRP) in the book of "Orlicky's Material Requirement Planning" to eliminate MRP's shortcomings while integrating the

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pull-based replenishment tactics. R. Miclo et al [11] consider that DDMRP is recognized as a right solution by combining best practices of MRPII, Lean, Theory of Constraints (TOC), Distribution Resource Planning, 6 sigma and with some innovations. DDMRP highlights MRP and Lean deficiencies.

1.3 Contribution

This study focuses on the efficient inventory management for manufacturer by CLL and DMBM. Moreover, this study will make scheduling system for manufacturer by Lagrangian relaxation with surrogate sub-gradient algorithm. This study will build a system with two CLLs to make the system of manufacturers from “push” to “pull”. In other words, the system can make them become demand driven.

DDMRP and DBM are the new concepts that were proposed a few years ago, so only a few theses focus on this aspect. These papers said that DDMRP can perform well. Even the forecast of demand is not good. The concern of the benefit that DDMRP can bring to the company is doubted. Additionally, enterprises not dare to take the risk to make some change.

For the problem of finding optimal adjustment factors, the ABC analysis and ICA are used to find the optimization of adjustment factors and extended DBM into DMBM.

In this study, we want to convince enterprises that DMBM is good for them. Concept of DBM and CLL are used to build up the inventory management system combining with scheduling system. simulation will be done using data from a manufacturer in China to get more practical analysis to compare the enterprise with DMBM. The comparison will show that DMBM can help company to increase profit and lower down inventory with customer satisfaction.

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1.4 Thesis Organization

This study includes two main topics. First, the adjustment factors and service levels for different products and materials while penetration is happening in DMBM and initialized of target inventory level. Second, job shop scheduling by Lagrangian relaxation with surrogate sub-gradient method.

In Chapter 2, the background knowledge of CLL, DBM, ABC analysis, ICA, and Lagrangian relaxation with surrogate sub-gradient method are reviewed.

In Chapter 3, the structure problem and model formulation for the manufacturer is described.

in Chapter 4, The optimization of adjustment factors and service levels by ABC analysis and the ICA is performed as well as the result of job shop scheduling by Lagrangian relaxation with surrogate sub-gradient method is shown.

In Chapter 5, the conclusion and future works are presented.

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Chapter 2　Background Knowledge

2.1　Closed-Loop Logistics (CLL)

CLL is designed for decreasing down inventory level and solving the problem of late information. It is not the same concept of the term that is used in remanufacturing. It is originated from the closed-loop control system. Graves and Willems [12] proposed that firms are expected to improve customer service by reducing delivery lead-times and increasing on time deliveries. The basic core of CLL originated from the closed-loop control system. Closed-loop systems are designed to automatically achieve and maintain the desired output by comparing it with the actual condition. It does this by generating an error signal which is the difference between the output and the reference input. In other words, a “closed-loop system” is a fully automatic control system. The control action of the system depends on the output. Sensor monitors the error and compare it with the input reference. The error signal is amplified by the controller, and the controller output makes the necessary correction to the system to reduce any error, like figure 2-1 below.

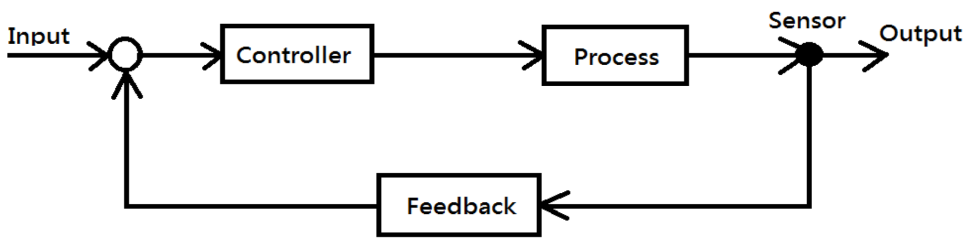

Figure 2-1　Closed-loop control system

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2.2 Demand Driven Material Requirement Planning

D. A. Smith, C. Smith R. [9] and Miclo et al [11] mentioned that DDMRP is a "multi-echelon materials and inventory planning and execution solution". DDMRP gathers the advantages of five methods as MRP, Distribution Requirement Planning (DRP), lean, six sigma, TOC.

There are 5 steps in the DDMRP and they are shown below:

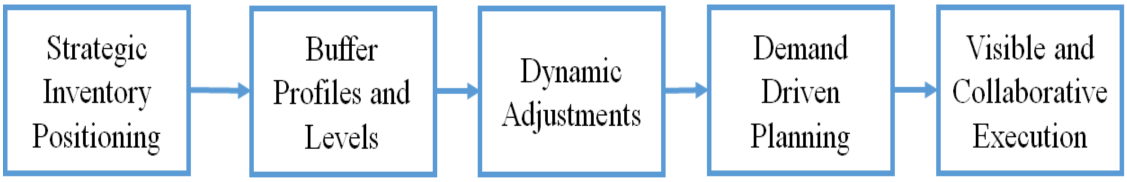

Figure 2-2 Five steps of DDMRP

Strategic inventory positioning is the first step and it is most strategic and original. At this stage, evaluations should be taken from a financial point of view if there are benefits, to position or not a buffer on an article of a bill of materials (BOM).

Second, how much inventory should be placed is decided in step of buffer profiles and levels. Buffer inventory is divided into 3 zones: red, yellow and green. When the inventory gets into the yellow zone, a replenishment order is put to reach the green zone upper level. The size of three zones is calculated as below:

1. The size of the green zone is determined by one of three ways:
   - $100\% \times ADU \times ASRLT \times LT \times \mathrm{PAF}.$
   - A significant minimum order quantity.
   - An imposed minimum order cycle.

   The size of the green zone is one of the ways that yields the largest number. This zone determines the frequency of order generation and the order size.

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2. The size of the yellow zone is the mean in-process replenishment quantity which is determined by the equation below:
   - $100\% \times ADU \times ASRLT \times \mathrm{PA}F$
3. The size of the red zone is the sum of red base and red safety. They are determined by the formula below:
   - Red base = $100\% \times ADU \times ASRLT \times LT \times \mathrm{PA}F$.
   - Red safety = red base × *VAR*.

   Red zone is the safety embedded in the buffer position.

where *ADU* is average daily usage and *ASRLT* is actively synchronized replenishment lead-time which is an original concept of DDMRP. It is the longest unprotected sequence in the BOM of a buffered article. It is a sum of lead-time. *LT* is lead-time factor which is used to decide the size of red zone and green zone. When the lead-time is long, *LT* should be small, and vice versa. The shorter the *LT* is, the higher the replenishment frequency is. *VAR* is variability factor that is used to protect from uncertainty. It is a part of the red zone. *PAF* is planned adjustment factor. *PAF* is used in the stage of dynamic adjustments to raise or lower the buffer size for seasonality, promotions or else.

In the end, the visual planning and execution tables are used to make decisions.

2.3 Dynamic Buffer Management (DBM)

The concept of DBM comes from DDMRP and TOC. DBM is a dynamic system with visualization format. DBM mainly focuses on the stock of finished-goods and has five color zones. There are five color-coded zones that comprise the total buffer. As Figure 2-3, light blue means that stock is redundant; green means that stock is sufficient;

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yellow means that stock is balanced; red means that it is going to be used up; dark red means that stock out.

Figure 2-3 Five color zones of DBM

The size of the initial buffer is depending on the equation below:

$$Initial\ Buffer\ Size = LT \times ADU \times VAR \times SL \qquad (2.1)$$

where *LT* is lead-time in the unit of day. *ADU* is average daily usage. *VAR* is variation factor. *SL* is service level.

Buffer penetration that is mentioned in chapter 1.3 is buffer size less quantity on-hand and buffer penetration rate is buffer penetration divided by buffer size. Table 2-1 shows the relationship between penetration rate and five zones:

Table 2-1 Buffer zones and buffer penetration rates

Buffer penetration rate	Color of zone
<0%	blue
0~33%	green
33%~66%	yellow
66%~100%	red
>100%	deep red

The fundamental origin is from the notion of DDMRP which advocates that the manufacturer should produce along with real demand rather than forecast.

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The ideal range is hoping the inventory is kept in the yellow interval because yellow zone means balance stock instead of redundancy or stock-out. DBM is based on the assumption that the customer's demands of customer follow normal distribution. Therefore, through the concept of service level, the manufacturer can set the target of customer to satisfy.

Based on several factors, different materials and parts behave differently. However, many also behave very similarly so that parts and materials are grouped into like ‘‘buffer profiles’’. Buffer profiles make a unique top level and zone definition for each part or material. Four key factors including item type, supply and demand variability, lead time and minimum order quantity form the various groups.

In the practical use of DBM, there are penetration happened which is caused by many reasons that may bring about fluctuation including latest customer's demands are comparatively large, latest customer's demands are comparatively small, and safety stock basis set is wrong. In order to make the inventory kept in yellow zone, this study does the optimization of adjustment factors and service levels by ICA algorithm.

2.4 ABC Analysis

Inventory is hard to keep so Bruckner and Wrede [13] proposed that classifying the inventory into different groups. Different groups of inventory need different policies to manage.

ABC analysis is a well-known technique to classify inventory into three categories. The ABC analysis suggests that inventories of an organization are not of equal value. Thus, the inventory is grouped into three categories (‘A’, ‘B’, and ‘C’) in order of their estimated impact on overall inventory cost. There is no fixed threshold for each class,

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different proportion can be applied based on objective and criteria. ABC Analysis is similar to the Pareto principle in that the 'A' items will typically account for a large proportion of the overall value but a small percentage of number of items. One type of threshold is shown as Figure 2-3. Items that categorized into group 'A' are those making about 80% of company's business but only taking up 10% of inventory. They are critical to the functioning of the company. Group 'B' inventory items are those representing about 15% of company's business and taking about 20% of inventory. Group 'C' items are those representing only 5% of company business but taking up about 70% of inventory. Figure 2-4 shows the relationship between cumulated value percentage and cumulated portion.

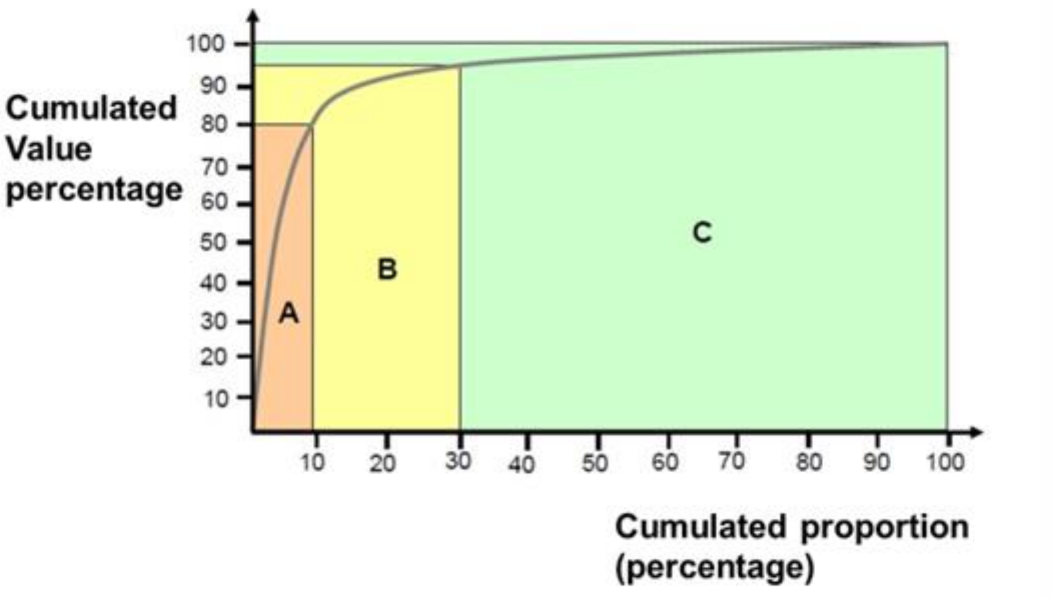

Figure 2-4 Three types of classification of ABC analysis

This classification technique is based on only single measurement such as annual dollar usage or percentage of company business. It has been recognized that other criteria, like inventory cost, part criticality, lead time, …… and so on are also important

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in inventory classification. Research on decision tools for multi-criteria inventory classification (MCIC) has been developed for 20 years. Techniques like cross-tabulate matrix methodology by Flores et al. [14], a solution procedure blending clustering analysis and operations constraints for inventory classification that was proposed by Partovi et al. [15], AHP that proposed by Cohen and Ernest [16] and Meta-heuristics that proposed by [17], artificial neural network (ANN) that proposed by [18]. They have been applied on the problem, but they are difficult for average material managers to understand how to use. A very recent attempt by Ramanathan [19] is to develop a weighted linear optimization model to the problem in 2006. The basic concept of model that L. N. Wan proposed [20] is closely similar to the concept of data envelopment analysis (DEA). Wan has developed a DEA-like linear optimization to do classification for the MCIC problems. It is easy to use and understand. The scheme of the classification technique will be introduced in chapter 3.2.

2.5 Imperialist Competitive Algorithm

Different methods for evolutionary algorithm for optimization, like genetic algorithm (GA), particle swarm optimization (PSO) and so on has been proposed to solve optimization problems for a long time. Imperialist competitive algorithm is inspired by imperialistic competition which Atashpaz-Gargari and Lucas [21] proposed in 2007.

In the paper that Hosseini and Khaled [24] proposed, ICA needs less iterations to reach global optimum than continuous GA and PSO. Moreover, ICA yields a higher quality solution than what PSO and GA do. It is applicable for multi-objective optimization problem and it is not limited by local solution or global solution.

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First, ICA needs to initialize population which comprises countries. The term "country" is used for an array. We form an array of variable values to be optimized. A "country" is a $1\times N_d$ array. The array is defined by

$$country = [p_1, p_2, ..., p_{N_d}] \tag{2.2}$$

There are two types of countries: imperialist and colony. The overall number of country defined by N_{pop} We should select N_{imp} of the most powerful countries, imperialist, to form the empires. The remaining N_{col} countries are colonies and assigned to an empire. Colonies are divided among imperialists based on their power to form initial empires. the initial number of colonies of an empire should be directly proportionate to its power.

$$C_n = c_n - \max_i\{c_i\} \tag{2.3}$$

where c_n is the cost of nth imperialist and C_n is its normalized cost. The normalized power of each imperialist is defined by

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{N_{imp}} c_i} \right| \tag{2.4}$$

From another point of view, the normalized power of an imperialist is the portion of colonies that should be possessed by that imperialist.

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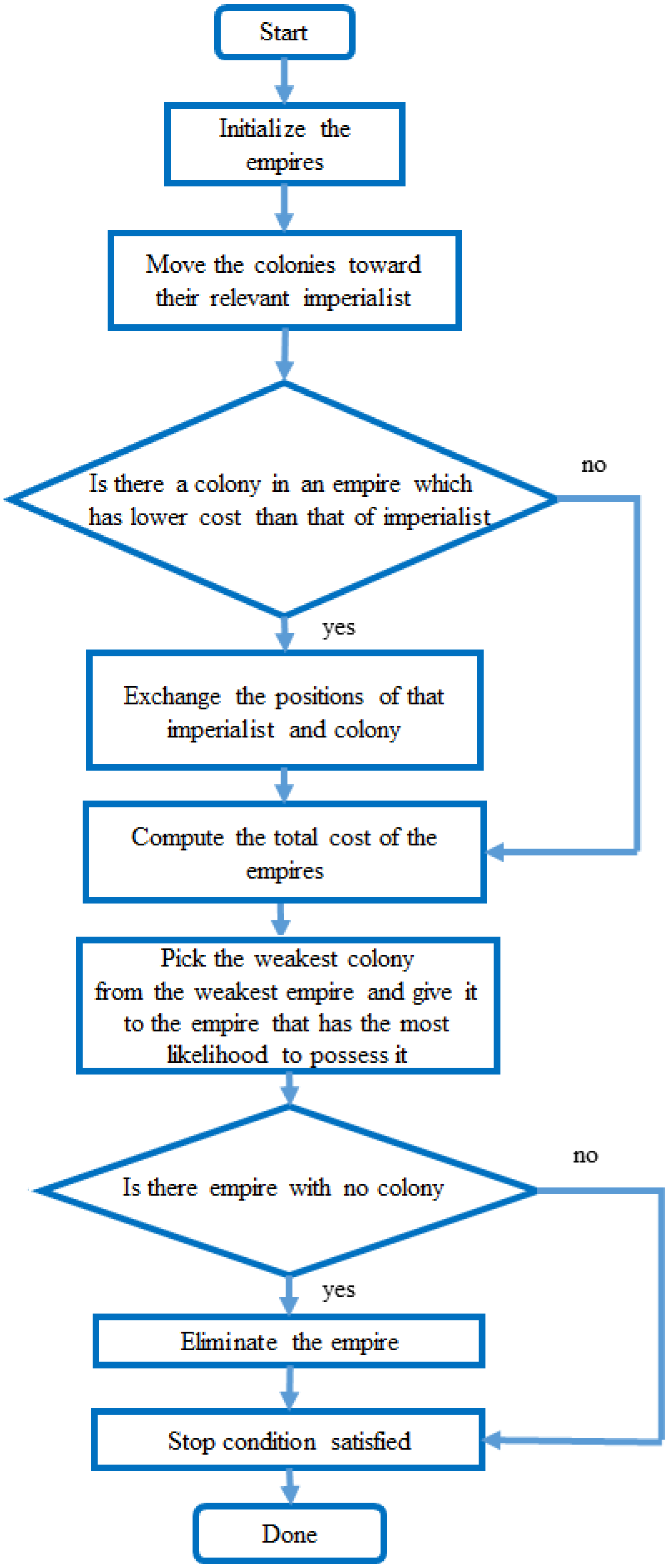

Figure 2-5 Flowchart of ICA

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Second, imperialists countries started to move their colonies to make improvement which is x units. The direction of movement is the vector form the imperialist. The x obeys uniform distribution and it is defined by

$$x \sim U(0, \beta \times d) \tag{2.5}$$

where β is a number larger than 1 and d is the distance between the colony and imperialist.

In order to search globally, there's a random vector θ, added to the direction of the movement. θ obeys uniform distribution and it is defined by

$$\theta \sim U(-\gamma, \gamma) \tag{2.6}$$

where γ is an adjustment factor that makes the deviation from original direction.

Third, after the movements of colonies are done, the power of each country should be updated. If there's a colony reaching a position with lower cost than the one of imperialist, they should exchange the position. In this way, we can keep countries moving toward the recently best position.

Fourth, imperialistic competition starts. The empire that is recently most powerful to possess the weakest colony from the weakest empire. The power of empire is defined by

$$TC_n = \cos t(imperialist_n) + \delta \times mean(\cos t(colonies\ \ of\ \ empire_n)) \tag{2.7}$$

where TC_n is the total cost of nth empire. δ is a positive number and it is lower than one.

After all empires except the most powerful one collapse and all the colonies are in the control of the most powerful imperialist, the algorithm stops.

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2.6 Lagrangian Relaxation (LR)

Fisher [22] says that LR is a tool that is increasingly being used in large-scale mathematical programming applications. LR is a relaxation method which simplify a difficult problem. A solution to the relaxed problem is an approximate solution to the original problem and bounded. Because it is a relaxation, the optimal value of LR problem will bound the optimal value of the real problem.

LR is applied to traveling salesman problems, general integer programming, mixed integer problems, location problems and scheduling problems. Chen and Luh [23] have made LR become a practical approach for complex scheduling problems. The method penalizes violations of inequality constraints using a Lagrange multiplier, which imposes a cost on violations. These added costs are used instead of the strict inequality constraints in the optimization. In practice, this relaxed problem can often be solved more easily than the original problem and cost less time to get better solution.

2.6.1 Surrogate Sub-Gradient Method (SSG method)

SSG method solves the problem that Lagrangian dual problems for separable integer programming problems require optimally solving all sub-problems at each iteration to obtain a sub-gradient direction. SSG method only needs approximate optimization of one or several sub-problems to get a sub-gradient direction. So SSG method is powerful for large-size problem and it takes less time to get right direction. The introduction is given below.

Consider an integer programming problem like below

$$\min_{x} J_{IP} = \sum_{i=1}^{I} J_i(x_i) \tag{2.8}$$

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subject to $Ax \le b$ and $x_i \in Z^{n_i}$, $i = 1, ..., I$ (2.9)

where $x = (x_1, x_2, ..., x_n)^T$ is an $n \times 1$ decision variable with $n = \sum_{i=1}^{I} n_i$ and Z is the set of integers.

The LR of IP is given by

$$L(\lambda) = \min_{x \in Z^n} \left[\sum_{i=1}^{I} J_i(x_i) + \lambda(Ax - b) \right] \tag{2.10}$$

The Lagrangian dual problem is

$$\max_{\lambda \ge 0} L(\lambda) \tag{2.11}$$

where λ is a vector of Lagrangian multipliers.

As an extension of the Lagrangian dual, surrogate dual is introduced.

$$\tilde{L}(\lambda, x) = \left[\sum_{i=1}^{I} J_i(x_i) + \lambda^T (Ax - b) \right], \quad x \in Z^n \tag{2.12}$$

And its SSG is defined as follow

$$\tilde{g}(x) = Ax - b \tag{2.13}$$

With the definition above. The steps of SSG methods are listed below.

(0) λ^0 is initialized and minimize sub-problems to get x^0.

$$x^0 = \arg\min_{x \in Z^n} \left[\sum_{i=1}^{I} J_i(x_i) + \lambda^0 (Ax - b) \right] \tag{2.14}$$

(1) The step is used to update multipliers. Given the current condition (λ^k, x^k) at the kth iteration, the Lagrangian multipliers are updated according to equation below.

$$\lambda^{k+1} = \lambda^k + s^k \tilde{g}^k \tag{2.15}$$

where $\tilde{g}^k = \tilde{g}(x^k) = Ax^k - b$, with step size s^k satisfying

$$0 < s^k < (L^* - \tilde{L}^k) \Big/ \left\| \tilde{g}^k \right\|^2 \tag{2.16}$$

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where $L^*=L(\lambda^*)$ is the optimal objective of the Lagrangian dual problem. $\tilde{L}^k = \tilde{L}(\lambda^k, x^k)$ which is the objective of surrogate dual at the *k*th iteration.

In this step, s^k should be obtained by the equation below.

$$s^k = \beta\left(L^* - \tilde{L}^k\right) \Big/ \left\|\tilde{g}^k\right\|^2 \tag{2.17}$$

L^* should be obtained, but it is hard to get it. An estimation of L^* is made to get s^k. The estimation is defined as bellow.

$$L^U = \left(1 + w/\theta^\rho\right) \times \tilde{L}^{[k]} \tag{2.18}$$

where $\tilde{L}^{[k]}$ is the best surrogate dual to iteration $k-1$. w is a parameter which is chosen within [0.1, 1.0]. ρ is a parameter which is chosen within [1.1, 1.5]. θ is adaptively adjusted by the formula below.

$$\theta = \begin{cases} \max(1, \theta - 1), & if \quad \tilde{L}^k > \tilde{L}^{[k]} \\ \theta + 1, & otherwise \end{cases} \tag{2.19}$$

(2) After obtaining λ^{k+1} in step 1, approximating optimization should be performed to get x^{k+1}. x^{k+1} should satisfy the condition that $\tilde{L}(\lambda^{k+1}, x^{k+1}) < \tilde{L}(\lambda^{k+1}, x^k)$. If the condition is not met, then $x^{k+1} = x^k$.

(3) This step is a checking point. The stopping criteria is given by $\left\|\lambda^{k+1} - \lambda^k\right\| < \varepsilon_1$ and $\left\|x^{k+1} - x^k\right\| < \varepsilon_2$. ε_1 and ε_2 are small error. If they are met, then stop. If the criteria are not satisfied, then go back to step 1.

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Chapter 3 Methodologies

3.1 Framework of System

In this study, the inventory management system and scheduling system is built under the concept of DDMRP. Both of them are developed for a manufacturer with multiple production lines and multiple products. So the manufacturer can become pull system from push system and exactly know how much quantity place.

Table 3-1 shows some information that is necessary to build the system and run the simulation.

Table 3-1 Information to build inventory management system and scheduling system

Order information	**Product information**	**Material information**
Order code	Product type	Material type
Product type	Bill of material	Inventory level
Quantity of order	Inventory level	Lead time
Order date	Product price	Average unit cost
Due date	Lead time	Annual dollar usage
	Average unit cost	
	Annual dollar usage	
	Flow of production	

For the scheduling system, the information above is not enough. Table 3-2 shows information needed for the scheduling system.

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Table 3-2 Information to build scheduling system

Production information
Machine type
Number of each machine type
Processing time on each machine type

The data we get is from January 2013 to December 2014. Through the data from the company and simulation, we can know the performance of the system. The performance index will be introduced in chapter 3.3.

This study is about CLL and it can be used to build up inventory management system and scheduling system. This study used the same concept of closed-loop. The overall framework is like figure 3-1 below.

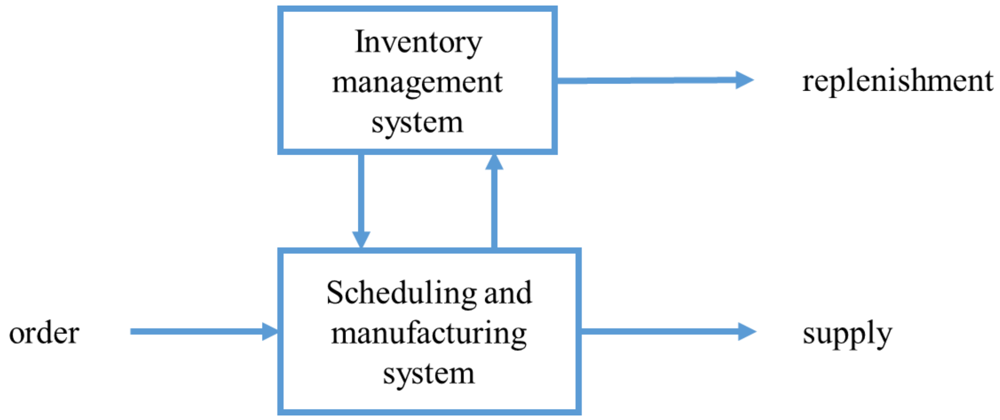

Figure 3-1 Framework of DDMRP

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3.1.1 CLL in Scheduling System

CLL is framework of this study's problem illustrated in Figure 2-2 focusing on the automatic control focuses on the manufacturer's activities. Production is the most significant origin to bring about the quantity of the product and then affect the quantity of inventory. The most significant advantage of this CLL is that the system can transfer real-time information immediately to shorten the lead-time and reduce the probability of the bullwhip effect in the manufacturing system. Moreover, this CLL can reduce inventory that kept and make the manufacturer become demand driven. The CLL of manufacturing is like figure 3-2 below.

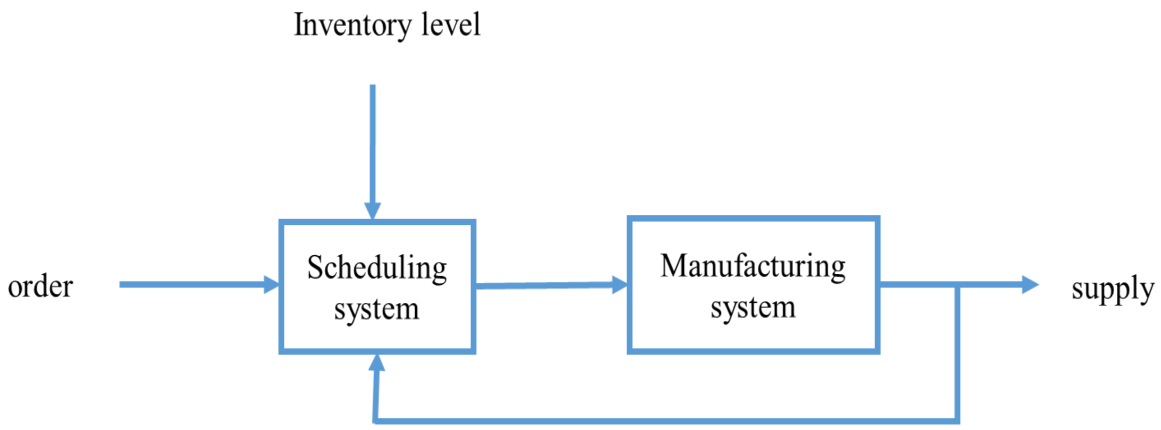

Figure 3-2 CLL of Scheduling and manufacturing system

Depending on the order of customers and the inventory level, we can do the schedule. The manufacturer can do as what scheduling plan says and monitor production lines. If there's anything wrong, production delay for example, the system can get the information and do reschedule to make up for the mistake happened in the production line. How to do the schedule will be introduced in 3.3.

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3.1.2 CLL in Inventory Mangement System

It’s not only apllied in manufacturing but also in inventory management, so the enterprise can control all of the activities happened in the supply chain and receive information about inventory and work-in-process (WIP). The CLL of inventory management system is like figure 3-3 below.

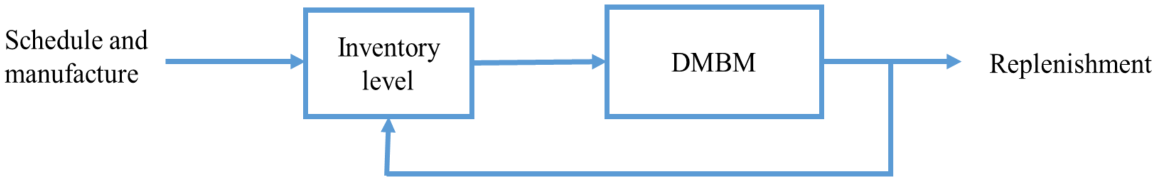

Figure 3-3 CLL of inventory management system

According to the manufacturing schedule, the consumption of materials and can be known and then DMBM in the inventory management system can do the replenishment by the consumption. There are some problems, like stock-out and low inventory level. If the problems occur, DMBM should adjust the inventory buffer. It will be introduced in 3-2.

3.1.3 Procedure of System

New orders and replenishments of materials will make some change to the schedule. The system gets the information from the new orders and replenishment and do the scheduling at the beginning of each day in order to get optimal solution.

The system does the scheduling according to the orders received and the inventory level. Depending on the inventory level, there are 2 circumstances and 2 solutions:

1. The materials are sufficient to fulfill all orders:

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Under the circumstance 1, the system does the scheduling according to the orders received.

2. The materials are not sufficient or out of stock to fulfill all orders:

However, under the circumstance 2, the system cannot do the scheduling on those orders without sufficient materials. The system should pick the orders that are more valuable and pressed for time to be on the production schedule.

After scheduling, the system asks production line to work. After manufacturing, the system checks that if there's any order due next day. If so, check the non-buffer product is enough or not and check the buffer products is enough or not. While the sum of the products is enough, then product can be sent. However, if there's not enough products, because of forbidden of backorder, the whole order is one-day late.

The definition of non-buffer product is that the product manufactured not for the buffer. Buffer product is produced to avoid lateness of fulfilling customer demand.

If the buffers of product reached the replenishment point, then the quantity should be determined under the circumstances. The need of product becomes order next day.

Because of production, there is consumption of materials. If buffers of materials reached the replenishment point, then the quantity is determined and become replenishment order sent to the suppliers. The flowchart of daily work of the system shown in the Figure 3-4.

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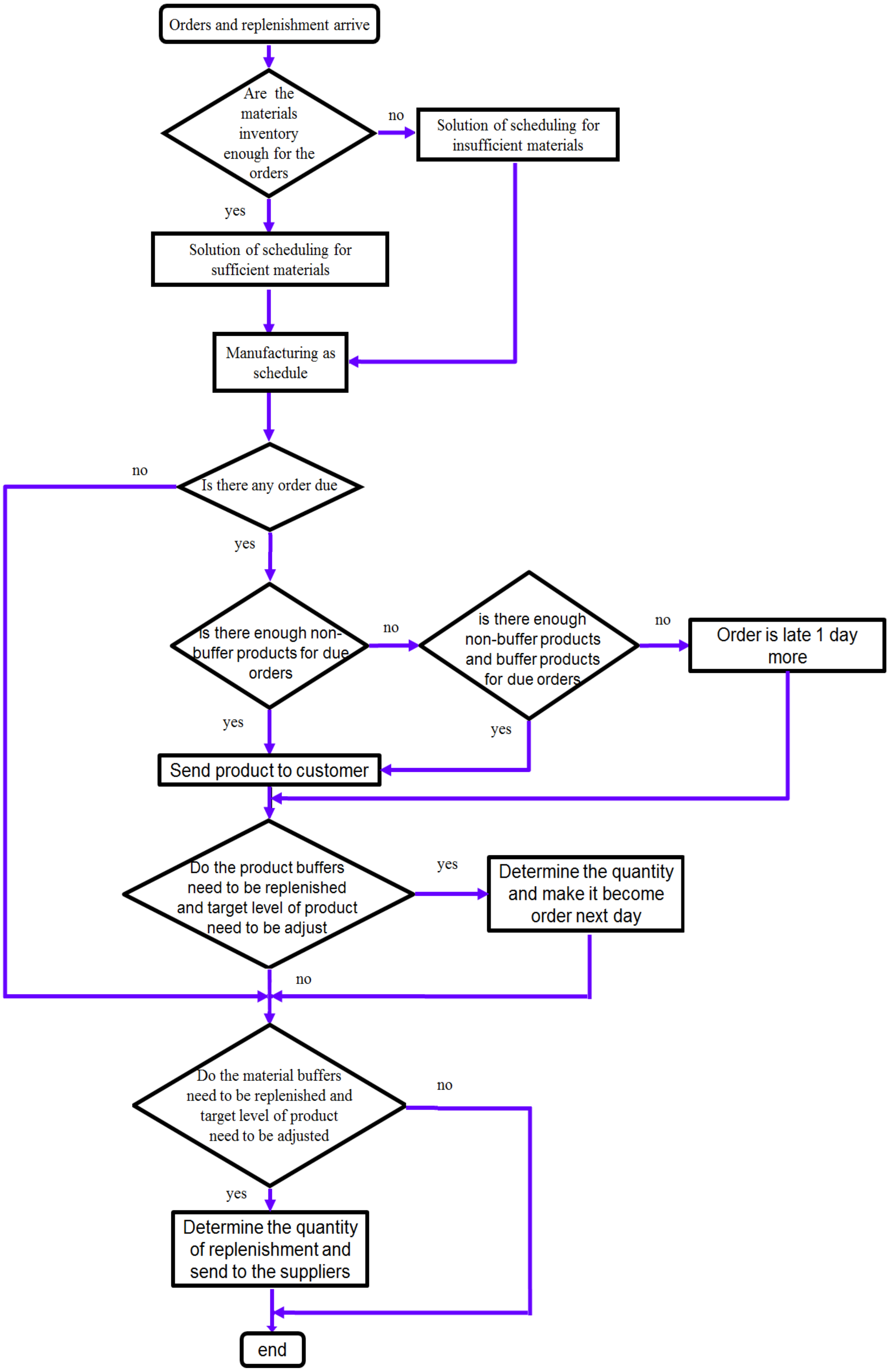

Figure 3-4 Flowchart of the system

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3.2 Scheduling System

In this study, the scheduling approach for job shop that H. Chen and P. Luh [23] introduced is quoted because production flow can be customized for any company that uses this system and this approach can obtain near optimal schedules with quantifiable quality in a reasonable computation time for practical scheduling problems.

3.2.1 **Problem Formulation**

There are N types of parts. Part is equivalent to product in this study. Each type of machine has M_h identical machine for h machine ($1 \le h \le H$). the completion of each part i ($1 \le i \le N$) requires a series of N_i operations. Operation can be performed on a machine belonging to a set of alternative machine type H_{ij} ($H_{ij} \subseteq \{1, ..., H\}$). Operation cannot preempt. The following symbols will be used in the problem formulation.

B_i : beginning time of part i

C_i : completion time of part i

c_{ij} : completion time of operation (i, j)

D_i : due date of part i

E_i : earliness of part i, which is $\max(0, D_i - C_i)$

T_i : lateness of part i, which is $\max(0, C_i - D_i)$

m_{ij} : machine type selected to process operation (i, j)

$M_{h\tau}$: number of available machine type h at time τ

O_h : set of operation that can be performed on machine type h

t_{ijh} : processing time of operation (i, j) on machine type h

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w_i : lateness weight of part i

β_i : earliness weight of part i

δ_{ijh} : operation index over time for machine of type h with $\delta_{ijh}(\tau)=1$, if operation (i, j) is performed on a machine of type h at time τ. Otherwise $\delta_{ijh}(\tau)=0$. In other word, $\delta_{ijh}(\tau)=1$ for $m_{ij}=h$ and $c_{ij}-t_{ijh}\le\tau\le c_{ij}$, and else $\delta_{ijh}(\tau)=0$.

In this study, in order to make the manufacturer become more demand driven and lower the inventory kept in the warehouse, the objective is considered to modeled as a weighted tardiness and earliness cost. Objective function is:

$$\min_{\{m_{ij}\},\{c_{ij}\}} J, \quad with \quad J=\sum_i w_i T_i + \sum_i \beta_i T_i \tag{3.1}$$

Operation precedence constraint is:

$$c_{i,j-1}+t_{i,j,m_{ij}} \le c_{i,j} \quad i=1,....,N \quad j=1,...,N_i \tag{3.2}$$

Machine capacity constraints is:

$$\sum_{i,j}\delta_{ijh}(\tau)\le M_{h\tau}, \quad 0\le\tau<\infty, \quad h=1,...,H \tag{3.3}$$

Equation (3.3) is relaxed. The reason for relaxing the precedence constraints is that the number of such constraints does not depend on the time horizon so that relaxation can lead to a time horizon-independent approach. The relaxed sub-problems, which are parallel machine problems to minimize the weighted earliness and tardiness criterion are difficult to solve. So it should be reformulated.

After introducing Lagrangain multiplier u_i, v_i and λ_{ij} to relax constraints that are implied by earliness (E_i) and lateness (T_i) and the operation precedence constraint (3.2), the primal problem can be decomposed into three problems tardiness

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sub-problem P_T, earliness sub-problem P_E, and the sub-problem P_{MC} to determine m_{ij} and c_{ij}.

$$P_T: \min_{T_i \geq 0} \sum_i (w_i - u_i) T_i \tag{3.4}$$

$$P_E: \min_{E_i \geq 0} \sum_i (\beta_i - v_i) E_i \tag{3.5}$$

$$P_{MC}: \min_{\{m_{ij}\},\{c_{ij}\}} \underline{L} \tag{3.6}$$

with $\underline{L} = \sum_i (u_i - v_i) C_i - \sum_i (u_i - v_i) D_i + \sum_{ij} (\lambda_{i,j+1} - \lambda_{ij}) c_{ij} + \sum_{ij} \lambda_{ij} t_{ijm_{ij}}$

It is subjected to constraint (3.3).

P_{MC} can be reformulated depending on the different relationship between operation and machine. There are three different ways to decompose the problem.

1. Machine sub-problem:

If each operation has only one eligible machine type to process, $t_{ijm_{ij}}$ should be a constant. By regrouping the terms in $\underline{L}$ according to machine types, P_{MC} can be further decomposed into a set of sub-problems, one for each machine type.

$$\underline{L} = \sum_h L_h - \sum_i (u_i - v_i) D_i \tag{3.7}$$

where

$$L_h = \sum_{(i,j)\in O_h} \tilde{w}_{ij} c_{ij} + \sum_{(i,j)\in O_h} \lambda_{ij} t_{ijm_{ij}} \tag{3.8}$$

$$\tilde{w}_{ij} \equiv \begin{cases} u_i - v_i - \lambda_{ij}, & j = N_i \\ \lambda_{i,j+1} - \lambda_{ij}, & 1 \leq j < N_i \end{cases} \tag{3.9}$$

Since the Lagrangian multipliers are set, $\sum_i (u_i - v_i) D_i$ should be a constant. So P_{MC} can be decomposed into H sub-problems (P_h), one for each

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machine type h.

$$P_h: \ \min L_h \tag{3.10}$$

$$\text{subject to } \sum_{ij} \delta_{ijh}(\tau) \le M_{h\tau}, \quad 0 \le \tau < \infty$$

$$1 = M_{h\tau}, \quad 0 \le \tau < \infty$$

it is a single machine scheduling problem to minimize the weighted completion time of operations.

2. Machine type sub-problem

If the group contains only one machine type but having multiple machines, its corresponding sub-problem is an identical parallel machine scheduling problem to minimize weighted completion time of operations. The way to decompose it is as the same as machine sub-problem.

$$P_{hs}: \ \min L_h \tag{3.11}$$

$$\text{subject to } \sum_{ij} \delta_{ijh}(\tau) \le M_{h\tau}, \quad 0 \le \tau < \infty$$

$$1 \le M_{h\tau}, \quad 0 \le \tau < \infty$$

3. Machine group sub-problem

Some operations may have more than one eligible machine types to process. In order to decompose the problem into sub-problems, machine types should be grouped when the set of operations that can be performed on this group of machine types. In this case, its corresponding sub-problem is an unrelated parallel machine scheduling problem to minimize the sum of the weighted completion time and the weighted processing time of operations. It is reformulated as follow.

$$P_G: \ \min L_G, \qquad L_G = \sum_{(i,j)\in O_G} \tilde{w}_{ij} c_{ij} + \sum_{(i,j)\in O_G} \lambda_{ij} t_{ijm_{ij}} \tag{3.12}$$

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$$\text{subject to} \sum_{ij} \delta_{ijh}(\tau) \le M_{h\tau}, \quad 0 \le \tau < \infty, \quad h \in G$$

where G is a set of machine types, $O_G = \bigcup_{h \in G} O_h$ is the set of operations that can be performed on a machine type belonging to G.

The solution of these sub-problems will be presented in the next section 3.2.2.

3.2.2 Solution of Scheduling Problem

This approach is a two-level structure including decomposition and coordination like the figure shown below.

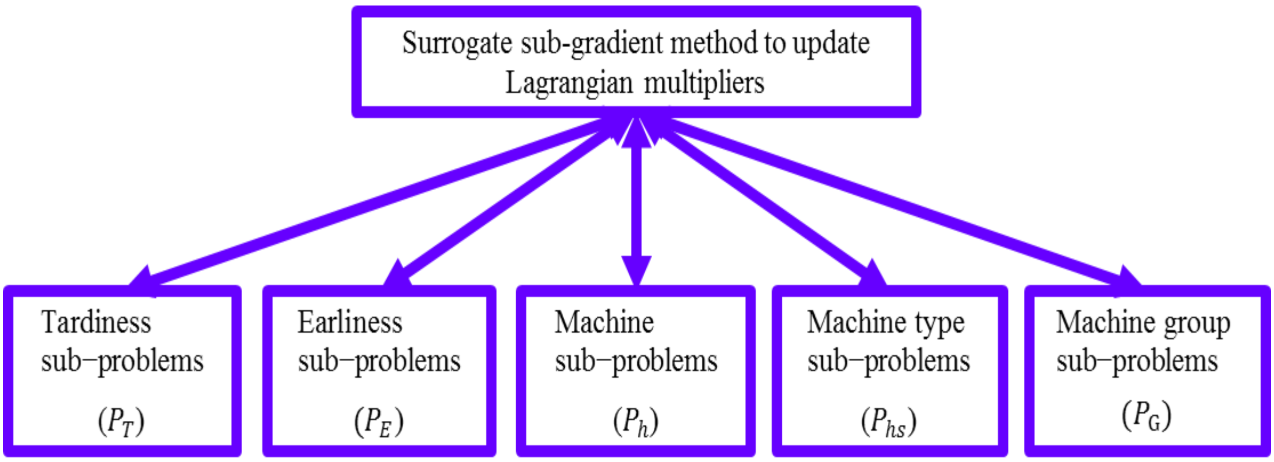

Figure 3-5 Two-level decomposition and coordination structure

At the beginning, multipliers are given to solve all the sub-problems at the low level. In order to solve the sub-problems, heuristic methods are given. Then, the set of multipliers are iteratively adjusted by SSG method at the high level based on the degree of constraint violation. The procedure stops when the stopping criteria is satisfied.

LR with SSG method has introduced in section 2.6.1. The algorithms to solve machine, machine type and machine group sub-problems are listed.

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1. Algorithm for machine sub-problems

   Each machine sub-problem is optimally solved by using the Smith's weighted shortest processing time (WSPT) rule.

2. Algorithm for machine type sub-problems

   Each machine type sub-problem is approximately solved by using a parameter list scheduling heuristic. It provides a near-optimal schedule for the machine type sub-problem.

3. Algorithm for machine group sub-problems

   All operations that can be processed by machine type h are arranged in a non-decreasing order of the ratio $t_{ih}/\tilde{w}_i$. This forms H operation lists which are indexed by machine type where some operations may appear in more than one list. The algorithm calculates the cost $\tilde{w}_i c_i + \lambda_i t_{ih}$ for each list and its first operation i. For calculation, c_i is obtained that operation i will be assigned to the earliest available machine of type h next. The selected operation is then assigned to the earliest available machine of the selected machine type with minimum cost and then its duplications in other lists are removed. This procedure stops when all operations are assigned. Algorithm 3 is enhanced by a local search procedure to improve the solution quality. The local search procedure reallocates an operation to another machine type at each step until the condition holds or further improvement of a solution is impossible.

The solutions that is got form heuristic are usually infeasible because of the violation of precedence constraints. In order to get feasible solution, there are two ways.

1. The orders of operations given by sub-problem solutions are used to construct a

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directed graph, where each node is an operation and each arc is a precedence between operations or an order between two operations given by sub-problem solutions. The heuristic dispatches operations from source nodes of the graph to sink nodes. If all preceding operations of the operation i have been dispatched, the operation i can be dispatched next. If the graph has no loop, all operations can be successively dispatched in this way, leading to a feasible schedule. Otherwise, a loop will be detected and then a recovery policy, changing the order of two operations in the graph, should be made to break the loop.

2. The heuristic dispatches operations according to a priority defined by the cost $\tilde{w}_{ij}c_{ij} + \lambda_{ij}t_{ijm_{ij}}$ that depends on the multipliers given by the dual solution. c_{ij} is obtained by assigning operation (i, j) to the earliest machine that is available of type m_{ij} next. At each step, algorithm calculates dispatching operations to their eligible machine types. Algorithm selects the operation with minimum cost to be dispatched next and the machine type that the operation is assigned to. The procedure stops when all the operations are dispatched.

3.3 Dynamic Multi-Buffer Management

DBM is the application from DDMRP. The model of DBM is based on the statics of real demand under different service level. The objective of DBM is to place buffer inventories so that the lead-time of deliver can be efficiently shorten. There are five color zones that represent different service level which is expected to satisfy a scale from 0% to 100% in DBM.

DBM is good for finished goods, but materials. This study makes a progress in DBM into DMBM and do the classification on products and materials to apply different

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management policies on different group.

In this study, buffers will be built for all materials, but not for all product. Buffers for products will only build for rare urgent orders. The product that produced

3.3.1 ABC Classification for Products

In this study, the ABC classification method that is used is a data envelopment analysis (DEA) like model proposed by Wan [20]. The model that proposed by Wan is simple and cost less computation time when there are too much criteria and too many items.

The procedure of the model can be simply described as follow. An inventory with I items and these items are to be classified based on J criteria. Measurement of the ith item under the jth criteria is denoted as y_{ij}. The score of the ith item is defined as S_i. S_i can be easily obtained as

$$S_i = \max_{j=1,\ldots,J} \left(\frac{1}{j} \sum_{k=1}^{j} y_{ik} \right) \tag{3.13}$$

In this study, three criteria, ADU, average unit cost and lead-time, are considered. All of them are used in classifying materials. The first two of them are use in classifying product.

The steps of the method are shown below:

(1) Calculate S_i

(2) Sort the S_i's in descending order and defined as S'

(3) Group the inventory items by principle of ABC analysis. Top 10% of the S' are type ‘A’, the next 20% of S' are type ‘B’ and the last 70% of S' are type ‘C’.

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3.3.2 **Initialization of DMBM**

After the ABC classification, target value of buffers should be initialized to correspond to the practical situation for different type of item. According to the formula (2-1), the target inventory level is the produce of LT, ADU, variation factor and service level. LT, ADU and variation factor is known for each item. They can be obtained by

LT : the average lead time

variation factor: coefficient of variation

$$ADU: \quad ADU = (\sum_{t=1}^{t+length} demand_t) / length$$

Where dem_t is the quantity of customer's demands so far. $length$ is the time started from $t = 1$ till now.

However, the service level should be determined. So ICA can be used to find the actual value of factors. The historical data is used for ICA to find the optimal value of factors. The data form t year is used to train the factors to be used in t+1 year. For example, the data form 2013 year is used to train the factors to be used in 2014 year. The procedure of ICA training will be introduced in chapter 3.2.4.

3.3.3 **Policies of Inventory Management**

In this chapter, replenishment policy and how to adjust target inventory level are introduced. Discussion is made respectively from material and product.

For material, after manufacturing, the inventory level should be checked. If the inventory level reached, got into or below the yellow zone, a replenishment should be ordered. The quantity of the replenishment should be:

$$Re = TIL - IL \tag{3.14}$$

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where *Re* is the quantity of material. *TIL* is the target inventory level. *IL* is the recent inventory level.

Target inventory level should be adjusted according to the market demand. Here is the Eliyahu Goldratt's Target Level Management Rules:

1. When a penetration into the red zone occurs, monitor how deep the penetration is. If the penetration is too deep or it persist for too long then the target inventory level should be increased.
2. If the stock rises excessively or it has remained in the blue zone for a whole time of replenishment then the target level should be decreased.
3. Every time you increase the target level wait for a replenishment cycle before starting to check again.
4. Every time you decrease the target level wait for the inventory to get down below the new green level and only then start to check again for the conditions to decrease the target level further.

The following are the rules made in this study according to Eliyahu Goldratt's rule

- For material:
  [1] If the penetration persist in red zone for two replenishment cycle, the target inventory level should be increased by a portion α.
  [2] If it is stock-out, the target inventory level should be increased by a portion α.
  [3] If the penetration is persisted in blue zone for two replenishment cycle, the target inventory level should be decreased by a portion α.
- For product:
  [1] Classify products into buffered product and non-buffered product. buffered

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products are set to prevent from dissatisfaction of customer. In this study, the product with top 20% high ADU is selected to be buffered product.

[2] Buffered product is used when there is lateness of delivery can happen.

[3] For buffered product, If it is stock-out, the target inventory level should be increased by a portion α.

[4] For buffered product, if the penetration is persisted in green and blue zone for a long time, it should be decreased.

[5] For non-buffered product, if there's late delivery, non-buffered product should be changed into buffered product.

If the target inventory level should be increased in the recent period, the quantity of replenishment should be:

$$Re' = Re + \alpha \cdot TIL \tag{3.15}$$

where Re' is the quantity of replenishment with increased target level. *Re* is the quantity of material. *TIL* is the target inventory level. α is a ratio > 0. Most of the papers said that α should be around 1/3.

For products, the difference between materials is the check point. The timing to check the inventory level of product is after sending the product to customer and the rest is the same as material side. Moreover, this causes orders and it needs to be put into manufacturing schedule.

The historical data is used for ICA to find the optimal value of α. The data form *t* year is used to train the factors to be used in *t+1* year. For example, the data form 2013 year is used to train the factors to be used in 2014 year. The procedure of ICA training will be introduced in chapter 3.2.4.

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3.3.4 **Factors Finding with ICA**

In this chapter, how to find optimal factors is introduced. The factors that ICA will find are the adjustment factors for each type of products and materials and service levels for each type of products and materials.

Each solution, or country, is set to be like below:

$$\begin{aligned} country = [&SL_{PA}, SL_{PB}, SL_{PC}, SL_{MA}, SL_{MB}, SL_{MC}, \\ &a_{PA}, a_{PB}, a_{PC}, a_{MA}, a_{MB}, a_{MC}] \end{aligned} \tag{3.16}$$

Where SL_{TD} is the service level for type T and type *D*. $T \in (M, P)$. M is material and *P* is product. *D* is the classification result of ABC analysis. In other words, $D \in (A, B, C)$. α_{TD} is adjustment factor for type T and type *D*. $T \in (M, P)$. M is material and *P* is product. *D* is the classification result of ABC analysis. In other words, $D \in (A, B, C)$.

Objective function is set to be weighted sum of Inventory-Dollars-Days (IDD) and Throughput-Dollar-Days (TDD). These two indexes will be introduced in chapter 3.4. The objective function is shown below:

$$\min_{country} W_{IDD} \cdot IDD + W_{TDD} \cdot TDD \tag{3.17}$$

Where W_{IDD} is the weight for *IDD*. W_{TDD} is weight for *TDD*. Both of them can be adjust by enterprises.

IDD is mainly used to reflect current situation of inventory. The higher the IDD is, the more the money is used in storing, buying and manufacturing those materials or products. Therefore, lowering down IDD is set to be the objective. At the meanwhile, customer satisfaction should be as high as possible which means that late deliveries of products should be as low as possible. In other words, TDD should be as low as possible. The objective function above is constructed to lower down the cost used in

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inventory and keep high customer satisfaction.

If the enterprise wants more on-time delivery than lowering down the inventory, then $W_{IDD} < W_{TDD}$. If the enterprise wants more about lowering down the inventory than om-time delivery, then $W_{IDD} > W_{TDD}$.

Algorithm of using ICA in DMBM is listed below:

(1) Give initial solution to each country and form empires. Calculate the objective function and record the minimum one as the best solution so far. To get the objective function, we run the procedure of system with data from 2013.

(2) Move colonies toward their relevant imperialist (Assimilating).

(3) If there is a colony in an empire which has lower cost than that of imperialist, then we exchange the positions of that colony with the imperialist.

(4) Compute the total cost of all empires (Related to the power of both imperialist and its colonies).

(5) Pick the weakest colony from the weakest empire and give it to the empire that has the most likelihood to possess it. The likelihood is calculated in the stage of imperialistic competition.

(6) Eliminate the powerless empires.

(7) If there is only 1 empire, stop. If not, go to step 2.

3.4 Performance Appraisal

In this chapter, the performance indexes inventory-dollar-day (IDD) and throughput-dollar-day (TDD) are introduced.

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1. TDD:

   TDD is mainly on account of delivery reliability. Therefore, when the delivery company or department promised customer orders cannot be reached, value of the TDD will show the extent not reached. It is calculated as effective production output value × number of day of orders delayed. The higher the TDD, the longer the delay on behalf of the order will be and will cause serious loss to the company. The company must pursue zero TDD. TDD also can be treated as an index to decide the priority of shipment and manufacturing.

2. IDD:

   IDD is an index of efficiency of inventory management. The higher stock will result in wasting materials, as well as enhancing inventory costs. It is calculated as stock value × number of days staying in the warehouse. The higher the inventory value is, the higher the value of IDD will be when the quantity of the inventory is the same. The company's goal is to minimize value of IDD, so that the company can do efficient inventory management.

In order to know the performance of the system built in this study, a simulation is taken to do the analysis with the ABC analysis by data from 2013 and the factors found by ICA. The factors will be put into the system and run with the data from 2014 and then the comparison will be made between the system installed and without.

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Chapter 4 Case Study and Results

4.1 Test of Each Framework

Three systems, scheduling system, inventory management system and whole system, will be tested by the data from a China manufacturing company. The assumptions for each framework to be tested are listed below:

Table 4-1 Assumptions for each framework

	Assumptions
Scheduling System	1. Growth and decline of inventory level follows the historical data. 2. Machine never breaks down and works 24 hours a day. Each machine stops to check at the end of every month. 3. The Chinese new year comes, Machines stops. 4. Processing time of jobs in each machine that are used in scheduling are assumed to be the average of its processing time in each one. 5. Growth and decline of inventory level follows the historical data. 6. Machine never breaks down and works 24 hours a day. Each machine stops to check at the end of every month. 7. The Chinese new year comes, Machines stops. 8. Processing time of jobs in each machine that are used in scheduling are assumed to be the average of its processing time in each one.

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Inventory Management System	1. The manufacturing plan follows the historical data (WSPT rule, the revenue of each order). 2. Lead-time of material replenishment is deterministic and it is the same as average of its lead-time of each material. 3. Capacity of the warehouse is not limited. 4. Replenishment quantity is not limited. 5. There is no longer the minimum order quantity (MOQ). 6. Replenishment and order arrive at the start of each day. 7. Backorder is not allowed.
Whole System	1. Machine never breaks down and works 24 hours a day. Each machine stops to check at the end of every month. 2. The Chinese new year comes, Machines stop. 3. Processing time of jobs in each machine that are used in scheduling are assumed to be the average of its processing time of each one. 4. Lead-time of material replenishment is deterministic and it is the same as average of its lead-time of each material. 5. Scheduling system and inventory management system are independent. 6. Lead-time of material replenishment is deterministic and it is the same as average of its lead-time of each material. 7. Capacity of the warehouse is not limited. 8. Replenishment quantity is not limited. 9. There is no longer the minimum order quantity (MOQ). 10. Replenishment and order arrive at the start of each day. 11. Backorder is not allowed.

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4.2 Company Introduction

The DMBM is developed in this study will be tested by the data from a China manufacturing company. The company provides data which manufactures ceramics and product associated with ceramics. The data is from December 5th 2013 to December 30th 2015. There are three types of product, glaze, printing glaze and frit. Forty-seven products in total the company sale. Seventy-five types of material are used to manufacture products. Frit is not only a type of material but also a product because it does not need any production. Due to frit's lead-time, while doing the ABC classification, it is material. The detail information will be shown in chapter 4.4.1 along with ABC classification and the production environment will be introduced in chapter 4.3.

The company always gets more orders than the machines can handle. In other words, machine capability ratio is always at maximum so the company needs to seek outsourcing to fulfill customer's orders. At this situation, how many IDD and TDD can be reduced and still at the maximum machine capability ratio will be found out.

4.3 Results of Scheduling System

4.3.1 Comparison with Company Data

It has been implemented in C# on a PC with 1.8 GHz CPU. Numerical testing has been made to compare the approach with the Lagrangian Relaxation with Surrogate Sub-Gradient Method with company scheduling and manufacturing data.

For production environment, the company does not manufacture frit. The company buys frit to sale. Sixteen batching machines are identical to each other for glaze and printing glaze batching. Ten machines are set for printing glaze to be ball-milled. One

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packing line for frit are set in the manufacturing environment. Six machines are set for glaze to be blended. Sixteen packing machines for glaze and printing glaze are set. Each of the machine can produce 100 kilogram of the product. The information about product manufacturing process is shown below:

Table 4-2 Check List of manufacturing process

Product type	**Process 1**	**Process 2**	**Process 3**	**Process 4**	**Process 5**	**Total time**
Glaze (Production)	orders and Recipe review (30 min.)	material requisition （30 min.）	material batching （30 min.）	material blending （30 min.）	warehouse-in inspection and packing （30 min.）	2 h. and 30 min.
Printing glaze (Production)	orders and Recipe review (30 min.)	material requisition （30 min.）	material batching （30 min.）	ball-milling （15 h.）	warehouse-in inspection and packing （4 h.）	20 h. and 30 min.
Frit	orders and Recipe review (10 min.)	packing and delivery （10 min.）				20 min.

For parts, with the capacity of machine and order data from the company, orders from the customers can be separated into parts that machine can process. Processing time of parts that are used in scheduling are assumed to be the average of its processing time. They are listed in table 4-1.

For examples, Example 1 is made by the data between January 1st 2013 to December 30th 2013. Example 2 is made by the data between January r 1st 2014 to December 30th 2014.

For problem formulation, the weight for tardiness come from the profit of the part made. In order to solve the problem, the parameters for Lagrangian Relaxation approach

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is set, ω = 0.5, ρ = 1.3. When it runs thirty iterations, the approach stops. Lagrangian multipliers are set to be 0 at first. The result of comparison is made by comparing order fill rate (OFR) and it is listed below:

Table 4-3 Comparison of OFR between company and LR

	Example 1		Example 2	
Comparison sets / Variables	Company	LR	Company	LR
OFR	0.84021	0.84129	0.75231	0.75234
Improvement	1.0001213		1.000042	

Because machine capability ratio is at maximum, the order fill rate only can improve a little bit. However, we cannot say the LR with SSG method is better than company's scheduling.

4.3.2 Comparison with Cplex

It has been implemented in C# on a PC with 1.8 GHz CPU. Numerical testing has been made to compare the approach with the LR approach with surrogate sub-gradient method and the integer programming solver of Cplex.

For examples, Example 1 is made by the data between December 5th 2013 to December 23rd 2013. Example 2 is made by the data between June 2nd 2013 to October 25th 2013. Example 3 is made by the data between July 15th 2013 to November 24th 2014. The complexity of examples is shown below:

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Table 4-4 Construction of examples

Part numbers \ Examples	Example 1	Example 2	Example 3
Part numbers of glaze	717	8718	5338
Part numbers of printing glaze	101	1937	23878
Part numbers of frit	159	21086	50571
Total number of Part	4530	31741	79733

For problem formulation, the setting of LR is the same as that in chapter 4.2.1. the Results are listed below:

Table 4-5 Results comparison of LR with surrogate sub-gradient method between Cplex

Example set	Example 1		Example 2		Example 3	
Variables \ Comparison sets	LR	Cplex	LR	Cplex	LR	Cplex
Objective Value	12.688	12.678	974.55	898.95	2345.61	2134.11
Ratio of objective reachment	0.999211232		0.915901886		0.900895455	
Time Consumption (seconds)	0.4589	1.158	45.236	1587.76	61.265	2642.35

The larger the part number of example is, the more complex the example is and the more time the example consumes. However, the time consuming of example 2 and example 3 are different because the feasible solution construction of glaze and printing glaze are more complex than frit.

Comparing to the results of Cplex, the results Lagrangian Relaxation with Surrogate Sub-Gradient Method are less time-consuming. It takes three to four

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iterations to converge well. However, with the growth of complexity, LR with surrogate sub-gradient method losses its strength to get the optimal solution.

4.4 Results of Inventory System

4.4.1 Results of ABC Classification

To start to find DMBM factors of 2014, we should first do ABC analysis of 2013. The factors used in ABC analysis are normalized. The result of 2013 is listed below:

Table 4-6 Result of ABC analysis of material

Name	ADU	VAR	Lead time	ABC
A.10.PK.BOHF	0.0696	0.615	30	C
A.10.PK.CIGB	0.0099	0.552	31	C
A.10.PK.FOBI	0.0701	0.453	30	C
A.10.PK.GACA	0.0310	0.487	31	C
A.10.PK.HACE	0.0067	0.495	30	C
A.10.PK.JOCB	0.3216	0.590	30	C
A.10.PK.KABI	0.1549	0.588	30	C
A.10.PK.MOHT	0.1445	0.537	30	C
A.10.P.MUTO	0.1220	0.617	30	C
A.10.PK.DEDI	0.2836	0.636	31	C
A.10.PK.LACE	0.0112	0.500	28	C
A.10.PK.DICA	0.2154	0.597	29	C
A.04.PK.MGM0386	0.0034	0.633	56	C
A.04.PK.MGM1101	0.0045	0.602	56	C
A.04.PK.MGM1206	0.0037	0.552	56	C
A.04.PK.MGM1216	0.0013	0.477	56	C
A.04.PK.MGM2102	0.0021	0.462	56	C
A.04.PK.MGM2103	0.0007	0.589	56	C
A.04.PK.MGM2105	0.0047	0.433	56	C
A.04.PK.MGM2107	0.0022	0.555	56	C
A.04.PK.MGM2500	0.0062	0.475	56	C
A.04.PK.MGO0206	0.0028	0.634	58	C

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A.04.PK.MGO0301	0.0038	0.488	62	C
A.04.PK.MGT0049	0.0090	0.635	55	C
A.04.PK.MGT0307	0.0056	0.541	55	C
A.04.PK.MGT0309	0.0013	0.546	55	C
A.04.PK.MGM0113	0.0035	0.545	65	C
A.04.PK.MGT0023	0.0139	0.472	65	B
A.04.PK.GO0206	0.0030	0.481	62	C
A.04.PK.GO0207	0.0058	0.498	62	C
A.04.PK.GO0210	0.0001	0.425	62	C
A.04.PK.GO0211	0.0002	0.625	62	C
A.04.PK.GO0212	0.0035	0.625	62	C
A.04.PK.GO0238	0.0002	0.605	63	C
A.04.PK.GO0278	0.0007	0.565	63	C
A.04.PK.GO0279	0.0008	0.532	63	C
A.04.PK.GO0286	0.0050	0.457	63	C
A.04.PK.MGM0298	0.0149	0.425	50	C
A.04.PK.MGM0299	0.0192	0.469	50	C
A.04.PK.MGM0302	0.0122	0.511	40	C
A.04.PK.MGM0322	0.0251	0.622	40	C
A.04.PK.GT1058	0.0001	0.530	40	C
A.04.PK.GT1059	0.0002	0.454	40	C
A.04.PK.GT1076	0.0065	0.497	40	C
A.04.PK.GT2108	0.0049	0.557	40	C
A.04.PK.GT4500	0.0037	0.617	40	C
A.04.PK.GO0287	0.0008	0.483	40	C
A.04.PK.GO0327	0.0002	0.607	40	C
A.04.PK.GT0025	0.0003	0.531	76	B
A.04.PK.GT0026	0.0064	0.625	76	B
A.04.PK.GT0038	0.0002	0.561	76	B
A.04.PK.GT0152	0.0010	0.460	76	B
A.04.PK.GT0156	0.0007	0.477	76	B
A.04.PK.GT0228	0.0010	0.598	76	B
A.04.PK.GT0325	0.0005	0.571	76	B
A.04.PK.GT1047	0.0004	0.438	76	B
B.04.GT1048N	1.0000	0.948	80	A

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B.04.GM3101	0.0599	0.955	79	A
B.04.GO0211	0.3451	0.620	79	A
B.04.GT1058	0.4064	0.854	85	A
B.04.GT1018	0.1796	1.000	85	A
B.04.GO0278	0.0030	0.859	74	B
B.04.GO0327	0.4853	0.638	74	A
B.04.GO0279	0.1949	0.999	85	A
B.04.GO10381	0.0928	0.827	85	A
B.04.GO0207	0.1014	0.634	75	B
A.04.PK.GM0289	0.0037	0.503	65	B
A.04.PK.GM0295	0.0325	0.598	63	C
A.04.PK.GM0298	0.0054	0.434	62	C
A.04.PK.GM0386	0.0064	0.459	64	C
A.04.PK.GM1026	0.0053	0.599	64	C
A.04.PK.GM2500	0.0029	0.540	59	C
A.04.PK.GM3101	0.0025	0.586	67	B
A.04.PK.GM3103	0.0014	0.613	65	B
A.04.PK.GM3204	0.0056	0.426	63	C

Table 4-7 Result of ABC analysis of product

Name	TYPE	ADU	VAR	ABC
B.01.KS0826N	glaze	0.130	0.986	C
B.01.KS2106	glaze	0.131	0.967	C
B.03.KD0273	printing glaze	0.043	0.912	A
B.01.KS10336	glaze	0.196	0.983	C
B.01.KS0856	glaze	0.115	0.986	C
B.01.KS10212	glaze	0.052	0.994	C
B.03.KD0194	printing glaze	0.034	0.967	A
B.01.KS2739	glaze	0.178	0.970	C
B.01.KS10110	glaze	0.079	0.978	C
B.01.KS7713	glaze	0.392	0.948	C
B.01.KS0869	glaze	1.000	0.747	C
B.03.KD10050	printing glaze	0.032	0.986	B
B.03.KD10305	printing glaze	0.022	0.997	B

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B.01.KS0006C	glaze	0.133	0.978	C
B.01.GL9801	glaze	0.092	0.983	C
B.01.KS2117	glaze	0.066	0.972	C
B.01.KS2209	glaze	0.153	0.983	C
B.03.KD0160	printing glaze	0.023	0.967	B
B.03.KD0196	printing glaze	0.063	0.893	B
B.03.GD0171	printing glaze	0.011	0.989	C
B.03.KD0818	printing glaze	0.336	0.826	B
B.01.KS0086	glaze	0.084	0.981	C
B.03.KD0156	printing glaze	0.010	0.992	B
B.03.KD0809	printing glaze	0.007	0.981	C
B.01.KS0285	glaze	0.314	0.975	C
B.03.KD0242	printing glaze	0.013	0.972	A
B.03.KD7108	printing glaze	0.009	0.983	C
B.01.KS10231	glaze	0.149	0.978	C
B.01.KS10206	glaze	0.148	0.992	C
B.03.KD0338	printing glaze	0.038	0.961	C
B.03.SDB3006	printing glaze	0.036	0.978	C
B.01.KS10285	glaze	0.045	0.992	C
B.03.KD0270	printing glaze	0.021	0.986	C
B.03.KD0172	printing glaze	0.057	0.975	C
B.01.KS10028	glaze	0.190	0.989	C
B.01.KS2104	glaze	0.021	1.000	C
B.03.KD10049	printing glaze	0.010	0.992	A

All the factors, ADU, VAR and lead-time, are normalized to do the ABC analysis. Frit is only for sale without manufacturing, so it is in the material part due to its lead-time are apart from other products. The lead-time factor is not in the product part because the lead-time of products is manufacturing time.

According to the result of ABC classification of materials, most of Frit are classified into type A and type B. Some of the material of producing printing glaze and general purposed material for glaze and printing glaze is classified into type B.

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According to the result of ABC classification of products, most of printing glaze are classified into type A and type B and all of Glaze are classified into type C. We can tell that printing glaze is more valuable than glaze.

4.4.2 **Results of ICA**

The setting of ICA is listed below:

Table 4-8 Setting of ICA

N_{pop}	N_{imp}	β	γ	δ
150	15	1.500	0.250	0.150

Less countries are easy to cause the optimal solution limited to local solution especially on the wide environment so this study set the N_{pop} to be 150. The number of empire is determined by opinions that Hosseini and Khaled [24] suggested. N_{imp} is usually 10–13% of the number of overall countries so N_{imp} is 15. β should be 1.5 to make its way to imperialist and δ should be 0.15 to make the effect of cumulative power of colonies on determining the power of each empire lower. According to the literature, setting $\gamma = \pi/4$ compromises between solution accuracy and search time for most of the case studies.

The optimization needs the weight of WTDD and WIDD to be set and the different combination of weights leads to different results. In order to know the results of different weight of WTDD and WIDD, different weights of WTDD and WIDD that ranges between 0.1 and 0.9 are simulated. Moreover, we want to keep high customer satisfaction so WTDD = 0.95 and 0.99 and WIDD = 0.05 and 0.01 are simulated.

The factors of DMBM from 2013 are shown below:

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Table 4-9 The result of DMBM factors - 1

Factors \ Weights	W_{TDD} 0.1, W_{IDD} 0.9	W_{TDD} 0.2, W_{IDD} 0.8	W_{TDD} 0.3, W_{IDD} 0.7	W_{TDD} 0.4, W_{IDD} 0.6	W_{TDD} 0.5, W_{IDD} 0.5
SL_{PA}	1.4715	4.1486	0.391	1.8736	1.367
SL_{PB}	1.8866	1.2562	1.5637	5.2275	2.568
SL_{PC}	0.8783	0.5257	0.0384	0.0734	0.207
SL_{MA}	0.0015	0.0502	0.113	0.1027	1.516
SL_{MB}	0.0419	0.4234	0.0428	1.5141	2.87
SL_{MC}	0.0547	0.1842	0.0979	0.3028	0.569
α_{PA}	1.6233	0.9508	0.4507	0.6555	0.405
α_{PB}	0.4022	0.1265	0.4586	0.3239	1.086
α_{PC}	0.5721	0.8851	0.6656	1.3886	0.876
α_{MA}	0.8276	0.5637	0.4587	0.3302	0.783
α_{MB}	0.9055	0.4894	0.2906	0.8171	0.62
α_{MC}	0.2281	0.1959	0.2946	0.0086	0.63

Table 4-10 The result of DMBM factors - 2

Factors \ Weights	W_{TDD} 0.6, W_{IDD} 0.4	W_{TDD} 0.7, W_{IDD} 0.3	W_{TDD} 0.8, W_{IDD} 0.2	W_{TDD} 0.9, W_{IDD} 0.1	W_{TDD} 0.95, W_{IDD} 0.05	W_{TDD} 0.99, W_{IDD} 0.01
SL_{PA}	2.3494	4.4981	5.2291	1.808	3.648	3.764
SL_{PB}	3.0208	4.1071	2.6618	1.189	4.528	4.166
SL_{PC}	1.9969	1.6509	1.1944	3.229	1.495	4.685
SL_{MA}	0.0984	0.099	0.1719	0.164	0.166	0.210
SL_{MB}	0.9899	1.1172	1.1143	0.969	0.959	1.208
SL_{MC}	1.2243	1.404	1.4019	2.338	2.453	2.447
α_{PA}	0.5422	0.4549	0.1609	0.952	0.773	0.610
α_{PB}	1.006	0.8317	1.2703	0.204	0.348	0.403
α_{PC}	0.3141	0.797	0.6112	0.5629	0.481	0.433
α_{MA}	0.6717	0.6729	0.388	0.5026	0.518	0.376
α_{MB}	0.2891	0.4533	0.3804	0.4919	0.454	0.340
α_{MC}	0.0273	0.2001	0.196	1.0499	0.879	0.904

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Discussion is made under the concept of ABC analysis and TOC. Under the concept of TOC, the material with higher service level should be less in order to make the performance index, IDD, lower. So, under the result of ABC analysis, the material classified into type A should be less keeping in the warehouse, those classified into type B should be medium and those classified into type C can be higher. So the service level of type A should be the lowest, service level of type B should be medium and service level of type C should be biggest among three type. For product, customers give suggestion about service level of products sometimes. If they do not, it is the same as the discussion for material.

But the results of the service levels are far away from the common sense. At different level of W_{TDD} and W_{IDD}, service levels fluctuated and there is nearly no pattern to follow. The reason that it happened are:

1. The interaction of service levels and the adjustment factors.
2. Optimization of ICA lead to the near-optimal solution.

The adjustment factor can be not only around 0.3, but also be larger than 1. Adjustment factor can range from nearly zero to 1.

The factors of service level and adjustment factors are gotten from ICA and the system should be tested under the data from 2014.

The result of IDD and TDD at different weights from 2013 (the best of ICA) and 2014 are listed below

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Table 4-11 Results of IDD and TDD from 2013 at different weights of inventory management system - 1

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.1	0.9	0.2	0.8	0.3	0.7	0.4	0.6	0.5	0.5
OFR	0.1920		0.2683		0.3907		0.4584		0.5154	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	5887531		3040175		6553884		16276435		4165499	
Type B	59486330		64113671		59533907		84148309		59889186	
Type C	88999848		88999848		94733862		156145570		384224964	
Total Product IDD	154373710		156153695		160821653		256570314		448279650	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	1429833		16099231		52811079		45688786		23528378	
Type B	3976454		40556544		2134915		179304898		48910188	
Type C	24313418		49992975		33549076		106487944		613040340	
Total Material IDD	29719704		106648750		88495070		331481628		685478906	
Total IDD	184093414		262802444		249316723		588051942		1133758555	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	1911169018		854350704		266126435		34090998		163333494	
Type B	147916212		81867910		113574315		304920086		28342955	
Type C	664093926		710395930		190160209		196370426		237729943	
Total TDD	2723179157		1646614543		569860959		535381510		429406391	

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Table 4-12 Results of IDD and TDD from 2013 at different weights of inventory management system - 2

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.6	0.4	0.7	0.3	0.8	0.2	0.9	0.1	0.95	0.05	0.99	0.01
OFR	0.6467		0.6434		0.6946		0.8062		0.8391		0.8402	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	13529784		15548187		20234118		18295120		22072526		24072526	
Type B	92938073		98349089		76925533		92574885		129020906		130020906	
Type C	287374853		293601168		288532712		587738589		789071222		789971222	
Total Product IDD	393842709		407498444		385692363		698608595		940164655		944064655	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	49842364		50384722		563214525		126600516		135983368		148414436	
Type B	88364137		105911545		109375345		85314809		94531644		94548764	
Type C	472159414		558988925		112352583		887136233		993433632		992955442	
Total Material IDD	610365916		715285192		784942454		1099051558		1223948645		1235918642	
Total IDD	1004208625		1122783636		1170634817		1797660153		2168013300		2179566893	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	123123842		120422644		27667880		132566		120635		132301	
Type B	10409843		2071726		39760882		150365		141343		146455	
Type C	155272705		118205048		57212549		5445793		4028924		5364106	
Total TDD	288806390		240699419		124641311		5728724		4290902		5642862	

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Table 4-13 Results of IDD and TDD from 2014 at different weights of inventory management system - 1

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.1	0.9	0.2	0.8	0.3	0.7	0.4	0.6	0.5	0.5
OFR	0.0415		0.1334		0.2138		0.4397		0.3774	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	5953724		2801542		1716107		345256845		9090832	
Type B	37478763		400528014		59036189		876958996		34836153	
Type C	9130611		10117848		22232347		32235738		38685405	
Total Product IDD	52563099		413447403		82984643		1254451580		82612390	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	1088686		4783962		1716107		18866886		26869034	
Type B	6695223		69677421		59036189		415796365		915791499	
Type C	25974517		69930721		22232347		89119655		160716328	
Total Material IDD	33758426		144392103		82984643		523782906		1103376862	
Total IDD	86321525		557839506		165969287		1778234486		1185989251	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	228122994		245560670		220816255		75488888		152035469	
Type B	247031171		594126907		240532318		58423356		216701088	
Type C	2612708511		1543053411		1227334233		164514691		136540471	
Total TDD	3087862677		2382740987		1688682806		298426935		505277027	

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Table 4-14 Results of IDD and TDD from 2014 at different weights of inventory management system - 2

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.6	0.4	0.7	0.3	0.8	0.2	0.9	0.1	0.95	0.05	0.99	0.01
OFR	0.2929		0.2746		0.3345		0.7018		0.7446		0.7499	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	5749364		6237423		69524223		15301247		16661358		17001386	
Type B	5749368		674484		17980358		242845605		27288752		272860230	
Type C	55677825		44587562		221681394		597914670		675276437		655608191	
Total Product IDD	67176557		51499469		309185975		856061523		719226547		945469807	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	42533213		42657091		66554412		65573233		69758758		71547445	
Type B	240128316		281284093		295425817		195461839		209723004		216655995	
Type C	475400944		556373872		539416302		945081145		997973754		1052714931	
Total Material IDD	758062473		880315056		901396531		1206116218		1277455516		1340918371	
Total IDD	825239029		931814525		1210582505		2062177740		1996682063		2286388178	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	157025301		220816255		122680302		12820124		12563721		12435520	
Type B	363414036		250532318		108150220		8204265		8023771		8040180	
Type C	232620006		277334233		347529487		25264185		22948139		22442855	
Total TDD	753059342		748682806		578360009		46288574		43535631		41918555	

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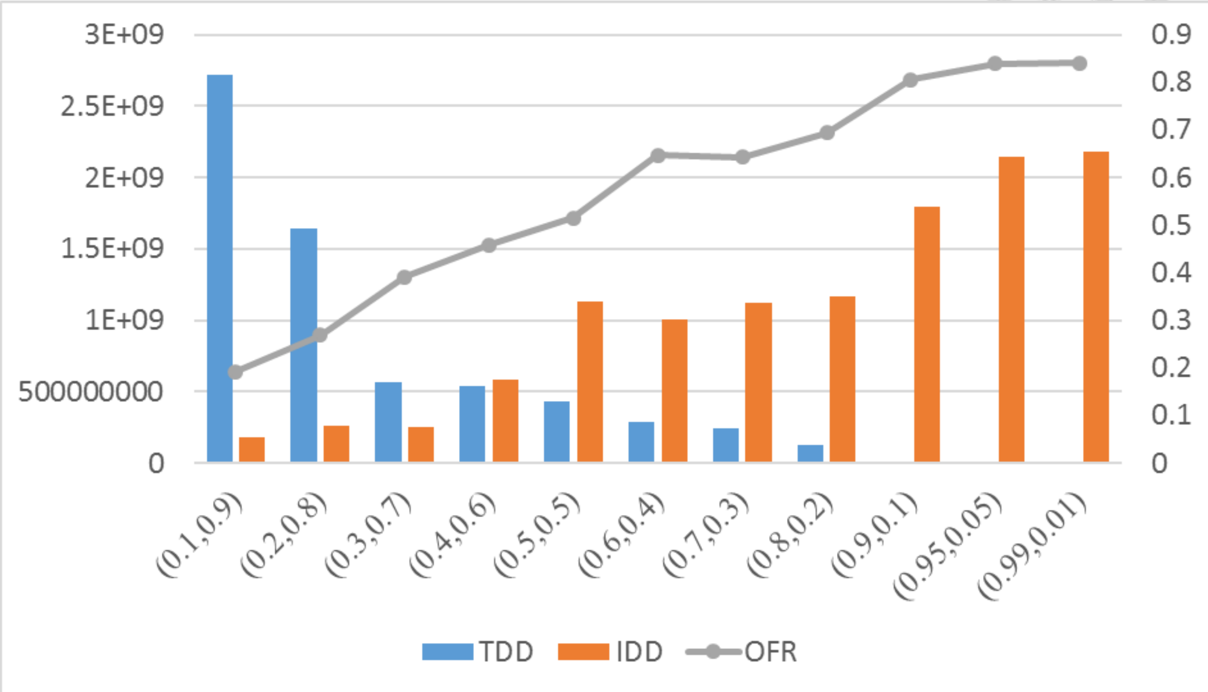

Figure 4-1 Relationship between TDD, IDD and OFR of inventory management system of year 2013

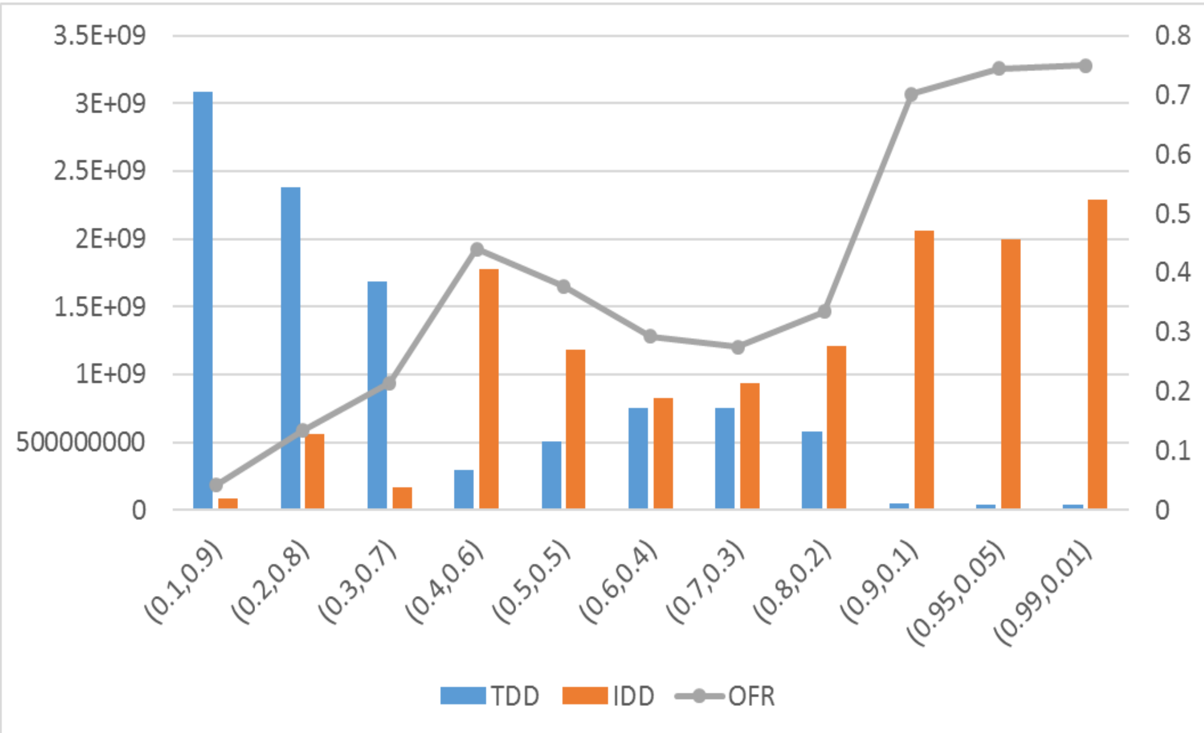

Figure 4-2 Relationship between TDD, IDD and OFR of inventory management system of year 2014

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Table 4-11, 4-12, 4-13 and 4-14 show that as the value of WTDD being larger and TDD being smaller. Average OFRs also becomes larger as the IDD being larger and TDD being smaller.

The fluctuation in the data of 2014 should be the problem that the factors getting from 2013 does not fit in data 2014 well with that factors, but overall trend is the same as 2013. The larger the value of W_{TDD} is, the larger the OFR should be.

4.4.3 Comparison with Company's Historical Data

In this chapter, results of simulation of DMBM will be compared with historical data of the company and they are listed below:

Table 4-15 Comparison between company data and inventory management system from 2013

Variables \ Systems	Company data	Inventory management system
OFR	0.8402	0.8402
	Product IDD	Product IDD
Type A	32738635.57	24072526.15
Type B	162526133	130020906.43
Type C	884767769	789971222.34
Total Product IDD	1080032538	944064654.93
	Material IDD	Material IDD
Type A	182217713.5	148414435.56
Type B	117219239.1	94548763.62
Type C	1182186022	992955442.49
Total Material IDD	1481622975	1235918641.66
Total IDD	2561655512	2179566893.18
	Product TDD	Product TDD

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Type A	109395.69	132300.76
Type B	198515.74	146455.27
Type C	4684144.55	5364106.11
Total TDD	4992055.98	5642862.14

Table 4-16 Comparison between company data and inventory management system from 2014

Systems / Variables	Company data	Inventory management system
OFR	0.7501	0.7499
	Product IDD	Product IDD
Type A	21081718.59	17001385.96
Type B	324703673.77	272860230.06
Type C	747393338.10	655608191.32
Total Product IDD	1093178730.46	945469807.34
	Material IDD	Material IDD
Type A	80133137.93	71547444.58
Type B	236155035.02	216655995.43
Type C	1136932125.02	1052714930.58
Total Material IDD	1453220297.97	1340918370.58
Total IDD	2546399028.43	2286388177.92
	Product TDD	Product TDD
Type A	11887329.32	12435519.94
Type B	7932394.86	8040179.91
Type C	18421345.28	22442855.23
Total TDD	38241069.47	41918555.08

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Table 4-17 Difference between historical data and simulation of DMBM

Variables \ Years	Year 2013	Year 2014
Average OFR	1.19E-05	-0.0003
Total IDD	-0.1492	-0.1021
Total TDD	0.1304	0.0962

With the inventory management system using the data from past year, 2013, the reduction of total IDD of the year, 2014, can be around 10% at the value of W_{TDD} equals 0.99 and W_{IDD} equals 0.01. The results with W_{TDD} higher than 0.9 are almost the same but OFR of the result with W_{TDD} equals 0.95 and OFR of the result with W_{TDD} equals 0.9 are a little bit lower than the OFR of the result with W_{TDD} equals 0.99. However, average OFR will be reduced or stay at almost the company level and total TDD is increased a little bit as tradeoff.

4.5 Results of Whole System

4.5.1 Comparison with inventory management system

Under the assumption of independent of scheduling system and inventory management system, the factors of service level and adjustment at chapter 4.4.2 and the result of ABC classification at chapter 4.4.1 can be used while testing the whole system.

The result of IDD and TDD at different weights from 2013 (the best of ICA) and 2014 of whole system are listed at the tables next page (page 64 - page 67).

The Relationship between TDD, IDD and OFR of whole system of year 2013 is almost the same as that the results of the inventory management, but the OFR of whole system of year 2013 are slightly larger than the results of the inventory management. The Relationship between TDD, IDD and OFR of whole system of year 2014 is also

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almost the same as the results of the inventory management of year 2014. However, the way whole system fluctuated is not the same as inventory management system, it should be the effect of LR scheduling interacting with the DMBM. The figures are listed below:

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Table 4-18 Results of IDD and TDD from 2013 at different weights of whole system - 1

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.1	0.9	0.2	0.8	0.3	0.7	0.4	0.6	0.5	0.5
OFR	0.2359		0.2900		0.3842		0.4625		0.5565	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	1120444		4203782		1832322		6156054		4690520	
Type B	45567518		57148550		45219129		83864170		61183672	
Type C	11966827		19489961		39359511		42781396		325252023	
Total Product IDD	58654788		80842294		86410962		132801620		391126214	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	1442343		16142771		52811079		45688786		22708747	
Type B	4056020		40139300		2199021		184983427		46455714	
Type C	22564824		71321949		30387257		85458184		592887075	
Total Material IDD	28063187		127604020		85397357		316130397		662051536	
Total IDD	86717975		208446313		171808318		448932017		1053177750	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	1652490722		511331057		32242525		207058922		58030145	
Type B	138018887		78945840		305007306		100535665		120819264	
Type C	680395930		801981626		225144670		234000008		121638214	
Total TDD	2470905539		1392258523		562394500		541594595		300487623	

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Table 4-19 Results of IDD and TDD from 2013 at different weights of whole system - 2

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.6	0.4	0.7	0.3	0.8	0.2	0.9	0.1	0.95	0.05	0.99	0.01
OFR	0.6855		0.7103		0.7835		0.8069		0.8106		0.8395	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	4890520		2992806		3268996		17596455		19551617		20777489	
Type B	64183672		29938961		45607912		113958404		121232345		130077623	
Type C	216525914		228082993		240918468		696580177		733242292		790131780	
Total Product IDD	285600106		261014760		289795376		828135036		874026253		940986892	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	49842364		50384722		112352583		129728925		138009495		141114003	
Type B	89514418		112593444		113171707		86588619		86778923		95152328	
Type C	476413503		568309644		576588376		917783357		904700919		1006341400	
Total Material IDD	615770285		731287811		802112666		1134100901		1129489337		1242607731	
Total IDD	901370391		992302571		1091908042		1962235937		2003515590		2183594623	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	11316874		30317273		12294709		121243		117606		110331	
Type B	23416120		49158175		1485658		230043		219461		204738	
Type C	47062189		66613313		109504057		5447550		5126144		4739368	
Total TDD	81795183		146088761		123284424		5798836		5463211		5054437	

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Table 4-20 Results of IDD and TDD from 2014 at different weights of whole system - 1

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.1	0.9	0.2	0.8	0.3	0.7	0.4	0.6	0.5	0.5	0.6	0.4
Average OFR	0.1074		0.2160		0.2568		0.3152		0.4001		0.4651	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	5065487		1554562		6608318		294153259		1109832		5749364	
Type B	30154645		412012354		14473678		771204597		3483653		21318010	
Type C	10256458		12558125		63184370		32351738		38685405		55677825	
Total Product IDD	45476590		426125042		84266366		1097709593		43278890		82745199	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	1354562		5096833		1540216		20093234		26869034		38666557	
Type B	6862531		70534453		25612831		432142214		915791499		228693634	
Type C	19329451		63689181		46535377		83367310		160716328		424465129	
Total Material IDD	27546544		139320467		73688424		535602758		1103376862		691825320	
Total IDD	73023134		565445509		157954789		1633312351		1146655751		774570519	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	184945993		100070370		1555605035		70000815		112009647		142284021	
Type B	1821483018		195810074		190790613		52623515		190026805		341437228	
Type C	1522361142		1900236980		210970936		174514691		159038108		250277395	
Total TDD	3528790153		2196117424		1957366583		297139021		461074560		733998644	

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Table 4-21 Results of IDD and TDD from 2014 at different weights of whole system - 2

	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}	W_{TDD}	W_{IDD}
Weights / Variables	0.6	0.4	0.7	0.3	0.8	0.2	0.9	0.1	0.95	0.05	0.99	0.01
Average OFR	0.4651		0.2850		0.3445		0.7023		0.7421		0.7490	
	Product IDD		Product IDD		Product IDD		Product IDD		Product IDD		Product IDD	
Type A	5749364		5825318		6740484		13012648		13415101		14271384	
Type B	21318010		20962603		14980257		259491824		271151331		285422454	
Type C	55677825		43786944		246813945		600843594		634470532		674251363	
Total Product IDD	82745199		70574865		268534686		873348066		919036964		973945200	
	Material IDD		Material IDD		Material IDD		Material IDD		Material IDD		Material IDD	
Type A	38666557		38722849		67446644		70580847		71293785		75844452	
Type B	228693634		251146512		283786416		175957982		191598692		19558869	
Type C	424465129		621331228		604146258		989364317		999889469		1052515231	
Total Material IDD	691825320		911200589		955379319		1235903147		1262781946		1323868553	
Total IDD	774570519		981775453		1223914005		2109251212		2181818911		2297813753	
	Product TDD		Product TDD		Product TDD		Product TDD		Product TDD		Product TDD	
Type A	142284021		214794430		12006821		14820124		14034657		13315350	
Type B	341437228		523004793		90564215		8204265		8081201		8097610	
Type C	250277395		1661760950		491499003		22264185		21437739		20017391	
Total TDD	733998644		2399560173		594070039		45288574		43553597		41430351	

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Figure 4-3 Relationship between TDD, IDD and OFR of whole system of year 2013

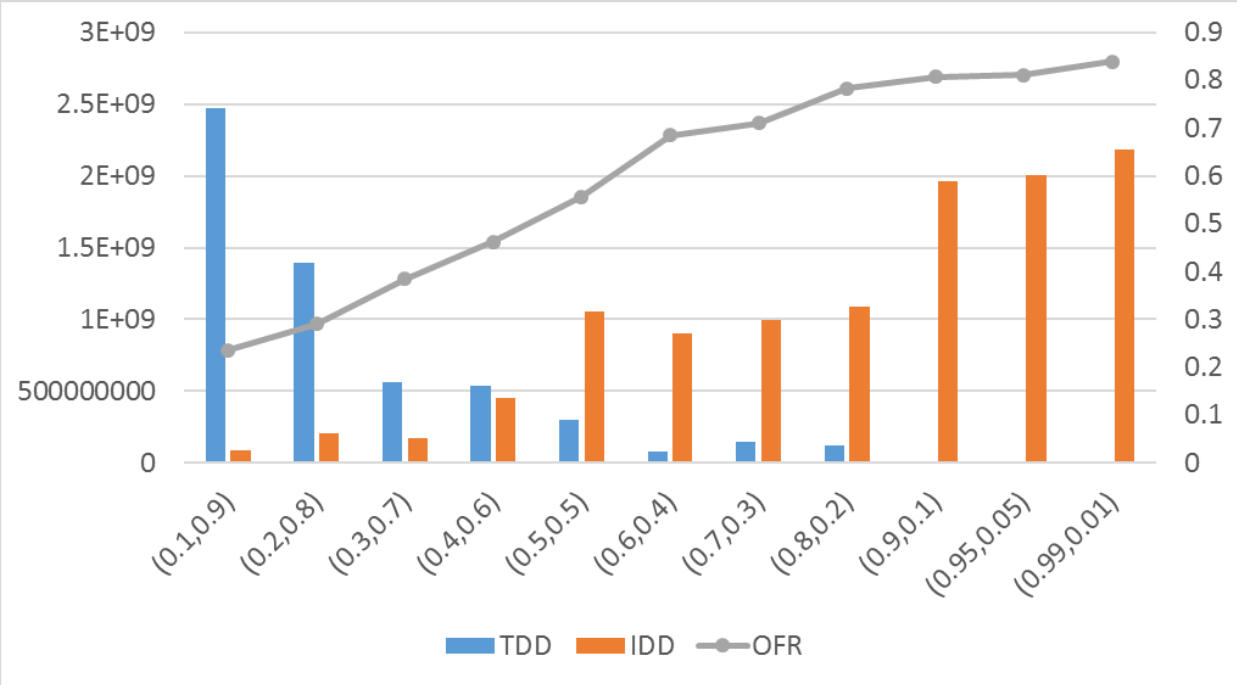
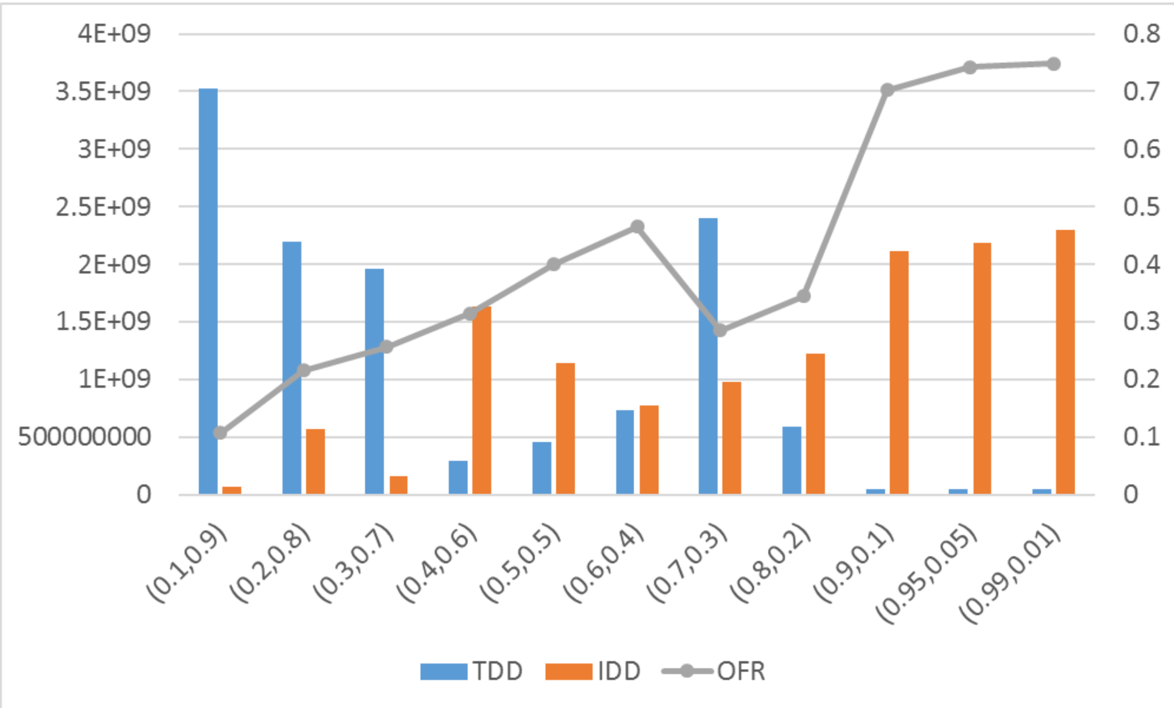


Figure 4-4 Relationship between TDD, IDD and OFR of whole system of year 2014



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4.5.2 Comparison with Company's Historical Data

In this chapter, results of simulation of whole system will be compared with historical data of the company and they are listed below:

Table 4-22 Comparison between company data and whole system from 2013

Variables \ Systems	Company data	Whole system
OFR	0.8402	0.8395
	Product IDD	Product IDD
Type A	32738635.57	20777488.81
Type B	162526133	130077623
Type C	884767769	790131779.7
Total Product IDD	1080032538	940986891.6
	Material IDD	Material IDD
Type A	182217713.5	141114002.8
Type B	117219239.1	95152328.33
Type C	1182186022	1006341400
Total Material IDD	1481622975	1242607731
Total IDD	2561655512	2183594623
	Product TDD	Product TDD
Type A	109395.69	110330.9571
Type B	198515.74	204738.3679
Type C	4684144.55	4739368.143
Total TDD	4992055.98	5054437.468

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Table 4-23 Comparison between company data and whole system from 2014

Variables \ Systems	Company data	Whole system
OFR	0.7501	0.749
	Product IDD	Product IDD
Type A	21081718.59	14271384
Type B	324703673.8	285422454
Type C	747393338.1	674251363
Total Product IDD	1093178730	973945200
	Material IDD	Material IDD
Type A	80133137.93	75844452
Type B	236155035	19558869
Type C	1136932125	1052515231
Total Material IDD	1453220298	1323868553
Total IDD	2546399028	2297813753
	Product TDD	Product TDD
Type A	11887329.32	13315350
Type B	7932394.86	8097610
Type C	18421345.28	20017391
Total TDD	38241069.47	41430351

Table 4-24 Difference between historical data and simulation of whole system

Variables \ Years	Year 2013	Year 2014
Average OFR	-0.0008	-0.0015
Total IDD	-0.1476	-0.0976
Total TDD	0.0125	0.0834

With the inventory management system using the data from past year, 2013, the reduction of total IDD of the year, 2014, can be around 9% at the value of W_{TDD} equals

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0.99 and W_{IDD} equals 0.01. The results with WTDD higher than 0.9 are almost the same but OFR of the result with WTDD equals 0.95 and OFR of the result with WTDD equals 0.9 are a little bit lower than the OFR of the result with WTDD equals 0.99. However, average OFR will be reduced or stay at almost the company level and total TDD is increased a little bit as tradeoff.

The whole system reduces more IDD for year 2013 than 2014, due to year 2013 is for training. However, with the DMBM and near-optimal factors of service level and adjustment factor, around 10% of IDD can be reduced.

4.6 Comparison with DMBM and Whole System

Table 4-26 and 4-27 show that whole system reduces more on type ‘A’ product, because the penalty on earliness production of type ‘A’ products is larger than other types of products. However, type ‘A’ material become larger while the late production of type ‘A’ products. Moreover, OFR of whole system is a little bit larger than DMBM but TDD of year 2013 is not the same as that in year 2014. It is owing to that LR with surrogate sub-gradient method only gets to near-optimal.

The ratio of tradeoff, TDD as denominator and IDD as numerator, between TDD and IDD is listed below:

Table 4-25 Tradeoff ratio between IDD and TDD

Years / Systems	Year 2013	Year 2014
DMBM	1.14411892	1.061803272
Whole system	11.81040368	1.170539604

The table above can let the company know that what is the relationship between IID and TDD.

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The ratio between two systems in the table 4-26 and 4-27 is index of whole system as numerator and index of DMBM as denominator.

The ratios between two systems are around 1 so we can say that there is nearly no difference between two systems.

Table 4-26 Comparison between DMBM and whole system in year 2013

Variables \ Systems	Whole system	Inventory management system	Ratio between two systems
OFR	0.8395	0.8402	1.0008
	Product IDD	Product IDD	Product IDD
Type A	20777488.81	24072526.15	1.1586
Type B	130077623	130020906.4	0.9996
Type C	790131779.7	789971222.3	0.9998
Total Product IDD	940986891.6	944064654.9	1.0033
	Material IDD	Material IDD	Material IDD
Type A	141114002.8	148414435.6	1.0517
Type B	95152328.33	94548763.62	0.9937
Type C	1006341400	992955442.5	0.9867
Total Material IDD	1242607731	1235918642	0.9946
Total IDD	2183594623	2179566893	0.9982
	Product TDD	Product TDD	Product TDD
Type A	110330.9571	132300.76	1.1991
Type B	204738.3679	146455.27	0.7153
Type C	4739368.143	5364106.11	1.1318
Total TDD	5054437.468	5642862.14	1.1164

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Table 4-27　Comparison between DMBM and whole system in year 2014

Systems / Variables	Whole system	Inventory management system	Ratio between two systems
OFR	0.7489	0.7499	1.0013
	Product IDD	Product IDD	Product IDD
Type A	14271384	17001385.96	1.1913
Type B	285422454	272860230.1	0.9560
Type C	674251363	655608191.3	0.9723
Total Product IDD	973945200	945469807.3	0.9708
	Material IDD	Material IDD	Material IDD
Type A	75844452	71547444.58	0.9433
Type B	19558869	216655995.4	11.0771
Type C	1052515231	1052714931	1.0002
Total Material IDD	1323868553	1340918371	1.0129
Total IDD	2297813753	2286388178	0.9950
	Product TDD	Product TDD	Product TDD
Type A	14315350	12435519.94	0.8687
Type B	8097610	8040179.91	0.9929
Type C	21017391	18442855.23	0.8775
Total TDD	43430351	38918555.08	0.8961

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Chapter 5 Conclusions and Future Works

5.1 Conclusion

Dynamic Multi-Buffer Management with adjustment factors and service levels setting by Imperialist Competition Algorithm and with ABC classification of products and material was better than traditional MRP, so the present study contributes preliminary research on the value of the adjustment factor and service level by Imperialist Competition Algorithm with ABC classification of products and materials.

However, the Lagrangian Relaxation with Surrogate Sub-Gradient Method cannot be compared with the WSPT rule, due to the maximum machine capability ratio. But we can know that Lagrangian Relaxation with Surrogate Sub-Gradient Method takes less time to get to the near-optimal solution with satisfaction around 90%.

This study suggests that the company implement the Dynamic Multi-Buffer Management to reduce more inventory-dollar-day. Dynamic Multi-Buffer Management can work well no matter what is the scheduling system.

Moreover, value of WTDD gets larger, order fill rate gets closer to the optimal rate, therefore if a company wants to fulfill more customer's order, the value of WTDD should get higher as compare to IDD.

Although most of the assumptions may not completely reflect the real situation, we still believe that this method can help companies to reduce inventory level. The mechanic of the system is not difficult to understand.

5.2 Future Works

This study focuses on the quantity of inventory in each warehouse, without connecting individual warehouse although the same product was stored in different

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place to shorten the lead-time. Future research should investigate the connections among different warehouses.

Moreover, the interaction between Dynamic Multi-Buffer Management and Lagrangian Relaxation with Surrogate Sub-Gradient Method based on different data set can be found in the previous, but it is not known how it works. In the future, the interaction mechanism should be found to help improve the Dynamic Multi-Buffer Management to reduce more inventory-dollar-day and throughput-dollar-day.

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