A KNOWLEDGE-BASED DECISION SUPPORT SYSTEM FOR MANAGING LOGISTICS OPERATIONS UNDER RISK CONSIDERATIONS

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A Knowledge-based Decision Support System for Managing Logistics Operations under Risk Considerations

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CERTIFICATE OF ORGINALITY

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Abstract

In order to survive in today's highly competitive business environment, the function of the warehouse in a supply chain is no longer only to keep a large amount of stock in storage. Instead, customer orders with high product varieties in small quantities are often received by the logistics service providers (LSPs), with requests for customized value-added services and timely delivery. However, each type of stock keeping unit needs different handling methods due to its specific characteristics, which increases the pressure on LSPs and forces them to change their strategic goals for achieving shorter order cycle times, lower costs, and better customer service. Therefore, the fulfillment of customer orders in the warehouse becomes challenging in order to satisfy increasing customer demand in terms of responsiveness, cost effectiveness and flexibility. In addition, due to the uncertainty and rapid changes in the business environment, the performance of warehouse operations is not only affected by the logistics strategy planning process, but also the possible risks that may occur during the logistics operations. Since the decision making process is one of the complicated processes involved in warehouse operation, attention should be paid to establishing a knowledge-based decision support system to support the planning of responsive logistics strategies that can be formulated to fulfill the demand of high efficiency and quality in logistics service requirements.

In order to facilitate the decision making process in warehouse operations, an intelligent system, namely the Knowledge-based Logistics Operations Planning System (K-LOPS) is proposed to formulate a useful action plan by considering the potential risks faced by the LSPs. The proposed system consists of three modules: real-time data collection module (RDCM), warehouse risk assessment module

(WRAM), and, logistics strategy formulation module (LSFM). RDCM collects real time logistics data, which enables instant monitoring of the inventory and resources status in the warehouse. WRAM provides a systematic approach in categorizing the potential risk factors considered by customers based on the different product characteristics, and is an important step to meet customer expectation. LSFM formulates the logistics operations strategy including critical operation procedures, useful guidelines and workflow to deal with the potential risks faced when fulfilling customer orders. Since the operational mechanism of LSFM relies on past explicit knowledge in order to provide references in formulating new solutions, a newly-designed algorithm, namely iterative dynamic partitional clustering (iDPC) algorithm, is integrated into the search engine to improve the performance in retrieving accurate and useful past similar cases.

To validate the feasibility of the proposed system, two cases studies have been conducted in a third party logistics company and a wine distribution hub, both of which are based in Hong Kong. Through the pilot run of the system in the two case studies, improvement of follow-up action formulation and warehouse operation effectiveness was observed. Meanwhile, a generic methodology related to the design and implementation of the proposed system is described, which provides a roadmap for the logistics service providers to follow.

The major contribution of this research is in the design and implementation of an effective system, which facilitates appropriate decision making in providing diverse logistics strategy formulation, by emerging real-time data capturing technology and hybrid artificial intelligent techniques for risk assessment and decision making in the logistics industry.

Publications Arising from the Thesis

(**6** international journal papers have been published or accepted and **1** international paper is under review. **4** conference papers are published)

List of International Journal Papers

[1] Lam, C.H.Y., Choy, K.L., Ho G.T.S. and Lee, C.K.M. (2014), An order picking operations system for managing the batching activities in a warehouse, *International Journal of Systems Science*, Vol. 45 (6), pp. 1283-1295.

[2] Choy, K.L., Sheng, N., Lam, H.Y., Lai, K.W. Ivan, Chow, K.H. and Ho, G.T.S. (2014), Assess the Effects of Different Operations Policies on Warehousing Reliability, *International Journal of Production Research*, Vol. 52 (3), pp. 662-678.

[3] Choy, K.L., Gunasekaran Angappa, Lam, H.Y., Chow, K.H., Y.C. Tsim, Ng, T.W., Tse Y.K. and Lu X.A. (2014), Impact of Information Technology on the Performance of Logistics Industry: The Case of Hong Kong and Pearl Delta Region, *Journal of the Operational Research Society*, Vol. 65 (6), pp. 904-916.

[4] Lam, H.Y., Choy, K.L., Ho, G.T.S., Kwong, C.K. and Lee, C.K.M. (2013), A Real-Time Risk Control and Monitoring System for Incident Handling in Wine Storage, *Expert Systems with Applications*, Vol. 40 (9), pp. 3665-3678.

[5] Lam, C.H.Y., Choy, K.L., Ho, G.T.S. and Chung, S.H. (2012), A Hybrid Case-GA-based Decision Support Model for Warehouse Operation in Fulfilling Cross-Border Orders, *Expert Systems with Applications*, Vol. 39 (8), pp. 7015-7028.

[6] Lam, C.H.Y., Choy, K.L. and Chung, S.H. (2011), A Decision Support System to Facilitate Warehouse Order Fulfillment in Cross-Border Supply Chain, *Journal of Manufacturing Technology Management*, Vol. 22 (8), pp. 972-983.

[7] Lam, H.Y., Choy, K.L., Ho, G.T.S., A Knowledge-based Logistics Operations Planning System for mitigating risk in warehouse order fulfillment, *International Journal of Production Economics* (*Submitted in October 2013*).

List of Conference Papers

[1] Lam, H.Y. and Choy, K.L. (2013), A Knowledge-based Workflow Management Model for Measuring the Performance of Warehouse Operations, *The application of Engineering Business Management Conference*, Bangkok, Thailand, 25 July 2013, pp. 1-7.

[2] Choy, K.L., Lam, H.Y., Lee, C.K.H. and Lin, C. (2013), A Hybrid Decision Support System for Storage Location Assignment in the Fast-Fashion Industry, *Proceedings of the Portland International Conference for Management of Engineering and Technology PICMET 2013*, *San Jose, California, USA, 28 July – 1 August 2013,* pp. 468-473.

[3] Lam, H.Y., Choy, K.L., Chung, S.H. and Poon, T.C. (2010), A Cross-Border Workflow Management Framework for Measuring the Performance of Warehouse Operations, *Proceedings of the 8th International Conference on Supply Chain Management and Information Systems SCMIS 2010*, Hong Kong, 6-8 October 2010, pp.1-8. (Best Paper Award)

[4] Lam, C.H.Y., Choy, K.L. and Chung, S.H. (2010), Framework to measure the performance of warehouse operations efficiency, *Proceedings of the 8th IEEE International Conference on Industrial Informatics INDIN 2010*, Osaka, Japan, 13-16 July 2010, pp.634-639.

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List of Abbreviations

AHP	Analytical hierarchy process
AI	Artificial intelligence
CBM	Cubic meter
CBR	Case-based reasoning
CBSC	Cross border supply chain
DSS	Decision support system
GA	Genetic algorithm
HKQAA	Hong Kong Quality Assurance Agency
iDPC	Iterative dynamic partitional clustering
K-LOPS	Knowledge based logistics operations planning system
KPI	Key performance indicator
LSFM	Logistics strategy formulation module
LSP	Logistics services provider
NNR	Nearest neighbor retrieval
OFP	Order fulfillment process
RDCM	Real-time data collection module
RFID	Radio frequency identification
SA	Simulated annealing
SCRM	Supply chain risk management
SKU	Stock keeping unit
SOP	Standard operating procedure
WMS	Warehouse management system
WRAM	Warehouse risk assessment module

Chapter 1 Introduction

1.1 Research Background

With sustained development in information and communication technology, businesses and markets are no longer confined to geographical borders. They are linked to form a complex international network such that trading occurs right across the supply chain. Several parts of business processes, such as sourcing of raw materials, manufacturing, and storage, are outsourced to have lower operation costs (i.e. labor and rental cost) and increased profit. However, the current situation of direct shipment from various suppliers to warehouses located in different countries increases the global shipping cost and inventory levels kept in each warehouse. In addition, due to the effects of globalization, logistics service providers (LSPs) have changed their strategic goals to achieve shorter order cycle times, lower costs, and better customer service in order to survive in this highly competitive business environment. The supply chain has become complex in satisfying increasing customer demand in terms of responsiveness, cost effectiveness and flexibility (Gunasekaran et al., 2001). Instead of keeping a large amount of stock for long-term storage, the warehouses of LSPs have been examined as to their functions in handling orders that contain fast-moving items with large product variety (Chow et al., 2006). Customers are allowed to place delivery orders based on actual sales demand. Therefore, delivery orders containing large varieties of product types in small quantities are frequently received. Adding to the complexity of the situation, nowadays, a warehouse not only acts as a storage area, but also acts as a transit point before goods are transferred for further production. The goods are consolidated in the warehouse and loaded into trucks for delivery. In order to save time in waiting for completion of the loading, LSPs need to have a good plan and carefully coordinate the transportation and warehousing activities in order to fulfill customer orders within the minimum shipping and receiving cycle times (Mason et al., 2003). Hence, planning of warehouse order picking activities effectively becomes highly challenging, so that an order can be picked and delivered at a designated time according to customer requirements.

Meanwhile, the fulfillment of customer orders with good quality standards and on time delivery becomes difficult to achieve due to the complicated legal and quality requirements of imported goods in many countries. Achieving these requirements for high value goods is especially important, which means the goods have to meet superior quality standards along the whole supply chain. Due to the uncertainty and rapid changes in the business environment, the performance of warehouse operations is not only affected by the logistics strategy planning process, but also the possible risks that may occur during logistics operations. Effective risk management brings the advantages of efficiency improvement to the warehouse, and enables the warehouse to manage risk efficiently despite higher severity of risks, and rapid recover after a disruption, for business continuity (Tang, 2006). Risk is intuitive and can occur under any event or circumstance with unreliability or uncertainty. It refers to any factor that would disturb the warehouse activities with the possibility of loss, damage, or any other undesirable event. Since risks will affect a business organization's performance significantly in the short-term and long-term, logistics companies may suffer losses if they fail to deal with the problems and risks properly. Thus, it requires continuous attention to risk management in planning warehouse operations, which further increases the complexity in the decision making process in logistics strategy formulation.

Therefore, this research aims to develop a Knowledge-based Logistics Operations Planning System (K-LOPS), with a combination of real-time data capturing technology and artificial intelligence techniques, in order to meet the challenges of providing applicable decision support knowledge for demanding customers who seek high quality services.

1.2 Problem Statement

Traditionally, the warehouse was used to store inventory during all phases of the logistics process from both the upstream (i.e. suppliers, manufacturers), and the downstream (i.e. retailers) parties (Stock and Lambert, 2001). The major functions of the warehouse are to receive stock keeping units (SKUs) from suppliers, store the SKUs, pick SKUs and pack them for shipment, and finally ship the completed orders to customers (Gu et al., 2007). Due to significant change in the global business environment, the function of the warehouse is no longer to keep a large amount of stock as storage only. Instead, there are many varieties of SKU and each type of SKU needs different handling methods due to its specific characteristics. It is complicated for the warehouse manager to make decisions when planning order handling instructions. As might be expected in a densely populated city while resources are limited in the warehouse of LSPs, it is important to fully utilize warehouse resources for the order fulfillment process (OFP) so as to match the tight transportation schedule. According to Veronneau and Roy (2009), the processes of direct delivery and consolidation at the logistics center in a cruise supply chain are complex and therefore the order can only be completed within a short period of time. Li (2011) addressed the importance of understanding the order fulfillment needs by examining relational benefits provided by LSP. Therefore, warehouse operation efficiency becomes one of the critical factors in competing with competitors in terms of operation time, cost and customer satisfaction, by considering all parameters involved in the warehouses, resources and dynamics of inventory movement.

To have better control on warehouse operation, information systems, such as the warehouse management system (WMS), have been introduced for information storage, planning and reporting, from the time of receipt of goods to the time of shipping them (Faber et al., 2002; Shiau and Lee, 2010). In the last decade, WMS has been widely used to increase competitiveness. In general, WMS increases the visibility of warehouse operations, which allows the warehouse manager to keep track of the status of the orders and inventory level. Figure 1.1 shows the existing decision making process using WMS in the logistics industry. By inputting the order attributes, such as the type of logistics service requested, SKU details and delivery schedule, the WMS can generate various reports to provide information for order handling and picking operations. Through extracting relevant information from the WMS, the warehouse manager can make sure that the daily operations, such as assigning stock to storage locations and order picking, are carried out satisfactorily. However, most of the WMSs do not support planning and monitoring of the use of warehouse resources but only focus on managing warehouse operations. The selection and assignment of resources, such as material handling equipment and labor, solely relies on the knowledge of warehouse experts. It is difficult for an expert to handle complex customer orders with available warehouse resources based on past experience, normal practice and personal judgment. Furthermore, once warehouse operations problems such as delivery delays and material shortages occur, it increases the risk of cargo damage and loss.

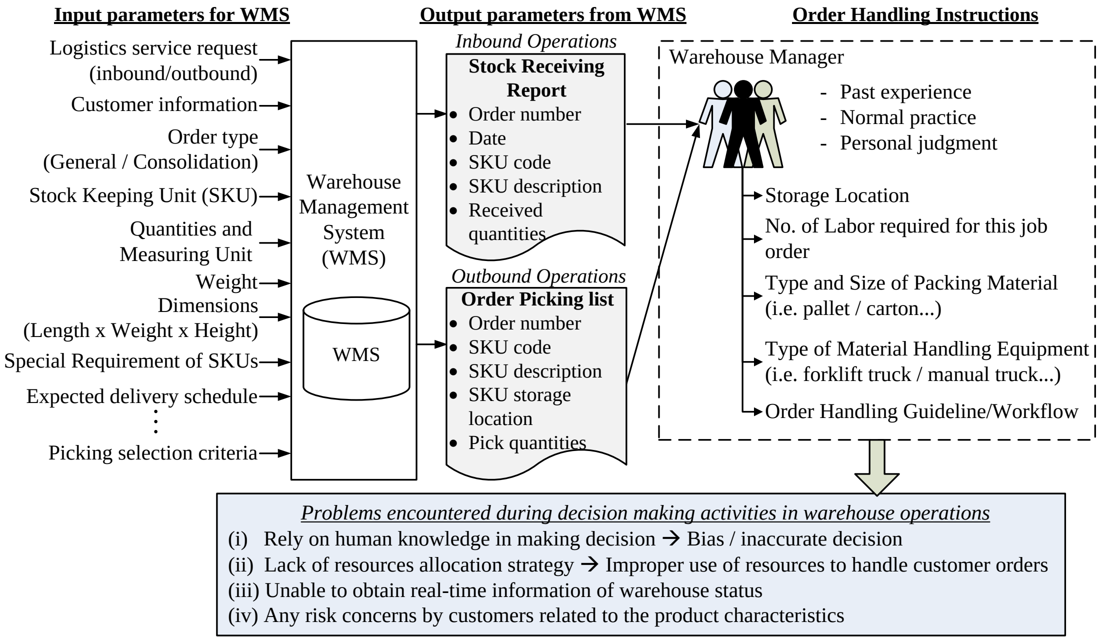


Figure 1.1 Existing problems in the decision making process of the logistics industry

A number of approaches and systems have been designed and developed to improve warehouse operations, performance and customer satisfaction. However, an integrated intelligent system, which is able to support the function of real-time data capturing and decision-making activities of risk assessment and resources allocation, is still an area that requires in-depth study and investigation. There are still four major problems to be resolved. These are summarized as follows:

(i) How to design a reliable intelligent system to obtain explicit knowledge for effective strategy formulation in order to support the decision making activities within the warehouse.

(ii) How to acquire logistics operations data and monitor operational status using Radio Frequency Identification (RFID) technology

(iii) How to link up the risk assessment concept from the customer's perspective with the logistics operations activities in warehouse

(iv) How to implement the intelligent system so as to provide relevant and appropriate knowledge for decision making on resources allocation.

As the company is required to handle a large number of orders for diversified products, making a wrong decision in the logistics operations would affect the warehouse performance and service quality to customers. Current order fulfillment decisions are made based on the knowledge of the warehouse manager. It is difficult for the warehouse manager to give appropriate order handling instructions with consideration of the product characteristics and existing warehouse operations. Thus, bias and subjective judgment may result in an inaccurate decision. The lack of a resources allocation strategy may mean that no suggestions on resources allocation are provided on how to handle the order when a possible risk occurs, resulting in improper use of resources and loss of customer satisfaction.

1.3 Research Objectives

The specific objectives of this research are:

(i) To present generic system architecture that allows an analysis to be made on facilitating and providing knowledge support during operations planning

(ii) To develop an intelligent system for supporting the decision making process in planning and controlling the warehouse operations by considering the initiation of risk concerns and special characteristics when fulfilling customer orders

(iii) To develop an effective clustering algorithm for improving the searching performance in retrieving past explicit knowledge from case repositories

(iv) To establish a logistics strategy formulation model incorporating Analytical Hierarchical Processing (AHP) and Case-based Reasoning (CBR), which is supported by the proposed clustering algorithm, to improve the quality of decision making for enhancing the operations efficiency in the warehouse

1.4 Significance of the Research

According to the literature, traditional decision support models have focused on optimizing warehouse design and operations including layout design, storage location assignment methods, order picking and routing activities to tackle the problem of inefficient warehouse operations. However, in practical situations, the warehouse performance is not limited to the measure of efficiency and operation time only, as providing customized services according to customer requests are a critical concern in achieving customer satisfaction such that long term business relationships can be maintained. Therefore, instead of focusing on the optimization function to improve the operation efficiency, offering effective knowledge support and guidelines for order fulfillment is essential so as to provide insights into how the warehouse can cope with various customers in order to increase competitiveness. As shown in Figure 1.2, this research is concerned with the introduction of K-LOPS, aiming at achieving customer satisfaction and providing decision support functions for warehouse operations in the logistics industry, supported by the newly designed iterative Dynamic Partitional Clustering (iDPC) algorithm. This enables logistics supervisors to formulate and adjust action plans based on past explicit knowledge from various customer specifications. The iDPC algorithm, which is integrated into the case based reasoning engine, offers an innovative approach for retrieving past cases by considering multiple ordering features at the same time. It ensures that all possible combinations of variables in forming case clusters are considered, which improves the performance in selecting the most similar case among the group in the latter stages. The system also considers the critical warehouse activities in the order fulfillment process, with the functions of risk assessment and operations strategy planning based on various customer requests. By integrating the concept of risk management in warehouse operations, the warehouse manager is able to examine the risk factors of concern to customers that will greatly affect customer satisfaction if a problem occurs but inappropriate handling solution is provided. Thus, customer expectation is also taken into consideration when formulating logistics strategies. To summarize, the work presented in this thesis contributes significantly to the development of an intelligent decision support system for encouraging customer participation in planning various logistics operations, which in turn helps the LSP to achieve the objectives of improving warehouse operations by initiating risk management.

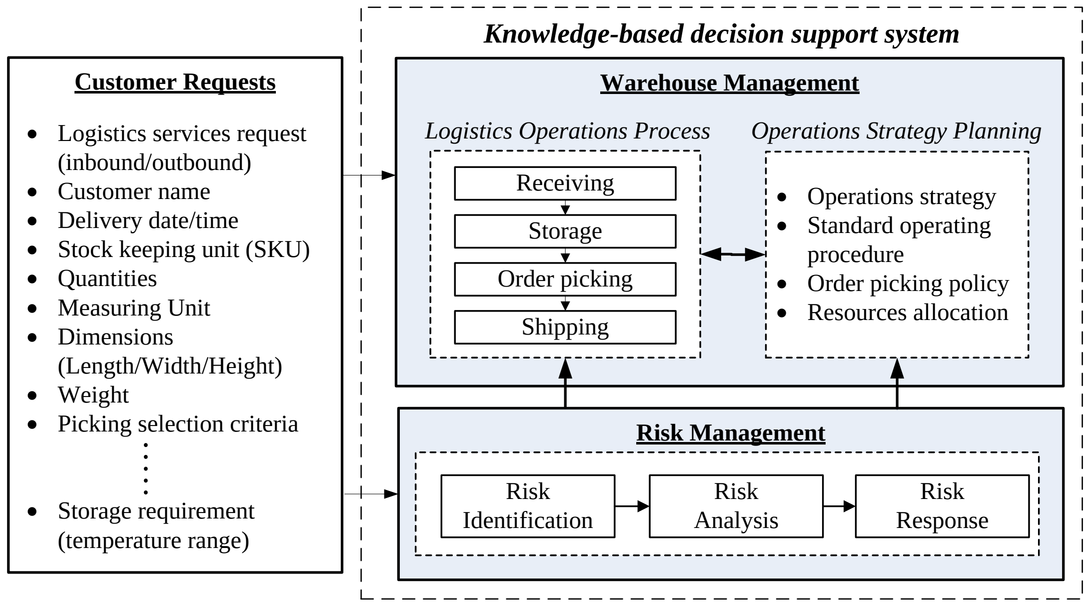


Figure 1.2 Knowledge domain of decision support system for warehouse operations

1.5 Thesis Outline

The thesis is divided into seven chapters, as follows:

(i) Chapter 1 states the research problems that occur in existing warehouse operational management, and describes the background and motivation for this research. The research objectives and significance are also presented.

(ii) Chapter 2 is an academic review, which shows existing situation and problems in the logistics industry, and the degree of application of risk management concepts in the supply chain. The warehouse operation challenges faced by LSPs in fulfilling customer orders are then highlighted. The analysis of decision support systems and existing artificial intelligent techniques adopted in warehouse activities are discussed and reviewed. In addition, current real-time data capturing technologies are also reviewed.

(iii) Chapter 3 is divided into two main sections. The first section introduces the system architecture of K-LOPS. The second section describes the infrastructure of K-LOPS, which consists of a real-time data collection module (RDCM), a warehouse risk assessment module (WRAM) and a logistics strategy formulation module (LSFM). The algorithm of iterative dynamic partitional clustering algorithm (iDPC) is also presented to support the case retrieval process in LSFM. These three modules are developed to achieve the research objectives for enhancing warehouse operations.

(iv) Chapter 4 provides the generic implementation guide of K-LOPS from the design stage, through structural formulation of each module, to the implementation and evaluation stage.

(v) Chapter 5 focuses on operating the system in two logistics companies based in Hong Kong. Parts of warehouse operations processes within these two companies' workflow are chosen to demonstrate the feasibility of the proposed methodology. A K-LOPS software prototype is developed and the related operations mechanism for supporting the decision support process is also explained in this chapter.

(vi) Chapter 6 explains the results and presents an analysis of the system. It consists of two sections. The first section discusses the comparison of system performance in the knowledge-based logistics operations planning system. The second section discusses the overall performance of the two case studies after the implementation of K-LOPS.

(vii) Chapter 7 draws the conclusions from the study. In this chapter, the contributions made by this research are presented, and areas for future research are identified.

Chapter 2 Literature Review

2.1 Introduction

The focus of this research is on the design of a knowledge-based decision support system for integrating the risk management concept, from the customer's perspective, with the logistics operational activities in the warehouse by providing relevant and appropriate explicit knowledge. The aim is to provide a comprehensive review on the past literature related to the current research areas. It is divided into three major sections. The first section reviews the evolution of the current supply chain environment, in which the current situation of the supply chain environment and an overview of warehouse operations challenges are presented. Then, an overview of risk management in warehouse operations and related studies on existing risk management approaches in warehouse management are conducted to show the importance of the risk management concept in managing the warehouse. The second section provides an overview of intelligent systems for warehouse management, where existing information systems in warehouse management and existing artificial intelligent techniques adopted in warehouse activities, including fuzzy logic, analytical hierarchical processing, rule-based reasoning, case-based reasoning, genetic algorithms, are presented. The third section reviews the current automatic data capturing technologies, including barcode technology and radio frequency identification technology. Finally, a summary on the literature review is presented to provide an insight on the research direction.

2.2 Evolution of Current Supply Chain Environment

Supply chain management is defined as the alignment of objectives and the integration of resources across company boundaries in order to create value (New and Payne, 1995; Lorentz, 2008). According to Mentzer et al. (2000), managing the supply chain effectively is important as it coordinates various business functions across multiple parties in order to enhance the performance of the business and efficiency of the supply chain. The supply chain process can be presented as workflow by controlling and planning of the sequences of activities which have to be executed within an organization (van der Aalst and van Hee, 2002). It involves the flows of information, material, finance and service in a network which involves a number of parties from the upstream to the downstream (Mentzer et al., 2001). To manage the workflow within the supply chain, one of the key factors is to control the order fulfillment process (OFP). The OFP starts when the customer's order is received and finishes when the required services or goods are delivered (Lin and Shaw, 1998). It includes all the activities involved in defining customer requirements, designing the logistics planning and completing customer orders within the whole supply chain (Lin and Lin, 2006). At the operational level, OFP focuses on transactions, while at the strategic level, management can focus on making critical improvements to the processes that influence the financial performance of all parties (Croxton, 2003). In addition, Zhang et al. (2009) stated that the OFP should be focused on the operational level in assisting companies to respond quickly to various customer requirements and on time delivery with lower cost. Various techniques are used to solve the OFP model. Chen and Huang (2006) have considered the fuzzy operation cycle time in fulfilling customer orders. An order fulfillment optimization model is presented by Amer et al. (2010) to fulfill orders through the effective monitoring and controlling of supply chain variables. In order to ensure the OFP can be completed effectively, the current situation of the supply chain environment and an overview of warehouse operations challenges are first presented. After that, an overview of risk management in warehouse operations, and related studies on existing risk management approaches in warehouse management are discussed.

2.2.1 Current Situation of Supply Chain Environment

With advanced information technologies, supply chains nowadays are no longer limited to geographical borders; instead, they are linked in a complex worldwide network for trading (Gunasekaran, 1998; Lemoine and Dagnæs, 2003). Thus, cross-border trading has become an important issue recently because goods now flow in the supply chain across the international boundaries in different tax regions. According to the Bank (2007), cross-border trading is defined as "the flow of goods and services across international land borders within a reach of up to 30 kilometers." It usually occurs when products are significantly cheaper in one place than another. Generally, substantial time and costs are involved in the process of the cross-border system. These include: (i) trucking from one location to another, (ii) handling costs and associated times of inspections for pre-clearance and storage, (iii) costs of loading and unloading; (iv) drayage costs and times of border crossings, and (v) inspections on each side of the border (Haralambides and Londono-Kent, 2004). Similar to the general supply chain, a supply chain with a cross-border function refers to the logistics flow of goods across international borders between separate geographical locations. There are a number of typical cross-border supply chains worldwide, such as (i) Indonesia–Malaysia–Singapore (Shen, 2003), (ii) US–Mexico (Hausman and Haytko, 2003), and (iii) Hong Kong–China Pearl River Delta region

(Yang, 2006). The existence of the cross-border supply chain is due to unique geographic characteristics and the close connections between the two places, with frequent cross-border trading activities (Leung et al., 2006). The products obtained are usually located in a place separate from the manufacturing plants or retailers. Figure 2.1 shows an example of a supply chain across two separate regions in the actual case of Hong Kong and the Pearl River Delta Region cities of China.

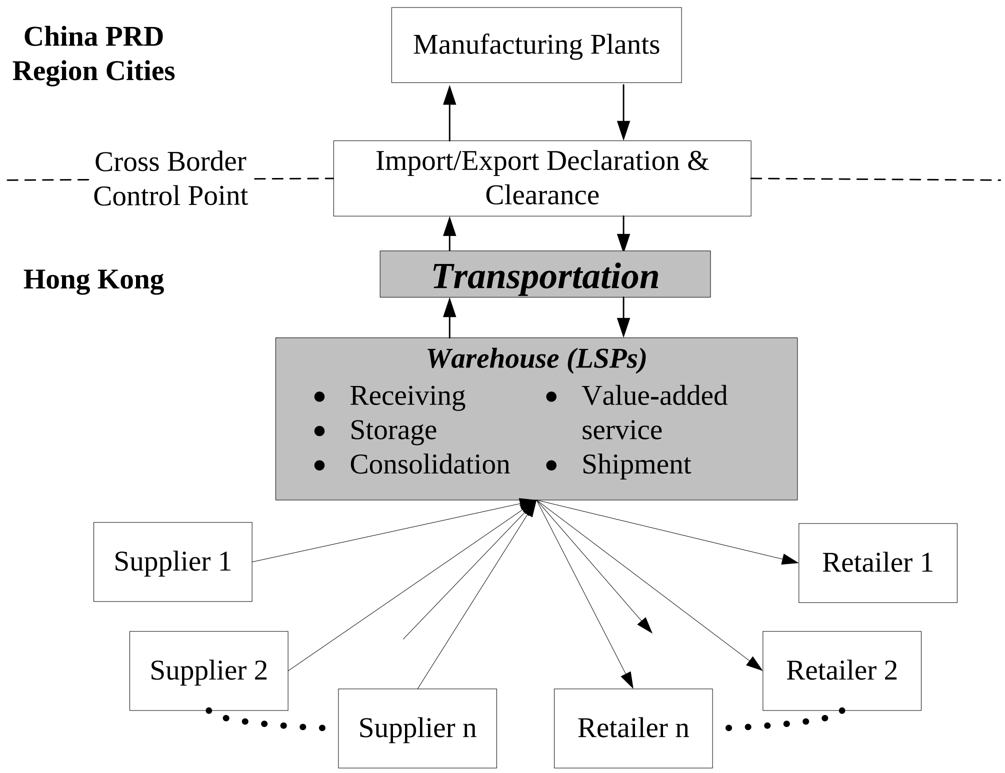


Figure 2.1 Supply chain across two separate regions between Hong Kong and China

Since the return of Hong Kong to China in 1997, Hong Kong has become a special administrative region of China, but the existing business activities have remained unchanged (Shen, 2003). The transportation and cargo delivery between Hong Kong and China still needs to pass through one of the control points to ensure import/export quality and to fulfill legal requirements. These control points include Man Kam To, Sha Tau Kok, Lok Ma Chau and Shenzhen Bay. According to the statistics of Hong Kong Customs and Excise Department, the total number of goods trucks passing through all control points exceeded 7.6 millions in the year 2012. This indicates that cross-border land transportation is one of the important logistics activities between Hong Kong and China. With this type of supply chain, the products are first consolidated and stored in the same place before delivery arrangements are made.

Various operations research techniques have been developed to assist in the planning of activities being undertaken by constituent elements in the supply chain (Leung et al., 2002; Gunasekaran et al., 2008; Wang and Cheng, 2010). The European Union (EU) nations have eliminated border controls to allow smoother passage of goods and the standardization of procedures; however, requirements have not been implemented in Eastern Europe (Prater et al., 2001). This contributes to increased complexity, uncertainty, and supply chain exposure. Haralambides and Londono-Kent (2004) investigated the political and social administrative issues of the supply chain system across the U.S. and Mexico border in order to maintain an efficient cross-border system. Leung et al. (2002) also suggested a linear optimization model to reduce the transportation costs of manufacturing activities in the supply chain. Lai et al. (2003) introduced a transportation system within a supply chain to take into consideration the production capacity and sales constraints for the electronics industry. It also synchronized the operations of production, transportation, warehouse inventory and sales, so as to minimize the total transportation and inventory costs. Leung et al. (2006) described a goal-programming model for multi-objective logistics problems in a supply chain under fleet management, while a framework for incorporating decision-makers' opinions for determination of goal priorities and target values was suggested. Cheung et al. (2008) considered the regulatory policies and primitive resources to improve the logistics problems in the supply chain. Most of the research focused on transportation problems in order to lower the operation cost, however little attention was paid to managing the operations in warehouses. As a buffer in the supply chain for storage, a warehouse can be used to provide temporary storage before receiving a delivery order from customers, consolidate products from different sources of suppliers, and provide value-added services such as packing/repacking and palletization (Gu et al., 2007; De-Koster and Warffemius, 2005). Many companies also realized that integrating inventory control and delivery policies in the warehouse can save a significant amount in costs (Cha et al., 2008). Therefore, various operations can be carried out in the warehouse to suit customer delivery requirements within the supply chain.

2.2.2 Overview of Warehouse Operations Challenges

In today's complex and dynamic supply chain network, warehousing is an essential component for linking the chain partners within the supply chain. The importance of warehouses to many multinational manufacturers in the supply chain has been examined by Prater et al. (2001). Its major roles include buffering the material flow, including raw materials, semi-finished goods, or finished goods along the supply chain, to accommodate the variability caused by factors such as product transportation; consolidation of products from various suppliers to customers; value-added-processing and product customization (Gu et al., 2007).

2.2.2.1 Warehouse Design and Operation

With increasing and diversified activities performed in a warehouse, the warehouse design and operation have been recognized as one of the key concerns for improving the warehouse operation performance (Gu et al., 2010). The design of a warehouse is one of the concerns in warehouse management in which it provides a fundamental framework for conducting various types of warehouse activities. According to Rouwenhorst et al. (2000), warehouse design is defined as a structural approach to meet a number of performance criteria at the strategic, tactical and operational level. The criteria may include investment and operational costs, storage capacity and throughput, response time and order fulfillment quality. On the other hand, warehouse operations refer to the processes that guide physical activities, from product receipt, material movement and storage, to order selection (Lumsden and Mirzabeiki, 2008). The warehouse operations are mainly divided into four processes, which are receiving, storage, order picking and shipping. When performing such operations, various types of documents associated with the flow of products are handled. The data received with each corresponding operational activities are very useful to evaluate and analyze the efficiency of the warehouse.

(i) Receiving and shipping

In general, receiving and shipping provide the connection between a warehouse and the external environment. Truck scheduling, loading and unloading problems are the major concerns in these two processes in allocating the material handling resources and working out the delivery schedule efficiently (Berg and Zijm, 1999).

(ii) Storage

In the storage process, goods received from the suppliers are placed in a storage area until delivery orders are received to ship the goods to customers.

- Three storage decisions

According to Hou et al. (2010), there are three fundamental decisions, when dealing with the storage function, in warehouse management: i) what is the quantity of stock keeping units (SKUs) that need to be kept in the warehouse; ii) what is the frequency and time needed to perform a replenishment for an SKU's inventory; iii) where should the SKU be allocated, stored, distributed and moved to, from among different storage areas. The storage location assignment problem is to allocate incoming products to storage locations in storage warehouses or zones for the purpose of lowering the material handling cost and improving space utilization.

- Three storage policies

An appropriate storage location assignment helps to minimize total travelling time, or travelling distance, for order pickers in the warehouse. There are three major types of storage policy: random storage, class–based storage and dedicated storage. The concept of random storage is to randomly assign all incoming products to any available empty location in the warehouse (Peterson, 1997). This method is only applicable in a warehouse which is equipped with a computerized system to keep track of the location assigned to each product. The random storage policy results in high space utilization because every feasible empty space in the picking area can become a candidate to store any incoming product (Fukunari and Malmborg, 2008). A class–based storage assignment policy is a hybrid type of random and dedicated storage policy (Muppani and Adil, 2008). ABC theory is the usual method to divide the items into three classes, according to Pareto's Law. Pareto's Law is based on the popularity of the SKU to decide on the storage location in a warehouse. According to Mulcahy and Sydow (2010), the law reveals that 85% of the volume shipped to customers accounts for 15% of the SKUs. The travel distance can be reduced, as each zone location is assigned with items according to their popularity. A dedicated storage policy requires products to be stored in a fixed location. Every SKU is assigned to a unique storage location. This policy requires sufficient spaces for every product to be reserved for the purpose of storing the maximum inventory level. Therefore the space utilization is the lowest among all storage policies.

(iii) Order picking

Among the four major functions of a warehouse, order picking has been identified as the most labor-intensive and most costly activity in operations, which accounts for 55% of the total operating expenses (De-Koster et al., 2007). The most common objective of the order picking system is to maximize the service level, subject to resource constraints, such as labor, machines, and capital as well as the accessibility to all items (Chiadamronga and Kawtummachai, 2008). Any underperformance in order picking can lead to unsatisfactory service and high operational cost for the warehouse, and consequently, for the whole supply chain. When there is an incoming customer order, as order picker is assigned to pick the order items, simultaneously, according to their storage location. According to Yu and De-Koster (2009), there are four major factors affecting the order picking operation performance, namely, (i) warehouse layout design (i.e., zoning), (ii) storage location assignment strategy, (iii) routing policy in order picking, and (iv) batching practice to handle the orders in groups. From the previous literature, a number of studies on these four factors have been conducted to increase the picking efficiency (Hsieh and Tsai, 2006; Taghavi and Murat, 2011). Hwang and Cho (2006) presented a model to evaluate the order picking performance with respect to minimizing the travel distance of the picker, by considering the warehouse design parameters, such as warehouse size, rack size, and number of aisles. Pan and Wu (2009) investigated the influence on different storage assignment policies to allocate receiving items to suitable storage areas in order to reduce the order picking time. Roodbergen and De Koster (2001) compared the optimal and heuristics routing approaches with the objective to formulate the shortest order picking route.

2.2.2.2 Challenges on improving order picking efficiency

To increase the order-picking efficiency in a warehouse, researchers have focused on batching, routing, and facility planning and design, which can better utilize the space and increase the material flow in the warehouse (Baker and Canessa, 2009). The order batching problem refers to the decision making on effectively consolidating several orders into batches, so that the order processing operations can be improved and optimized. It is usually applied when the customer orders contain high product variety, small order sizes, and short response times. By combining several orders into batches before the order picking process, the total picking time and efficiency can be improved significantly by serving a group of orders at once (Petersen, 2000). Generally, consideration on travel times and distances of the order picker are usually employed in the order batching problem to increase the picking efficiency. Gademann and Van de Velde (2005) considered minimizing the total traveling time needed to pick all the items by developing a branch and price algorithm, and an approximation algorithm. It is found to be a NP-hard problem if there are more than two orders assigned in a batch. Hsu et al. (2005) developed a genetic algorithm (GA) based order batching method to group customer orders into batches in which the total travel distance is minimized. Hsieh and Huang (2011) suggested two batch heuristics approaches called k-means batching and self-organization map batching, which construct batches by considering the total travel distance and the average picking vehicle utility. Moreover, Tsai et al. (2008) proposed a GA-based picking model that could formulate the optimal batch picking plan by minimizing the sum of travel cost and earliness and tardiness penalties, resulting in the most effective travel path. Furthermore, order batching can increase the efficiency of order picking if orders with similar item requests or storage locations are picked together. Chen and Wu (2005) proposed to recognize the association between customer orders by initially considering the customer demand patterns, and then grouping orders into batches by the clustering method. Won and Olafsson (2005) considered the sequential order batching and picking problem that first grouped the orders into batches, and formulated the shortest routes by the classic traveling salesman problem (TSP). On the other hand, the savings algorithm proposed by Clarke and Wright (1964) has been adopted in the order batching problem. This savings algorithm is one of the suggested methods to effectively formulate a batch plan by considering the saving of cost or travel distance if two storage locations are traveled to at the same time (Dukic and Oluic, 2007). Ho et al. (2008) developed order-batching methods, such as the seed-order selection rule and the accompanying order selection rule for order picking in the warehouse, in order to minimize the travel distance of the pickers. On the other hand, according to Chan and Chan (2011), the storage assignment problem is a major task faced by the warehouse manager for order picking in warehouse design. Rim and Park (2008) defined the order-picking plan as a decision-making process for deciding which orders should be picked to maximize the order fill rate subjected to the availability of the inventory. Therefore, order picking in a warehouse plays an important role in improving delivery efficiency. Coming up with an effective plan in the order delivery process, with the appropriate product palletization, is a challenge for warehouse managers in decision making. With limited time to respond to the operations arrangement and to meet the tight delivery schedule requested by customers, decision makers are hard put to provide appropriate planning after considering both government regulatory policy requirements and customers' specific delivery needs. However, the current studies always focus on ways to increase operational efficiency, assuming that there are unlimited labor resources available (Pan and Shih, 2008). Thus, consideration on assigning appropriate labor resources to pick the orders according to the order urgency is neglected.

2.2.2.3 Performance Measurement in Warehouse Operation

As warehouse operations are very complicated, there is a need for managing warehouses effectively in order to achieve the goal of cost efficiency and improvement of warehouse productivity. In addition, to be responsive and increase customer satisfaction, customers are allowed to place orders to the warehouse for frequent delivery. The pressure becomes high to complete customer orders with a short delivery lead time. Therefore, the order throughput time should be reduced so that the orders can be delivered within the requested time window (Nieuwenhuyse and De Koster, 2009). In view of the increasing challenges faced by logistics services providers in both warehouse design and operations, an effective way to evaluate and control the services provided by measuring the performance becomes important. This can improve the operational performance, which may lead to an increase in customer satisfaction. Therefore, it is necessary to measure the warehouse operation performance continuously to reflect the service level and operational efficiency of the warehouse. The performance of these operations not only affects the productivity and operation costs of a warehouse, but also the whole supply chain. To evaluate the warehousing operations efficiently, various research activities have been conducted and performance criteria suggested. Hwang and Cho (2006) stated that the facility size, workforce and system usage should be considered as key warehouse design and operational parameters for performance measurement. They believed that the travel time of transporters is one of the warehouse performance measures and it has to meet the required throughput considering the design of the strip and stack doors. Gunasekaran et al. (1999) suggested that reduction in lead time, inventory and throughput time, on-time delivery, improved effectiveness and improved quality are the key performance indicators (KPIs) for improving the efficiency of warehousing operations. Based on the operations requirement, KPI is defined and different approaches are used for analysis. Cai et al. (2009) presented a framework using a systematic approach to improving the iterative KPIs accomplishment in a supply chain context. It illustrated that the right choice of KPI is a critical element in making performance measurements for decision making. Besides, recent research has also paid attention to the performance of warehouse operation efficiency. Data envelopment analysis (DEA) was proposed by Hamdan and Rogers (2008) for 3PL to measure the performance of warehouse logistics operational efficiency and develop operations recommendations by examining the specific warehouse characteristics.

2.2.3 Overview of Risk Management in Warehouse Operations

Risk is defined as an exposure to the possibility of economic impact, physical damage or delay as a consequence of the uncertainty associated with the action performed (Chapman and Cooper, 1983; Jüttner et al., 2003). Risk taking is regarded as an integral and inevitable part of management in a business (March and Shapira, 1987; Zsidisin and Ritchie, 2008). Svensson (2002) mentioned that risk management is able to improve competitiveness, reduce costs and maintain profitability. Lubka (2002) also indicated that risk management acts as a way to help the company in achieving its goals. In general, risk management in the supply chain refers to the concept of Supply Chain Risk Management (SCRM), which would be beneficial to the parties involved in terms of cost reduction and profitability. SCRM refers to the management of supply chain risks through coordination or collaboration among the supply chain partners for the purpose of profitability and continuity (Tang, 2006; Manuj and Mentzer 2008). Due to the complex network in the supply chain, it is more risky to work with a number of firms to improve the financial performance and competitive advantages (Hauser, 2003). According to ISO 31000, risk management consists of three steps, (i) identification, (ii) assessment, and, (iii) prioritization of risks, that aims at minimizing, monitoring and controlling the probability and impact of unfortunate events (Carole and Olivier, 2012). Responses are given to mitigate or prevent the occurrence of risk.

(i) Risk identification is the first stage in the risk management process. The purpose is to recognize, reveal the potential risk and uncertainty, and clarify risk and uncertainty responsibilities in an organization. Both internal and external risks within an organization are taken into consideration (Zayed and Pan, 2008).

(ii) Risk assessment/analysis is the second stage in the risk management process. It involves the process of estimating the importance of risk based on the associated consequences and likelihood. The consequence of risks refers to the potential impact and severity of risks, while likelihood refers to the probability of risk occurrence (Lai and Lau, 2012).

(iii) Risk response is the last process of risk management. It is carried out to design the corresponding action to be performed for avoiding and mitigating the risk and uncertainty, so that any negative impact can be minimized. In general, four types of actions including accept, avoid, transfer and mitigate, are suggested to respond to the analysis result obtained in the previous stage.

In order to categorize the risk systematically, a number of taxonomies are studied in the literature. Ghoshal (1987) divides risk into four categories for strategic management which are macroeconomic risk (i.e. related to interest rates, wage rates, exchange rates and prices), policy risks (i.e. related to unexpected action of the governments), competitive risks (i.e. related to the uncertainty arising from competitor activities), and resource risks (i.e. related to the unanticipated difference in resource requirement within an organization). On top of the four categories suggested, Dey (2001) further classified the risk into five categories for the case of a cross-country petroleum pipeline project. Some sub-factors are also required under these five risk factors for detailed analysis of risks. The consideration of risks include technical (i.e. technical design, equipment and material risks), acts of God (i.e. natural disasters), financial, economic and political risk (i.e. inflation, change of government policy and law), operational (i.e. vendor and consultant failures), and statutory clearance (i.e. environmental and land acquisition). Lubka (2002) classified risks in the area of environment and health, which considers the physical environment such as natural disasters, the social environment such as social disorder and riots, the political environment such as foreign investment and taxation, the cognitive environment such as carelessness and human factors, the operational environment, the economic environment and the legal environment. Christopher and Peck (2004) and Manuj and Mentzer (2008) classified sources risks in the following four categories for a supply chain, which are supply, demand, operational, and security risks. To summarize, the classification of risks depends mainly on the current situation and type of problem involved.

The warehouse operations involve a number of processes which increase the complexity in effective planning. Depending on the type of warehouse and product to be handled, the concern paid and the customer requirement are also different. Warehouses handling general cargo may focus on the order fulfillment efficiency, while providing good quality control is important for a warehouse used to handling special goods that are sensitive to temperature. Thus, product characteristics may sometimes impose constraints and uncertainties on warehouse operations planning. Examples of handling fashion goods and high value goods are given below to show the differences in warehouse operations planning requirements.

(i) Fashion Goods

In the fierce time-based competition in the fast-fashion markets, the product life cycle is becoming shorter. Businesses have to quickly react to changes in the market for the purpose of maintaining their market share (Choy et al., 2009). Therefore, fast fashion has become a trend in the fashion industry in recent years. The concept of fast fashion is to reduce the lead times for getting a new fashion product into the stores, in order to satisfy consumer demand in peak seasons (Barnes and Lea-Greenwood, 2006). As the product life cycle becomes shorter and shorter, the cycle time from the centralized distribution center to the retail distribution centers is also reduced. A fast response to changing fashion trends and consumer demand has become the main focus of retailers in the fast-fashion industry (Brun and Castelli, 2009). Time delays will lead to a greater risk of stocks being obsolescent and there will be less time in which to make a profit (Christopher, 2005). Due to such time pressure, lead-time is critical in managing the supply chain of fashion products (Fernie and Sparks, 2009). It is especially true for retail stores which need to handle large quantities of products for sale in a short period of time. This brings pressure on the warehouses of retailers and therefore effective warehouse management is important to ensure that the store can respond quickly in order to fulfill customer demand. Caniato et al. (2011) suggested that the analysis of supply management strategies for luxury goods are conducted based on company size, selling volume, product complexity, product fashionableness and brand reputation. Panda et al. (2008) suggested that the demand of fashionable and seasonal products fluctuates and is hard to predict and replenish. According to Lin et al. (2009), since the product life cycle of fashionable products is short, the product goes out of fashion if a long time is spent on the manufacturing process and in extra storage time in warehouse. Therefore, it shows that the handling of fashionable goods depends mainly on the processing time in each stage of the supply chain so as to match the short life cycle of such goods.

(ii) High Value Goods

High value goods refer to those items, in which the value in both cost and functional impact are high, such as luxury goods with famous brand names, apparel, medicines and electrical appliances. They are usually expensive, which can generate high profit for the product owner. Godey et al. (2011) studied consumer behavior on buying high value goods and found that it is highly affected by the quality of the brand and the country of origin. Due to high cost, the quality of high value products is emphasized and much attention is paid to maintain a high standard of products. Instead of focusing on cost reduction strategies, the production of high value goods are more concentrated on achieving high quality and flexibility along the supply chain (Lamming et al., 2000). Meanwhile, the goods owner tends to monitor and control the whole process closely so as to maintain a stable supply with good quality. Thus, special care in handling goods and the quality control process should be carried out for each customer order.

Classified as a high value product, wine is relatively expensive in price and of a high standard in terms of quality. In recent years, the global demand for wine has shifted from traditional wine consumption markets such as Europe and America to Asia, while the demand for wine is forecast to grow further in the coming years. However, due to lack of suitable conditions for wine production in most Asian countries, wine is usually imported to fulfill the increasing demand. Thus, the need for regional wine distribution hubs, that can serve a wide geographic region, has raised suggestions for centralizing business activities for achieving global economies of scale (Oum and Park, 2004; Garcia et al., 2012). Wine has a unique and complex nature compared to other fast moving consumption goods as there is a specific wine production cycle, while the production highly depends on the climatic conditions, origin and quality of the grapes (Getz and Brown, 2006; Hollebeek et al., 2007; Bernabeu et al., 2008). Regions that are able to provide suitable conditions for wine production are limited. Generally, wine can be classified into two categories according to the countries where it is produced, which are the "Old World" including France, Italy and Spain, and "New World" such as the United States, Australia, Chile and New Zealand (Campbell and Guibert, 2006). Other non-wine producing countries can only import wine to fulfill the increasing demand for wine (Somogyi et al., 2011). The wine supply chain has therefore shifted from the local market to external markets. Wines are shipped to target markets for consumption. Hence, the establishment of a regional distribution center to serve a wider geographic region is critical in order to lower the total logistics cost and increase the sales volume (Hussain et al., 2008; Cholette, 2009; Cusmano et al., 2010). However, as there are strict requirements for handling wine, which is fragile and sensitive to the external environment, it is a challenge to manage the operational conditions during storage.

Differing from general food and beverage products with a limited shelf life, some wine has the special characteristic of aging potential that allows it to be stored for a long time. Its value and quality may improve over time if certain reactions occur between chemical compounds and volatile substances in wine in a suitable environment (Parr et al., 2011; Silva et al., 2011). However, the composition of wine may also change for the worse under inappropriate storage conditions. In particular the quality of red wine can deteriorate easily (Gomez-Plaza et al., 2000; Blake et al., 2010). According to previous studies, there are a number of factors that have a negative impact on wine quality, such as temperature, humidity, light exposure and vibration (Gomez-Plaza et al., 1999; Chung et al., 2008; Butzke et al., 2012). These factors bring potential risks that may affect the wine quality. It is important to control and manage these risks in the storage environment to maintain the quality of wine during storage (Verdu et al., 2004; Marin et al., 2007). In addition, different types of wine have particular logistics activities and storage specifications, which further increase the risk for quality deterioration (Dollet and Diaz, 2010; Roy and Cordery, 2010). However, most of research focuses on how the composition of wine changes under different storage conditions; studies related to managing risks under storage conditions and in maintaining the quality of the wine, are limited. Particularly, when an incident occurs unexpectedly that violates the storage criteria, the product quality is likely to deteriorate and cause depreciation in value. Providing a quick response with respect to corrective and follow-up actions is essential to reduce the loss in wine quality and to maintain customer satisfaction. With such limited time available for formulating an immediate action plan to deal with the risk and uncertainty, it is hard to find out the cause of incidents and evaluate whether the wine is affected, without appropriate guidelines being given at the time.

2.2.4 Related Studies on Existing Risk Management Approaches in Warehouse Management

Concerning sustainable development of a business, it is very important to implement risk management that assess risks faced by the organization and develop contingency plans to mitigate the consequences as a result of risks and assure continuity of risk management in an organization (Pai et al., 2003). Most of the literature emphasizes the importance of risk management in terms of advantages. According to Kaplan et al. (2001), risk can be represented in a quantitative way by considering the relative risk, the relativity of risk, and acceptability of risk.

The following equation shows the representation of risk (R),

$$R = \{(s_i, p_i, x_i)\}, \quad i = 1,2,..., N$$

where s_i is a scenario identification or description;

p_i is the probability of the scenario; and

x_i is the consequence or evaluation measure of the scenario

To deal with the concept of risk management in an organization, it is ineffective that the company only uses implicit knowledge and experience for risk management. This is because they may be a lack of sensitivity in estimating the probability of possible outcomes induced by the risks. Meanwhile, an organization may tend to focus on critical performance rather than risk outcomes. Therefore, it is very important for a company to adopt a different risk management model and approach, with a quantitative model and qualitative plans to assess risks. In the literature, it is found that a number of tools and techniques, i.e. conceptual models or mathematic models, were introduced to manage risks (Beasley et al., 2005; Jiang et al., 2009). Hierarchical holographic modeling, enterprise-wide risk management, and risk filtering and ranking management are three commonly used modeling methods for risk management.

(i) Hierarchical Holographic Modeling (HHM)

HHM has been widely and successfully used for identifying risk scenarios as a general system (Haimes et al., 2002). It acts as a tool to consider, identify, and coordinate the whole system under different risk scenarios. Any relevant situations that may be faced by different industries are considered. The risks identified are then presented in the form of a diagram to show various perspectives based on particular system requirements and the categorization of the sources of risk. This methodology provides a comprehensive and holistic view with the organizational, managerial and functional decision-making structures. In addition, HHM is able to reflect the complex and large scale systems with all important and critical aspects by offering multiple visions and perspectives, and intricate relationships that can strengthen risk analysis. Lambert et al. (2001) suggested that HHM should be applied with qualitative and quantitative information in understanding the sources of risks. Thus, mathematical models, including probability analysis and Monte Carlo simulation, are proposed by some researchers. However, these methods may focus on a single system but fail to consider the whole situation faced by the industry (Haimes, 1981).

(ii) Enterprise-wide Risk Management (ERM)

Based on the concept of HHM, ERM has emerged as a new paradigm for managing the portfolio of risks faced by organizations, which provides significant sources of competitive advantages to an organization (Stoh, 2005). It has the ability to manage the risks faced in an enterprise using qualitative ways in measuring risks (Beasley et al, 2005). It is designed to identify potential events that may affect the parties involved and to manage possible risk. Due to the reason that not all risks identified using HHM are suitable for application in a specific industry, ERM is therefore proposed to identify risks that are faced by a particular enterprise. In fact, the warehouse operation offered by different service providers varies, and may provide different ERM structures in particular warehouses. According to Tillinghast-Towers (2004), ERM is able to create and improve shareholder values because of the decision making process with risk-based considerations and capital allocations. Through the literature, it is found that ERM is an effective tool for measuring interactions of various risk events, so that an organization has a clear picture of risks (Beasley et al., 2005).

(iii) Risk filtering, and ranking management (RFRM)

Differing from HHM and ERM, which aims to identify the risk focused by the business environment and within the organization, RFRM is a method to filter and prioritize the results of failure modes and effects analysis. It is represented in quantitative and qualitative matrix scales in terms of likelihood and consequence, which shows the degree of risk factors (Morgan et al., 2000). To prioritize each risk factor, a risk rating is calculated by multiplying the likelihood of risk (L_i) and risk consequence (X_i). By classifying the risks into different ranking groups, a pre-defined action is suggested as a response to handle the risk. Lai and Lau (2012) used the rating approach to determine the risk response action, in which the responses include accept, avoid, transfer and mitigate. It is suggested that the detailed action plan for managing risk depends on the existing situation which is determined by the company.

Based on the above studies regarding the existing risk management approaches, it is found that most of the research managed and assessed the risk using conceptual models (Boer et al., 2001; Cachon, 2001). Although a conceptual model is able to provide a comprehensive and holistic view on the risk factors that may be faced by the industry and the organization, the assessment criteria are only limited to the likelihood and consequence of risk. Multi-objectives and multi-factors decisions cannot be made. Meanwhile, the responses provided are applied to the general situation only. It is unable to cope with the existing operational situation. In view of the importance of managing risks in warehouse operations, it is critical to have a system providing effective knowledge and considering the potential risks that may bring negative impact to the warehouse in order to provide quality services and maintain customer satisfaction.

2.3 Overview of Intelligent System for Warehouse Management

Information systems are recognized to be useful in managing resources in a supply chain in a similar way to the contribution in managing manufacturing systems (Christopher, 2000). One type of information systems is the logistics information system, which is a computer-based information system that supports all aspects of logistics management, including the coordination of various activities. It is capable of providing fewer human errors and lower costs in making various decisions. The warehouse management system and decision support system are examples of information that are frequently considered by researchers to improve the accuracy of inventory control and the efficiency of warehouse operations.

2.3.1 Existing Information System in Warehouse Management

To control the warehouse operation and product flow in the warehouse, there is a need to make use of the information systems in managing the warehouse. Information systems, such as the Warehouse Management System (WMS), are recognized as useful means by which to manage resources, and are adopted for collecting data of warehouse operations in order to solve various problems in a warehouse. It provides, stores, and reports the information necessary to efficiently manage the flow of products within a warehouse, from the time of receipt to the time of shipping (Faber et al., 2002). The main function of WMS is to manage the inventory through tracking the movements of products, storing of materials within a warehouse, sharing accurate inventory information with the clients (Helo and Bulcsu, 2005; Kim et al., 2008). Therefore, implementation of WMS is considered as a key to achieve high performance in warehouse operations, which deals with receipt, storage and movement of goods to customers. Researchers have focused mainly on optimizing the warehouse operation processes using WMS. Shiau and Lee (2009) emphasize that the separation of the picking and packing processes in WMS usually brings extra storage buffers and relatively longer operating time, and a hybrid algorithm was developed to generate a picking sequence for combining picking and packing operations. Chen et al. (2005) introduced a clustering procedure for an order batching problem using WMS before picking a large set of orders for minimizing the travel distance or travel time. After operations planning with WMS, other considerations affect the management of limited warehouse resources, such as storage space, material handling equipment, packing material and labors. However, WMS is only a management system that does not have functions related to decision making on outbound order fulfillment procedures in warehouses.

With the limitation of WMS in making decisions in logistics operations, a decision support system (DSS) is used to support complex decision-making and problem solving (Shim et al., 2002). According to Moynihan and Padmanabhan, (2006), DSS is able to integrate model utilizing optimization, heuristics and simulation. The architecture of a DSS consists of three fundamental components, which are the database or knowledge base, the model or the decision context showing the user criteria, and a user interface. One type of DSS is defined as Intelligent Decision Support Systems (IDSS) which applies artificial intelligence techniques to make decision (Arnott and Pervan, 2005). Research suggested that the use of DSS can improve the decision quality (Lee et al., 2008). An IDSS can be used for evaluating and providing a more accurate outcome (Phillips-Wren et al., 2009). There were wide applications of DSS in the past. Power and Sharda (2007) suggested that quantitative models embedded in a DSS can help managers make better decisions. Omero et al. (2005) dealt with the problem of assessing the performance of a set of production units, and then applied fuzzy logic to decision support systems. Chow et al. (2006) developed a RFID-based resource management system (RFID-RMS) to select the most suitable resource usage packages for handling warehouse operation orders using the RFID technology to capture the useful data and resources status. Choy et al. (2008) proposed an intelligent performance measurement system (K-LPMS) for measuring the performance of 3PL providers and their supply chain partners in order to fulfill different customers requirements through accessing the capacity of each partner. Wen et al. (2008) presented a knowledge-based decision support system for measuring enterprise performance to reduce subjective judgment on performance measurement.

2.3.2 Existing AI Techniques Adopted in Warehouse Activities

Since the decision-making process in warehouse operation planning has been growing difficult for manual analysis, a decision support system using AI techniques is considered to assist the process. Artificial intelligence (AI) has the ability to learn from experience and to handle uncertain, fuzzy, and complex information in a competitive and quality demanding environment (Isiklar et al., 2007). A number of well-known AI techniques for decision-making, including fuzzy logic, AHP, rule-based reasoning, case-based reasoning and genetic algorithm, are discussed.

2.3.2.1 Fuzzy Logic

Fuzzy logic is a multi-valued logic system developed to deal with imprecise or vague data. The use of fuzzy logic reflects the qualitative and inexact nature of human reasoning in which the precise value of a variable can be replaced by a linguistic description (Pham and Pham, 1999; Shim et al., 2002). The design of fuzzy logic involves situation analysis, knowledge acquisition, data collection, fuzzification, fuzzy interference engine and defuzzification. The mechanism of rule-based reasoning is shown in Figure 2.2.

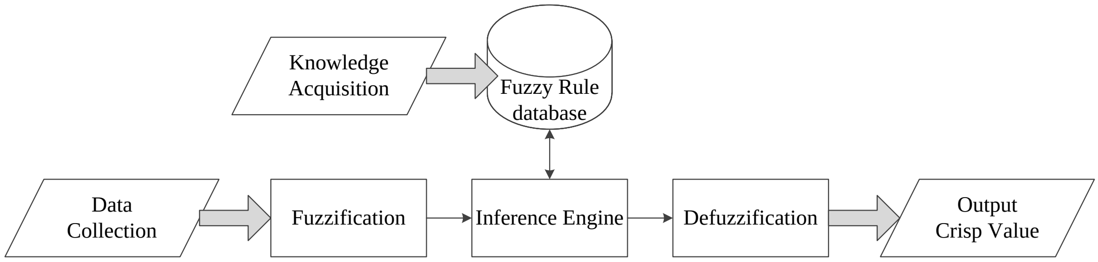


Figure 2.2 Mechanism of rule-based reasoning

With the data collected in the related process, fuzzification is performed to convert the input data set into fuzzy sets, where the fuzzy sets are defined if the boundary of a piece of information is not clear-cut. To carry out this fuzzification process, two decisive factors have to be specified in order to determine the overall features of the fuzzy sets, i.e. universe of discourse and membership function. The universe of discourse is normally divided into several regions which belong to different predicates such as short (S), relatively short (RS), normal (N), relatively long (RL) and long (L). The membership function, which ranges between 0 to 1, refers to the degree that the input value belongs to which fuzzy term, for example, 0.75 belongs to relatively long (RL) and 0.25 belongs to long (L). Figure 2.3 shows an example of fuzzy sets presented in triangular shapes.

The inference engine then converts the input fuzzy set into an output fuzzy set through an inference process. The representation of the fuzzy system is in the form of IF-THEN rules, for example, IF speed is low THEN stopping_distance is short. The fuzzy rule is said to be fired if the input variable matches with the condition. Shore and Venkatachalam (2003) presented a fuzzy logic model to assist in the decision-making process for ranking potential suppliers with vague, ambiguous, and imprecise data. A fuzzy classifier model was proposed by Morandin et al. (2008) for generating the best production sequence for the decision maker. Wang and Lin (2007) developed an intelligent resource allocation model using genetic algorithms and fuzzy inference, which can minimize the lateness of orders with specific due dates. King et al (2004) used fuzzy logic to solve the distribution network reconfiguration problem. Furthermore, Petrovic et al (2007) stated that fuzzy logic can be used to solve the problems related to decision making with the aim of optimizing one or more objectives. The use of fuzzy rules can provide flexibility in determining the output value based on vague variable input values and actual situation status.

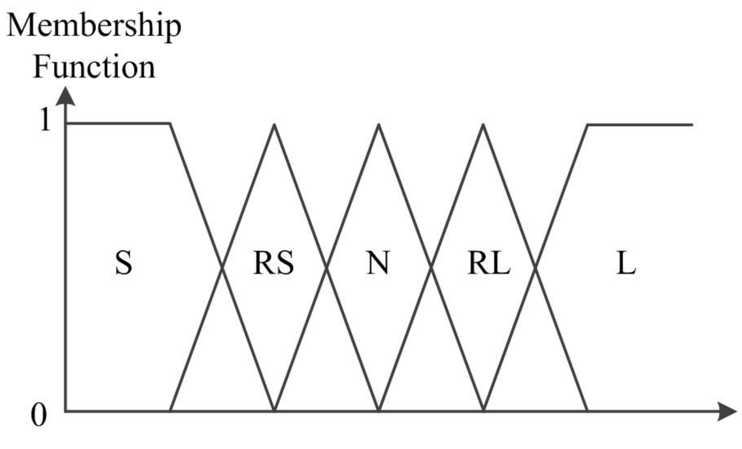


Figure 2.3 Fuzzy sets of a variable

2.3.2.2 Analytical Hierarchy Process

The analytical hierarchy process (AHP) is a flexible approach that allows subjective factors to be considered in risk analysis. It integrates multi-criteria decision-making methodology with both quantitative and qualitative criteria (Gerdsri and Kocaoglu, 2007). It is important that the hierarchy should be clearly constructed because different complexities of the hierarchy results in different rankings (Ishizaka and Labib, 2011). Figure 2.4 shows a hierarchical structure of AHP consisting of a goal, three criteria and three alternatives.

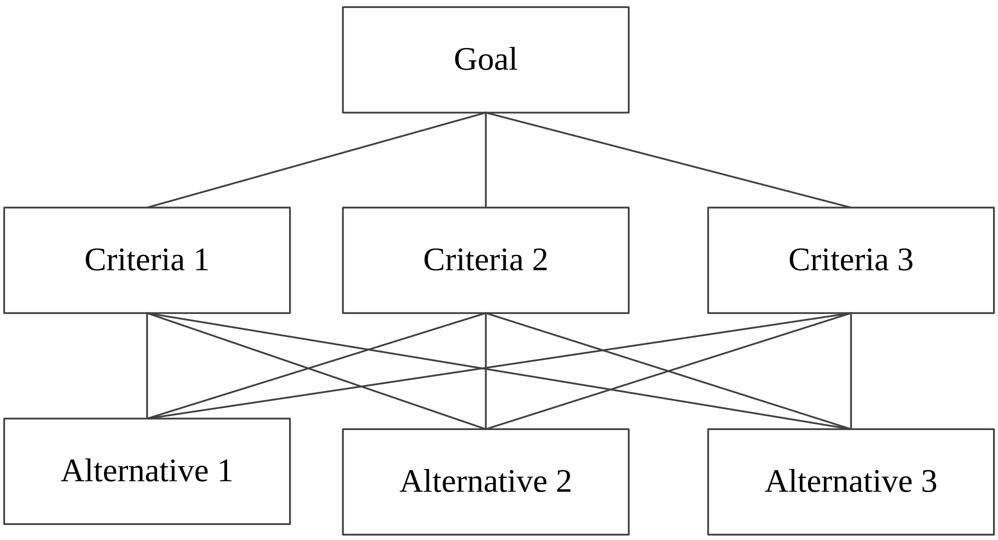


Figure 2.4 Hierarchical structure of AHP

With the developed hierarchy, the company could compare and determine the relative importance of options (Dey, 2001). Pair-wise comparison starts from the second level and ends in the lowest hierarchy level. Criteria are then paired up and evaluated based on the designated scale. Zayed and Pan (2008) used AHP to determine the weights of risk areas in a Chinese highway project in which a higher weighting value resulted in higher importance of the option. Chan and Kumar (2007) proposed a fuzzy extended analytic hierarchy process (FEAHP) approach in a global supplier selection problem. In the study, the critical decision criteria including cost, quality, service performance and supplier's profile with the risk factors for the development of an efficient system were considered. Wang et al. (2008) proposed an integrated AHP–DEA approach to evaluate the risks of bridge structures so as to determine the maintenance priorities of the bridge structures. To sum up, AHP is able to assess the defined alternatives effectively, based on various decision support criteria by conducting pair-wise comparison. Therefore, it is useful to prioritize risk factors in a systematic way due to the ability of making use of the quantitative approach that could increase the accuracy.

2.3.2.3 Rule-based Reasoning

Rule-based reasoning (RBR) is used to solve a predefined problem which stores its knowledge as a set of production rules. With reference to Looney and Alfize (1987), the term rules can be defined as an IF-THEN structure where the IF part, called the antecedent (condition) relates to given information or facts, and the THEN part, called the consequent (conclusion or action) gives the corresponding result. Figure 2.5 shows the mechanism of an RBR cycle, which is composed of three basic structures. They are (i) fact database, (ii) knowledge database, and (iii) inference process. The central idea of RBR is to apply rules to the target problem to get an approximate answer (Gayer et al., 2007). Thus, one of the main advantages of RBR is time saving in obtaining the result by computer program. Chow et al. (2007) proposed a strategic knowledge-based planning system (SKPS) to make use of a rule-based expert method to group similar order shipments according to a set of predefined premises for the freight forwarding industry. Iassinovski et al. (2007) suggested the use of rule-based tools to provide decision making in finding the best pattern for SKU. A fuzzy rule-based system was proposed by Lee and Chen (2008) for sparse fuzzy rule-based systems based on the ranking values of fuzzy sets. Although RBR is capable of presenting knowledge in the form of rules, it does not have the ability to learn from the experience. In addition, the defined rules are usually simple to show the IF-THEN relationship. There is no interaction between rules that make it difficult to observe how an individual rule relates to the overall strategy.

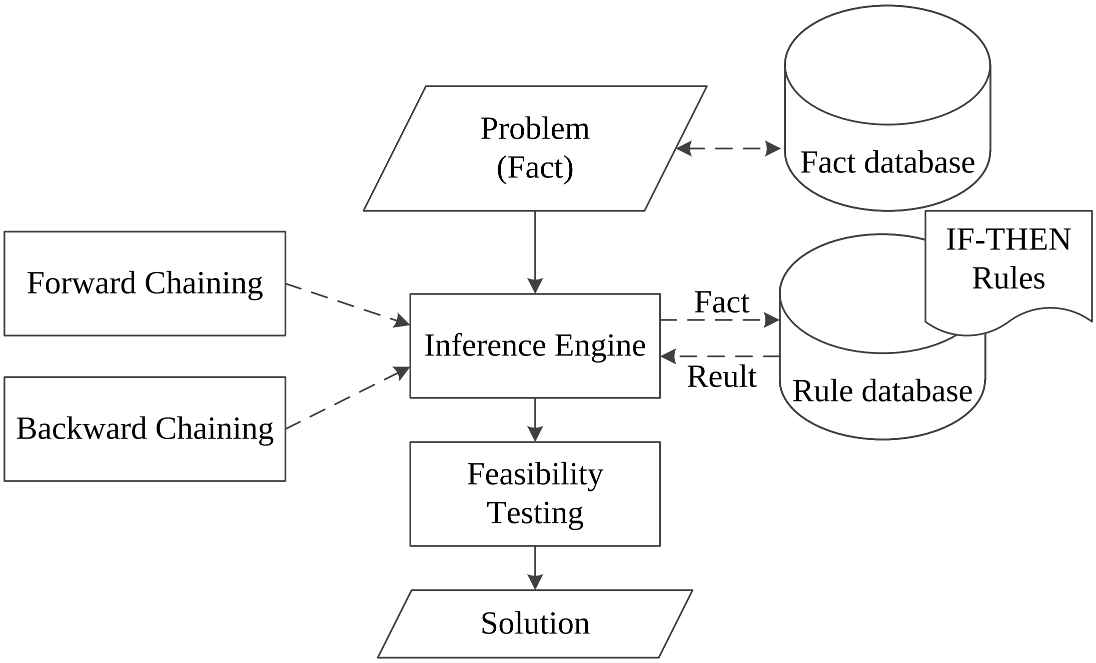


Figure 2.5 Mechanism of RBR Cycle

2.3.2.4 Case-based Reasoning

Case-based reasoning (CBR) is one of the well-known knowledge repository and learning techniques widely adopted in decision making, based on previous experience to solve various types of problem, including both risk and non-risk problems (Kim et al., 2010; Oztekin and Luxhoj, 2010; Li and Sun, 2011). It is an artificial intelligence technique that has the capability of self-learning to improve decision making. CBR captures prior experience and turns it into explicit knowledge in the form of a problem description and solution which is expected to be useful for solving new problems (Craw et al., 2006). By using CBR, similar previous experience can be provided to support the decision making process for a new problem instead of an intuitive estimation approach (Kolodner, 1993; Madhusudan et al., 2004; Wang et al., 2008). According to Castro et al. (2011), CBR is a useful tool to solve problems with associated risk, as past similar situations can be retrieved to reduce significant error and the chance of the incident leading to serious consequences. Goh and Chua (2009) applied the CBR approach to construction hazard identification in which past knowledge is presented in the form of incident cases and risk assessment methods. Yurin (2012) proposed using CBR as an effective and successful aid to solving problems in the prevention of repeated failures in the safe operation of mechanical systems. Chow et al. (2006) applied CBR to formulate the most suitable resource usage packages for handling warehouse operation orders and found that the proposed CBR engine can retrieve and analyze useful knowledge in a time saving and cost effective manner.

Generally, the CBR process consists of four *Re* activities as a cycle: (i) retrieve the most similar case, (ii) reuse the case(s) to attempt to solve the problem, (iii) revise the proposed solution if necessary, and (iv) retain the solution as part of a new case (Aamodt and Plaza, 1994). Figure 2.6 shows the mechanism of a CBR cycle. With the past cases stored in the knowledge database, similarity features and indices are first defined for case retrieval. The CBR system can then retrieve similar cases by calculating the distances or similarities between the problem and the stored cases. In obtaining relevant cases that can be reused easily, effective case retrieval is the key process for finding useful similar cases in proposing a suitable solution (Qi et al., 2009; Stephane et al., 2010).

In recent years, the case retrieval method has been considered in a wide variety of applications, such as market plans (Changchien and Lin, 2005), warehouse operations (Chow et al., 2006), customer classification (Ahn et al., 2007), and railway transportation (Tsai, 2009). Nearest neighbor and inductive indexing are two commonly used case-retrieval methods. The nearest neighbor retrieval (NNR) method adopts an exhaustive search by calculating the problem description similarity between all past cases and the new problem to be solved. Although this method ensures that the most similar past case can be retrieved, its major disadvantage is its slow searching time and high storage requirement resulting from the increasing number of past cases stored (Jahromi et al., 2009). Therefore, the inductive indexing method is considered by researchers to reduce retrieval time. By categorizing a series of instances with similarities, the method determines which features distinguish cases well and then generates a tree structure to organize the case for retrieval (Shin and Han, 2001). Nevertheless, the inductive indexing method does not guarantee producing a case with the highest similarity because it is not required to compare the past cases one by one. To enhance searching speed and accuracy, researchers tried to integrate both NNR and the inductive indexing model as a hybrid approach called the *k-d* tree. Choy et al. (2005) used the *k-d* tree approach to develop a decision support system in the supplier selection process. Chow et al. (2006) designed a radio frequency identification-based resource management system to select the most suitable resource plans for handling warehouse operation orders by retrieving useful past experience in a time-saving and cost-effective manner. Another retrieval technique has also been proposed to combine a clustering algorithm with the NNR model to retrieve the cluster that contains similar cases for comparison. Cluster-based retrieval can reduce searching time by grouping the related information into the same cluster (Kang et al., 2007). Poon et al. (2009) suggested a three-step case-retrieval process by using clustering approach to retrieve past cases for selecting material handling equipment on the basis of order specifications within a warehouse. With the use of the clustering approach in case retrieval, the retrieving process performance is increased in terms of time efficiency and effectiveness (Can, et al., 2004).

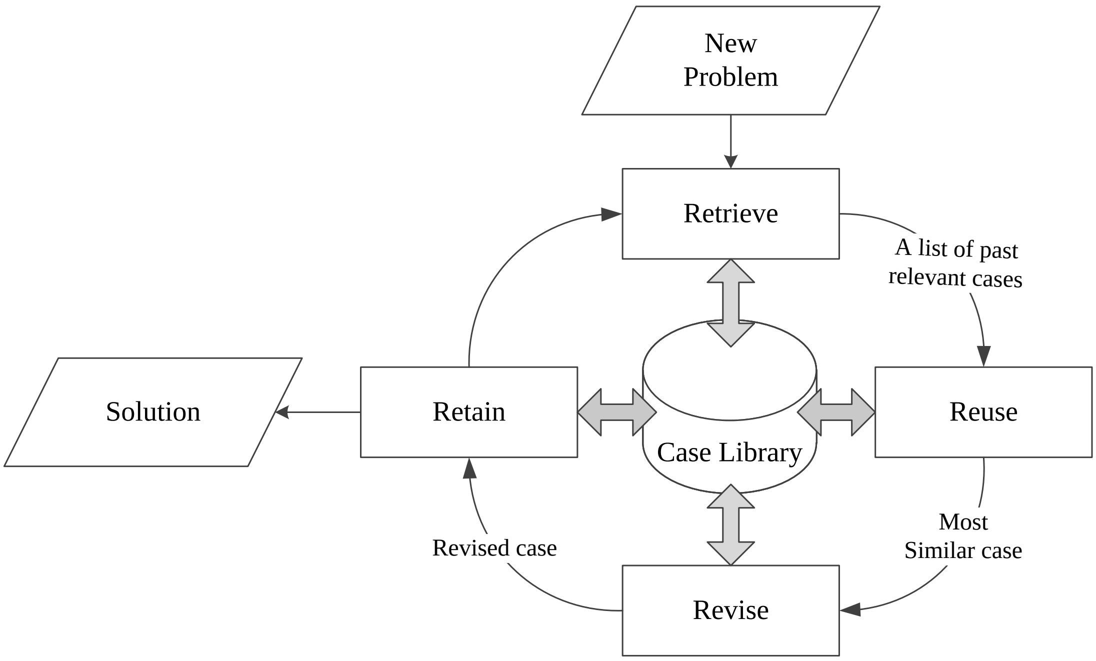


Figure 2.6 Mechanism of CBR Cycle

2.3.2.5 Genetic Algorithm

The Genetic Algorithm (GA) was first proposed and investigated by Holland (1975), and is a well-known heuristics and optimization technique for solving complex problems (Javadi et al., 2005). It is a stochastic search algorithm based on the mechanics of genetics and natural selection (Cus et al., 2006). Figure 2.5 shows the flow of the basic genetic algorithm. The GA operation is first started by encoding the problem into simple chromosomes and searching for nearly optimal solutions through a population of solutions and a number of generations. The performance of the GA generation can be reflected by the fitness function evaluation. Through performing crossover and mutation, GA can reproduce offspring and explore a new searching area that prevents the searching result from falling into the local optima. The parameters that should be defined before the GA process include initial population, number of generations, crossover rate and mutation rate.

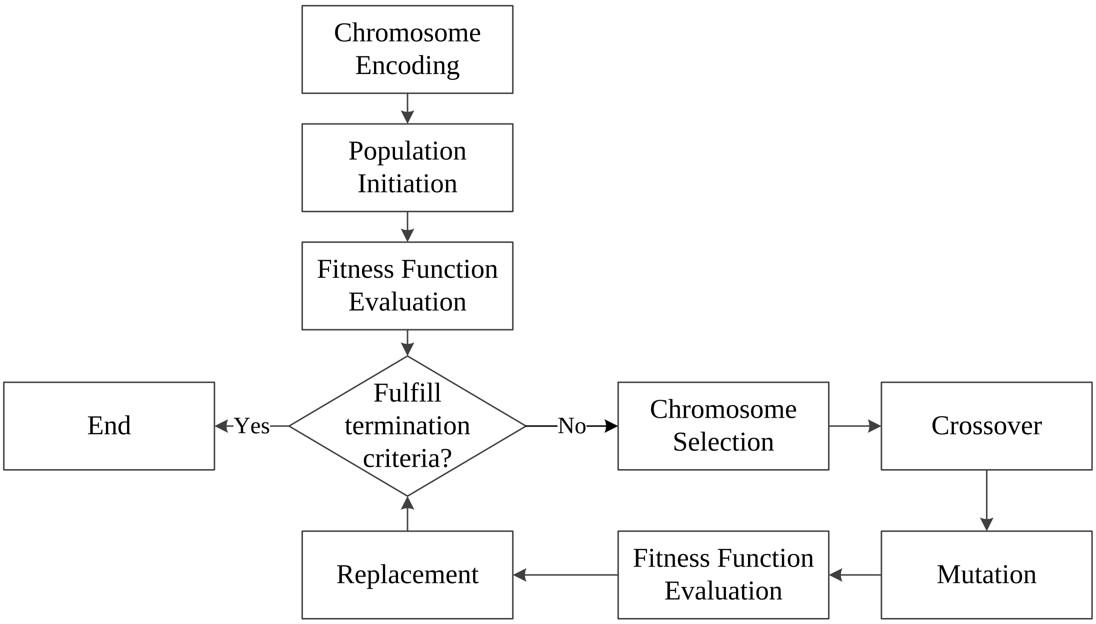


Figure 2.7 A flow of basic genetic algorithm

GA has been widely applied in warehouse problems. A warehouse layout problem was considered by Zhang et al. (2002) to suggest an effective assignment method with GA so as to lower the travel costs. Hsu et al. (2005) suggested that the speed of product movement within a warehouse can be improved significantly by effectively consolidating orders, and applying the GA to deal with the order batching problem to minimize the total travel distance. In order to maximize the warehouse performance in terms of efficiency and customer service quality, a flexible order-picking system (FOPS) integrated with GA was proposed by Manzini et al. (2005) to control the order picking operations. Li et al. (2006) claimed that the traditional manual method to allocate orders for minimum delivery time was inefficient. Therefore, GA approach, which deals with complex data, was adopted in making decisions for precise and fast delivery of goods.

2.3.2.6 Summary of AI Techniques

In brief, it is found that AHP is a feasible approach for assessing and prioritizing the identified risk factors by conducting a series of comparisons based on the decision making criteria. It is a useful tool for integrating the risk management concept and the planning of warehouse operations. On the other hand, in order to provide knowledge in the formulation of useful solutions, CBR has learning ability and can learn from past experience and provide useful explicit knowledge. However, although case clustering has been found to be an effective approach in retrieving past cases as a group, dividing the cases into groups with a similar value of features is a challenge. Castro et al. (2009) observed that most case-retrieval techniques usually consider attribute similarity and their weights as the important factors in retrieving past cases. Sheu (2007) suggested that grouping customers' orders based on multiple customer demand attributes with fuzzy clustering techniques can increase logistics operation efficiency. Chang et al. (2008) integrated CBR with fuzzy logic to deal with the uncertainties found in knowledge representation, attribute description, and similarity measure in retrieving similar cases from the case library. The abovementioned studies only convert order attribute values into linguistic terms before clustering. The decision made on finding the cluster centers was not discussed.

Given that a clustering result is sensitive to the initial centers, the Genetic Algorithm (GA) has been suggested by Laszlo and Mukherjee (2007) in searching for the cluster center of the *k*-means clustering algorithm, which allows for producing a near-optimal cluster result. Kim and Ahn (2008) applied the *k*-means clustering algorithm based on the GA to optimize the initial population in an online shopping market. Their results showed that the GA *k*-means clustering method might improve segmentation performance compared with other typical clustering algorithms. Chang et al. (2009) developed a clustering algorithm based on GA with gene rearrangement to reduce the degeneracy in GA generations and came up with similar cluster results as the *k*-means clustering algorithm. Thus, it become a valuable research area to determine the optimal center for enhancing the searching performance by the integration of GA in the case clustering process in CBR.

2.4 Current Automatic Data Capturing Technologies

To enhance the speed and accuracy of information sharing, automatic data capturing technologies are required to increase the operation visibility. In this section, two commonly used data capturing technologies in the market are introduced: bar-code system and Radio Frequency Identification (RFID) system.

2.4.1 Barcode Technology

A barcode is a machine-readable printed symbol representing the data related to the attached object (Palmer, 2001). It is usually printed or affixed to the product package for scanning and identification purposes. By using infrared light, it allows the scanning device to read the label, i.e. when a character starts and ends, so that the stored data is captured automatically. The structure of the barcode consists of the height and the width. It encodes alphanumeric characters and symbols into black and white stripes, dots, or squares. In general, one-dimensional (1D) barcodes and two-dimensional (2D) barcodes are two barcode systems that are commonly used. The barcode symbol is represented by parallel lines only for 1D barcode while a combination of dots, squares and other geometric patterns is used to form a 2D barcode. Compared to a 1D barcode, a 2D barcode can store more information due to its complex structure in data representation, and in some cases, different characters from different languages.

In the last decade, the barcode has been a popular technology that is widely adopted in the areas of retail, logistics, warehousing and healthcare as it is economical to install and read. By reading the barcode label with a barcode scanner, the data stored in the barcode can be decoded for identification of an item. There are a number of barcode standards in the industry such as Uniform Product Code (UPC), European Article Numbering (EAN) system, code 39 and code 128. The UPC standard consists of numerical digits only which are uniquely assigned to each trade item. Each digit is represented by a unique pattern of two bars and two spaces. The first digit of the symbol represents the product and the last one is the checking digit. EAN is the European version of UPC, which shows more information on a product. The first three digits of an EAN symbol show the EAN Association Country Prefix, which identifies the territory of the EAN organization issuing the number. For the following 4/5-digits, the company reference, identifying the manufacturing company, is shown. Following that will be the item reference that is allocated by the company in showing the product category and the last digit serves as the accuracy check on the entire number by the scanning devices. Code 39 is the most commonly used barcode, which contains capital letters and numbers. It is represented by 5 bars, and 4 spaces for each barcode character. Code 128 is a very high-density barcode standard for both alphabetic symbols and numeric digits, which can encode the entire 128 ASCII character set.

Although barcode technology is considered fully developed, there are still problems and limitations when using the barcode system (Jones et al., 2004; Hunt et al., 2007). Resulting from the increasing complexity of data and information required in the operation process, the barcode system is no longer adequate with its limited storage capacity. The read range of a barcode system is short and requires close proximity for scanning a product. Meanwhile, a clear line of sight is required to scan the barcode. If the line given by the barcode scanner is blocked by another object, the barcode data is unable to be captured. Besides, the barcode is usually printed on paper or plastic which will be easily damaged in a moist environment or with frequent human contact. As the barcode is printed directly on paper or the product, only static data, i.e. the item number, can be stored such that no modification or update of data is allowed. Thus, a new barcode has to be printed to replace the old one if the data stored in the barcode is updated.

With the limitations of the bar-code system, a number of research papers have been published to adopt Radio Frequency Identification (RFID) technology instead of bar-code system in data capturing.

2.4.2 Radio Frequency Identification Technology

Radio Frequency Identification (RFID) is one of the emerging technologies that allows automatic identification and real-time data capturing (Gruninger et al., 2010; Sarac et al., 2010). It can detect and identify objects by transmitting radio wave signals to enable communication between the reader and tags. This technology has been adopted in various industries to reduce inventory losses (Bottani and Rizzi, 2008; DeHoratius and Raman, 2008), increase the operational efficiency (Chow et al. 2006; Poon et al., 2009) and improve information accuracy (Delen et al., 2007; Piramuthu, 2007; Agrawal et al., 2009). An RFID system typically comprises three essential components: tag, reader and antenna.

(i) RFID tag

An RFID tag is a small, essential and major device which can store a wide range of data for the tagged object. It can communicate with the RFID reader through radio signals without physical contact with the object. A tag is usually composed of a microchip and antenna which enables the receiving of radio signals and transmitting the stored information back to the antenna. According to Brown (2007), RFID tags can be adopted under various environments, such as demanding temperatures and humidity. There are three types of RFID tags: passive tag, active tag, and semi-active tag, which are distinguished according to the way they are powered.

Passive tags do not have any power battery. They rely on the detection of radio signals emitted from the reader within a readable range, and then transmit the stored data to the reader. However, in some harsh environments, such as tags attached to an object containing metal and water, the tag may not function properly due to the reflection and absorption of radio wave energy. Since the passive tag is simple in operation, the shelf life of a passive tag is usually longer than the other types of tag, and it is generally cheaper than the active and semi-active tags. Since there is no built-in battery inside a passive tag, the maximum read range is limited.

Active tags contain an independent power battery, which can make use of its own power source to transmit stored data to the reader directly. Active tags are able to work with sensors to store more types of data, such as temperature, humidity and other variables. With the built-in battery, active tags can provide a longer read range over the other tags, but the shelf life of an active tag is limited. An active tag is unable to work once the battery is used up in a short period of time. It will increase the operating cost for regular tag replacement. Meanwhile, the cost of active tags is much higher than passive tags which contain no battery.

Semi-active tags contain a build-in battery that can be powered to transmit signals. Since semi-active tags have similar characteristics to active tags and passive tags, they are called semi-active tags or semi-passive tags. Unlike the active tag that always transmits radio signals, the semi-active tag will not transmit any signal until it is activated by absorbing enough radio energy from the reader. This can allows the semi-active tag to save considerable energy compared to the active tag. Although the shelf life is longer than the active tag, the semi-active tag still needs to be replaced after a certain period of time when the battery is used up.

(ii) RFID reader

An RFID reader is a major and essential device that can read and write data to the RFID tags. According to Lahiri (2006), a reader contains eight main components, which are transmitter, receiver, microprocessor, memory, controller, communication interface and reader. The reader emits radio signals to the surroundings through the antenna to activate the tag. Once the data reflected from the tag is received, the reader will communicate with the computer system for decoding the data obtained.

(iii) RFID antenna

An RFID antenna is a device that is attached to the reader to emit and receive radio signals. It is made of copper wires and is connected to a reader which allows exchange of data between the tag and reader. A single RFID reader is capable of supporting up to four antennas. The orientation and position are important to define a suitable reading zone for the antenna to collect the maximum data. Normally, the antenna is positioned at a fixed place to achieve the maximum reading accuracy.

Although both the bar-code system and RFID technology are able to capture data automatically, the adoption of RFID technology has some advantages over barcode systems (Wyld, 2006; Hunt et al., 2007). Table 2.1 summarizes the comparison between bar-code system and RFID technology.

Table 2.1 Comparison between bar-code system and RFID technology

	Bar-code	**RFID**
Line of sight	Line of sight is required for bar-code	No line of sight is required for reading the RFID tag
Data readability	Bar-code can only be read one by one manually, which increases the chance of human error in scanning	Large number of tags can be read automatically at the same time, without the need of human contact
Read range	Limited distance is available, which is restricted by the line of sight of bar-code system	Significantly longer read range compared to bar-code, due to the use of radio wave signal
Type of data	Bar-code can only identify the type of item; same type of item will contain same bar-code number	Item with RFID tag has unique number that can distinguish itself from the same type of item
Sustainability	Bar-code can be damaged easily with frequent contact in scanning, and is hard to read under harsh environment	RFID tag can work under harsh environment, and is not damaged easily since frequent contact is not required
Real time control	Bar-code can only be tracked manually	RFID provides real time control function by the communication between reader and tag

With the use of RFID technology, automatic data capturing is enabled. According to the past literature, RFID technology is widely adopted in the business area. In order to detect and prevent quality problems, Lyu Jr et al. (2009) designed a quality assurance system by the adoption of RFID to inspect product quality so that the production process can be monitored in real-time. Lao et al. (2012) proposed a RFID-based food operations assignment system with passive tags on incoming food to help the distribution center to control food safety activities, such that the inventory quality can be improved significantly. Apart from identifying tagged objects, RFID tags with a sensor embedded have been developed recently to capture various real-time data, such as temperature and humidity (Abad et al., 2009; Amador and Emond, 2010). Such technology is useful when handling goods such as perishable products, fresh food and pharmaceuticals that are sensitive to the storage and transportation environment (Jedermann and Lang, 2007; Cakici et al., 2011). As temperature is the most critical factor affecting the safety and quality of perishable foods, Kang et al. (2012) developed a RFID sensor tag-based cold chain system to keep track of the timestamps and temperature data of frozen foods during storage and transportation. Hu and Cole (2010) suggested embedding the RFID tag into the plastic cover of a bottle closure such that packaged bottle products can be detected efficiently using the UHF RFID system. Singh et al. (2011) applied the RFID tags on wine bottles to ensure security and privacy protection of wine during the transportation process. Wang et al. (2012) proposed an RFID-based quality evaluation system to monitor the whole wine supply chain where complete information from wine production to sale in the market is recorded to prevent counterfeiting.

In summary, it is found that RFID technology has a better performance in automatic data capturing compared to the bar-code system.

2.5 Summary

After reviewing the literature of warehouse operations challenges within the supply chain, risk management concerns and various technologies, it is concluded that acquiring and retrieving appropriate past explicit knowledge are criteria in the formulation of logistics strategies. As the warehouse operations are very complicated and involve the activities of resource allocations, inventory control, picking and delivery arrangement, warehouse planning based on experienced knowledge is crucial in order to achieve the goal of cost efficiency and effectiveness. Past records and explicit knowledge become important in providing references for solving a current problem. In addition, to provide quality services and maintain customer satisfaction, logistics companies not only need to manage the warehouse operations in knowledgeable approaches effectively, but should also take into consideration the potential risks that may bring negative impact to the warehouse. Therefore, in order to provide an ability in capturing real time data, assessing risk factors, and manipulating the knowledge in decision support, the integration of RFID technology, AHP, and CBR supported by GA in optimizing the case retrieval process is proposed in this research study for fulfilling customers' demands.

Chapter 3 Knowledge-based Logistics Operations Planning System (K-LOPS)

3.1 Introduction

In this chapter, the design of the knowledge-based logistics operations planning system (K-LOPS) is presented to support the decision making process in planning and controlling warehouse operations. Figure 3.1 shows the operation flow of the K-LOPS. It provides a systematical approach to facilitate the decision making processes and provide knowledge support during warehouse operations planning.

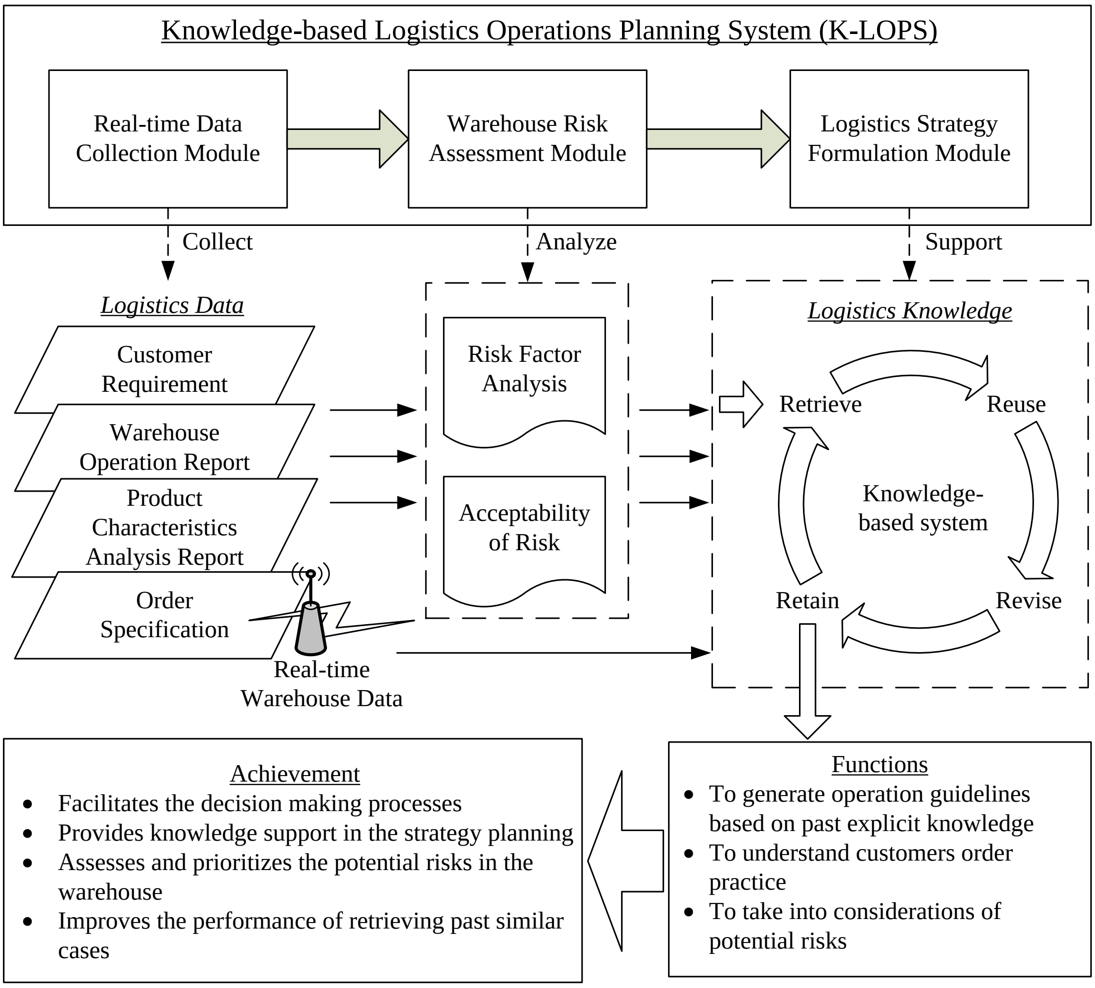


Figure 3.1 Operation flow of the K-LOPS

The system makes use of RFID technologies to collect real-time warehouse data and relevant logistics data. Analysis of logistics data is performed to prioritize the potential risks and examine the acceptability of the risk factor through AHP and the fuzzy logic approach. This information is further used to support knowledge manipulation using the CBR technique. A new algorithm, namely the iterative dynamic partitional clustering algorithm (iDPC), is integrated into the CBR engine to improve the performance in retrieving similar past cases. By adopting this knowledge-based system, the operational guidelines can be generated based on past explicit knowledge while the potential risks that may affect customer satisfaction are also taken into consideration. In the following sections, the systems architecture of K-LOPS, i.e. real-time data collection module, warehouse risk assessment module, and logistics strategy formulation module, are described.

3.2 System Architecture of K-LOPS

The system architecture of K-LOPS is shown in Figure 3.2. It consists of three modules, which are the (i) real-time data collection module (RDCM), (ii) warehouse risk assessment module (WRAM), and (iii) logistics strategy formulation module (LSFM). In the RDCM, relevant data are collected to coordinate with warehouse operations in fulfilling customer orders. RFID technology is adopted to collect real-time data, and to monitor the real-time inventory status and physical storage conditions in a warehouse. In the WRAM, the identified potential risk factors are categorized and presented in a hierarchical structure. The risk factors are then ranked according to their importance in maintaining customer satisfaction. The risk with the highest importance level is then included as an input parameter of the LSFM module to formulate the logistics operations strategy using case-based reasoning.

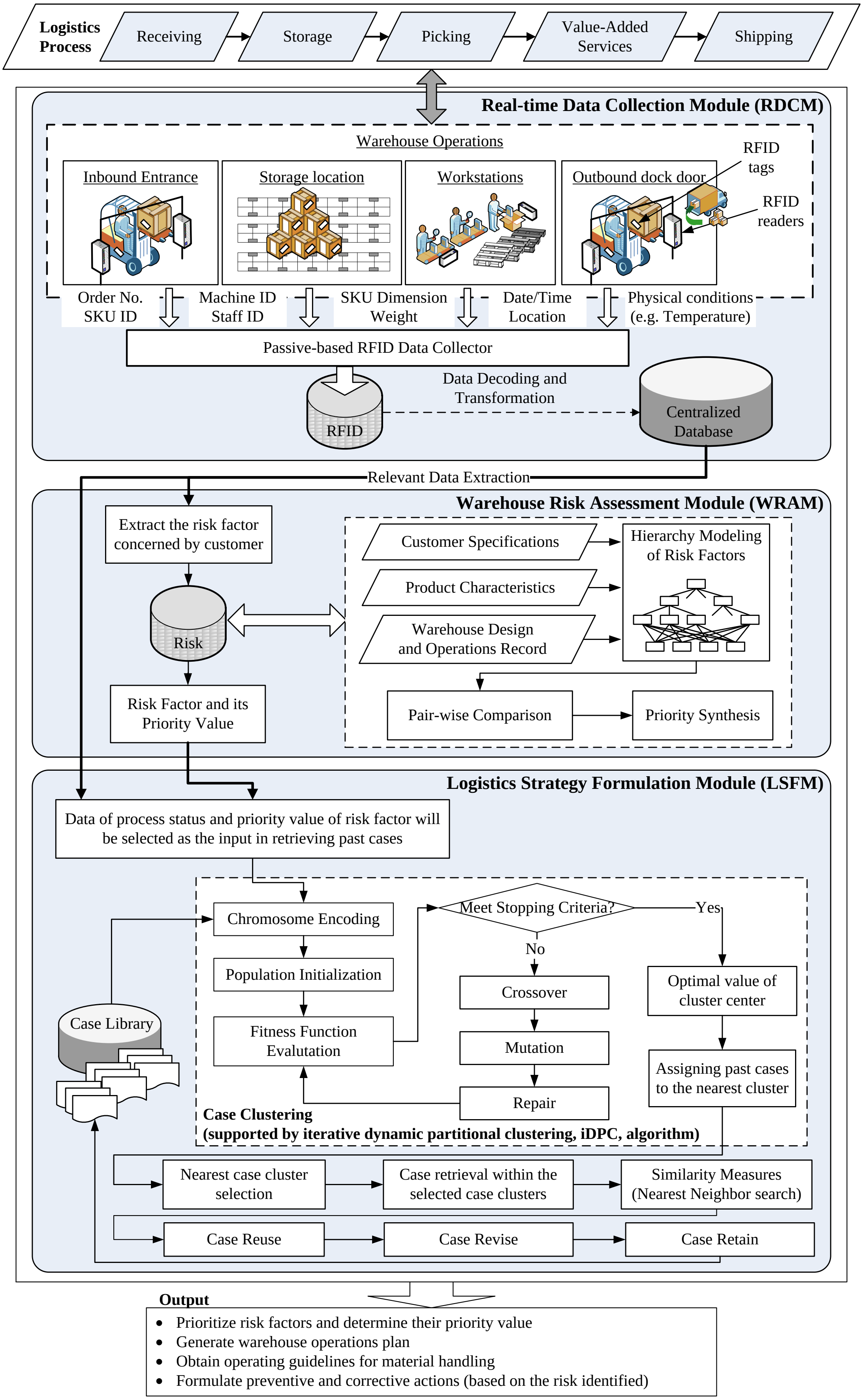


Figure 3.2 System architecture of K-LOPS

3.3 Real-time Data Collection Module (RDCM)

In this module, RFID technology is applied to collect real-time operations conditions to visualize the current status of each SKU. Different RFID devices are adopted to collect data via the transmitting radio frequency signal. A RFID tag is attached to each SKU to record its identity and exchange data with the RFID reader. The reader with the antennas is attached to the fixed facility in the warehouse, such as the main entrance, storage racks and the dock door, to transmit and receive the radio frequency signals. Once the reader has received the signal returned by the RFID tags, the received data is decoded into useful information and stored in the centralized database.

As the warehouse has to handle various types of SKU, the setting of RFID equipment and the type of data required are different so as to ensure that the data collected is useful for decision making. For an SKU that is sensitive to the storage environment, a semi-passive RFID tag with temperature and humidity sensors is attached to each SKU to report the current storage conditions to the system. The tag contains a built-in power battery that uses its own power source to emit signals and communicate with the RFID reader. However, the battery is usually used to assist in collecting environmental parameters using the sensor. Unlike general passive RFID tags, semi-passive tags can avoid the chance that important data is missed due to insufficient energy being received to give a response to the reader. In order to effectively monitor the storage conditions in the warehouse, two types of data are stored in the RFID tag, which are static and dynamic data. Static data refers to the details of the SKU that is stored in the tag during the inbound operations such as SKU number, type of SKU, physical dimension of SKU and quantity. Dynamic data refers to the data of storage conditions including temperature and humidity, and warehouse operation data including the operation time, and resources that are available for use, such as different types of pallets and labor. This type of data varies over time. With such information, the storage conditions for each SKU can be detected in real time basis. Figure 3.3 shows the setting of RFID equipment for real-time data capturing.

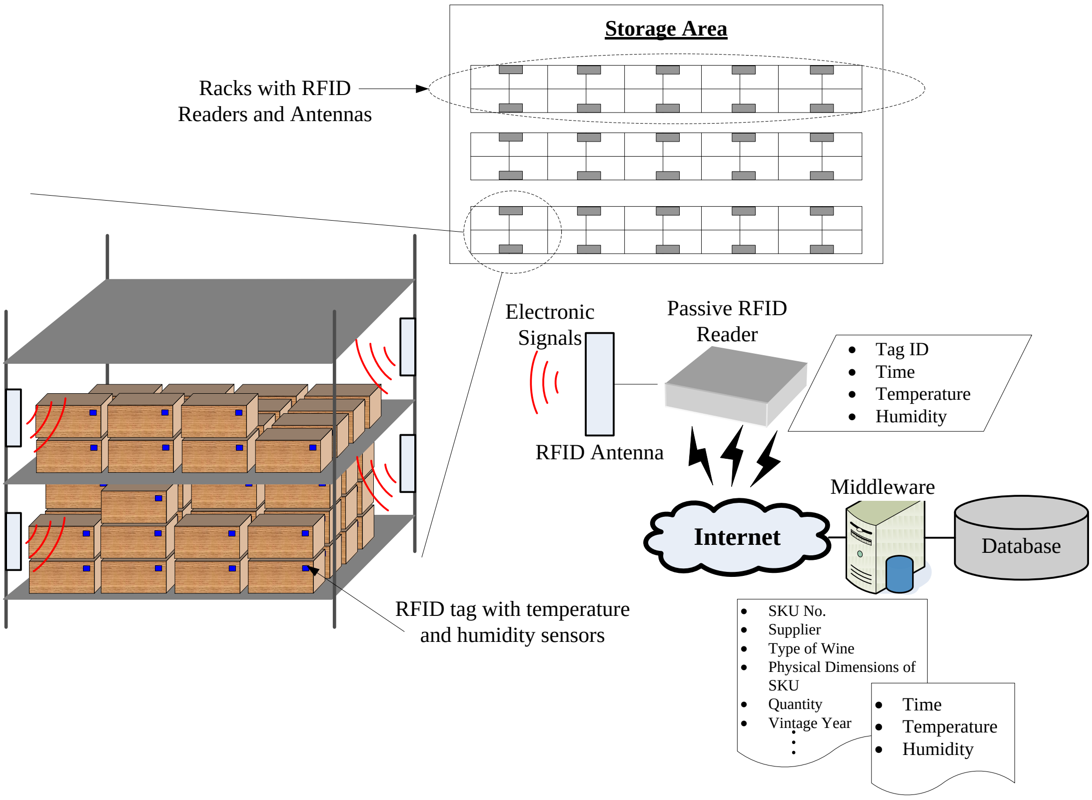


Figure 3.3 Setup of RFID equipment for real-time data capturing

In addition, two categories of data related to customer requests and product information are collected. For each customer request, the delivery order information, such as delivery schedule, location, product type, quantity, etc., is important for the warehouse manager, allowing him to have an understanding of the delivery pattern of various customers. Product information includes the characteristics of SKU, specific handling requirement and optimum storage condition. All the collected data are stored in the centralized warehouse.

3.4 Warehouse Risk Assessment Module (WRAM)

Due to the uncertainty and rapid changes in the business environment, the performance of warehouse operations is not only affected by the logistics strategy planning process, but also needs attention to the possible risks that may occur during the logistics operations. Effective risk management brings advantages of efficiency improvement to the warehouse, improves the financial performance and competitive advantages (Hauser, 2003). It enables the warehouse managers to handle risk efficiently despite higher severity of risks, and to rapidly recover after a disruption (Tang, 2006). Since risks will affect a business organization's performance significantly in the short-term and long-term, logistics companies may suffer losses if they fail to deal with problems and risks properly. Thus, risk management requires continuous attention in planning warehouse operations.

In this module, the potential risks that may affect warehouse operations are analyzed to figure out the major types of risks of concern to the customers. As different product characteristics have their specific needs and handling methods during inbound and outbound operations, the type of risks that the customer pays attention to also varies. If the warehouse cannot deal with the situation to prevent any delay and loss that may be suffered by the customer, customer satisfaction may decrease which may lower the reputation of the warehouse. Therefore, it is critical to identify and analyze the importance of potential risk factors based on customer expectations and the warehouse situation before it occurs. As the importance of risk factors is a subjective judgment, the WRAM makes use of the AHP technique to provide a systematic approach for quantifying and prioritizing the risk level of each factor.

AHP is a flexible approach that allows subjective factors to be considered in risk analysis. It integrates multi-criteria decision-making methodology with both quantitative and qualitative criteria. Prior to the AHP analysis, an interview is conducted by the warehouse management team to identify the possible risks that the warehouse may encounter and to share the experience in managing the warehouse operations. After identifying the risk factors, a questionnaire is designed and distributed to both warehouse managers and customers. They are required to quantify the likelihood and consequence of risk in the warehouse in determining the importance of risk factors and sub-risk factors. With such information, AHP is adopted to determine the weights of the risk factors. The steps for prioritizing the risk level of each factor using AHP is shown below.

Step 1: Construct the identified potential risk factors in a hierarchical structure

With the interview results from the warehouse management team, a hierarchical structure is constructed to present the identified potential risk factors and criteria for judgment. Figure 3.4 shows an example of a hierarchical structure for AHP in four levels, with goal, criteria, sub-criteria and risk factors.

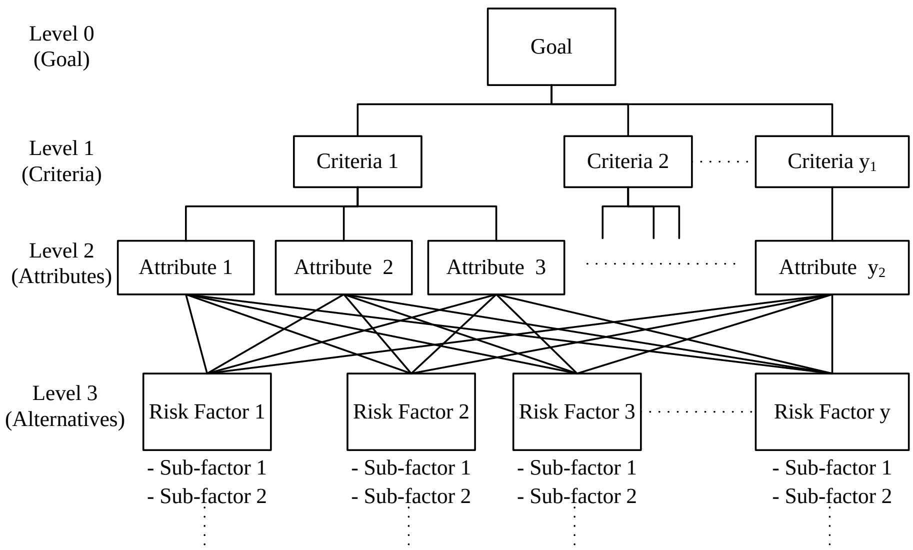


Figure 3.4 Hierarchical structure for AHP

Step 2: Conduct pair-wise comparison

The risk factors are assessed through a pair-wise comparison according to its likelihood of occurrence and the consequences/severity collected from the questionnaire. The mark is rated in accordance with a nine point scale to show the importance of the risk factor and its sub-risk factor. Table 3.1 shows descriptions of the nine point scale for weighting the likelihood and consequence/severity.

Table 3.1 Scale of likelihood and consequence/severity with description

Intensity of likelihood and consequence	**Definition**
1	Equal likelihood/consequence
3	Weak likelihood/consequence of one over another
5	Essential or strong likelihood/consequence
7	Demonstrated likelihood/consequence
9	Absolute likelihood/consequence
2, 4, 6, 8	Intermediate values between the two adjacent judgments

The weighting in each layer is calculated according to Saaty (1980). The result of the pair-wise comparison on the *y* criteria can be summarized in an (*y* x *y*) evaluation matrix *A*. As shown in Equation 3.1, every element α_{ij}, where $i = (1,2,..., y), j = (1,2,..., z)$, is the quotient of the weights of the criteria.

$$A = \left[\alpha_{ij}\right] = \begin{bmatrix} \alpha_{11} & \alpha_{12} & \cdots & \alpha_{1z} \\ \alpha_{21} & \alpha_{22} & \cdots & \alpha_{2z} \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_{y1} & \alpha_{y2} & \cdots & \alpha_{yz} \end{bmatrix}, \alpha_{ii} = 1, \alpha_{ji} = \frac{1}{\alpha_{ij}}, \alpha_{ij} \neq 0 \qquad (3.1)$$

The priority vector W_i which shows the factor weighting is then calculated using Equation 3.2.

$$W_i = \frac{1}{y}\sum_{j=1}^{z}\left(\frac{\alpha_{ij}}{\sum_{i=1}^{y}\alpha_{ij}}\right), \quad \forall i = (1,2,...,y), j = (1,2,...,z) \qquad (3.2)$$

Step 3: Conduct synthesis of priorities

The final step is the process of synthesis of priorities. The consistency ratio (C.R.) is checked to ensure consistency of subjective perception and accuracy of the relative weights. C.R. equals the division of the consistency index (C.I.) by the random consistency index, where C.I. is calculated using Equation 3.3. The C.R. has to be lower than 0.1, otherwise the matrix is considered inconsistent.

$$C.I. = \frac{\sum_{i=1}^{y}\left(\sum_{i=1}^{y}\alpha_{ij}\right)\times W_i - y}{y-1} \qquad (3.3)$$

Step 4: Repeat Step 2 and 3 for the risk factor with highest priority vector

As each factor contains a number of sub-factors, Steps 2 and 3 are repeated to assess the importance of the sub-factors for the risk factor with highest priority vector. Both the likelihood and consequences/severity are considered as the criteria because the likelihood of sub-risk factors can be evaluated with the detailed description.

3.5 Logistics Strategy Formulation Module (LSFM)

LSFM is the core module of K-LOPS, which makes use of the CBR technique to formulate a logistics strategy for the warehouse operations process. It assists LSPs by retrieving useful past cases to provide a solution to the current situation. In practice, a warehouse manager is required to plan the logistics strategy and operation instructions by considering customer requests, warehouse operations arrangements and available resources. The decision making process becomes complex with various order situations and multiple ordering features. The risk factor with the highest priority value is also included as one of the parameters in the case retrieval process. To provide a holistic approach in considering multiple features at the same time, a new algorithm, namely the iterative dynamic partitional clustering algorithm (iDPC), is adopted in the case retrieval process to classify past cases into different groups. The new algorithm helps to effectively select the most similar case among the group in the latter stage. Figure 3.5 shows the mechanism of iDPC in LSFM.

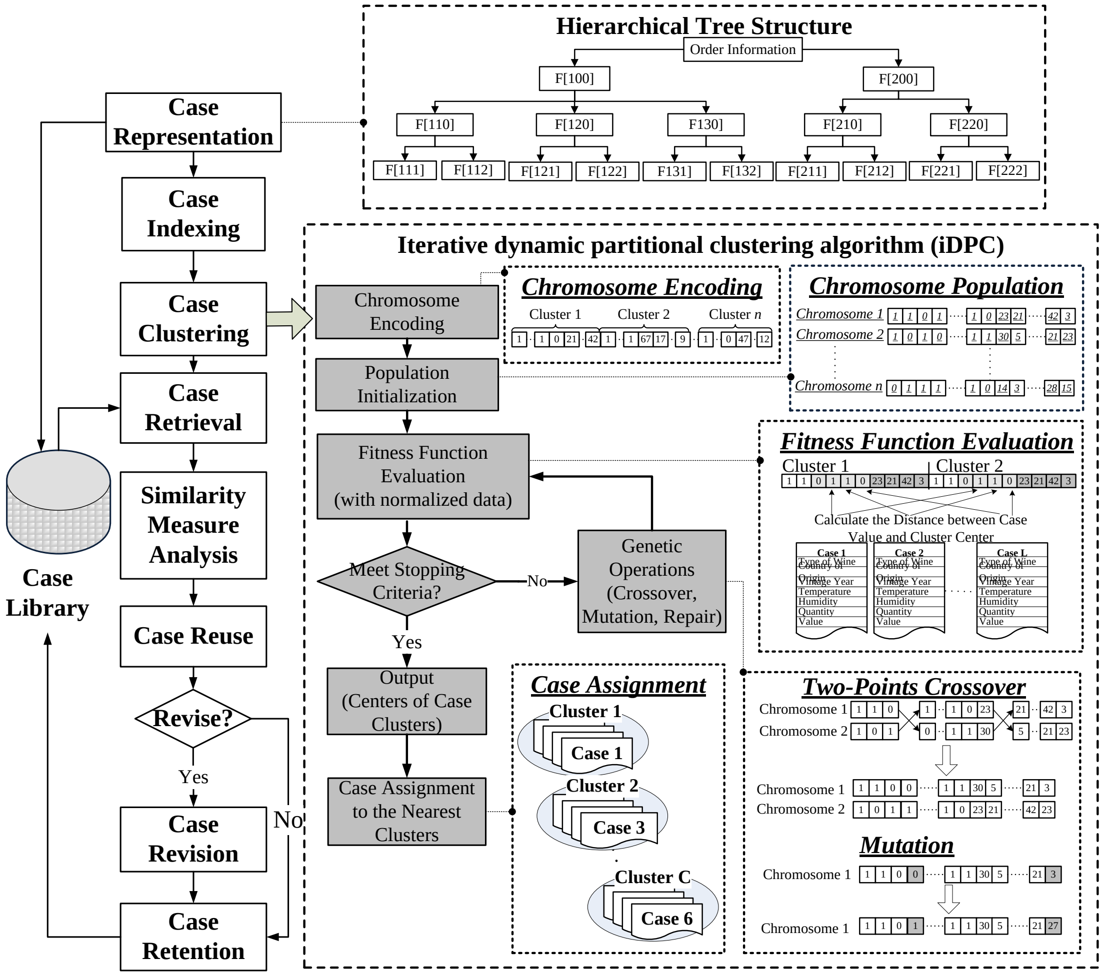


Figure 3.5 Mechanism of iDPC in LSFM

3.5.1 Case Representation

Case representation is the first step in a CBR cycle for presenting the past problem and solution in a structural form. The past records are stored as a form of case with the problem description and solution parts. The problem description part contains the customer information, specific order requirement and other criteria that can be used to select the past case. The solution part contains the operational guidelines that have been adopted to solve the specific problem. The steps for case representation are shown below.

Step 1: Identify the key attributes and parameters in the warehouse operations process

In order to effectively retrieve the past case from the case library, it is important to identify the key attributes and parameters in the warehouse operations process. The attributes can be used to describe the problem area and the selection criteria for past cases. They are defined based on customer orders and the warehouse situation such as the type of SKU, dimensions and weight of SKU, value-added services required, storage requirement and appropriate type of resources .

Step 2: Represent the case using hierarchical decision tree structure

The identified key attributes are represented by the construction of a hierarchical tree structure. The structural representation of the order cases allows for presenting the relationship between dimensions and attributes so that the corresponding dimensions are known when making decisions. For each case attribute located at the lower end of the branch in the tree, a continuous variable is attached to represent the corresponding value of the case attribute. Figure 3.6 shows the generic structure of a hierarchical decision tree.

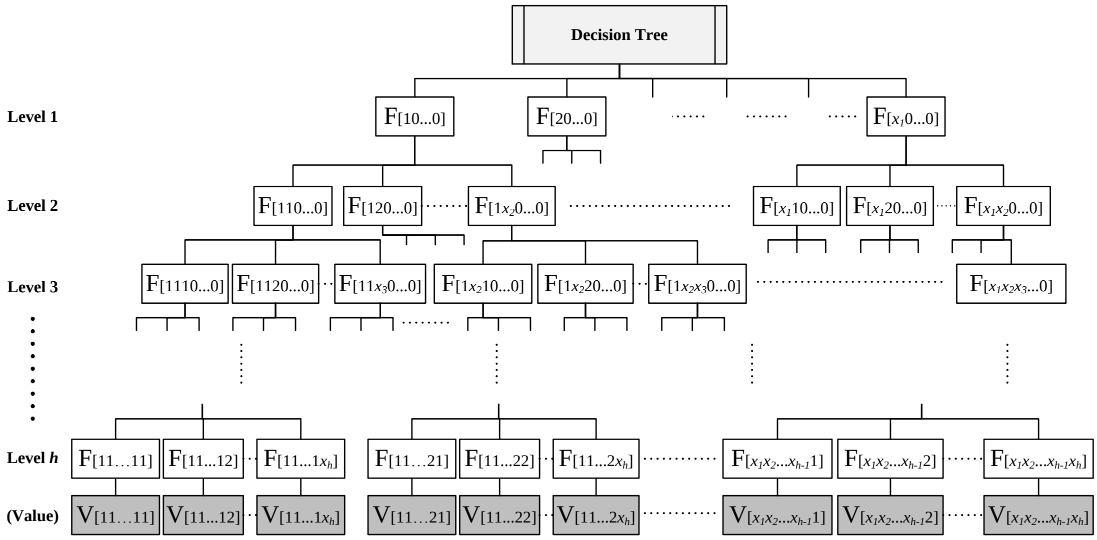


Figure 3.6 The generic structure of a hierarchical decision tree

$F_{[x_1 x_2 \dots x_l]}$ is the generic form that represents all the case features included in the tree structure, while $V_{[x_1 x_2 \dots x_l]}$ is the generic form that represents all the parameter values of the corresponding case feature, where

F : the function of case feature in the hierarchical decision tree

V : the function of parameter value of the corresponding case feature

l : the l^{th} hierarchy levels in the decision tree, $\forall l \in H$

h : the number of hierarchy levels in the decision tree

H : the index set of hierarchy levels in the decision tree, $H = \{1,2,...,h\}$

x_l : the number of case attributes in the l^{th} level of the hierarchical decision tree that belongs to the factor $F_{[x_1 x_2 ... x_{l-1} 0...0]}$, $\forall l \in H$

Figure 3.7 shows an example of a tree structure for an incoming order. Given that there are three levels in the tree, the case attributes are represented as $F_{[x_1 x_2 x_3]}$. With the attribute of $F_{[110]}$ as an example, the attribute is located in the first tree and is the first feature in the second level of the tree. Therefore, $F_{[110]}$ demonstrates the case attribute of SKU. At the bottom of the decision tree, the attribute should carry a numeric value for its corresponding case feature. Take the parameter *number of SKU* as an example. It is presented as the second factor in the third level of Branch 1 of the tree; therefore, x_1, x_2, and x_3 are set to 1, 1, and 2, respectively. The representation of this parameter then becomes $V_{[112]}$.

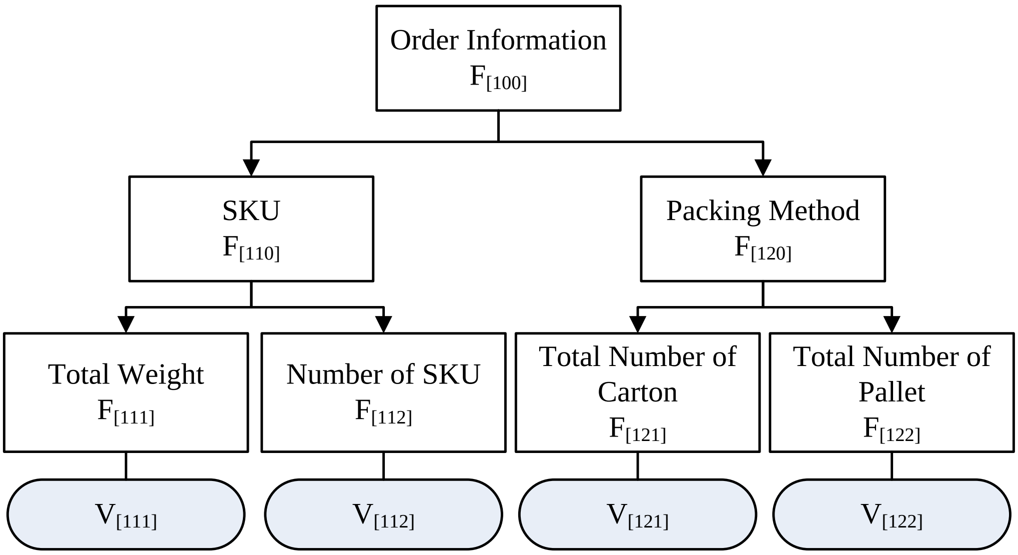


Figure 3.7 Example of hierarchical tree structure for an incoming order

Step 3: Characterize the case by indexing

Due to the fact that the past cases in the case library may have different problem descriptions, not all the attributes identified in the hierarchical tree structure have to be included in the case problem part. Therefore, except the basic customer order information such as order date and customer name in the problem part, a label must be assigned as an index to characterize the case. Figure 3.8 shows the case representation from a hierarchical decision tree. The hierarchical decision tree consists of two parts, which shows the case attributes in a hierarchy from level 1 to level *h* while the corresponding value of the attribute is at the lower end of the tree. Therefore, the past cases that are stored in the case library are also divided into two parts to show the presence of the case attributes and their values. In the first part of the case record, the value 0 and 1 is defined to indicate whether the attribute forms part of the case description. The record starts from level 1 of the hierarchy which shows the dimensions to be considered. Then, the record continues to show the value of level 2 until level *h*, with all attributes associated to the corresponding dimensions. The numeric value of corresponding attribute, which is shown at the end of each branch of the tree, forms the second part of the case record. Each case is given a case ID when it is stored in the case library.

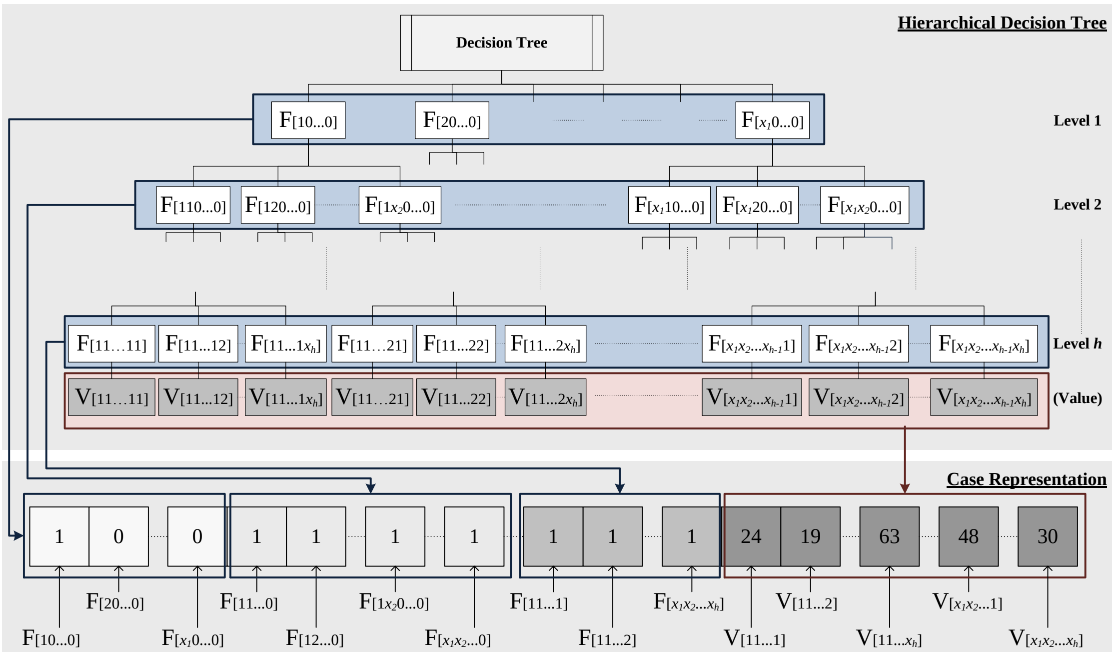


Figure 3.8 Case representation from hierarchical decision tree

3.5.2 Case Clustering by iDPC Algorithm

To provide a dynamic approach in considering multiple features at the same time, the new iDPC algorithm is proposed for classifying past cases into appropriate case groups. The algorithm allows effective selection of the most similar case among the group in the latter stage. Initially, the mechanism of iDPC algorithm is designed based on the k-means algorithm. The steps for classifying past cases into clusters in the CBR technique are shown below.

Step1: Define the number of cluster m, where $m \in M$

Step 2: Randomly assign m sets of mean values to the m cluster centers

Step 3: Calculate the distance (ε) between the past case k and the cluster center i, $\forall k \in P, i \in M$

Step 4: Compare the calculated distances (ε) of all cluster centers for the past case k

Step 5: Assign the past case k to the cluster i, that is the cluster with the minimum distance ε to the past case k

Step 6: Update the m sets of values for the cluster centers by calculating the means values of the past cases that belongs to the cluster i

Step 7: Repeat Step 2-6 after the renewal of the mean values of cluster centers

Step 8: Stop the process until the means values of cluster centers remains constant

However, the traditional *k*-means clustering algorithm relies mainly on the initial selection of the cluster centers. Hence, the result may fall into the local optimization if the initial center is chosen randomly (Bradley and Fayyad, 1998). Thus, the GA is applied to overcome this critical limitation and to search for the optimal initial center for case classification. The newly designed iDPC algorithm has been discussed and published in Lam et al. (2012) and Lam et al. (2013).

3.5.2.1 Chromosome Encoding

Prior to the case-clustering process, the first step is to represent the problem in a standard form to be handled by the GA. The past cases are first encoded into chromosomes, which contain a number of genes; each gene contains a value to represent the features. The chromosome is generally divided into two parts to show the combination of attributes and its values for the cluster centers. They are the case-feature (*F*) region and the parameter-value (*V*) region. Each part is encoded with different types of values, either binary or real numbers. In the *F* region, a binary variable whose value $\bar{f}_{[x_1 x_2 \ldots x_l]}$ is equal to *0* or *1* is used to indicate the consideration of a feature. If the value is *0*, the feature is not included in the case grouping; otherwise, the feature is considered as one of the important factors to divide the cases into groups. In addition to selecting existing features, the features presented at the lower end of each branch of the tree structure contain a real number $\bar{v}_{[x_1 x_2 \ldots x_l]}$, which indicates the corresponding value for the existing feature. Given that the searching operations of the GA follow a random selection, the parameter of each feature is bounded within a pre-defined region of the values to limit the value to an allowable region. The length of the chromosome depends on the type and number of features present in the case. Moreover, it can have more than one tree structure in representing the past cases. The generic form of the chromosome is shown as follows:

$$\left[\left[\bar{f}_{[x_1 x_2 \ldots x_H]} \bar{v}_{[x_1 x_2 \ldots x_H]}\right]^i\right]^j$$

where

$\bar{f}_{[x_1 x_2 \ldots x_H]}$: the value of attributes in the case-feature (*F*) region of the cluster

$\bar{v}_{[x_1 x_2 \ldots x_H]}$: the value of attributes in the parameter-value (*P*) region of the cluster

i : the i^{th} case cluster in the gene matrix, $\forall i \in M$

j : the j^{th} chromosome in the gene matrix, $\forall j \in N$

m : the number of case clusters defined in the chromosome

M : the index set of case clusters, $M = \{1,2,...,m\}$

n : the number of chromosome in the generation

N : Index set of chromosomes in the generation, $N = \{1,2,...,n\}$

The generic form repeats according to the defined number of clusters m, and each part consists of the F region and V region. Figure 3.9 shows a graphical representation of a chromosome. The F region contains all the features included in the case, whereas the V region contains only the features presented at the end of the tree structure with real numbers.

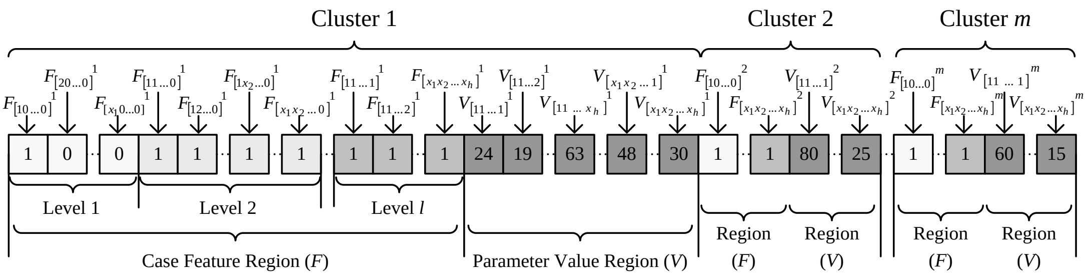


Figure 3.9 The generic graphical representation of a chromosome

Figure 3.10 shows the correlation between the case feature region and the parameter value region. In the first cluster, it shows that the case attribute $F_{[10...0]}^{1}$ contains x_2 sub-attributes which are presented from $F_{[11...0]}^{1}$ to $F_{[1x_2...0]}^{1}$. Then, the hierarchy levels of sub-attribute $F_{[11...0]}^{1}$ continue to build until the lower end of the branch is reached which are represented from $F_{[11...1]}^{1}$ to $F_{[11...x_h]}^{1}$. Hence, the corresponding value of the case attribute $F_{[10...0]}^{1} \cdot F_{[11...0]}^{1} \cdot ... \cdot F_{[11...1]}^{1}$ is represented as $V_{[11...1]}^{1}$.

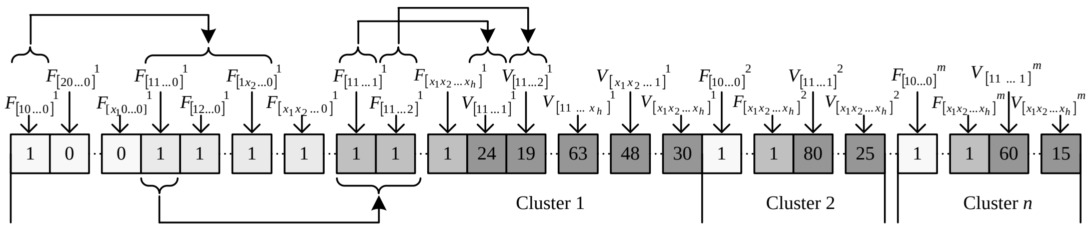


Figure 3.10 Correlation between the case feature region and parameter value region

3.5.2.2 Population Initialization

The aim of population is to provide a number of past cases as chromosomes for selection. The population size, n, is defined to control the number of chromosomes selected for GA operations, that is, crossover and mutation. Generally, chromosomes are extracted randomly from the case library and transformed into chromosomes. Therefore, an $n \times d$ matrix is formed where d is the total number of genes in a chromosome.

3.5.2.3 Case Assignment and Fitness Function Evaluation

Once the population of chromosomes is formed, the fitness value for each chromosome is calculated to evaluate the case similarity for the assigned case cluster. With the initial selection of cluster centers, the distance error between each case and cluster center are calculated using the *k*-means clustering algorithm. The objective of the *k*-means clustering algorithm is to obtain the partition for a fixed number of clusters with minimum total square-error. However, the random selection of the initial cluster centers may cause the result to fall into the local optima; hence, the GA is applied to search for the optimal initial center in the case clustering process. Thus, the smaller value of the distance error indicates that the chromosome is more suitable to classify that cluster with a better performance of the solution. The steps for case assignment and fitness function evaluation are shown below:

Step 1: Normalize the quantitative values of case parameter presented as the low end of the tree structure

Prior to the fitness function evaluation, it should be noted that bias may occur when calculating the fitness of attributes in a different range. The distance between the cluster center and the attribute with a large range of values is always larger than the attribute with a small range of values, which limits the chance of consideration. Therefore, the values of each attribute should be first normalized to avoid large differences between different attributes. This is calculated with Equation 3.4.

$$v'_{[x_1 x_2 \ldots x_l]} = \frac{v_{[x_1 x_2 \ldots x_l]} - v^{min}_{[x_1 x_2 \ldots x_l]}}{v^{max}_{[x_1 x_2 \ldots x_l]} - v^{min}_{[x_1 x_2 \ldots x_l]}} \tag{3.4}$$

where $v'_{[x_1 x_2 \ldots x_l]}$ is the normalized value of case attribute $F_{[x_1 x_2 \ldots x_l]}$, $v_{[x_1 x_2 \ldots x_l]}$ is the actual value of case attribute $F_{[x_1 x_2 \ldots x_l]}$, $v^{min}_{[x_1 x_2 \ldots x_l]}$ and $v^{max}_{[x_1 x_2 \ldots x_l]}$ are the minimum and maximum allowable values of the case attribute $F_{[x_1 x_2 \ldots x_l]}$ respectively.

Step 2: Identify the combinations of case attributes as the cluster center

Unlike the retrieval process of the typical CBR approach, the GA-based clustering approach considers multi-dimensional attributes at the same time. It aims to select the combinations of attributes that can divide the past cases with minimum distance error. Table 3.2 shows the matrix of combinations with one and two attributes for s_i attributes, where s_i is the number of case attributes considered as the center of the cluster i. All possible combinations of attributes based on the number of attributes considered is summarized in Table 3.3.

Table 3.2 Matrix of combinations with one and two attributes

		Attributes				
		F1	**F2**	**F3**	…	**Fs_i**
Attributes	**F1**	F1	F1 F2	F1 F3	…	F1 Fs_i
	F2	-	F2	F2 F3	…	F2 Fs_i
	F3	-	-	F3	…	F3 Fs_i
	⋮	-	-	-	⋱	⋮
	Fs_i	-	-	-	-	Fs_i

Table 3.3 Combinations of attributes based on the number of attributes considered

Number of attributes (s_i)	Combinations of attributes				
1	F1	F2	F3	…	Fs_i
2	F1 F2 F1 F3 ⋮ F1 Fs_i	F2 F3 F3 F4 ⋮ F2 Fs_i	F3 F4 F3 F5 ⋮ F3 Fs_i	…	Fs_{i-1} Fs_i
3	F1 F2 F3 ⋮ F1 Fs_{i-1} Fs_i	F2 F3 F4 ⋮ F2 Fs_{i-1} Fs_i	F3 F4 F5 ⋮ F3 Fs_{i-1} Fs_i	…	Fs_{i-2} Fs_{i-1} Fs_i
⋮	⋮	⋮	⋮	⋱	⋮
s_i	F1 F2…Fs_i	-	-	-	-

The cluster center that considers only one attribute is defined as 1-itemset (L_1). The attribute value in L_1 is presented as 1 in the chromosome, showing the presence of the attribute. The candidates in L_1 are then combined with each other to generate a new cluster center which considers two attributes at the same time. The combinations of two attributes are counted and a 2-itemset (L_2) is formed. The candidates in the itemset continue to combine with other attributes until L_{s_i} is generated.

Step 3: Calculate the distance error between the past cases and the center of the cluster

The distance error ε_{ik} measures the distance between the parameter value of the past case and each cluster center based on the squared-Euclidean-distance. It is calculated by Equation 3.5.

$$\varepsilon_{ik} = \sum_{l \in H} \sum_{b \in S} \sqrt{f_{i[x_1 x_2 \ldots x_l]} \times (T_{kb[x_1 x_2 \ldots x_l]} - Z_{ib[x_1 x_2 \ldots x_l]})^2}\ , \quad \forall i \in M, k \in P \qquad (3.5)$$

where

ε_{ik} : the distance error between the k^{th} past case and the assigned center of the i^{th} cluster

k : the k^{th} past case in the case cluster i, $\forall k \in P$

p : the number of past cases in the case library

P : the index set of past cases in the case library, $P = \{1,2,..., p\}$

b : the b^{th} attribute in the center of cluster i, $\forall b \in S$

s : the number of case attributes included as the center of cluster i

S : the index set of case attributes which belong to the center of cluster i, $S = \{1,2,..., s\}$

$T_{kb[x_1 x_2 \ldots x_l]}$: the normalized parameter value of the b^{th} case attribute in the k^{th} past case record

$Z_{ib[x_1 x_2 \ldots x_l]}$: the normalized parameter value of the b^{th} case attribute in the i^{th} cluster center

As this algorithm considers multi-dimensional attributes and searches for the best combination of attributes, the distance error is expected to be large if more attributes are considered together. The algorithm would then decrease the probability of a large combination of attributes to be chosen because of the high fitness function. To ensure that all combinations of case attributes can be evaluated, an amendment factor is included to adjust the combination effect with an increased number of case attributes to provide a reasonable result when more than one case attribute is considered at the same time. The amendment factor A_s is calculated using Equation 3.6.

$$Amendment\ \ factor\ \ A_s = \frac{\sum_{l \in H} \bar{f}_{i[x_1 x_2 \ldots x_l]}}{s_i}, \quad \forall i \in M \tag{3.6}$$

By considering the amendment factor A_s, the adjusted distance error ε'_{ik} is therefore becomes

$$Adjusted\ distance\ error\ (\varepsilon'_{ik}) = \varepsilon_{ik} \times A_s \tag{3.7}$$

Step 4: Assign the past case to the cluster with minimum adjusted distance error $(\varepsilon'^{\min}_{ik})$

After calculating the adjusted distance error between past case k with all m clusters, past cases are assigned to the cluster with minimum adjusted distance error

($\varepsilon'^{\min}_{ik}$). That is, if the k^{th} past case has the smallest adjusted distance error with the center of cluster i, when compared to the result of all m clusters, the k^{th} past case is then assigned to cluster i.

Step 5: Calculate the fitness value for the chromosome by summing the minimum adjusted distance error for all cases

In order to find out the fittest chromosome, a fitness function is needed to evaluate each chromosome in the population. After assigning the past cases to the cluster with minimum adjusted distance error, the fitness function is determined by Equation 3.8.

$$Minimize\ \ \lambda = \sum_{i \in M} \sum_{k \in P} \varepsilon_{ik} \times A_s \times z_{ik} \tag{3.8}$$

where λ is the fitness value and z_{ik} is a binary number that indicates whether the case k belongs to cluster i. It is a decision variable where $\sum_{i \in M} z_{ik} = 1, \forall k \in P$, so as to limit the number of past cases that can be classified into one cluster only. z_{ik} is equal to 1 if the case k belongs to cluster i, otherwise, z_{ik} is equal to 0.

3.5.2.4 Termination Criteria

The GA operation is terminated when the number of generations, g_τ, reaches the pre-defined setting g_{max}, where g_{max} is the maximum number of generations. The number of generations is usually set to a large number to provide more chances in searching, ensuring that different combinations are examined for the solution. By setting the maximum number of generations g_{max}, limited computational time can be used to obtain a reasonable solution.

3.5.2.5 Chromosome Selection

If the number of generations has not met the termination criteria, the GA process continues. Chromosomes are selected to form the mating pool so that a new solution can be generated. In order to obtain a better solution, the chromosomes with higher fitness values should have higher probabilities for retention. Roulette-wheel selection is one of the methods used in choosing chromosomes for the mating pool. Figure 3.11 shows an example of a roulette-wheel for chromosome selection. The wheel is divided into n segments according to the fitness value assigned to each solution.

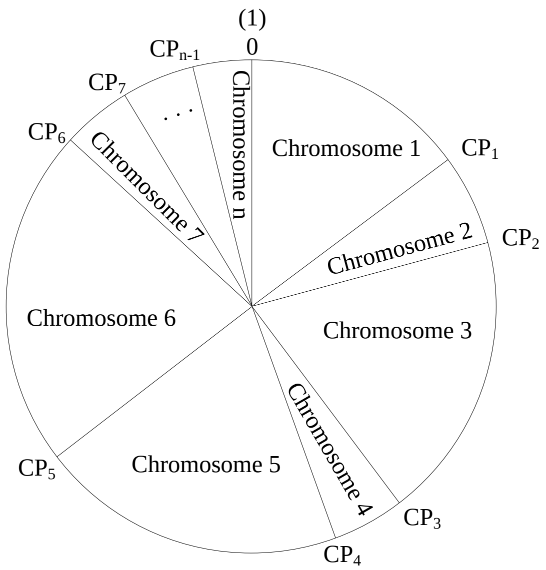


Figure 3.11 Roulette-wheel for chromosome selection

The steps for the chromosome selection using roulette-wheel are shown below.

Step 1: Calculate the selection probability for each chromosome

Generally, the chromosome with a large fitness value provides a better performance in solution. However, the fitness function defined for GA-based clustering is a minimization problem which provides a better solution with a smaller fitness value. Therefore, the selection probability should be defined with the fitness value in an inverse relationship. The probability of a chromosome being selected for the next generation is calculated using Equation 3.9.

$$SP_j = 1 - \frac{\lambda_j}{\sum_{j \in N} \lambda_j}, \quad \forall j \in N \tag{3.9}$$

where SP_j is the selection probability for the j^{th} chromosome, and λ_j is the fitness value of the j^{th} chromosome. With a larger fitness value, the chromosome should have a larger chance to be selected for generating new solution.

Step 2: Calculate the cumulative probability CP_j for each chromosome

The roulette wheel starts at the point 0 with a maximum point at 1. The cumulative probability CP_j accumulates the selection probabilities of all chromosomes. The cumulative probability CP_j for the j^{th} chromosome is calculated using Equation 3.10 to form the roulette wheel.

$$CP_j = \sum_{u=1}^{j} SP_u, \quad \forall j \in N \tag{3.10}$$

Step 3: Generate random number to select chromosomes for mating pool

To select the chromosome from the initial population, n random numbers between *0* and *1* are generated. Figure 3.12 shows the selection of chromosomes into the mating pool. The chromosome is selected according to the segment that the random number falls into. If the first random number falls between CP_4 and CP_5, chromosome 5 is selected to the mating pool. As the chromosome with a smaller fitness value has a greater segment in the roulette wheel, the probability that the chromosome can be selected is also higher. Besides, more than one random number may fall into that segment, showing that the chromosome may appear in the mating pool more than once. On the other hand, the chromosome with poor performance in initial population is likely to be replaced by another chromosome based on the random number generated.

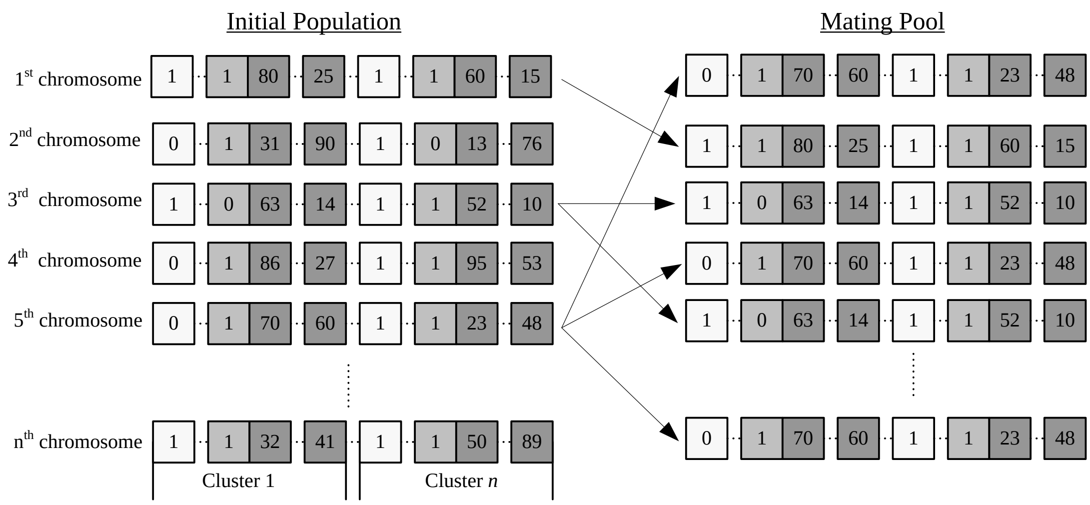


Figure 3.12 Selection of chromosome into mating pool

3.5.2.6 Chromosome Crossover

To produce a new offspring and search for better fitness function, crossover and mutation are the commonly used genetic operations. Crossover is the process of creating new chromosomes by exchanging the selected genes between pairs of chromosomes. There are several types of crossover that are commonly used, including one-point crossover, two-point crossover, multi-point crossover and random crossover. To select the chromosome to undergo crossover, the crossover rate α_g is first determined. The steps for selecting the genes for crossover are shown below.

Step 1: Generate n random numbers that ranges from 0 to 1 for the n chromosomes in the mating pool.

Step 2: Compare the random number of chromosome R_j with the crossover rate α_g

The j^{th} chromosome is selected to undergo the crossover process if the random number R_j is smaller than the crossover rate α_g. Thus, by setting a large value for the crossover rate α_g, there is a higher chance of performing crossover for the chromosome.

Step 3: Generate the random number to select the gene region for crossover

After selecting a pair of chromosomes for crossover, two random numbers, R_{st} and R_{end}, are generated to indicate the starting gene and the ending gene for crossover respectively. Figure 3.13 shows an example of two-point crossover operations. Assuming that two random numbers, R_{st} and R_{end}, are generated with values 14 and 32 respectively. Therefore, the gene region between the 14th gene, which is the case feature $F_{[11...2]}{}^1$ in Cluster 1, and the 32nd gene, which is the case feature $F_{[x_1 x_2 ... x_h]}{}^2$ in Cluster 2, are swapped with the same portion as chromosome A and B. Thus, two new offspring of chromosomes are produced to represent new cluster centers.

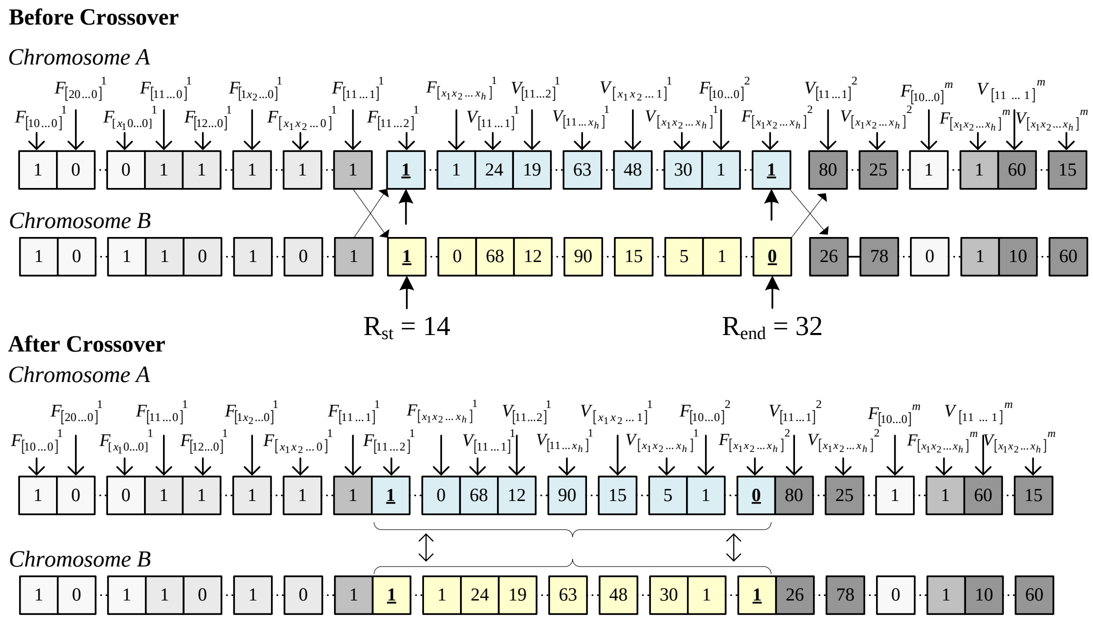


Figure 3.13 Before and after crossover for two chromosomes

3.5.2.7 *Chromosome Mutation*

Mutation is another operator that attempts to avoid the solution falling into the local optima by changing the value of genes in the offspring obtained from crossover. Each chromosome in the population has an equal chance to undergo mutation at a given mutation probability. To select the gene to undergo mutation, the mutation rate β_g is first determined. β_g is usually kept at a low value so as not to lose the genetic composition obtained from crossover. Due to different encoding schemes used in the case feature and parameter value region, the mutation operation is divided into two parts. The steps for selecting the genes for crossover are shown below.

Step 1: Generate d random numbers, $R_{[x_1 x_2 \ldots x_l]j}$, ranging from 0 to 1 for each gene of a chromosome in the mating pool

Step 2: Compare the random number of gene $R_{[x_1 x_2 \ldots x_l]j}$ with the mutation rate β_g

For the case feature region which is encoded in a binary number, a bit-flip mutation is applied. If the random number $R_{[x_1 x_2 \ldots x_l]j}$ for the gene $F_{[x_1 x_2 \ldots x_l]}$ is smaller than the mutation rate β_g, the gene $F_{[x_1 x_2 \ldots x_l]}$ is selected to undergo the mutation process. The value of the selected gene is either changed from 0 to 1 or from 1 to 0, indicating the presence of the case attribute. For the parameter value region which is encoded in a real number, the gene $V_{[x_1 x_2 \ldots x_l]}$ has to mutate if the random number $R_{[x_1 x_2 \ldots x_l]j}$ generated is smaller than the mutation rate β_g. The value of the selected gene is changed to any real number within an acceptable range. As a result, diverse solutions can be produced for generation. Figure 3.14 and 3.15 shows an example of the mutation process in the case feature region and parameter value region respectively. Any gene with a random number generated smaller than 0.1 has to mutate.

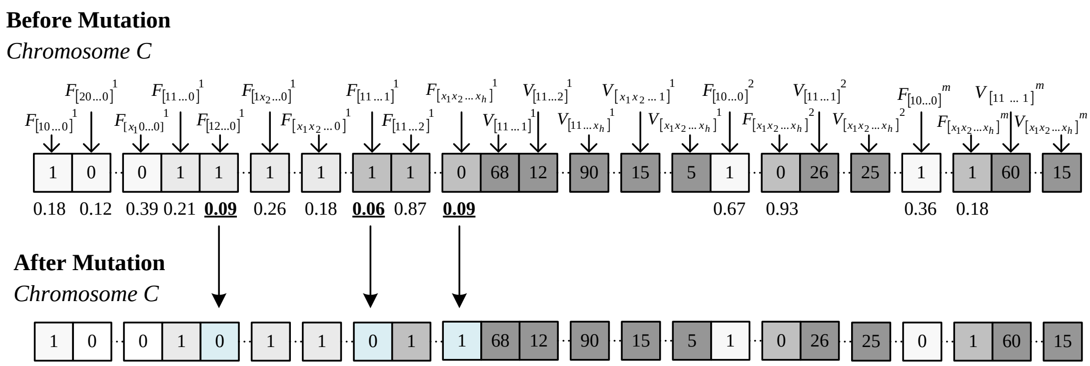


Figure 3.14 Before and after mutation for a chromosome in the case feature region

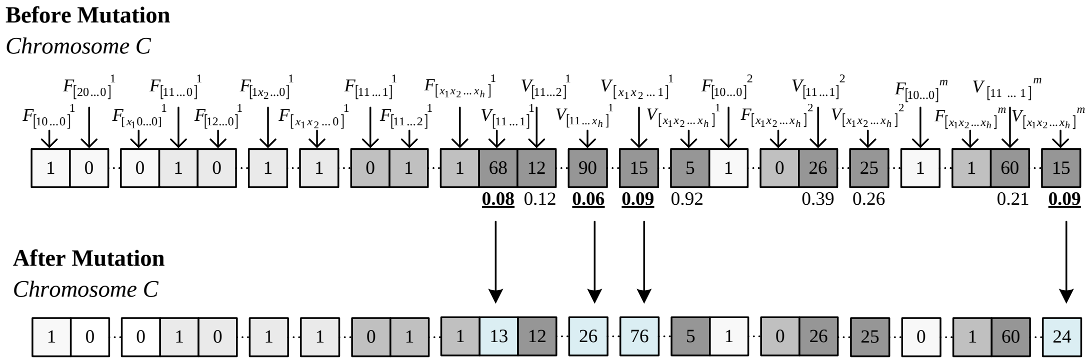


Figure 3.15 Before and after mutation for a chromosome in the parameter value region

3.5.2.8 Chromosome Repairing and Replacement

After performing crossover and mutation, inconsistencies may occur between the regions of the chromosome. Repairing is proposed to resolve the violation within the chromosome (Ho et al., 2008). There are three repair approaches suggested for this clustering model: (i) forward repairing, (ii) backward repairing, and (iii) range repairing. Forward repairing checks the consistency between the *F* region and the *V* region. It starts from the case feature region to the parameter value region. Figure 3.16 shows an example of forward repairing. As the values of case feature ${F_{[10\ldots0]}}^{1}$, ${F_{[11\ldots0]}}^{1}$ until ${F_{[11\ldots1]}}^{1}$ are all equal to 1, it indicates that the attribute ${F_{[11\ldots1]}}^{1}$ should be considered in the first cluster. However, it is found that its corresponding value of ${F_{[11\ldots1]}}^{1}$ is equal to zero. Since the value of this feature is a non-zero positive number; hence, a random number (*34*) is generated through forward repairing.

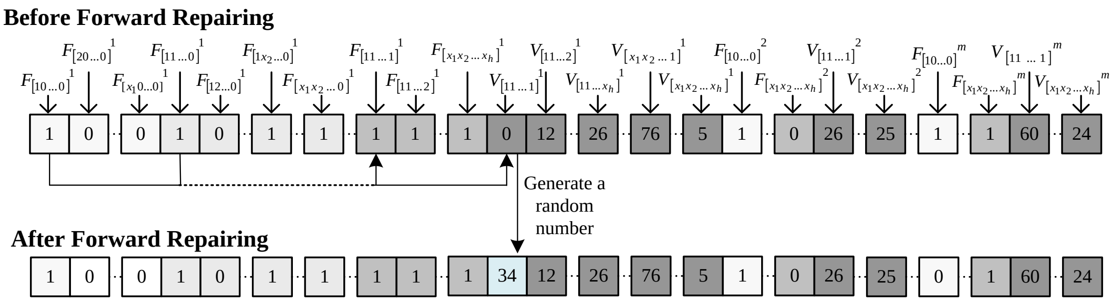


Figure 3.16 Example of forward repairing for chromosome

Backward repairing considers the consistency in an adverse direction which checks from the parameter value region to the case feature region. If there is a non-zero positive value in the parameter value region and its associated attribute is equal to 1, it indicates the presence of the case feature. The value of case features in the upper level of the tree should also equal to 1. Figure 3.17 shows an example of backward repairing.

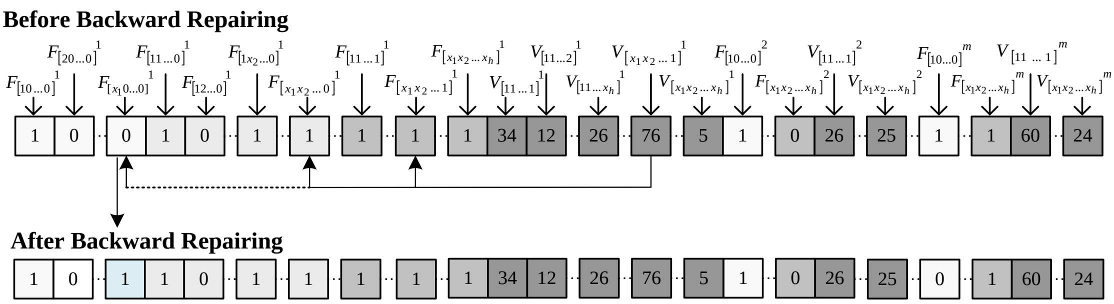


Figure 3.17 Example of backward repairing for chromosome

In the example, it is found that $V_{[x_1 x_2 \dots 1]}^{1}$ is a non-zero positive value while $F_{[x_1 x_2 \dots 1]}^{1}$ is equal to 1. The case attributes in the upper part of the tree associated to $F_{[x_1 x_2 \dots 1]}^{1}$ should also be checked to ensure that they are included for consideration. In this case, the last attribute in the 1st level of the hierarchical decision tree, $F_{[x_1 0 \dots 0]}^{1}$,is found to be zero, which violates the condition that the value of

${F_{[x_1 0 \ldots 0]}}^1$ should also be 1 if the value of ${F_{[x_1 x_2 \ldots 1]}}^1$ is 1 and ${V_{[x_1 x_2 \ldots 1]}}^1$ contains a non-zero positive value. Backward repairing is performed to change the value of ${F_{[x_1 0 \ldots 0]}}^1$ from 0 to 1.

In addition to forward and backward repairing, the values in the parameter value region should fall into an allowable range. The value is adjusted to the minimum number between the current value and the upper limit of the allowable range. After repairing, generation of the GA process is completed. A number of best-generated solutions will then replace the worst chromosomes for the next generation.

3.5.2.9 Chromosome Decoding

Once the termination criteria are fulfilled, the GA process is stopped, and the best chromosome generated with the largest fitness value is then extracted as the near-optimal solution. The extracted chromosome is decoded to a form that can be understood by others. In this model, appropriate cluster centers that result in better clustering of cases are represented by the chromosome as a set of case features and their corresponding values. Figure 3.18 shows an example of a chromosome with minimum fitness value after *n* generations.

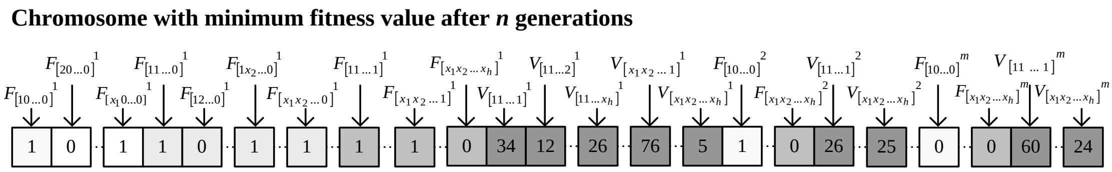


Figure 3.18 Chromosome decoding after n generations

The chromosome has to be decoded to obtain the *m* cluster centers. In the case feature region of the 1st cluster, the gene $F_{[10...0]}^{1}$, $F_{[11...0]}^{1}$, …, $F_{[11...1]}^{1}$ contains the value 1, indicating that the attribute $F_{[11...1]}^{1}$ is considered as one of the center attributes in the 1st cluster and its corresponding value is equal to 34. On the other hand, the value of the attribute $F_{[20...0]}^{1}$ is 0 which shows that $F_{[20...0]}^{1}$ is not included as an attribute in the 1st cluster center. After decoding the chromosome, the attributes and their values for the *m* clusters are obtained.

Table 3.4 Example of the *m* cluster center with attributes and values

	Case attribute	Value of the attribute
Center of Cluster 1	$F_{[10...0]}^{1} \cdot F_{[11...0]}^{1} \cdot ... \cdot F_{[11...1]}^{1}$	34
	$F_{[10...0]}^{1} \cdot F_{[11...0]}^{1} \cdot ... \cdot F_{[11...2]}^{1}$	12
	$F_{[10...0]}^{1} \cdot F_{[11...0]}^{1} \cdot ... \cdot F_{[11...x_h]}^{1}$	26
	$F_{[x_1 0...0]}^{1} \cdot F_{[x_1 x_2 ...0]}^{1} \cdot ... \cdot F_{[x_1 x_2 ...1]}^{1}$	76
	$\vdots$	$\vdots$
	$F_{[x_1 0...0]}^{1} \cdot F_{[x_1 x_2 ...0]}^{1} \cdot ... \cdot F_{[x_1 x_2 ...x_h]}^{1}$	5
Center of Cluster 2	$F_{[10...0]}^{2} \cdot F_{[11...0]}^{2} \cdot ... \cdot F_{[11...1]}^{2}$	26
	$F_{[10...0]}^{2} \cdot F_{[11...0]}^{2} \cdot ... \cdot F_{[11...5]}^{2}$	68
	$\vdots$	$\vdots$
	$F_{[(x_1-1)0...0]}^{2} \cdot F_{[(x_1-1)x_2 ...0]}^{2} \cdot ... \cdot F_{[(x_1-1)x_2 ...x_{h-1}]}^{2}$	92
$\vdots$	$\vdots$	$\vdots$
Center of Cluster *m*	$F_{[20...0]}^{m} \cdot F_{[21...0]}^{m} \cdot ... \cdot F_{[21...2]}^{m}$	13
	$F_{[20...0]}^{m} \cdot F_{[24...0]}^{m} \cdot ... \cdot F_{[24...1]}^{m}$	70
	$\vdots$	$\vdots$
	$F_{[(x_1-1)0...0]}^{m} \cdot F_{[(x_1-1)x_2 ...0]}^{m} \cdot ... \cdot F_{[(x_1-1)x_2 ...x_h]}^{m}$	45

Table 3.4 shows an example of m cluster centers which are represented by the case attributes and the corresponding values. Since GA generates the gene value in a chromosome randomly, the number of case attributes to be included in each cluster is also different. Figure 3.19 shows an example of a case grouping result with selected case attributes.

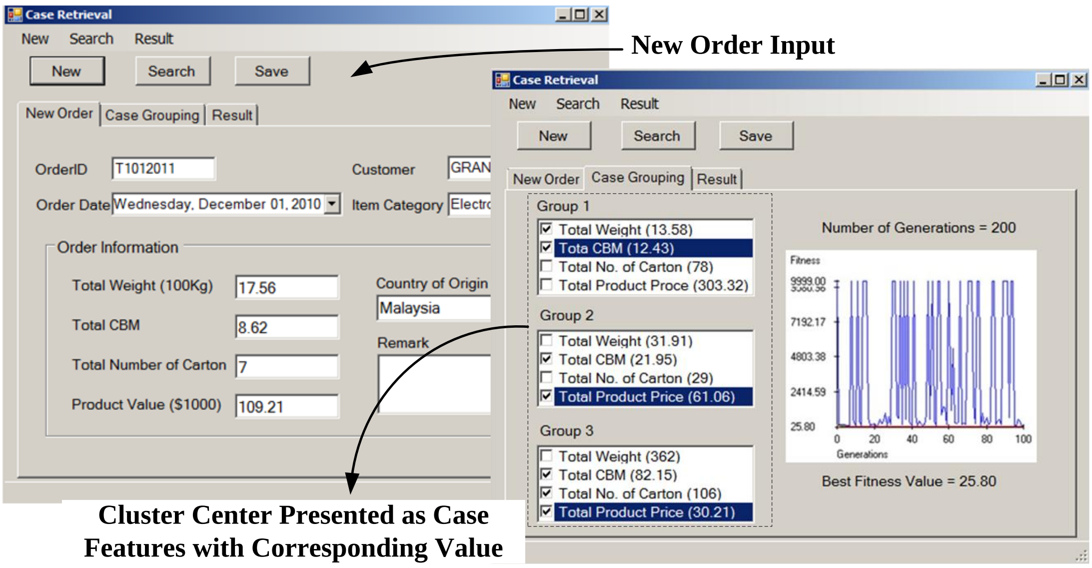


Figure 3.19 Case grouping result with selected case attributes

3.5.3 Case Retrieval

After the case-clustering processes, the past cases in the case library are divided into i clusters. The nearest neighboring retrieval (NNR) approach is then adopted to retrieve the cluster and past cases that are suitable for use by the new case. NNR adopts an exhaustive search by calculating the similarity of problem description between all past cases and the new problem to be solved. The cluster retrieval priority index, I_{CR}, for retrieving a similar case cluster is calculated using Equation 3.11.

$$I_{CR} = \frac{\sum_{l \in H} w_{[x_1 x_2 \ldots x_l]} \times sim(Z_i, T_{new})}{\sum_{l \in H} w_{[x_1 x_2 \ldots x_l]}}, \quad \forall i \in M \tag{3.11}$$

where $w_{[x_1 x_2 \ldots x_l]}$ is a weighting factor that indicates the importance of the case attribute $F_{[x_1 x_2 \ldots x_l]}$; sim is the similarity function; Z_i is the center of the i^{th} case cluster; T_{new} is the attributes of the new case.

The weighting factor, $w_{[x_1 x_2 \ldots x_l]}$, considers the importance of the case attribute in searching the past cases. The case attribute with a higher value of weighting factor shows the higher preference for the attribute to be included in case clustering. The similarity function, $sim(Z_i, T_{new})$, calculates the similarity value between the parameter value of case attributes for past cases in the case cluster i and the new case. $sim(Z_i, T_{new}) = 0$ if $\bar{f}_{i[x_1 x_2 \ldots x_l]} = 0$, which concludes that the case attribute $F_{[x_1 x_2 \ldots x_l]}$ is not included as the center of cluster i; otherwise the similarity measure, $sim(Z_i, T_{new})$, between the new case and center of the case cluster i is calculated using Equation 3.12.

$$sim(Z_i, T_{new}) = 1 - \frac{\left| \bar{f}_{i[x_1 x_2 \ldots x_l]} \times \bar{v}_{i[x_1 x_2 \ldots x_l]} - f'_{[x_1 x_2 \ldots x_l]} \times v'_{[x_1 x_2 \ldots x_l]} \right|}{100} \tag{3.12}$$

where $\bar{f}_{i[x_1 x_2 \ldots x_l]}$ must be equal to 1, showing that the attribute $F_{[x_1 x_2 \ldots x_l]}$ belongs to part of the i^{th} cluster center; $f'_{[x_1 x_2 \ldots x_l]}$ and $v'_{[x_1 x_2 \ldots x_l]}$ are the values of the attribute $F'_{[x_1 x_2 \ldots x_l]}$ and its corresponding value $V'_{[x_1 x_2 \ldots x_l]}$ of the new case respectively. The cluster with the highest value of I_{CR} is retrieved to search for similar past cases in the next step.

3.5.4 Case Reuse

In the retrieved i^{th} cluster, potential past cases are ranked in descending order according to the priority index I_P. The case with highest priority index I_P is expected to be the most similar case to the new problem in which the solution part of the retrieved past case can be used to formulate the operations guidelines for the new problem. The priority index I_P for retrieving a past similar case is calculated by Equation 3.13.

$$I_p = \frac{\sum_{l \in H} w_{[x_1 x_2 \ldots x_l]} \times sim(T_{ik}, T_{new})}{\sum_{l \in H} w_{[x_1 x_2 \ldots x_l]}} \tag{3.13}$$

where $sim(T_{ik}, T_{new})$ measures the similarity between the k^{th} past case in the cluster i and a new case. Given that a case description consists of both textual and numeric feature information, the similarity measures are then calculated with different methods which ranges from *0* to *1*. Given that a case consists of textual and numeric feature information, the similarity measures for textual features are determined by construction of similarity tables, while the similarity measures for numeric features are calculated based on the distance of the numeric attributes between past cases and a new order. Figure 3.20 shows an example of similarity tables for measuring the similarity value between textual features.

The similarity value for measuring the similarity between numeric features is calculated by Equation 3.14.

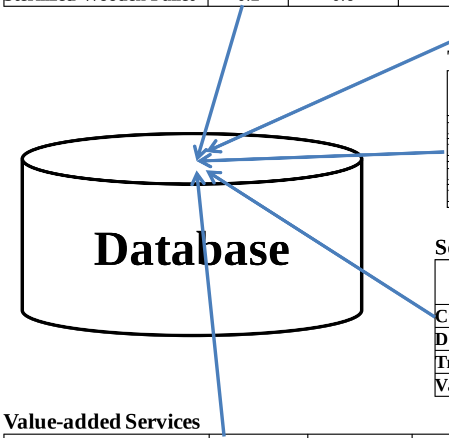
$$sim(T_{ik}, T_{new}) = 1 - \frac{\left| f_{ik[x_1 x_2 \ldots x_l]} \times v_{ik[x_1 x_2 \ldots x_l]} - f'_{[x_1 x_2 \ldots x_l]} \times v'_{[x_1 x_2 \ldots x_l]} \right|}{100} \tag{3.14}$$

Packing Materials

	Wooden Pallet	Non-Wooden Pallet	Sterilized Wooden Pallet
Wooden Pallet	1	0	0.2
Non-Wooden Pallet	0	1	0.6
Sterilized Wooden Pallet	0.2	0.6	1

Country of Origin

	China	Malaysia	Japan	Thailand
China	1	0.4	0.2	0.8
Malaysia	0.4	1	0.8	0.6
Japan	0.2	0.8	1	0.4
Thailand	0.8	0.6	0.4	1



Types of SKU

	Plastics Material	Electronics	Printer	Health Care Product
Plastics Material	1	0.8	0.4	0.2
Electronics	0.8	1	0.6	0.1
Printer	0.4	0.6	1	0.7
Health Care Product	0.2	0.1	0.7	1

Service Request

	Customs Declaration	Documentation	Truck Booking	Value-added Services
Customs Declaration	1	0	0	0
Documentation	0	1	0	0
Truck Booking	0	0	1	0
Value-added Services	0	0	0	1

Value-added Services

	Repacking	Palletization	Bar code labeling	Ship mark labeling	Others
Repacking	1	0.8	0.6	0.2	0
Palletization	0.8	1	0.2	0.4	0
Bar code labeling	0.6	0.2	1	0.8	0
Ship mark labeling	0.2	0.4	0.8	1	0
Others	0	0	0	0	1

Figure 3.20 Similarity measure for textual features in the case

Textual Attribute Similarity Table: Item Category

	Electronics	Printer	Plastics Materials	Other
Electronics	1	0.8	0.2	0
Printer	0.8	1	0.4	0
Plastics Materials	0.2	0.4	1	0
Other	0	0	0	1

Textual Attribute Similarity Table: Country of Origin

	China	Thailand	Malaysia	Japan	Other
China	1	0.4	0.6	0.2	0
Thailand	0.4	1	0.8	0.2	0
Malaysia	0.6	0.8	1	0.2	0
Japan	0.2	0.2	0.2	1	0
Other	0	0	0	0	1

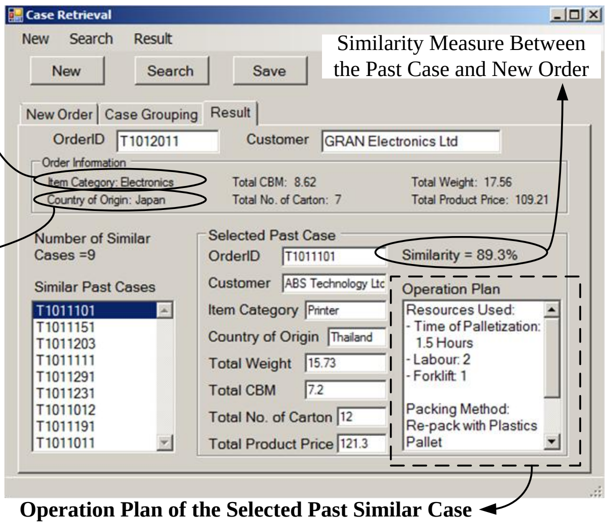


Figure 3.21 Similarity measure of past cases and a new order

They are then ranked in descending order based on their priority index with the new order. The past case with the highest priority index will be used as the solution to the new order. Other cases with lower similarity values may serve as references for case revision in the next step. Figure 3.21 shows an example of a similarity measure of past cases and a new order.

3.5.5 Case Revision and Retention

The best matched case is analyzed by comparing its common attributes with those of the input case. The solution of the past case can be revised according to the current situation to make it more adaptive to the requirement of the new case. The content of the solution includes suggested workflow, guidance and KPIs for managing the performance of warehouse operations which can be further modified to suit the need of the current situation. Figure 3.22 shows an example of a case revision based on the past case with highest priority index. The revised case can be retained in the case library for future use. Case retention is the process of incorporating useful knowledge from the new problem solving episode into the database of existing knowledge. The case is updated and stored if the solution successfully solves the case.

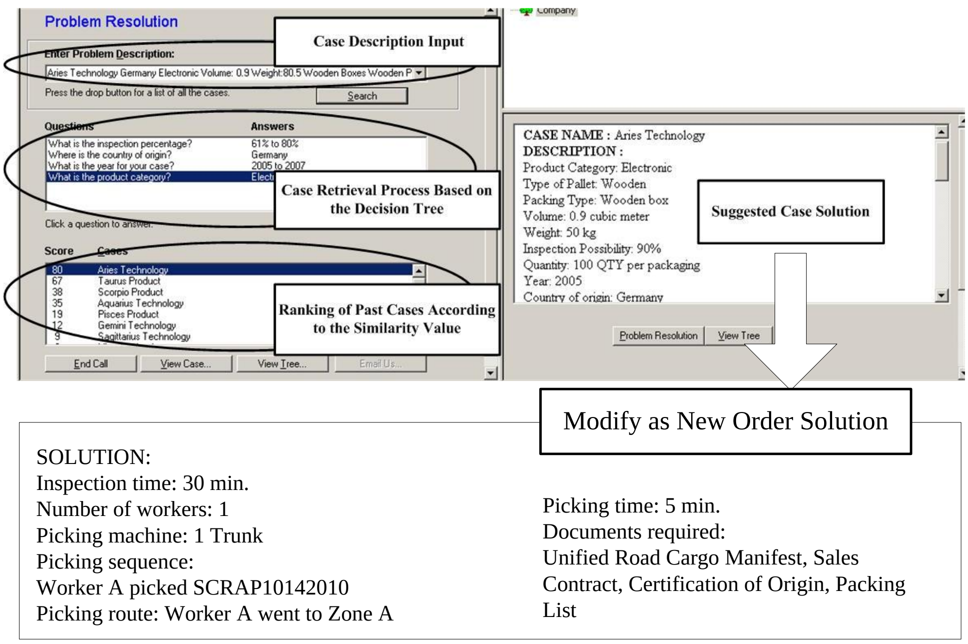


Figure 3.22 Case revision based on the past case with highest priority index

3.6 Summary

This chapter illustrates the system architecture of K-LOPS which contains three modules i.e. RDCM, WRAM and LSFM for supporting the data capturing, risk factor analysis and knowledge manipulation in warehouse operations planning respectively. In addition, the mechanism of the newly designed iterative dynamic clustering (iDPC) algorithm is also presented to enhance the searching performance of the case retrieval process in LSFM. In order to apply the proposed system, a roadmap of system implementation is shown in Chapter 4.

Chapter 4 The Implementation Procedures of the System

4.1 Introduction

In this chapter, the design and implementation of K-LOPS is described. It provides a systematic approach for supporting operations planning through the implementation of an intelligent decision support system based on the infrastructure design of the K-LOPS and iDPC algorithm. The system development in this research is shown in Figure 4.1. It is divided into five main phases: (i) Identification of problems and objectives, (ii) Structural formulation of real-time data collection module, (iii) Structural formulation of warehouse risk assessment module, (iv) Structural formulation of logistics strategy formulation module, and (v) System implementation and evaluation.

4.2 Phase 1 – Identification of Problems and Objectives

The aim of this phase is to identify the problems and objectives for a logistics company. This phase consists of two steps, which are (i) Step 1: Warehouse operations analysis, and (ii) Step 2: System development preparation.

Step 1: Warehouse operations analysis

In this step, the background and existing problems faced by the logistics company are first studied. By understanding the problem nature and company requirements, the objectives for system implementation can be defined to suit the target company. In particular, questionnaires and interviews are conducted in the logistics company to study the existing workflow of the logistics operations. Participants involved in this phase include the warehouse managers, logistics supervisors, information technology (IT) managers and warehouse workers. Both the inbound and outbound workflow in the warehouse, including receiving, storage, picking and delivery processes, are studied through a site visit to define the scope of the project and duration of system implementation.

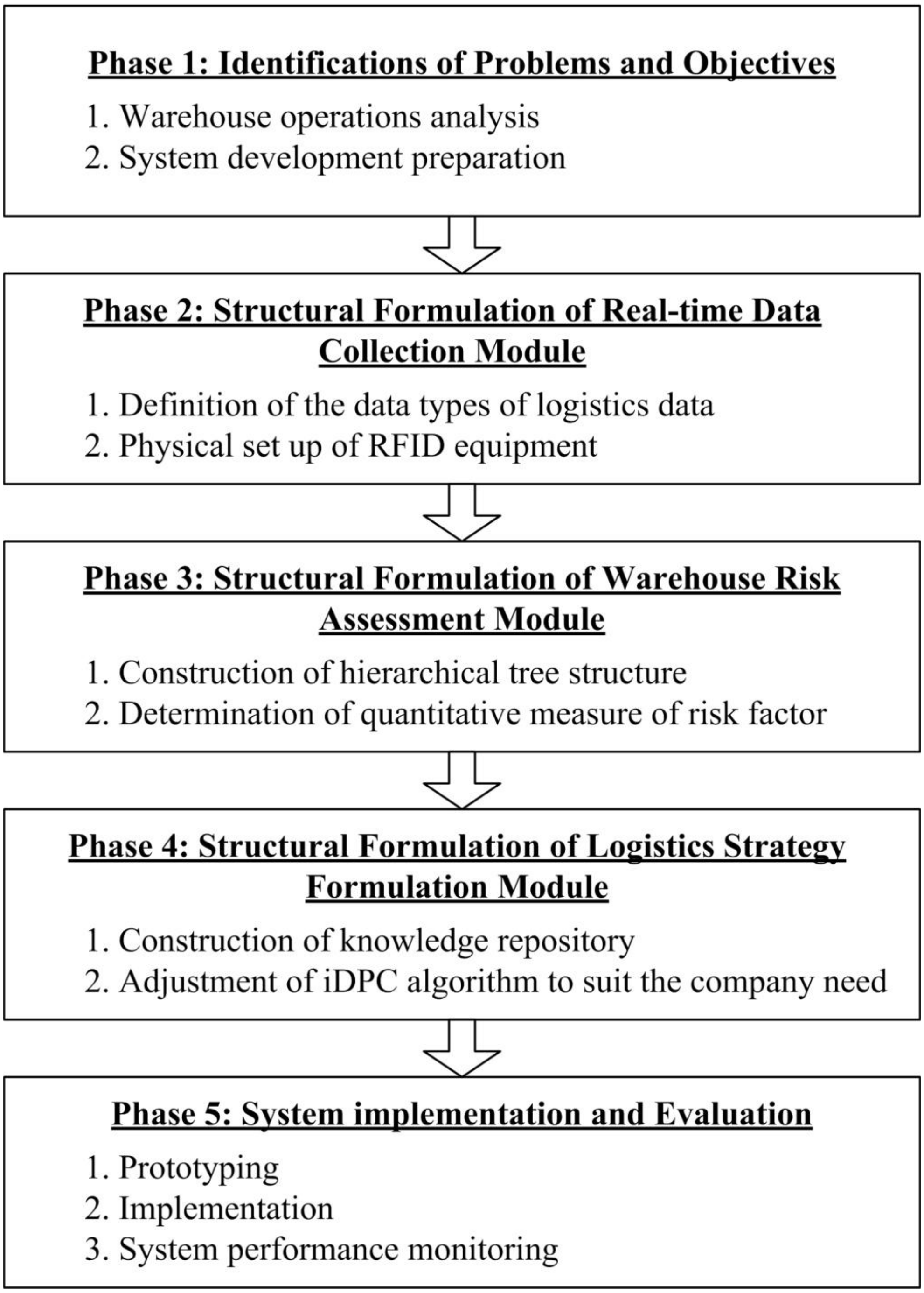


Figure 4.1 The implementation procedures of K-LOPS

Step 2: System development preparation

In this step, the logistics supervisors and warehouse managers have to define the requirements of warehouse operations planning. These requirements include the type of input data, data and operations flow during the logistics process, and the type of output data in graphic presentation and in a data flow diagram. The structural data flow diagram helps the system developers to construct the K-LOPS according to the need specified by the logistics supervisors and warehouse managers. The details of the existing information system work such as the warehouse management system (WMS) should also be studied to figure out the type of data that can be obtained from the system.

4.3 Phase 2 – Structural Formulation of Real-time Data Collection Module

The aim of this phase is to formulate the Real-time Data Collection Module (RDCM) of K-LOPS. This phase consists of two steps, which are Step 1: Definition of the data types of logistics data, and Step 2: Physical set up of RFID equipment.

Step 1: Definition of the data types of logistics data

In this step, different types of data within the warehouse operations are studied. The data type includes warehouse operations data, resource data, service specifications, inbound and outbound customer orders, and related attributes. In order to visualize the actual operations environment in the warehouse, the physical setup of RFID technology in capturing real-time data is designed. Real-time data such as order and SKU information, location and work status of material handling equipment, and the physical condition of the warehouse are collected by the RFID data collector, through the setting of RFID equipment. The signal received by the RFID equipment is then decoded and transformed into meaningful information for further processing. Besides, logistics companies usually adopt a warehouse management system (WMS) to provide, store, and report the information necessary for managing the flow of products efficiently within a warehouse, from the time of receipt to the time of shipping (Faber et al., 2002). The main function of WMS is to manage the inventory through tracking the movements of products, storing of materials within the warehouse, sharing accurate inventory information with the clients (Kim et al., 2008). Hence, the data related customer orders, resource data and inbound/outbound activities can be extracted from the WMS within the company. Figure 4.2 shows an example of the order and resource attributes that can be collected during warehouse operation processes. A centralized data warehouse is then constructed to store all the data collected from the RFID technology and WMS.

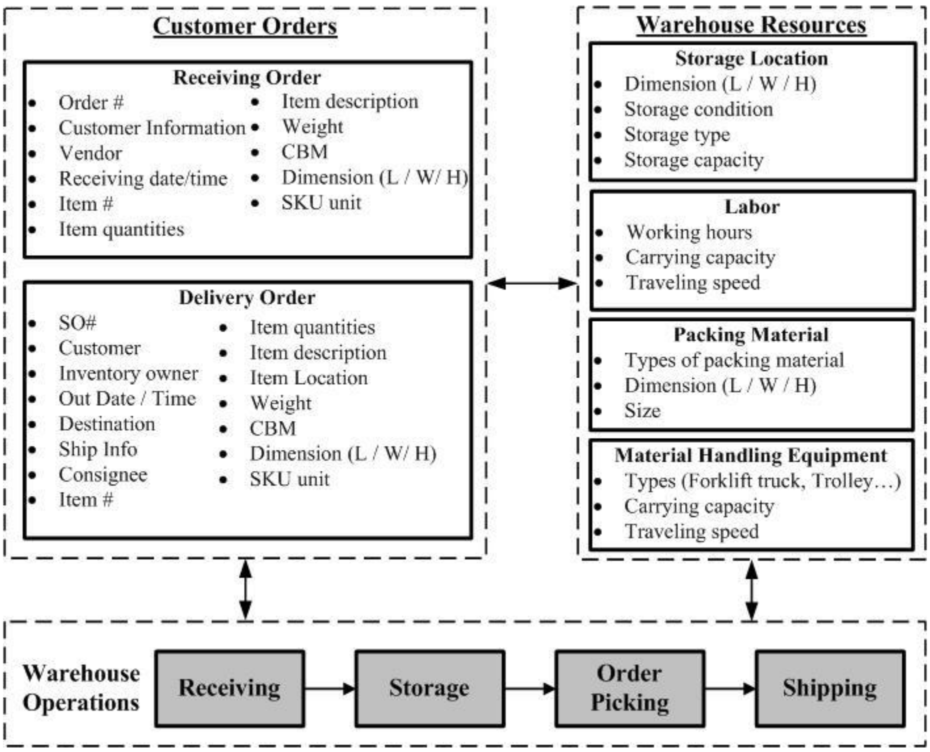


Figure 4.2 Example of order and resource attributes for warehouse operation processes

Step 2: Physical set up of RFID equipment

In this step, a set of RFID equipment is evaluated and selected according to the actual operation need and the reading performance of the equipment. The function of RFID is to capture real-time operations data such as the in-and-out movement of material handling equipment and SKUs, so as to determine the operating guidelines with the data collected. The selected RFID equipments including the RFID reader, antenna, active or passive, have to perform on-site tests in the warehouse in order to find out the most suitable setting for achieving good reading performance. A readability test has to be conducted to determine the RF coverage area within the warehouse. It refers to the region where the radio frequency signal can be received and reflected by the tagged objects when the objects pass though the RFID setting. Appropriate settings on the locations of reader, antenna and tags on the item would increase its reading performance and accuracy. The setup of RFID equipment within the warehouse varies according to the types and specifications of RFID equipment, layouts, daily operations flow and throughput of warehouse.

4.4 Phase 3 – Structural Formulation of Warehouse Risk Assessment Module

In this phase, the warehouse risk assessment module (WRAM) is constructed to identify and prioritize the type of risks of concern to both the warehouse manager and customer in handling a specific type of product. As different products have their own characteristics, the risk factors concerned when handling each product may vary. This phase consists of two steps, which are, Step 1: Construction of hierarchical tree structure for risk analysis, and Step 2: Determination of quantitative measure of risk factor.

Step 1: Construction of hierarchical tree structure for risk analysis

In this step, the hierarchical tree structure based on the AHP technique is constructed. The risk factors are defined according to the product characteristics, customer specifications and warehouse reliability. By conducting interviews with the warehouse manager and logistics supervisor, possible risk factors are identified and a hierarchical tree structure is constructed to represent the relationship of risk factors. Under each category of risk factor, sub-factors are also identified and included to specify the type of the risk factor concerned. The type of risk concerned by each customer may vary, and it depends on the situation of a particular warehouse and the product characteristics. Performance in financial status, operations processes and resources reliability is the major concern when assessing the risk and competitiveness in warehouse operations. In addition, selection of criteria is important in conducting a pair-wise comparison between the risk factors. In this study, the likelihood of occurrence and consequence/severity are defined as the criteria to prioritize the risk factors. All the risk factors and criteria associated with the hierarchical tree structure should be determined and constructed before the pair-wise comparison can be carried out.

Step 2: Determination of quantitative measure of risk factor

In order to obtain the risk factor with the highest priority value, a quantitative measure of risk factor is constructed in this step to conduct a pair-wise comparison between two risk factors. A nine point scale for weighting the likelihood and consequence/severity are defined and definition of the scale is shown in Table 4.1. The risk factors are compared in pairs under a specific criterion. Let's assume that "Cost" is one of the criteria to determine the importance of risk. When comparing two risk factors, the value "1" indicates that the two risk factors are equally important under the criterion of "Cost". If the weighting between the first and second risk factor is "3", it indicates that the first factor is slightly more important than the second factor when considering the cost factor required. The higher value indicates the increasing importance between two risk factors.

Table 4.1 Definition of the nine point scale for weighting the likelihood and consequence/severity

Point	**Definition**	**Description**
1	Equal importance	Two activities contribute equally to the objective
3	Slightly importance of one over another	The judgment is slightly tending to one over another
5	Medium importance	The judgment is strongly tending to one over another
7	Highly importance	Conclusive judgment as to the likelihood of one activity over another
9	Absolute importance	The judgment in favor of one activity over another is of the highest possible order of affirmation
2, 4, 6, 8	Intermediate values between the two adjacent judgments	

After comparing all risk factors under the criteria "Cost", the value is stored in the database in a matrix form. As shown in Table 4.2, a 4 x 4 comparison matrix for comparing 4 risk factors under the criteria "Cost" is presented. It is presented in a symmetric way where the quotient of the values between the two risk factors is equal to 1. For example, the weighting between risk factor 3 and risk factor 1 is equal to x_{31}, where x_{31} is larger than zero, which indicates that risk factor 3 is much more important than risk factor 1 when considering the criteria "Cost". Meanwhile, it also shows that the weighting between risk factor 1 and risk factor 3 is $1/x_{31}$, which is the reciprocal of the weighting between risk factor 3 and risk factor 1. By constructing the matrix form for comparing the risk factors, the priority vector can be computed according to the model defined.

Table 4.2 Sample of 4 x 4 comparison matrix of criteria "Cost"

Criteria = Cost	Risk Factor 1	Risk Factor 2	Risk Factor 3	Risk Factor 4
Risk Factor 1	1	$1/x_{21}$	$1/x_{31}$	$1/x_{41}$
Risk Factor 2	x_{21}	1	$1/x_{32}$	$1/x_{42}$
Risk Factor 3	x_{31}	x_{32}	1	$1/x_{43}$
Risk Factor 4	x_{41}	x_{42}	x_{43}	1

4.5 Phase 4 – Structural Formulation of Logistics Strategy Formulation Module

In this phase, the logistics strategy formulation module (LSFM) of K-LOPS is constructed. This is the most important phase to manipulate the data from previous modules for formulating useful logistics strategy in warehouse operations. As the iDPC algorithm is the core component supporting the functionality of LSFM, the parameter setting of the iDPC algorithm should be well defined when applying K-LOPS in the case companies. This phase consists of two steps, which are Step 1: Construction of knowledge repository, and Step 2: Adjustment of iDPC algorithm to suit the company need.

Step 1: Construction of knowledge repository

The concept of the CBR technique is adopted to formulate LSFM. Past cases stored in the case library are extracted as a reference in designing the solution for new problem. Prior to the formulation of LSFM, warehouse and logistics knowledge within the company is examined. This knowledge includes the standard operating procedures (SOPs), defined by the logistics supervisor, to provide various services to customers, the specification and working efficiency of material handling equipment, skill and experience of warehouse staff members, any special regulations and rules required when fulfilling the order, and solutions of past operations strategies and reports. As this knowledge may have different forms, in printed version or electronic form, they have to be edited and presented in a case-format so as to support the retrieval process. The information is obtained mainly through interview and collection of company reports. The logistics supervisor, warehouse manager and IT supporting team member are involved in this step to identify the type of knowledge which is useful in generating solutions for the new problem. The knowledge is then validated and transformed into a machine-readable format in the environment of Microsoft Visual Studio.Net.

(i) Identification of key attributes and parameters in representing a case

The content of the cases involves the case name, problem description, and solution. The attributes can be numerical, symbolic, or textual values to represent the key feature of the problem. The order details, including SKU information and services requirement, are used to describe the case problem. Therefore, they are identified as the input variables of LSFM in retrieving past cases. The resources allocated, operating guidelines and relevant documents required are defined as the solution part in providing suggestions in handling the new problem. The key attributes and parameters have to be defined prior to the implementation of LSFM.

(ii) Construction of hierarchical decision tree structure in representing a case

After identifying the key attributes involved in the warehouse operations process, a hierarchical decision tree structure is constructed to represent the case in a structural format. By using the tree structure, the dimensions and attributes concerned in the decision making process of the operations strategy are presented in detail which shows the relationship between the attributes. The number of levels in the tree and the sub-categories in the tree structure depends on the complexity of the case problem and it may vary according to the major concerns of the decision makers.

Step 2: Adjustment of iDPC algorithm to suit the company need

In this step, the parameter setting of the iDPC algorithm is adjusted to suit the current situation and needs of the company. To obtain a reliable result within a reasonable time, it is important to perform system testing and to fine tune the parameter settings for the algorithm. Therefore, the number of clusters defined in dividing past cases, crossover rate, mutation rate and termination criteria are considered in this step in order to find out the most suitable setting for the system.

(i) Determination of the number of clusters in dividing past cases

The number of clusters is preliminarily defined in this phase so as to facilitate the searching process. With an increasing number of clusters, the length of the chromosome also increases to take into consideration on any possibilities in case clustering. With a smaller number of clusters, more retrieved cases within the cluster are obtained, increasing the difficulty in finding a more appropriate solution to the new problem. However, if a large number of clusters are defined, a lot of time is required to generate the case grouping result. Hence, an experiment is performed to determine the appropriate system setting that can provide a balanced result between complexity and searching time.

(ii) Determination of crossover rate in LSFM

Crossover is one of the GA operators to reproduce new offspring by combining two individuals in a population. There are several types of crossover methods which include one-point crossover, two-point crossover, multi-point crossover and random crossover. Due to the length of the chromosome, a two-point crossover method is applied in this algorithm to select two genes in the chromosome for performing crossover. The crossover ranges between 0 and 1, in which the higher crossover rate increases the chance for the chromosome to undergo crossover operations. To select the crossover rate with better fitness performance, two settings of 0.7 and 0.9 are adopted to show the difference between the results. Figure 4.3 shows the MATLAB coding for selecting chromosomes to perform crossover operations. The system generates some random numbers that range from 0 to 1 for each chromosome. Crossover between pairs occurs only when the corresponding determining random number is higher than the crossover rate.

```
for i=1:floor(N1/2),
    for j=1:20*k,
        if R2(i,j)>crorate,
            NewChromo(2*i-1,j)=Select(2*i,(m+1)*k+1+j);
            NewChromo(2*i,j)=Select(2*i-1,(m+1)*k+1+j);
        else
            NewChromo(2*i-1,j)=Select(2*i-1,(m+1)*k+1+j);
            NewChromo(2*i,j)=Select(2*i,(m+1)*k+1+j);
        end
    end
end
```

Figure 4.3 MATLAB coding for crossover operations *(iii) Determination of mutation rate in LSFM*

Mutation is another GA operator for generating new solutions by making small random changes to the chromosome. It avoids the loss of genetic diversity by preventing the searching result to fall into a local optimum. Mutation can occur at any gene in a chromosome so as to enable a broader searching space. If a binary encoding scheme is used, the gene value would change from 0 to 1, or vice versa. If the encoding scheme is a real number, a random number is generated as the value of the gene. Consistency checking has to be performed after mutation, as the random change in the value of the gene may violate the problem solution. Repairing operation is carried out if inconsistency occurs. As the major function of mutation is to improve the fitness by making small changes to the current chromosome, a low mutation rate is often defined to limit the mutation probability (Holland, 1975). Figure 4.4 shows the MATLAB coding for selecting the genes to perform mutation operations. The system generates some random numbers ranging from 0 to 1 for each gene of the selected chromosome. Mutation occurs only when the correspondingly determined random number is smaller than the mutation rate.

```
for j=1:20*k,
    for i=1:N1,
        if R3(i,j)<mutrate,
            if j<=10*k,
                NewChromo(i,j)=1-NewChromo(i,j);
            else if mod(j,10)==1,
                    NewChromo(i,j)=1+mod(NewChromo(i,j)+ceil(11*rand(1)),12);
                else if mod(j,10)==0,
                        NewChromo(i,j)=1+mod(NewChromo(i,j)+ceil(4*rand(1)),5);
                    else
                        NewChromo(i,j)=1+mod(NewChromo(i,j)+ceil(2*rand(1)),3);
                    end
                end
            end
        end
    end
end
```

Figure 4.4 MATLAB coding for mutation operations *(iv) Determination of termination condition in LSFM*

The termination condition determines the stopping criteria for the GA process. The GA process stops and provides the chromosome with the best fitness value as the solution output after the termination condition is fulfilled. There are a number of termination conditions that are commonly used, such as the number of generations, time limit, fitness limit and stall generations (MathWorks, 2004). The number of generations refers to the maximum number of iterations that the GA performs. The algorithm stops if the maximum number of generations is reached. The time limit refers to the maximum time allowed for the GA to run before it stops. The fitness limit refers to the target fitness value defined by the users. The algorithm stops if the best fitness value is smaller than the fitness limit. For the stall generations, the maximum change in percentage and number of generations has to be specified. If the improvement of the fitness value is less than the percentage change after the number of generations specified, the algorithm terminates and the chromosome with best fitness value is generated. In this study, the iDPC algorithm stops if any one of the above conditions occur.

4.6 Phase 5 – System Implementation and Evaluation

System implementation and evaluation is the last step of the K-LOPS in logistics companies. Three steps, which are prototyping, implementation and system performance monitoring, are involved in this phase. In the first step, a prototype is designed and developed based on the infrastructural details and design methodologies from the previous phases, before K-LOPS can be used. Visual Studio.Net is the main programming language suggested for developing the prototype of K-LOPS in this research. Meanwhile, Microsoft SQL server is adopted to construct the database structure in RDCM and WRAM while MATLAB GA Toolbox is utilized to support the iDPC algorithm in LSFM. In the second step, the developed prototype is implemented and tested in the logistics companies to validate its feasibility in actual logistics operations environments. A team of operations staff is selected to adopt the prototype of the K-LOPS for performing daily operation tasks. Real logistics order data is used to test whether a reasonable solution can be obtained and how it performs in obtaining the result. During this step, any feedback obtained and suggested by the staff is collected to fine tune the design of the system.

In the last step, the performance of K-LOPS is evaluated after conducting a trial run in the case companies. To determine an appropriate GA setting for the system, a number of tests considering different GA operation settings, such as crossover rate and number of clusters defined, are carried out for comparing the running time and fitness performance. In order to show the performance of the proposed iDPC algorithm, it is necessary to compare it with the traditional case retrieval approach in CBR by comparing the fitness value obtained. Besides, the searching performance of the GA and Simulated Annealing (SA) are compared to illustrate the performance of using GA in the iPDC algorithm under different conditions. Furthermore, in order to measure the performance of K-LOPS in formulating the operations strategy, a survey was designed to collect the feedback from selected customers and the system users, i.e. the logistics supervisor and warehouse manager who has to plan the operating guidelines. The key performance indicators, including the operation time, degree of customer satisfaction, acceptability of logistics strategy suggested and adaptability of the past case solution, are measured and evaluated. The relevant experimental results are discussed in Chapter 6.

4.7 Summary

In this chapter, the implementation procedure of K-LOPS is presented. Five phases including Phase 1: Identification of problems and objectives, Phase 2: Structural formulation of real-time data collection module, Phase 3: Structural formulation of warehouse risk assessment module, Phase 4: Structural formulation of logistics strategy formulation module, and, Phase 5: System implementation and evaluation are described, showing the key steps that the logistics companies should pay attention to when implementing the system. By following the implementation procedure, the logistics company is able to adopt the proposed system in formulating a logistics strategy with K-LOPS. In order to validate the function of K-LOPS, two case studies conducted in the logistics industry are presented in the next chapter.

Chapter 5 Case Studies

5.1 Introduction

In order to validate the feasibility of adopting K-LOPS in providing risk analysis and useful explicit knowledge for supporting the formulation of a logistics operations strategy in the warehouse, application case studies were conducted in two Hong Kong based logistics companies: (i) a third party logistics company that is one of the leading logistics service providers in Hong Kong and Greater China, and (ii) a wine distribution hub that specializes in wine storage and distribution services. In case study 1, K-LOPS is adopted to analyze the major risks based on the types of services request and formulate the outbound operations process to fulfill cross-border orders in the third party logistics company. The amount of resources, workflow and guideline to conduct the logistics operation process are suggested by the system. In case study 2, K-LOPS is adopted to monitor the storage conditions by RFID and to formulate an immediate action plan for incident handling in the wine distribution hub. This chapter provides two profiles of the case studies which introduce the company background, existing practices and the problems faced by the companies. The implementation roadmap for applying K-LOPS in the companies is also described.

5.2 Case Study 1 – Third Party Logistics Company

Eastern Worldwide Company Limited (EWC) is one of the Hong Kong-based freight forwarding and logistics service providers, which was founded in 1973. EWC aims to achieve the three major service goals for its customers: (i) to minimize the finished goods inventory at the sales point, (ii) to shorten the lead time, and (iii) to maintain a higher visibility of the supply chain area. With the adoption of build-to-order logistics solutions and commitment to quality, EWC has developed to be one of the leading logistics service providers in Hong Kong and the Southern part of China. The company provides a wide variety of services to its customers, such as shipping and transportation services, on-site logistics and international freight forwarding services, warehousing and distribution, logistics consultation and project management service. With continuous development and expansion, EWC has become an asset-based logistics service provider with its own warehouses and fleet of vehicles. Since the return of Hong Kong to China in 1997, EWC have started to develop their business in China and thus the number of cross border orders between Hong Kong and China is continuously increasing.

5.2.1 Problem Definition of EWC

To increase competitive advantages in the logistics industry and maintain a leading position in regard to market share, the company needs to effectively manage its asset in their daily operation, in which the performance of the logistics service provided are kept at a satisfactory, or superior, level. In a typical cross border supply chain (CBSC), the warehouse is a transshipment center connecting suppliers and cross-border inspection points before goods are delivered to customers. Figure 5.1 shows the outbound operations workflow of the company. Cargo from different suppliers is first consolidated in the warehouse. The outbound process starts when a shipping order is received from the customer. The set of order instructions received, including the delivery date, product name and quantity, is sent to the warehouse for delivery arrangement. All these details are then recorded in the WMS to check the availability of the inventory and to generate the order list to choose the order from the storage zone. With the generated order list, the warehouse manager assigns a number of workers and resources to handle the order. To ensure the accuracy of the chosen orders, barcode scanning is applied to check the correctness of the product type and the quantity chosen. Then, all products are packed in cartons and palletized. With the requirement for transport across the cross-border inspection point, import/export documents are then prepared while the products are loaded on the delivery trucks. The inventory status is updated in the WMS to indicate the outbound status of the goods.

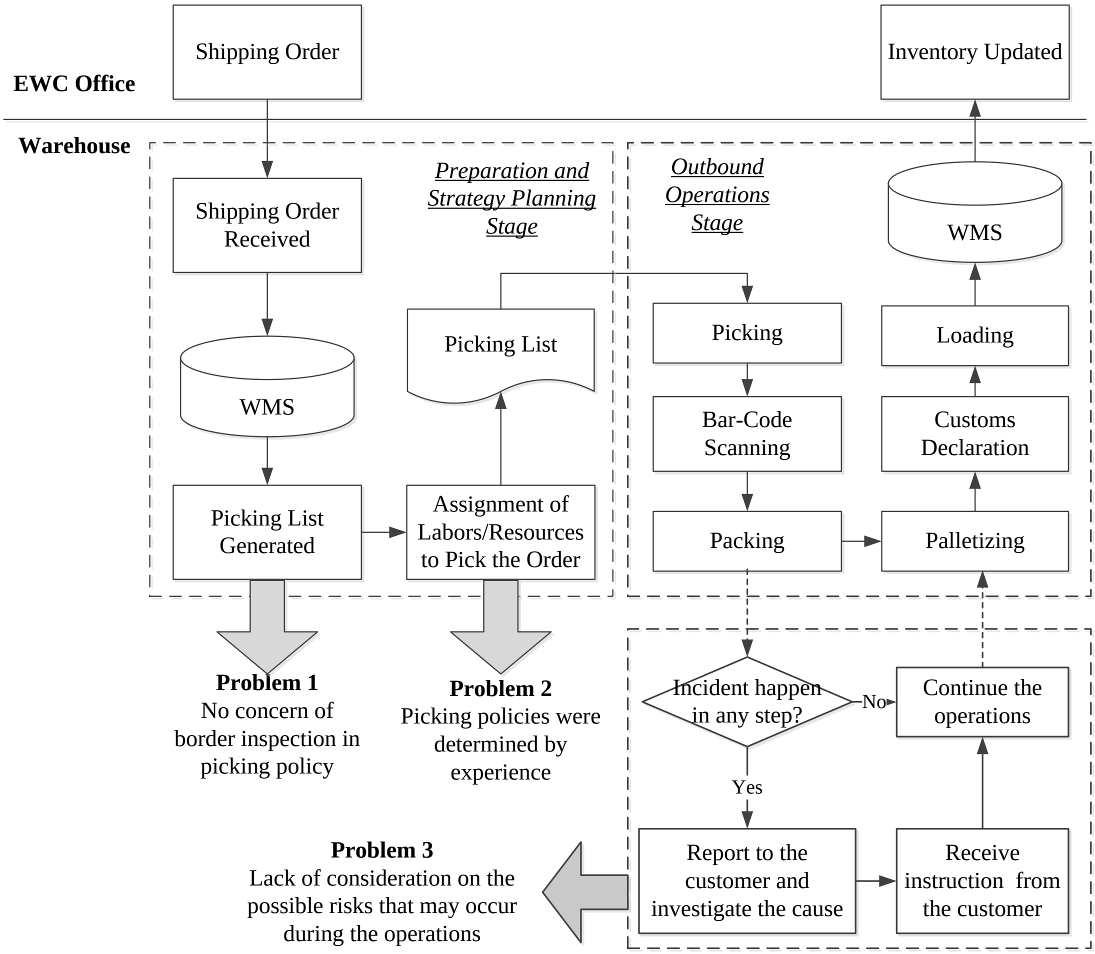


Figure 5.1 Outbound operations workflow of the company

The decision-making process is one of the complicated processes involved in warehouse operations for efficiently fulfilling various specific customer orders. This is especially true if the orders require cross-border delivery activities, such as palletization of the delivery goods according to regulation requirements. Figure 5.2 shows the existing palletization process which is performed based on personal experience. In these circumstances, the warehouse manager has to pay additional concern to the strict requirements in shipping instructions and inspection processes for the goods to be delivered across two regional boundaries. Thus, three major problems are found in the existing workflow, (i) lack of no concern about border inspection in the picking policy, (ii) the picking plan is determined by personal experience, and, (iii) lack of consideration on the possible risks that may occur during the logistics operation.

Figure 5.2 Existing palletization process based on human experience

(i) Problem 1 – Lack of concern about border inspection in the picking policy

To fulfill customer requirements within a limited period of time, warehouse operation planning should consider inspection regulations to polish the cross-border processes. A typical cross-border supply chain between two different locations is shown in Figure 5.3. The warehouse is a transshipment center connecting suppliers and cross-border inspection points before goods are delivered to customers. It performs four major functions: receiving, storage, order picking, and shipping. In addition to fulfilling customer requirements within a limited period of time, warehouse operation planning should also consider inspection regulations to polish the cross-border process.

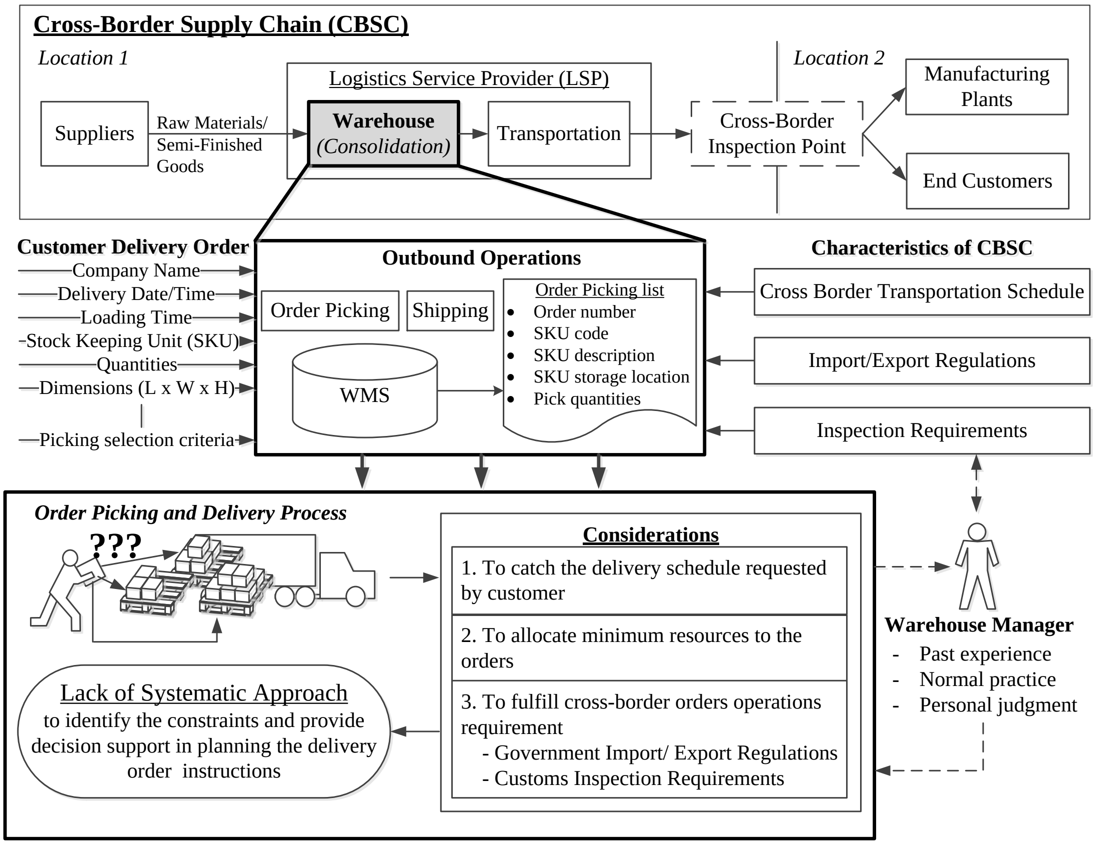


Figure 5.3 Warehouse order-picking and delivery process in the cross-border supply chain

Given that cross-border inspection points are located downstream of the cross-border supply chain, the warehouse delivery process should be emphasized. In inspection points, the goods delivered across regional boundaries are required to undergo cross-border inspection processes, including product examination and delivery document validation. To reduce the barrier effects of the cross-border supply chain, ensuring that delivery products comply with inspection regulations is important. Delivery time, operation costs, and chance of delay can be reduced if specific warehouse order-picking and delivery operations are arranged to suit any given situation. However, in the existing practice, there is a lack of concern about border inspection in the picking policy. To tackle the problem, the warehouse manager, when preparing a list, should take into consideration how likely it is for a unit load of goods to be inspected and the preventive action for the potential risks that may occur.

(ii) Problem 2 - The picking plan is determined by human experience

The decision making process depends on three considerations: the customer perspective, the warehouse operations arrangement, and regulatory policies. These considerations include

- to match the delivery schedule requested by the customer,
- to allocate minimum warehouse resources to the orders, and
- to fulfill cross-border order inspection requirements.

However, the existing WMS does not support this kind of decision making while the current decision-making processes depend primarily on the knowledge of warehouse manager. A systematic approach is lacking to identify the constraints and provide decision support in planning delivery-order instructions. Since the order picking process is a labor-intensive and costly activity to handle, the pressure on the warehouse manager to provide an effective and systematic delivery order handling instruction plan is increasing with limited time and resources.

(iii) Problem 3 - Lack of consideration on the possible risks

Warehouse operations become complex in providing various kinds of services that fit the specific requirements, especially for cross border orders. Due to the uncertainty and rapid changes in the business environment, the performance of warehouse operations is not only affected by the logistics strategy planning process, but attention also needs to be paid to the possible risks that may occur during the logistics operations. Since occurrence of risks may disturb the logistics operations and affect the warehouse performance significantly in the short-term and long-term, the company may suffer losses if they fail to deal with the problems and risks efficiently. Thus, continuous attention to risk management in planning warehouse operations is necessary to ensure the customer order can be satisfactorily completed on time. However, there is lack of consideration on the possible risks that may occur during the logistics operation. Inappropriate handling methods, and long inspection times, may result in lowering customer satisfaction.

5.2.2 Deployment of K-LOPS for Supporting Outbound Operations of Cross-border Orders

In order to tackle the above decision making problems, EWC decided to adopt the K-LOPS method to assist the planning process for handling outbound operations of cross border orders. Figure 5.4 shows the implementation procedure of the K-LOPS in EWC. The implementation procedure is divided into six steps: (i) RFID equipment set-up for data capturing, (ii) data collection through interview with warehouse representatives, (iii) hierarchy modeling of potential risk factors, (iv) pair-wise comparison and priority synthesis, (v) case clustering and retrieval, and (vi) case revision and retention. Through the data collected by the RFID equipment, the location of material handling equipment and the flow of SKU can be obtained. This information will be further used to revise the solution of a case based on the real time situation in the warehouse. After that, concerned risk by the customer, regarding the type of product to be handled, is identified, which becomes part of the consideration when generating new solution plan.

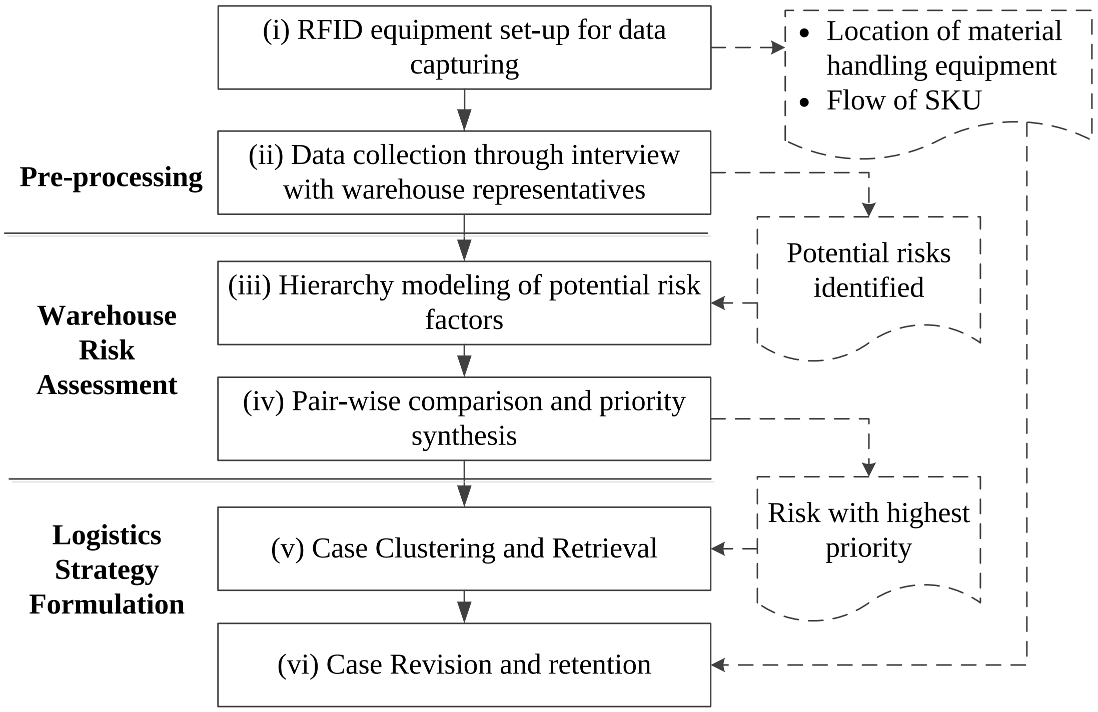


Figure 5.4 Implementation procedure of K-LOPS in EWC

(i) RFID equipment set-up for data capturing

To cope with the implementation of the K-LOPS in the EWC warehouse, RFID equipment, including RFID tags and readers, have to be set-up to capture the real time data during the operations. Firstly, passive RFID tags are stuck on each carton when they arrived at the warehouse which records the item ID, product information and its storage location. The tags are also attached to the material handling equipment, i.e. forklifts, to identify their identity and working locations. Figure 5.5 shows the passive RFID tags on the cartons and forklift. Then, the passive RFID readers are mounted in major passages to keep track on the movement of cargo and material handling equipments. As shown in figure 5.6, the passive RFID readers are mounted at the entrance to the dock door and the warehouse. The reader at the warehouse entrance records the in-and-out movement of the forklift, and indicates whether the forklift is working in the warehouse, while the reader on the dock door entrance records the loading sequence of the pallets. To ensure that the pallet is packed and loaded according to the guidelines given, the carton IDs on the pallet are transmitted to the reader when the pallet passed through the warehouse entrance and dock door with RFID reader. Warning is given if any carton is incorrectly packed or loaded on the container.

Figure 5.5 Passive RFID tag on carton and forklift

Figure 5.6 Passive RFID reader on dock door and entrance of warehouse

(ii) Data collection through interview with warehouse representatives

In order to have better understanding about the current situation of the warehouse, interviews with EWC warehouse representatives are conducted. A set of questions related to warehouse operations including major warehouse activities, processing, resources usage and managerial problems as well as possible warehouse risks, and cause of the risks and solutions are prepared for warehouse representatives. Table 5.1 shows a description of the risk factors of concern to the warehouse and customers. The potential risks are divided into 9 categories which are resource risk (A), managerial risk (B), physical environment risk (C), human risk (D), security risk (E), financial risk (F), market risk (G), regulatory/policy risk (H), and operations risk (I). In each category, the possible sub-risk factors that belong to the risk factors are also identified. Figure 5.7 summarizes the possible risks and their sub-risk factors identified through interview.

(iii) Hierarchical modeling of potential risk factors

The potential risk factors are then categorized in a hierarchical structure. To determine the importance of the risk factors, a three level hierarchical model is built which includes goal, criteria and alternatives. As it is difficult to evaluate the likelihood without any specific details of the risk and the description of risk factor is extensive, only consequence/severity are considered as criteria to estimate the impacts. Figure 5.8 shows the 3-level hierarchical structure for determining the importance of the risk factors.

Table 5.1 Description of the identified risk factors

Risk factor	Description
Resource risk (A)	Warehouse may suffer loss due to the unavailability of resources
Managerial risk (B)	It refers to poor managerial skills of senior management and insufficient conceptual skills to solve the problem and complex situation related to warehouse
Physical environment risk (C)	Physical environment such as the natural disasters would affect warehouse operations resulted in interruption of service, damage of cargoes and warehouse facilities
Human risk (D)	Warehouse labors/staffs with insufficient knowledge to carry out the logistics services
Security risk (E)	Security concern such as anti-theft facilities and security of IT system is important to protect the customer goods, especially high value goods, and ensure the safety of confidential customer information
Financial risk (F)	It refers to the cash flow problem of a warehouse
Market risk (G)	The company may suffer loss because of the warehouse's market situation and customer preference
Regulatory/ Policy Risk (H)	Unfavorable changes in regulations and policies would bring pressure and risk for the warehouse to suit the environment
Operations risk (I)	It results from the breakdown of internal procedures, systems and people, in which the factors directly affect the process of internal warehouse operations.

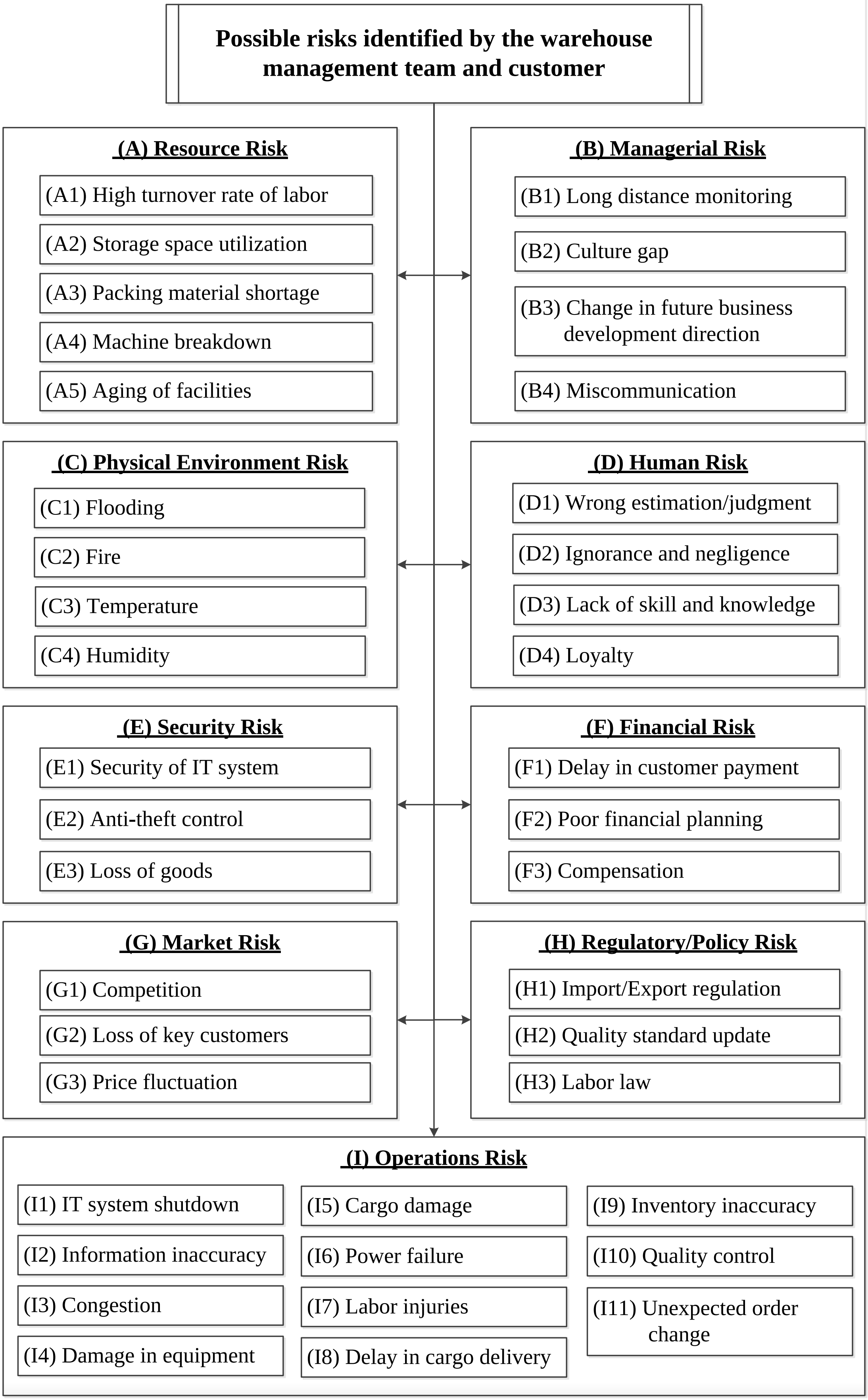


Figure 5.7 Possible risks and sub-risk factors identified through interview

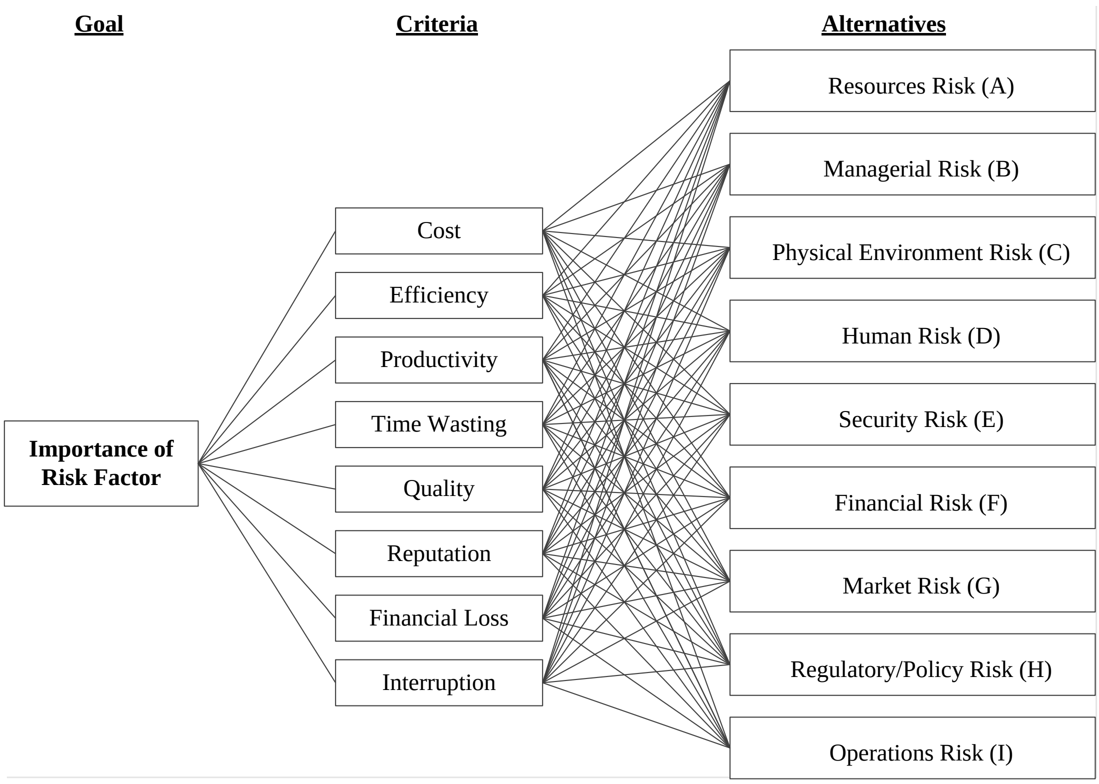


Figure 5.8 Hierarchical structure for determining the importance of risk factors

On the other hand, to determine the importance of the sub-risk factors, a four level hierarchical model is built which includes goal, criteria, attributes and alternatives. In the four-level hierarchy, both the likelihood and consequence/severity are considered as criteria because the likelihood of sub-risk factors can be evaluated with a detailed description. Figure 5.9 shows an example of the four-level hierarchical structure for determining the importance of sub-risk factors in operations risk. Eleven sub-factors are included which further shows the details concerned under the factors of operations risk.

In addition, to quantify the degree of consequence/severity, 8 criteria are defined: cost, efficiency, productivity, time wasting, quality, reputation, financial loss and interruption. Likelihood suggests how likely it is that an event or situation may take place, which is quantified by frequency, persistence and ability to control. Frequency refers to the number of times that an event occurs, which depends on the product nature and warehouse situation, while persistence refers to the time that an event continuously existed. The ability to control indicates whether the risk factors can be controlled by a number of actions. The likelihood is reduced if the risk factor can be easily controlled and avoided.

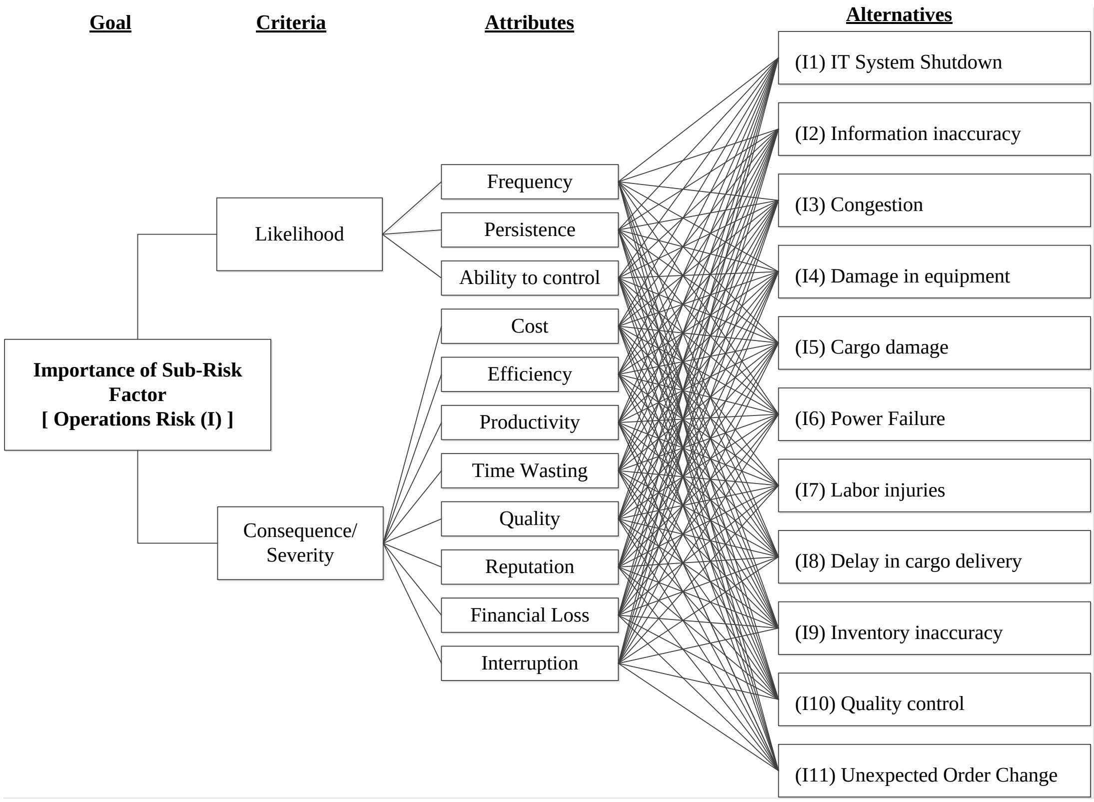


Figure 5.9 Hierarchical structure for determining the importance of sub-risk factors for operations risk

(iv) Pair-wise comparison and priority synthesis

Pair-wise comparison is then conducted to compare each alternative based on the criteria of likelihood and consequence/severity. For each risk factor, the importance is determined by the rating given for two criteria in pairs. Figure 5.10 shows an example of pair-wise comparison for all risk factors, based on the criteria of cost.

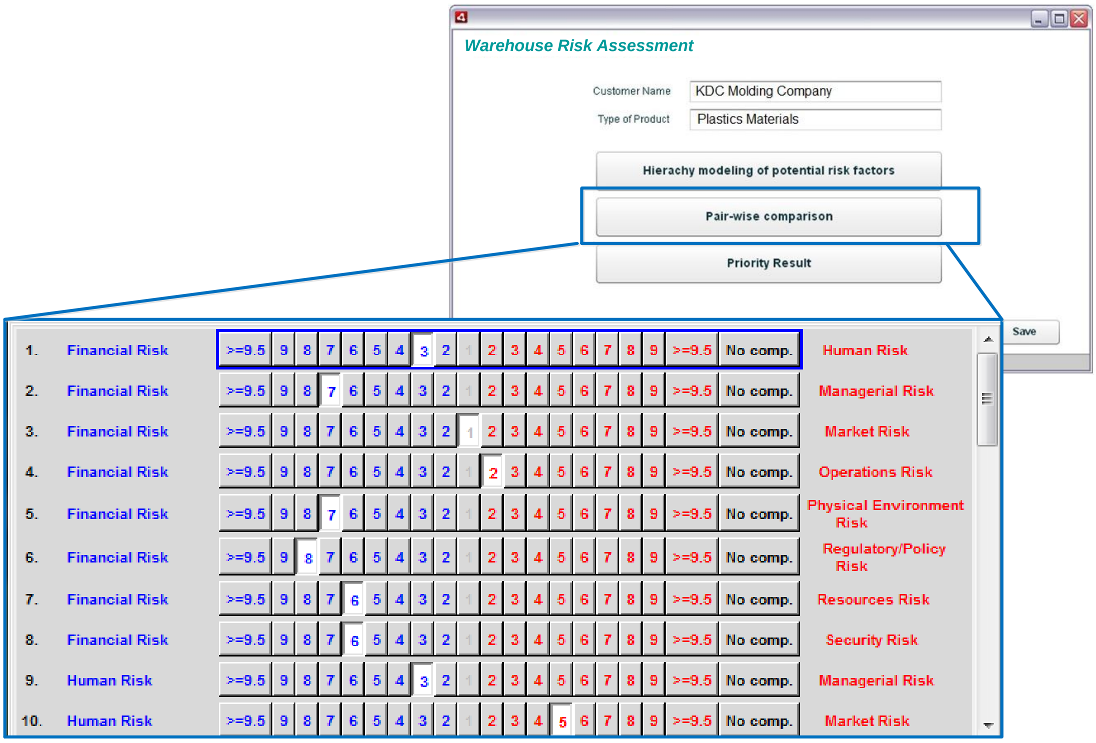


Figure 5.10 Example of pair-wise comparison for all risk factors based on cost

After comparing all the risk factors based on the defined criteria, the result of priority synthesis is obtained. Figure 5.11 shows the result of priority synthesis for the importance of risk factors. The priority vector of the criteria is first analyzed to find out the criteria that may bring negative impact on the risk factors. It is found that the consideration of cost and financial loss has the highest weighting (priority vector = 29.7%) compared to other criteria, followed by efficiency in which the priority vector is 18.4%. The result indicates that the impact of cost and financial loss would affect the profits of the company directly, while the warehouse pays much more attention on the operation efficiency in maintaining customer satisfaction. As the criteria of cost, financial loss and efficiency has a higher impact when evaluating the risk factors, the priority vector of the risk factors are further investigated based on these criteria.

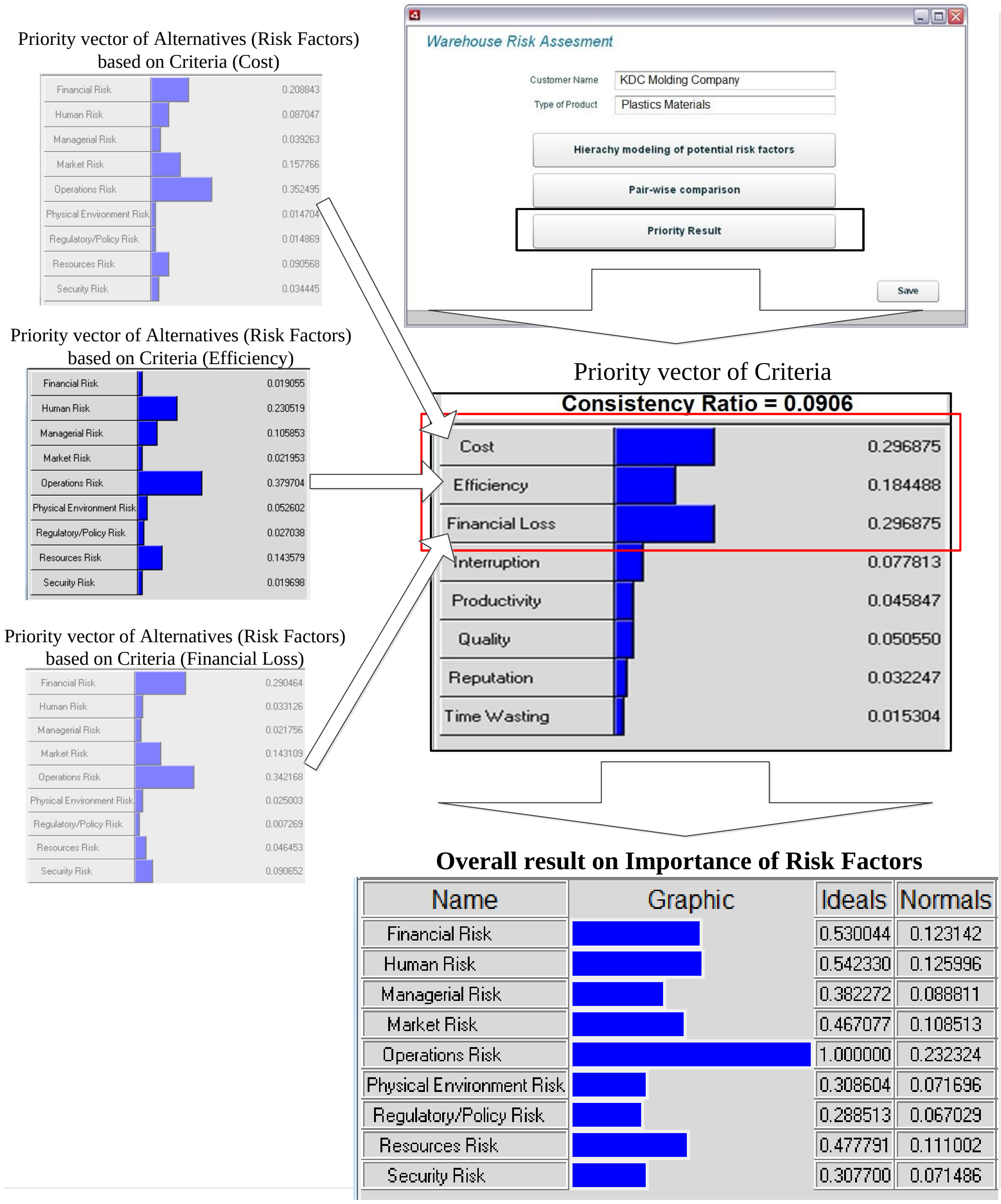


Figure 5.11 Result of priority synthesis for the importance of risk factors

For the criteria of cost, the operations risk has the highest weighting (priority vector = 35.2%), followed by financial risk and market risk with priority vectors of 20.9% and 15.8% respectively. For the criteria of efficiency, the consideration of operations risk has the highest weighting (priority vector = 37.9%), followed by human risk and resource risk with priority vectors of 23.1% and 14.4% respectively. For the criteria of financial loss, the operations risk has the highest priority vector of

34.2%, followed by financial risk and market risk with priority vectors of 29.0% and 14.3% respectively. It is found that the ranking of the importance of risk factors based on each criterion are different, except that the operations risk has the highest weighting in all three criteria. Based on the individual analysis results, the warehouse management team of EWC should provide a continual improvement plan for mitigating the high potential risks according to the corresponding criteria. To obtain the overall result on the importance of the risk factors, the nine risk factors are compared based on the criteria of cost, efficiency and financial loss. The results show that operations risk has the highest average weight of 23.2%. It implies that the operations risk may have significant impact on the warehouse's cost, efficiency and financial loss. In order to investigate the type of sub-risk factors that may affect the performance of the warehouse for operations risk, the likelihood and consequence/severity of risk are defined as the criteria to rank the sub-risk factors of operations risk. Figure 5.12 shows the result of priority syntheses for the sub-risk factors of operations risk. Among all identified sub-factors, delay in cargo delivery has the highest average weight of 15.1%; followed by information inaccuracy with average weight of 14.5% and cargo damage with average weight of 11.9%.

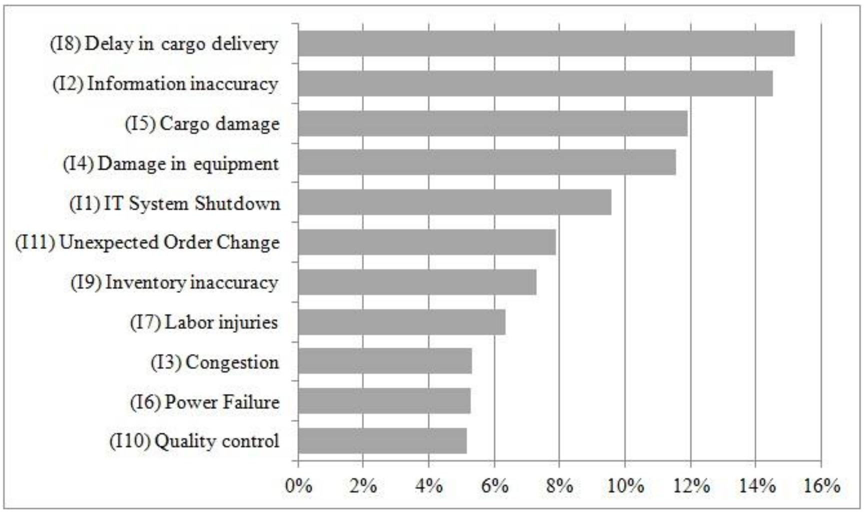


Figure 5.12 Priority syntheses for the sub-risk factors of operations risk

(v) Case clustering and retrieval

With the risk factors identified and ranked in the previous step, the risk factor with the highest priority vector is considered as the most important risk factor in the warehouse operations flow. It may bring a severely damaging result and lower customer satisfaction if the risk occurs. Therefore, when planning the logistics operations, this risk factor is included as one of the input parameters to retrieve from the similar past cases. The case cluster with the highest similarity value to the current situation is first retrieved while other case attributes such as product type and type of value added services required and the weighting of sub-factors are then compared to find out the most similar case within the case cluster.

Due to sequential order picking for palletization is very challenging among warehouse delivery activities, the EWC logistics supervisor is required to plan for an appropriate palletization plan based on the incoming customer order information and personal past experience before delivery. Prior to the planning process, the past customer order details are recorded and stored in a relational database for use. Figure 5.13 shows the tree structure to handle a cross-border order. As shown in the figure, the hierarchical decision tree structure is established and then divided into three main categories: case features of SKU, packing method, and order value. The cases are further divided into groups based on four key quantitative attributes: total weight, total CBM, total number of cartons, and total product price. These attributes are presented at the lower end of the decision tree with their corresponding values. Since the cargo in the delivery truck may be subjected to random inspection in the cross border inspection, it would reduce the searching time if related items are packed together.

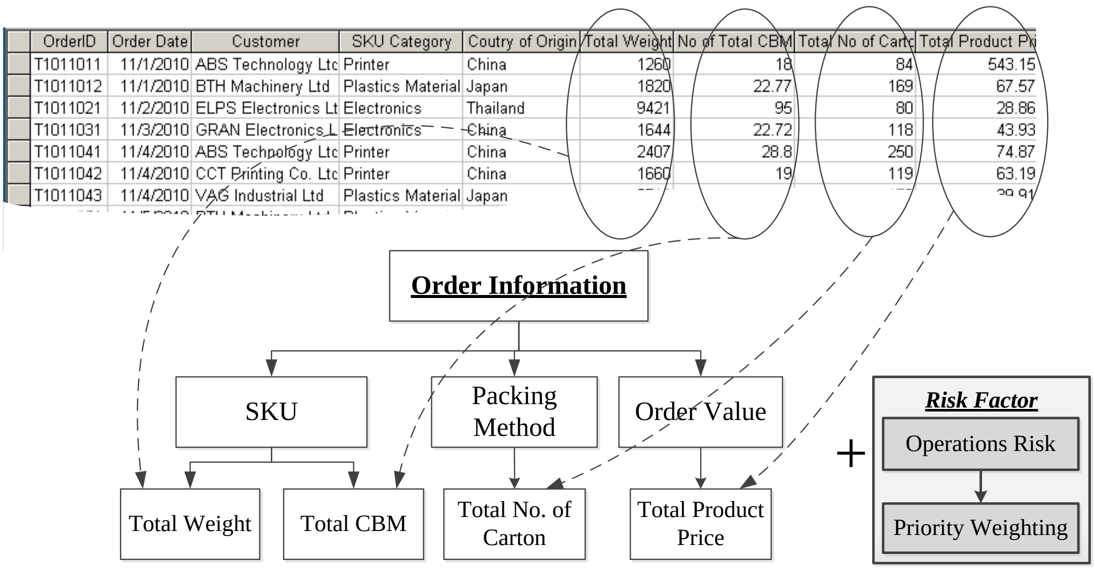


Figure 5.13 Tree structure to handle a cross-border order

With the tree structure defined based on the critical case features, the required parameter values of the incoming order information are inputted and recorded as a new problem. In addition to the decision-making parameters, other basic order information, such as customer details, item category and risk factors concerned, is also included. Figure 5.14 shows the interface for retrieving case cluster based on order information. The information concerning new customer orders including production information and service requirement is recorded in the system. The risk factor obtained in the previous module is also shown with its weighting to indicate its importance. Relevant past cases are retrieved by calculating the distance between the case parameter values and the cluster centers; with the goal of investigating the grouping solution with a minimum fitness value. With the defined number of clusters, the system first generates the initial cluster centers randomly and searches for better grouping results based on the iDPC algorithm. In this example, two clusters are selected, and two sets of initial cluster centers are generated. Subsequently, the GA is applied to prevent the results from falling into the local optima. By generating different possible solutions, various combinations of attributes and parameter values can be considered. In this study, three sets of case cluster centers are found with the support of the GA. After each GA generation, the three best solutions are kept for the next step. The searching process continues until the termination criterion is reached. As a result, the relevant case features and their values for each case cluster are suggested.

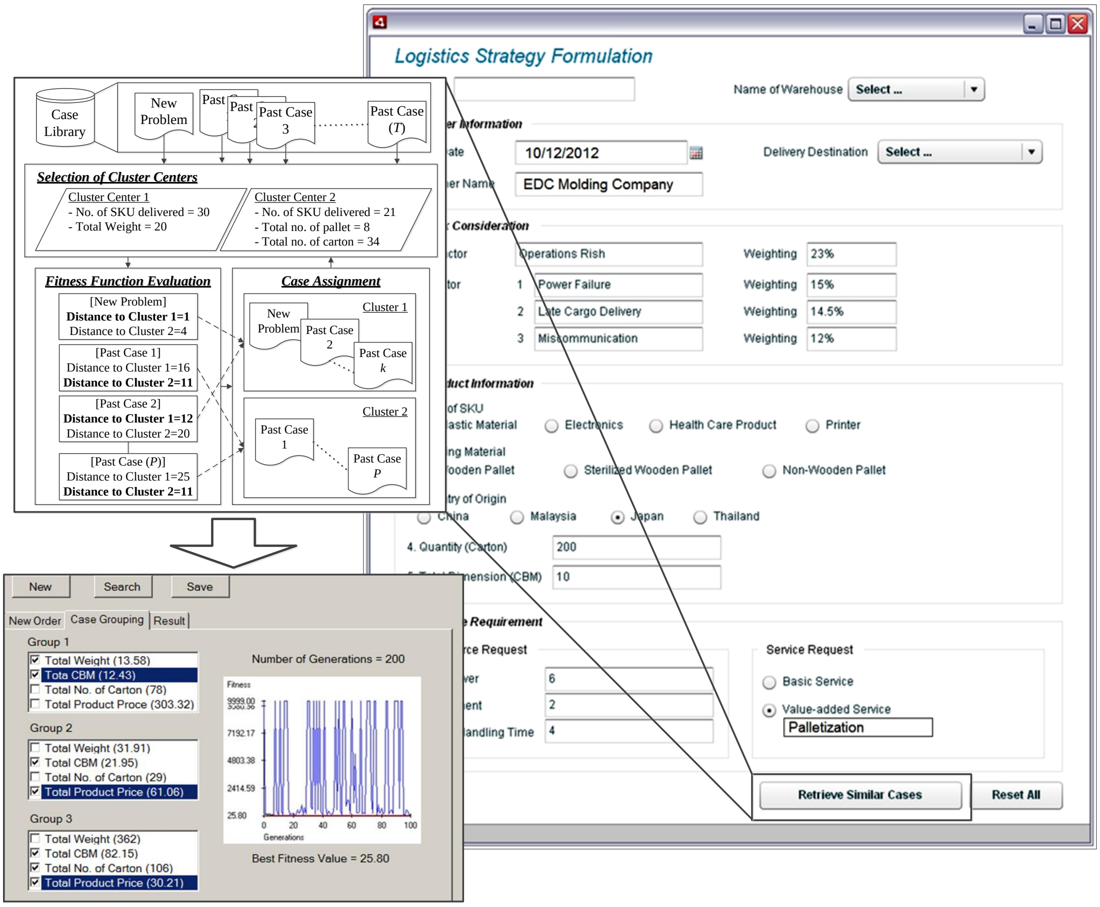


Figure 5.14 Interface for retrieving case cluster based on order information

After the case clustering process, each case cluster contains its own set of generated case features and parameter values as a cluster center. All past cases are assigned to the nearest cluster according to the distance between the cluster center and the cases. The similarity value between the new order and the past cases in the retrieved case cluster is calculated. The past cases are then prioritized to determine the past record with the highest similarity value to the new order. Figure 5.15 shows the similarity measures for prioritizing similar past cases within the case cluster.

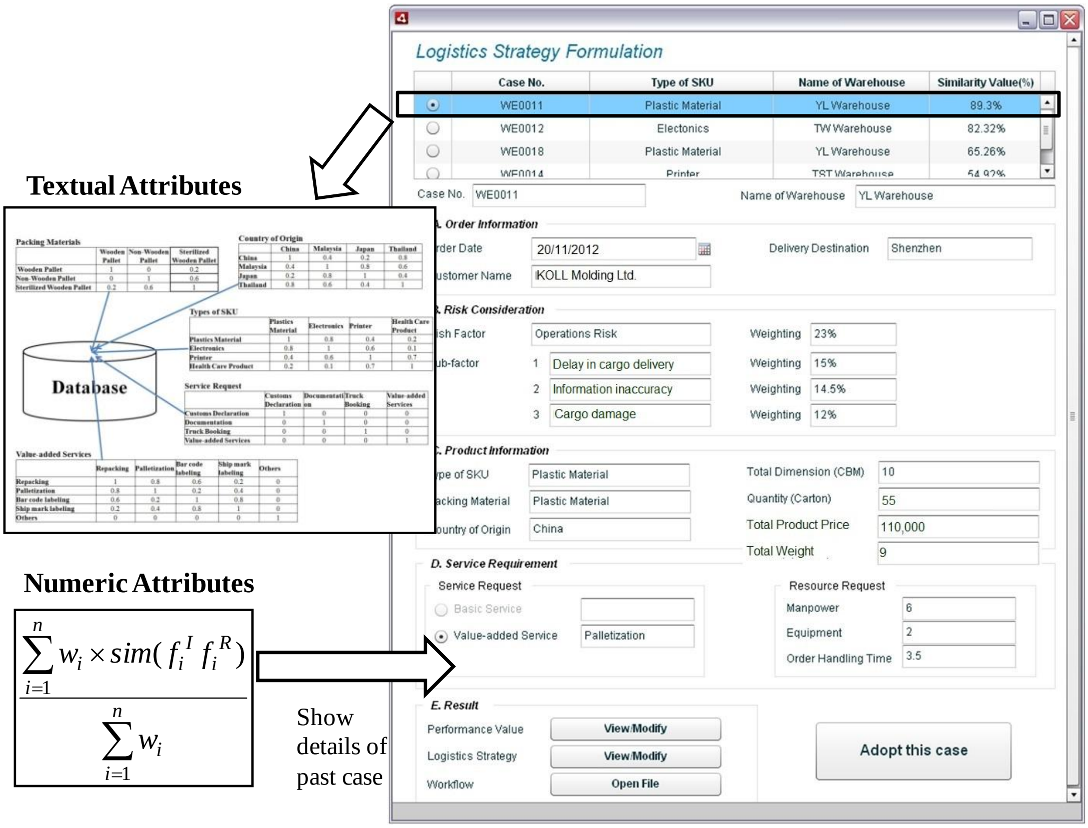


Figure 5.15 Similarity measures for prioritizing past similar case within the case cluster

For textual features, including item category and country of origin, their values are presented as strings. Quantitative features refer to the items included in the tree structure and are presented as numeric values. By comparing the string value of the past cases and the new order in the similarity table, the similarity values of the textual attributes are obtained. With reference to Equation 3.15, the similarity values of the numeric attributes are also calculated. In this step, the numeric customer order attributes, including order size, available processing time and available manpower, together with the weighting of the most important risk factor, are used to calculate the similarity value. Thus, the past cases are ranked in sequence, and the case (case no. WE001) with the highest similarity value of 89.3% is suggested as the solution to the new order. The warehouse manager can consider a handling plan for the order with reference to the past case.

(vi) Case revision and retention

The solution of the past case with the highest similarity value is adopted for the current situation. Meanwhile, details of the solution are able to be modified according to the specific needs of the customer. The solution content includes the type of key performance indicators (KPIs) is required to fulfill customer requirements, the workflow and guidelines for conducting the logistics operation process. Based on the type of risk concerned, the amount of resources and criteria check points to ensure proper cross-border operations are also suggested for the current situation.

Since the company allows its customers to place outbound orders based on the unit of a carton, value-added services such as palletization are required to consolidate and pack the picked cartons on a pallet before loading to the container. Once the delivery truck is ready for loading, the forklift would carry the pallet to pass through the warehouse entrance and put it onto the container. However, to fulfill the specific cross border orders, EWC would like to pack the same type of product in the same pallet and load the container in a pre-defined sequence as suggested by K-LOPS. In doing so, the influence can be reduced even if the cargo has to be inspected at the cross border control point. Figure 5.16 shows the logistics strategy formulation process based on the performance of the past case. With the passive RFID tags attached in all the cartons, information on the cartons is recorded in the system when the forklift passes through the dock door to load the cartons pallet on the delivery trucks. Thus, the system can monitor the loading efficiency of the forklift and check whether this outbound order can be finished on time. Further operations jobs can be allocated to the forklift according to the estimated finishing time. As specified in the resources requirement, 6 forklifts are required to perform the task. The nearest forklifts and the earliest available time are then indicated by the RFID technology. After revising the solution, details of the service requirement, risk factor concerned and the logistics operation solution are then stored in the case library as a new case.

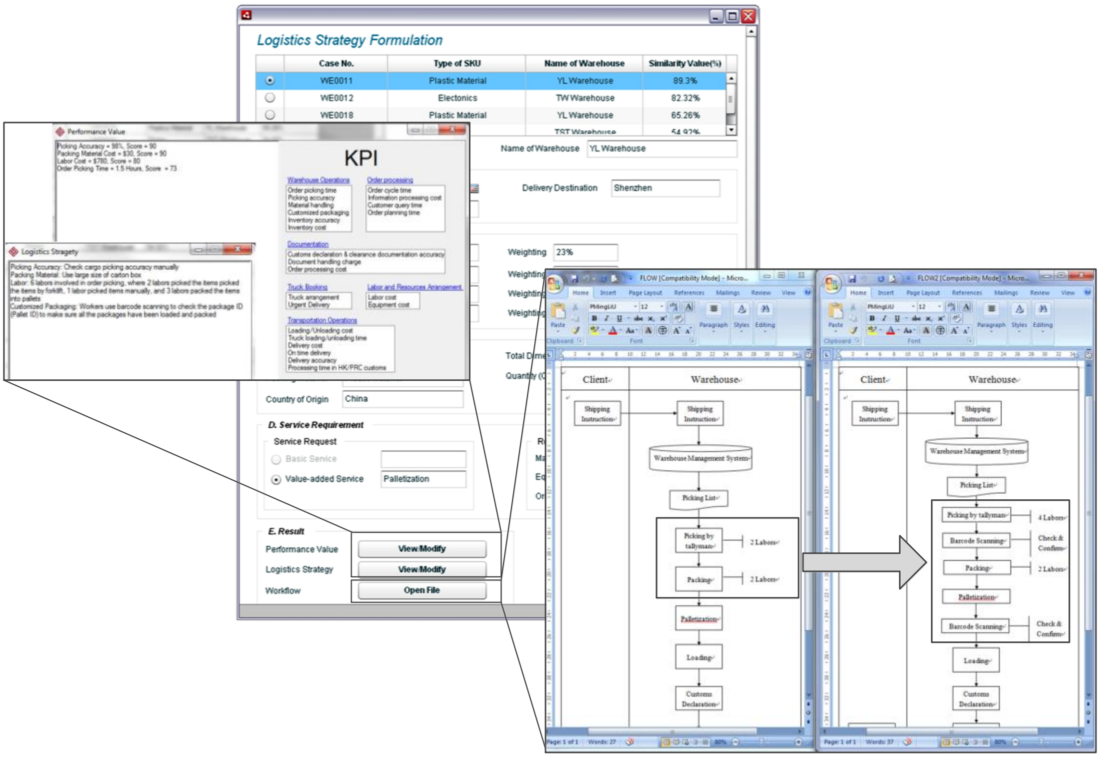


Figure 5.16 Logistics strategy formulation based on the performance of past case

5.3 Case Study 2 – Wine Distribution Hub

KYT (Alias) is a Hong Kong-based logistics company that specializes in wine storage and distribution services. It provides a wide range of logistics services for the wine industry, including wine storage, value-added services, transportation and distribution for wine replenishment. Since the Hong Kong Government decided to cut wine duty to zero in February 2008, there was a rapid growth in Hong Kong's wine trading and distribution business. Due to the convenient geographical location at the centre of Asia and the gateway to Mainland China's wine market, Hong Kong has developed into Asia’s leading wine hub with simplified procedures for the import and export of wine. KYT also took this opportunity to expand its business and established its own wine warehousing facility, a wine distribution hub. The role of the hub is to consolidate the wine imported from overseas for distribution to the local market. To ensure that the storage facilities are reliable and meet the qualified standard for maintaining good wine quality, the distribution hub is certified under the HKQAA for both fine wine and commercial wine storage. Figure 5.17 shows the storage facilities in KYT's distribution hub. As there are strict requirements for handling wine, which is fragile and sensitive to the external environment, it is a challenge to manage the operational conditions during storage.

Figure 5.17 Storage facilities in KYT's distribution hub

5.3.1 Problem Definition of KYT

Classified as a high value product, fine wine is expensive in price and of a high standard in terms of quality. In the current trend, wine is not only purchased for direct consumption, but increasing demand is focused on long term investment and for private collection. As shown in Figure 5.18, wine can be classified into two categories, which are commercial wine and fine wine. Commercial wine is usually made for easy consumption and has a fast turnover rate and short storage time. Most fine wine is used for private collections and undergoes long term storage. Such wine may further improve its taste and quality by being stored under proper storage conditions. In addition, both types of wines are highly sensitive to both the internal and external environment, and are especially affected by temperature, humidity, light and vibration. If wine is not handled properly during storage and transportation, not only will the taste of wine be spoilt, it can also cause depreciation in the wine's value. Therefore, having reliable wine storage facilities in a regional wine distribution hub is critical for maintaining the value and quality of wine along the supply chain.

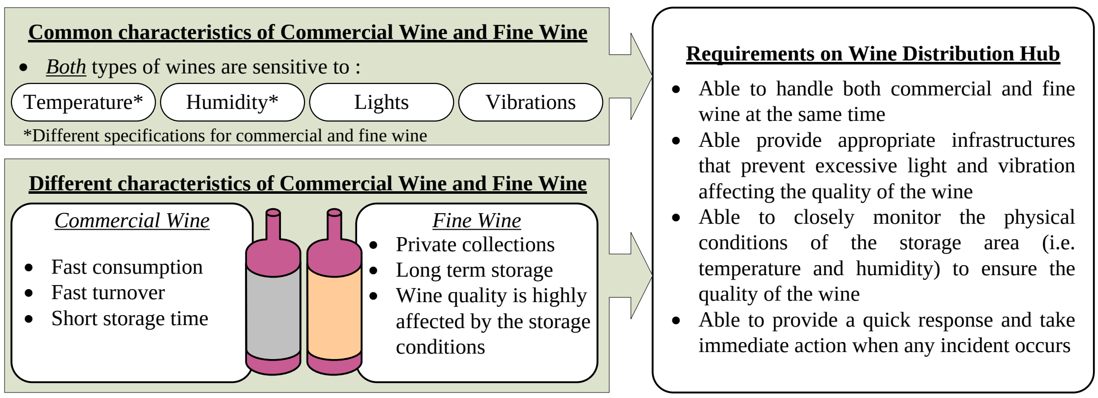


Figure 5.18 Requirements of a wine distribution hub based on the wine characteristics

According to the requirement of Hong Kong Quality Assurance Agency (HKQAA), there are different temperature and humidity requirements specified for fine wine and commercial wine. The temperatures for fine wine and commercial wine are 11°C – 17°C and 22°C respectively while the humidity at any point inside the storage area should be 55% – 80% and smaller than 50% respectively. Thus, the two categories of wine are kept separately in designated locations where electronic sensors are installed in fixed places to continuously monitor the physical storage conditions. To maintain good quality wine, three major problems are faced by the company during wine storage in the distribution hub. As shown in Figure 5.19, the problems are (i) inability to obtain a particular wine condition if wine is put in the wrong location, (ii) inability to provide immediate action if unexpected issues occur, and (iii) long response time to formulate follow-up action.

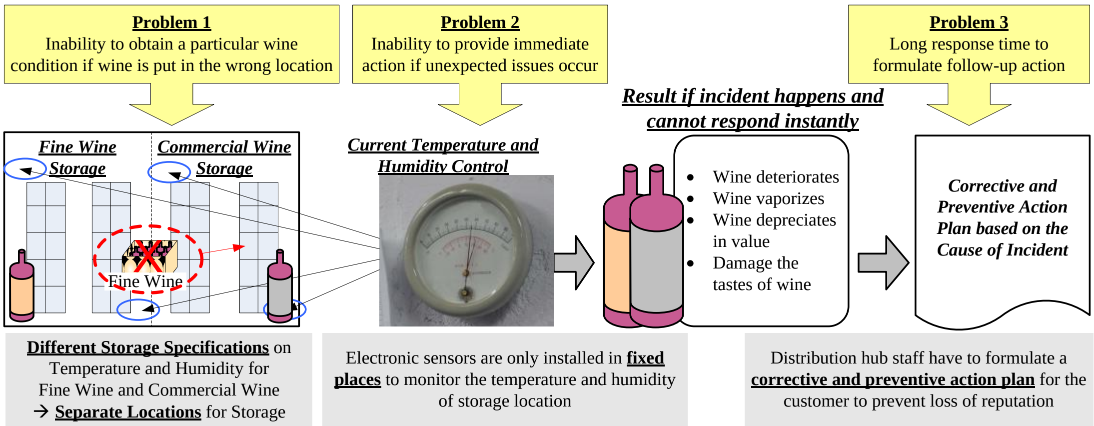


Figure 5.19 Problems faced by the company caused by inadequate physical condition monitoring operations

Problem 1 – Inability to obtain a particular wine condition if wine is put in the wrong location

Currently, the company relies on electronic sensors to monitor both the temperature and humidity measures in the storage areas. However, as the electronic sensors are installed in fixed locations, only the room temperature and humidity where the sensors are located can be measured, while blind spots can still exist in a huge storage zone even with sufficient refrigerating facilities. If fine wine is put in the wrong commercial wine storage area, the existing sensor system is unable to detect and measure the actual temperature and humidity. The wine could then deteriorate rapidly and depreciate in value.

Problem 2 – Inability to provide immediate action if unexpected issues occur

There is a lack of wine identification technology in the storage area. As shown in Figure 5.20, the warehouse staff have to manually record the temperature and humidity data twice a day to ensure that the storage conditions meet the standard. As the actual physical conditions of a particular wine cannot be measured in real-time conditions, the necessary action cannot be taken immediately if an incident occurs. The wine can deteriorate rapidly once the wine is stored in the wrong area where the physical conditions are not appropriate for storage. In addition, it is hard for the staff in the wine warehouse to notice the wine deterioration until a periodic stock check is performed.

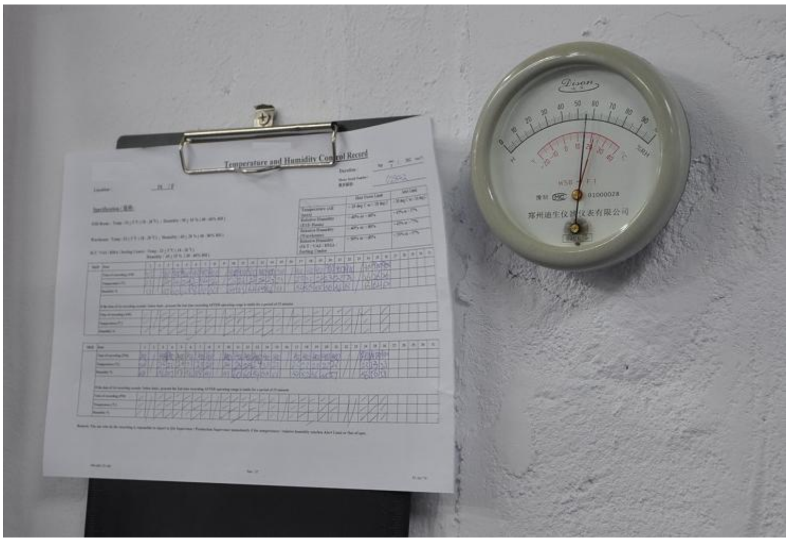


Figure 5.20 Recording temperature and humidity manually from electronic sensors

Problem 3 – Long response time to formulate follow-up action

If any incident occurs that violates the required wine storage conditions, the staff in the distribution hub have to formulate a corrective and preventive action plan for the customer based on the cause of the incident to prevent loss of reputation. Such contingency plan and follow-up action should be carried out immediately to reduce the chance of deterioration. However, there is lack of a decision support system to suggest possible actions according to the actual situation. Without the information on the possible cause of the incident, it may take a long time to formulate follow-up action to mitigate such risks.

5.3.2 Deployment of K-LOPS for Incident Handling in Wine Storage

As wine is a most valuable product and is very sensitive to storage conditions, controlling and managing the kind of risks mentioned are the most important factors in reducing the product damage rate and in maintaining customer satisfaction. This is especially true when an incident occurs unexpectedly and violates the criteria of suitable storage conditions. Improper incident handling and storage conditions may cause damage to the wine, resulting in depreciation of the wine's value. In order to tackle the above problems, K-LOPS is implemented in the company to keep track of the real-time physical storage conditions of wine and to provide follow-up action when necessary. Figure 5.21 shows the implementation procedures of K-LOPS. AHP analysis is performed in the warehouse risk assessment module to prioritize the risk. By applying the RFID technology, temperature and humidity for each SKU of wine is captured and monitored in real-time so that immediate action can be taken when storage conditions change abnormally. By understanding the customer specification and risk involved, CBR technology in the logistics strategy formulation module is applied to formulate an appropriate solution which includes feasible corrective and preventive action plan by retrieving past relevant knowledge. A shortlist of critical control actions, possible causes of incidents and corresponding actions can be generated to reduce the risk of deterioration in wine quality and the possible compensation cost incurred, while customer satisfaction can be maintained.

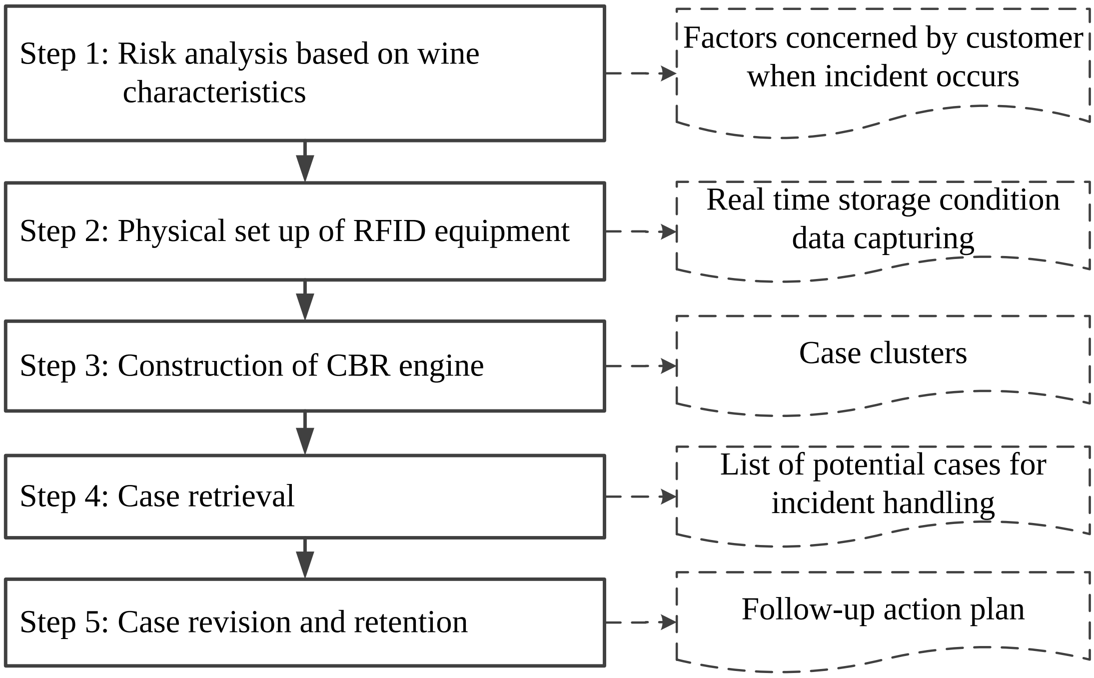


Figure 5.21 Implementation procedures of K-LOPS in KYT

(i) Step 1: Risk analysis based on wine characteristics

As different types of wine have particular logistics needs and storage specification, any irregularity would further increase the risk in quality deterioration. Particularly, when an incident occurs unexpectedly that violates the storage criteria, the product quality is likely to deteriorate and cause depreciation in value. Providing a quick response with respect to corrective and follow-up actions is essential to reduce loss in wine quality and to maintain customer satisfaction. In order to take into consideration of customer expectation, AHP analysis is undertaken to examine the factors that are of most concern by customers when handling an incident. If such factors are not neglected when formulating a follow-up action plan, customer satisfaction may decrease. Figure 5.22 shows the AHP structure for incident handling in the wine distribution hub. The model is used to prioritize and select the type of factors that are of concern to the customer when an incident occurs.

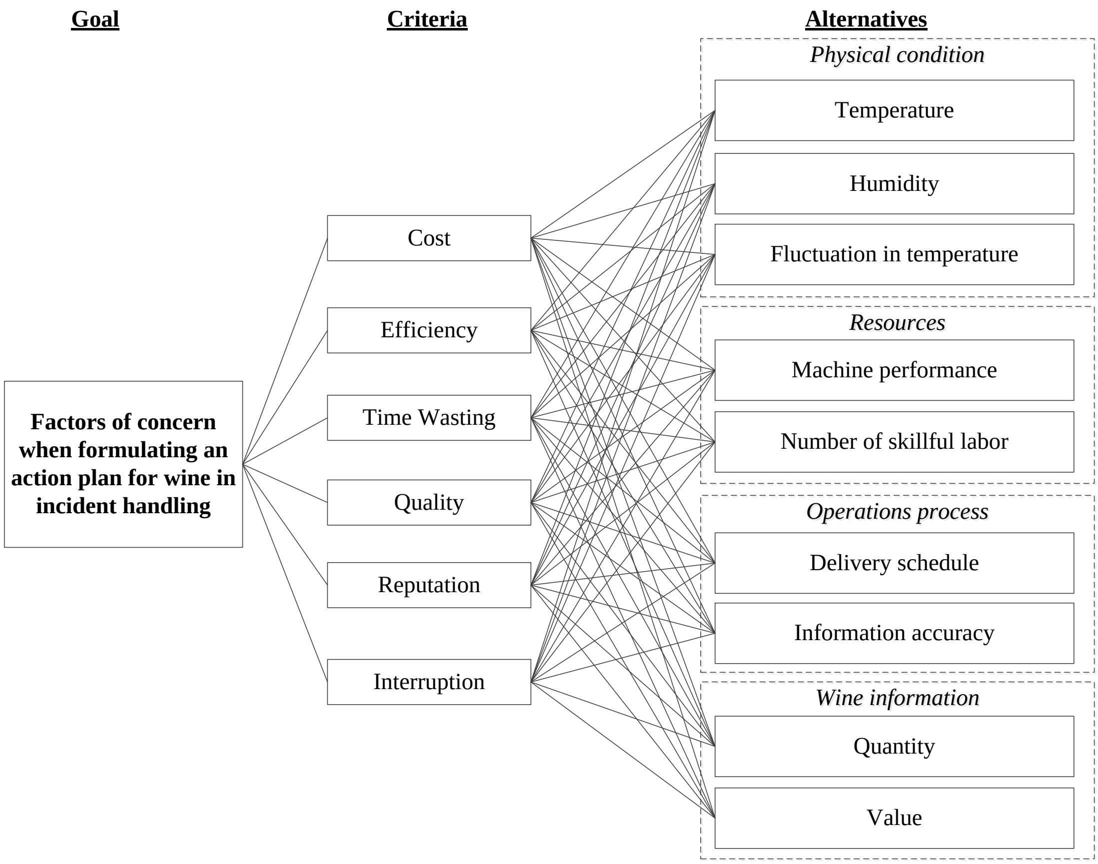


Figure 5.22 AHP structure for incident handling in the wine distribution hub

From the defined AHP structure, it is found that temperature, humidity and fluctuation in temperature are included as the potential risks concerning physical condition. These three factors matched the studies conducted by Chung et al. (2008) and Butzke et al. (2012) that unreliable physical storage condition would bring negative impact on wine quality. Besides, resource risks are always the problem faced by the warehouse as only limited resources are available to fulfil the needs of customer order (Ghoshal, 1987; Dey, 2001). Similar to the risks related to operations process, since the warehouse operations involve a number of processes, the complexity in effective planning may increase that would lead to unreliability or uncertainty in order fulfillment (Dollet and Diaz, 2010; Roy and Cordery, 2010). On the other hand, as the wine value and quality may improve over time, different handling methods may be needed when the storage period increases (Parr et al., 2011;

Silva et al., 2011). Therefore, changes in wine information were also considered as one of the risk categories that may affect the warehouse performance. Based on the review result of past literatures, nine factors are identified and they are grouped under four categories. Each factor is evaluated by five criteria including cost, efficiency, time, reputation and interruption. After performing AHP analysis, it is found that the factors of both physical condition and wine information have the highest priority value. The result shows that the warehouse management should pay attention to those factors under the category of physical condition and wine information when formulating a solution.

(ii) Step 2: Physical set up of RFID equipment

In order to obtain real-time data in the storage environment, RFID equipment including RFID reader, antenna and passive RFID tags with temperature and humidity sensors, are set up in the wine warehouse. Figure 5.23 shows the RFID setting in the wine distribution hub. As shown in the figure, wine is stored in wooden cartons and it is usually packed in the same carton used for delivery. In order to keep track of the actual storage conditions of the wine, the RFID tag with temperature and humidity sensors is attached to the wine carton so that the wine information and storage location can be recorded automatically by the reader. The RFID reader and antenna are installed at each level of the storage rack so that the whole area can be covered by the radio waves emitted by the antenna. The RFID tag records the temperature and humidity data continuously and transmits the stored data to the reader when it receives RF signals from the antenna. The data collected by the RFID technology is first passed to the middleware to decode the electronic signals and transform them into meaningful information, such as item number, type of wine, temperature and humidity data, and date/time of measurement. The information is then compared with the defined order specification to ensure that the storage condition meets the requirements. Table 5.2 shows the storage specification for fine wine and commercial wine in the HKQAA standard. By comparing the real-time temperature and humidity data collected with the specifications required for storage, notification can be given if there is a large fluctuation range or if the current temperature or humidity exceeds the allowable range and will probably cause the wine to deteriorate. If either one of the environmental measures exceeds the allowable range, an incident alert is given (in Figure 5.24) and the information is passed to the CBR engine to search for past similar follow-up action plans.

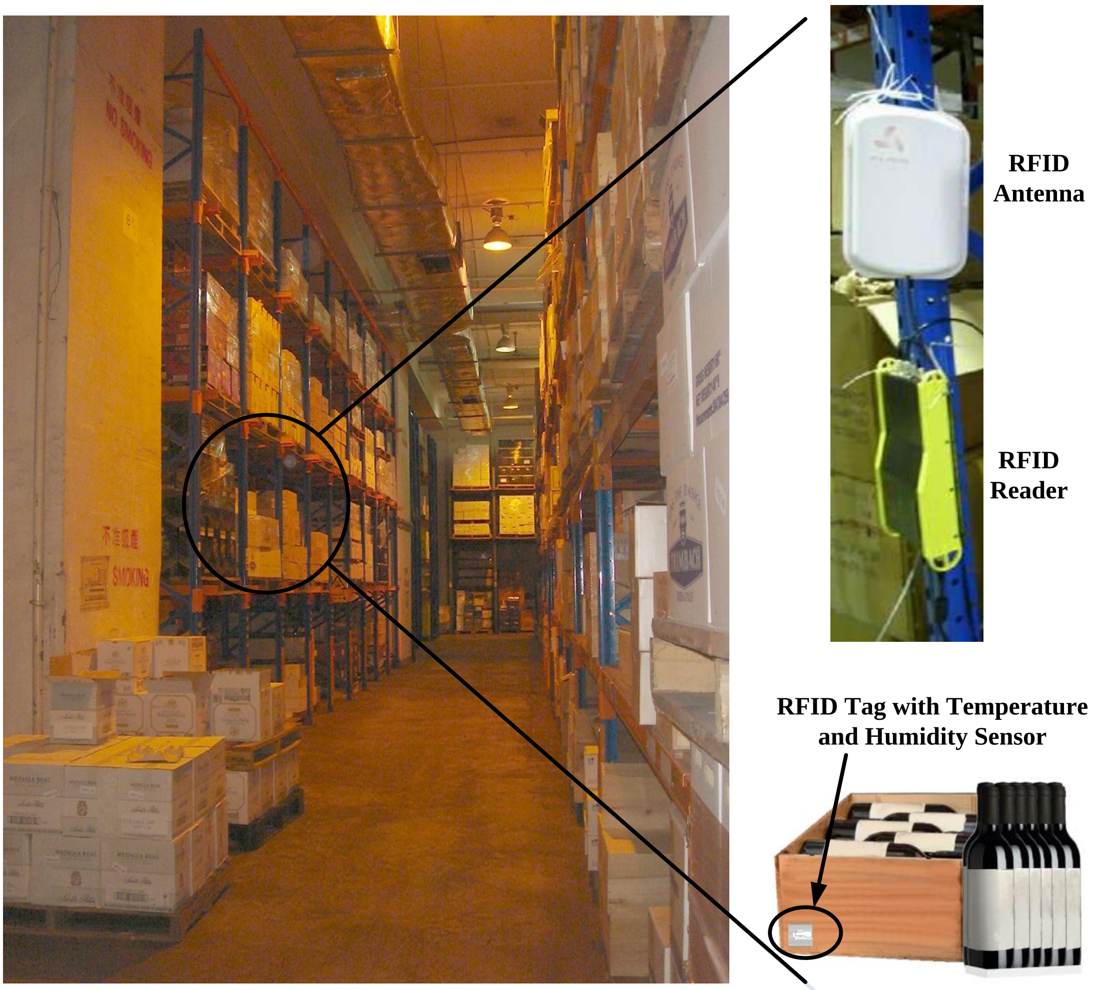


Figure 5.23 RFID set up in the wine distribution hub

Table 5.2 HKQAA storage specification for fine wine and commercial wine

	Requirement	Fine wine	Commercial wine
1	Storage temperature range	11°C – 17°C	22°C
2	Maximum daily fluctuation range	3%	5%
3	Maximum annual fluctuation range	5%	10%
4	Humidity	55% – 80%	> 50%

Figure 5.24 Monitoring real-time storage conditions in the work station

(iii) Step 3: Construction of CBR engine

With the physical data obtained by the RFID technology, the new incident data is passed to the case-based reasoning engine, which undertakes case retrieval, case reuse, case revision and case retention, for follow-up action planning. In order to divide past cases into different clusters with similar characteristics, multi-dimensional attributes are taken into consideration. Firstly, the CBR engine has to be constructed to suit the need for incident handling. When constructing the CBR engine, two types of information are required: specific parameters for case clustering and the weightings to show the importance of the parameters for case retrieval. The environmental parameters, including temperature and humidity, are important to the maintenance of a good condition for red wine storage. The loss in quality and value can be reduced if appropriate follow-up action can be formulated when an incident occurs unexpectedly. Therefore, a hierarchical tree structure based on the wine storage conditions in the distribution hub and wine information is constructed for chromosome encoding. As shown in Figure 5.25, the wine storage conditions refer to the real-time physically measured factors such as temperature, fluctuation in temperature and humidity, while wine information refers to the details of the SKU that may be affected by the incident, such as wine quantity and value. The attributes of past incident cases are shown in the form of a hierarchical tree structure. Now the values of each attribute should be determined in order to divide similar past cases into clusters.

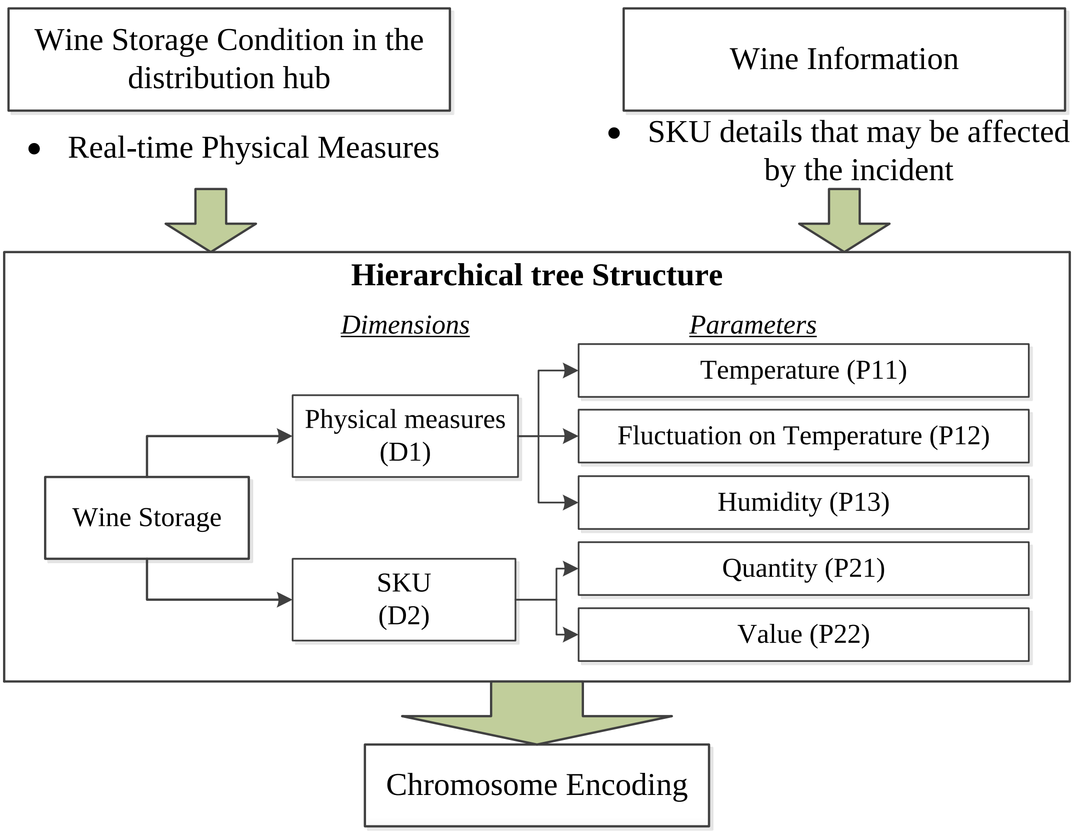


Figure 5.25 Construction of hierarchical tree structure

As the first step in GA operations, the chromosome is encoded to represent the case features and values of the cluster centers. The chromosome is divided into two parts which are (i) the dimensions (D) and parameters (P) region, $F_{[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}$,and (ii) case-value (V) region, $V_{[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}$. The dimensions and parameters region is encoded with binary numbers to denote whether the parameters are included as a key feature in the cluster. The case-value region is encoded with real numbers which shows the numeric value of the corresponding parameter. Both the dimensions, the parameters' region and the case-value region are repeated by the number of clusters pre-defined, n , to form a chromosome. Figure 5.26 shows a chromosome containing n clusters, with a dimensions and b parameters in each cluster. After that, the population size, s, is defined to control the number of chromosomes selected for the generations.

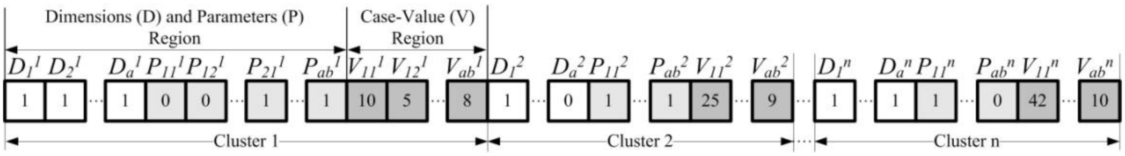


Figure 5.26 Chromosomes encoded for case clustering

Once the population of chromosomes is formed, the fitness value for each chromosome is formulated to evaluate the case in a similar way to the assigned case cluster. In order to divide cases into groups, the fitness function minimizes the weighted distances between past cases and the cluster center, and takes into consideration the importance of the parameters.

$$Fitness = Min\sum_{i=1}^{n}\sum_{k=1}^{p}\sum_{\alpha=1}^{a}\sum_{\beta=1}^{b}\sqrt{z_{ik}\times(O_{k[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}-R_{i[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]})^2\times A_l} \quad (5.1)$$

where z_{ik} is a binary number where $\sum_{i \in M} z_{ik} = 1, \forall k \in P$, so as to limit the number of past cases that can be classified into one cluster only. z_{ik} is equal to 1 if the case k belongs to cluster i, otherwise, z_{ik} is equal to 0. $O_{k[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}$ refers to the case parameters and their values in the k^{th} case record, while $R_{i[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}$ represents the i^{th} cluster center with the value of $F_{[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]} \times V_{[x_{11}x_{12}\cdots x_{\alpha\beta}\cdots x_{ab}]}$. As this algorithm can be applied to select multi-dimensional attributes and search for the best combination of attributes, the distance is expected to be large if more attributes are considered together. Therefore, an adjustment factor A_l, $A_l =$ total number of case parameters $\div$ number of case parameters, is proposed in the fitness function to compensate for the value increase when more than one case parameter is considered at the same time. Using the proposed iDPC algorithm in the case retrieval process, past cases stored in the case library are first divided into five clusters based on five key numeric parameters, namely: temperature, fluctuation in temperature, humidity, quantity and total wine value. In order to avoid large differences between parameter values, data in the past cases are normalized so that they range from 0 to 100. Figure 5.27 shows the processing status of the case clustering using the GA approach.

In the dimensions and parameters region, binary numbers of 0 and 1 are allowed for adjustment to indicate whether the parameter is considered as the cluster center or not. In the case-value region, real integer numbers between 0 and 100 are used to limit the range for crossover and mutation. Equation 5.1 is applied to minimize the fitness function for the GA search. The adjustment index, A_l, is set as 5, 3, 1.5, 1.2 and 1 respectively for considering up to five parameters together. The parameter settings for GA generations are defined as follows: population size = 200, number of generations = 2000, crossover rate = 0.9 and mutation rate = 0.05.

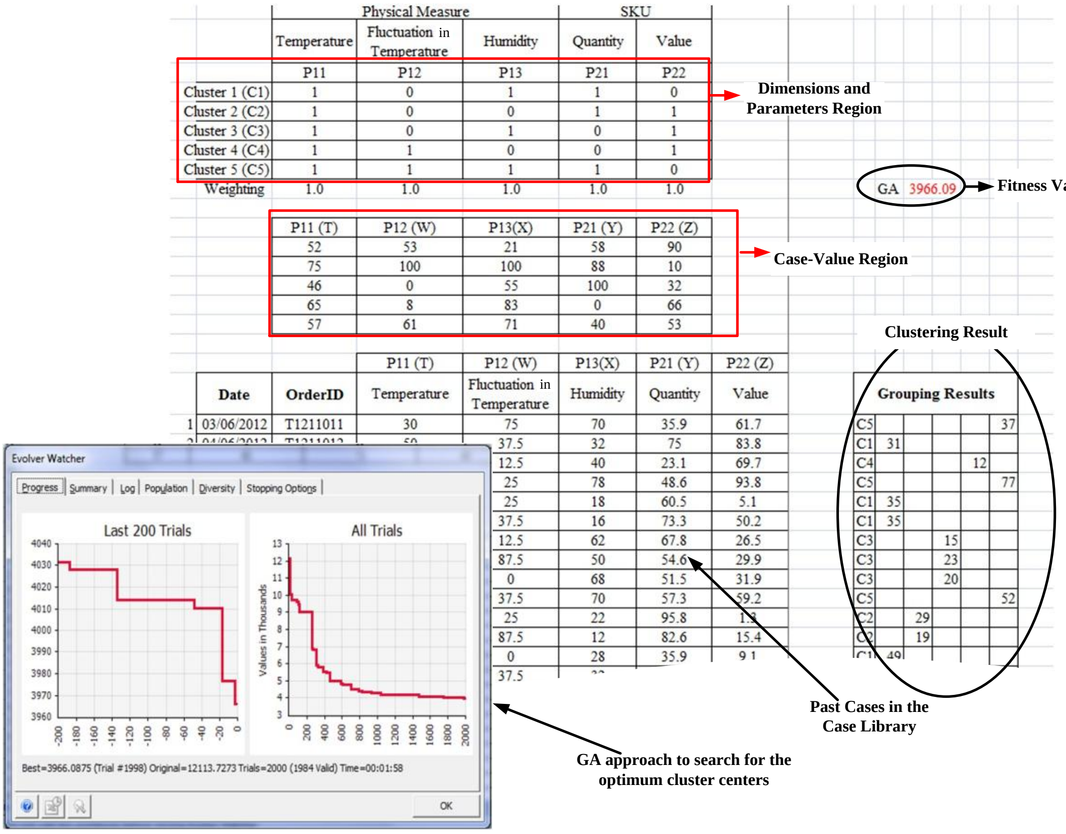


Figure 5.27 Case clustering using iDPC algorithm

To obtain the minimum fitness value, GA searches for the best combination of case parameters and their corresponding normalized values, and uses these to create the centre of the cluster. Table 5.3 shows the result of five cluster centers after performing 2000 generations with GA. Take cluster 1 as an example, it shows that only the parameters "Temperature", "Humidity" and "Quantity" are significant to represent the center of case cluster 1. The values which correspond to the three parameters are 52, 21 and 58 respectively. The centre of each cluster is represented by a different set of parameters and values, which successfully divides the past cases into five groups.

Table 5.3 Result of case clustering with GA

	Temperature	Fluctuation in Temperature	Humidity	Quantity	Value
Cluster 1	52	-	21	58	-
Cluster 2	75	-	-	88	10
Cluster 3	46	-	55	-	32
Cluster 4	65	8	-	-	66
Cluster 5	57	61	71	40	-

(iv) Step 4: Case Retrieval

With the data captured by the RFID technology, wine information such as the name, type of wine and storage conditions, including temperature and humidity values, are obtained. This information is then compared to that of the five cluster centers to find the cluster with the largest similarity value. Table 5.4 shows the importance of the parameters assigned to the new case.

Table 5.4 Importance of parameters assigned to the new case

Parameters	**Type of Parameters**	**Rank**	**Weighting**
Temperature	Numeric	Most important	1
Fluctuation in Temperature	Numeric	Less important	0.5
Humidity	Numeric	Least relevant	0.1
Quantity	Numeric	Least relevant	0.1
Value	Numeric	Less important	0.5
Type of Wine	Textual	Important	0.7
Country of Origin	Textual	Relevant	0.3
Storage Zone	Textual	Less important	0.5

The cluster retrieval priority index, I_{CR} is then calculated for retrieving the similar case cluster using Equation 3.12. The calculation of the cluster retrieval priority index for cluster 1 and the new problem is illustrated below as an example.

$$I_{CR}{}^{1} = \frac{\frac{100-|70-52|}{100}\times 1 + 0\times 0.5 + \frac{100-|40-21|}{100}\times 0.1 + \frac{100-|15-58|}{100}\times 0.1 + 0\times 0.5}{1+0.5+0.1+0.1+0.5} = 0.44$$

Using the same method, the cluster retrieval priority indices for cluster 2 ($I_{CR}{}^{2}$), 3 ($I_{CR}{}^{3}$), 4 ($I_{CR}{}^{4}$) and 5 ($I_{CR}{}^{5}$) are found to be 0.53, 0.52, 0.83 and 0.61 respectively.

The similarity value of the new problem and cluster 4 is found to be 0.83, which is the highest value among all the clusters. Therefore, past cases in cluster 4 are retrieved and they are ranked in descending order based on their similarity value to the new problem. Figure 5.28 shows the case retrieval process of K-LOPS.

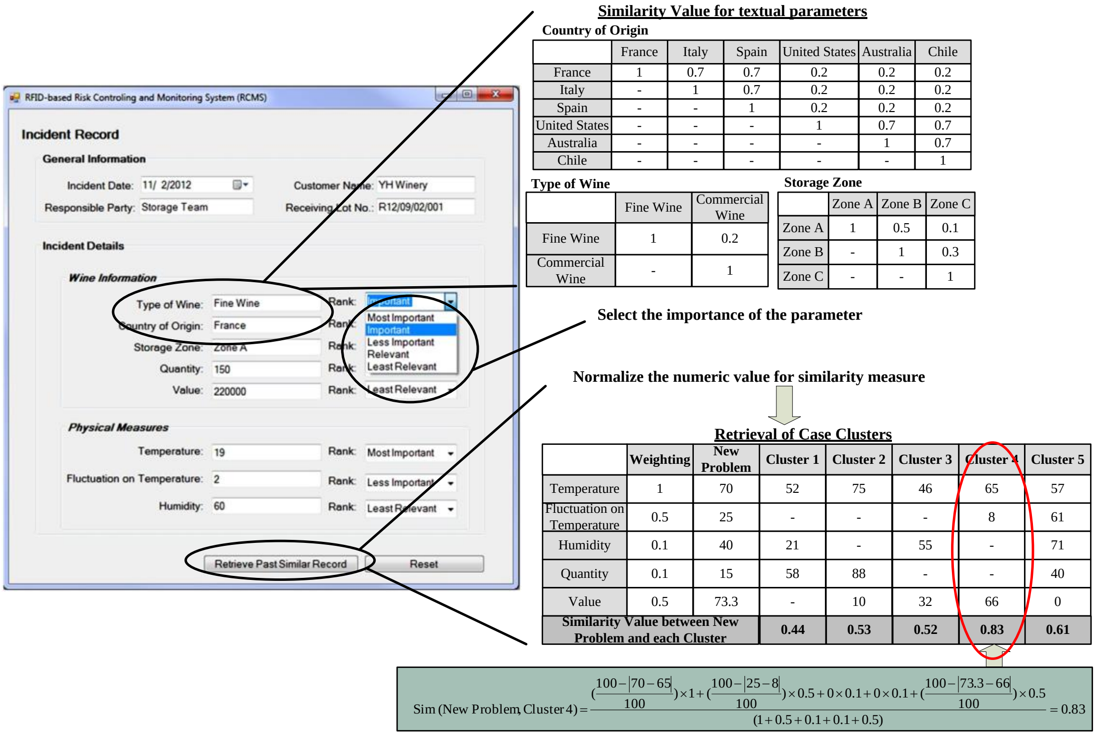


Figure 5.28 User interface of K-LOPS for retrieving similar past cases

(v) Step 5: Case Revision and Retention

The case ranked with the highest similarity value is considered as the most significant solution to the new problem. Figure 5.29 shows the procedure for a follow-up action plan formulation by retrieval of a similar past reference case. As shown in the figure, it is found that the similarity value of case no. T110219 is 95% which is the highest among the cases included in the retrieved case cluster. By viewing the details of the past case, follow-up action for solving the previous problem can be used as a reference to formulate a new solution. The solution to the past case can be modified to be the new action plan for the new situation. The additional and missing checking steps for finding the root cause can be added while some redundant information can be removed to suit the current needs. After designing the appropriate solution for the new problem, the case is saved and stored in the case library for future use.

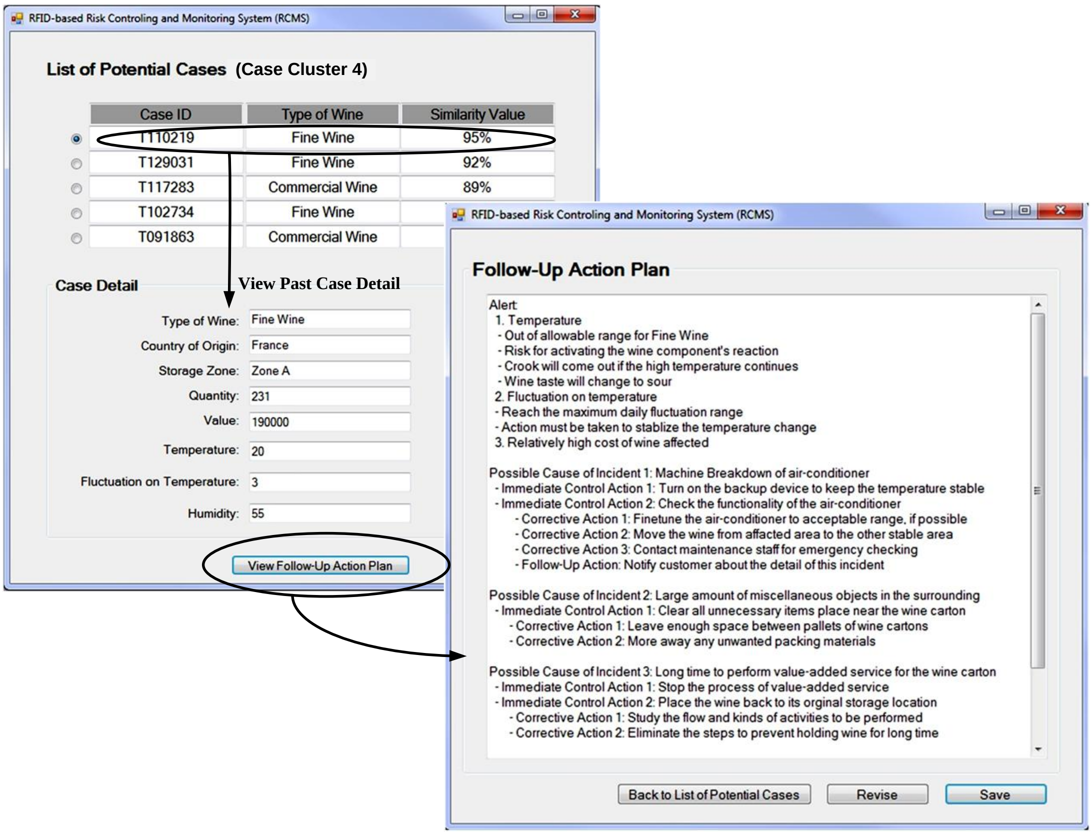


Figure 5.29 Formulation of follow-up action plan using a past reference case

5.4 Summary

In this chapter, two case studies of implementing the K-LOPS in a Hong Kong based-third party logistics company and wine distribution hub are presented. The roles of the three modules, i.e. RDCM, WRAM and LSFM, are illustrated. The new algorithm of the GA-based clustering approach in the case retrieval process has been illustrated through the adoption of the system. It provides an effective approach for dividing the case clusters by considering the best combination of multi-dimensional parameters. By following the implementation steps, the physical setup and preparation for the system are explained.

Chapter 6 Results and Discussion

6.1 Introduction

In this research, K-LOPS is proposed to support the logistics operations strategy planning during warehouse operations and to enhance the effectiveness of decision making when a problem occurs. K-LOPS adopts RFID technology, AHP and CBR techniques to collect real-time operations data and designs an action plan by taking into consideration the risk factors concerned from the customer's perspective. A new algorithm, iDPC, is presented for searching for the optimal value of case clusters by integrating the GA technique in the case clustering process to minimize the total distance error between a new problem and past cases. In this chapter, the results and discussion on two areas are presented. They are (i) results and discussion of system performance in the knowledge-based logistics operations planning system, and (ii) discussion of the use of K-LOPS in the two case studies.

6.2 Results and Discussion of System Performance in the Knowledge-based Logistics Operations Planning System

In this section, four experiments are conducted to examine the system performance of K-LOPS in supporting the decision making process in warehouse operations. Experiment 1 is a comparison of case retrieval time between the traditional nearest neighbor searching method and the proposed case clustering approach, supported by the iPDC algorithm. Experiment 2 is a comparison of the fitness value between the use of simulated annealing (SA) and the iDPC algorithm in the case clustering process. Experiment 3 is a comparison of different parameter settings for the iDPC algorithm. Experiment 4 is a comparison of the similarity value by combining different attributes as the cluster center using the iDPC algorithm.

(i) Comparison of case retrieval time

The case retrieval time of the traditional nearest neighbor (NNR) search and the proposed clustering approach with the iDPC algorithm are compared. With the case retrieval method of the NNR search, an exhaustive search is carried out to calculate the similarity of the problem description between the new problem and all past cases. On the other hand, using the case clustering approach supported by the iDPC algorithm, the case cluster that has the highest similarity value to the new problem is first extracted. Then, only the past cases that belong to the retrieved case clusters are compared with the new problem description to find the most similar past case. In order to illustrate the advantage of using the proposed case clustering approach with the iDPC algorithm, an experiment has been conducted to compare the case retrieval time between the NNR case retrieval approach and the iDPC algorithm.

In the knowledge repository, 370 past logistics cases are stored and each case consists of a number of attributes to represent the case. The experiment is conducted to show the retrieval time between the two approaches when the number of past cases in the knowledge repository increases. Figure 6.1 shows the result of the case retrieval time of the NNR searching method and the proposed case retrieval approach supported by the iDPC algorithm. The findings are summarized as follows.

- The case retrieval time of the two approaches increases when the size of the knowledge repository increases.
- When there is small number of past cases in the knowledge repository (number of past cases is less than 50), the case retrieval time is similar for the NNR

searching method and the proposed case retrieval approach supported by the iDPC algorithm.

- The difference of case retrieval time increases gradually when the size of knowledge repository is between 50 and 110.
- The difference increases significantly when the number of past cases in the knowledge repository is more than 110.
- With an increasing number of past cases stored in the knowledge repository, the case retrieval time for the proposed case clustering approach with the iDPC algorithm may decrease. It is because the retrieval time for the proposed case clustering approach depends on the number of past cases that belongs to the case cluster retrieved.

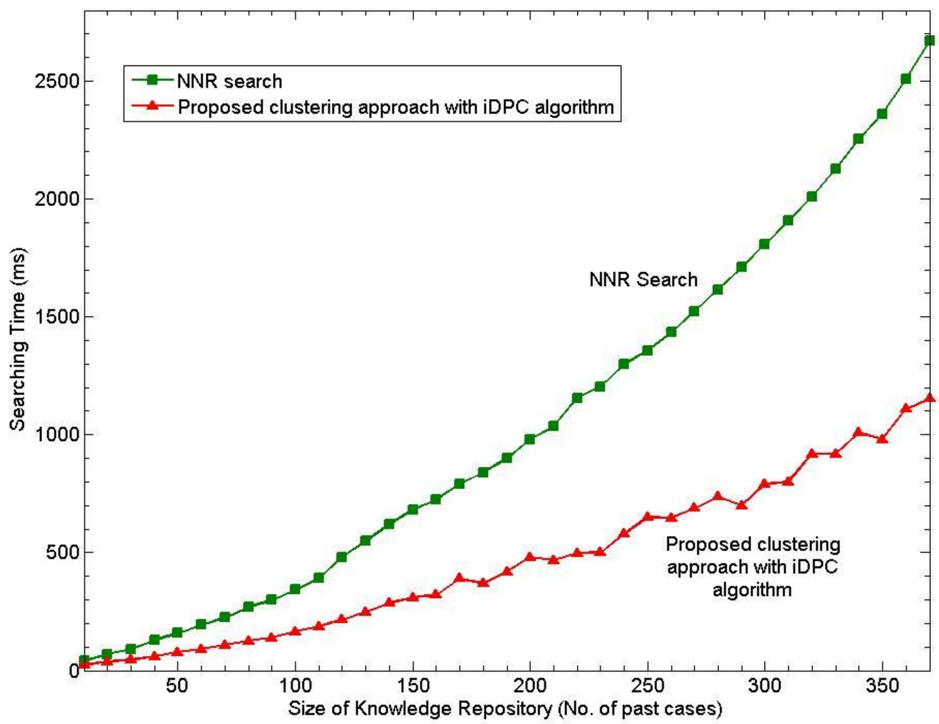


Figure 6.1 Comparison of case retrieval time between NNR search and proposed case clustering approach with iDPC algorithm

To summarize, the result of the experiment shows that the retrieval approach supported iDPC algorithm outperforms the NNR searching method with respect to the case retrieval time. By adopting the proposed case retrieval approach supported by the iDPC algorithm, the case retrieval is reduced which shortens the decision making time in K-LOPS.

(ii) Comparison of fitness value between SA and iDPC algorithm

In this experiment, a comparison of the fitness value between the SA approach and the proposed iDPC algorithm is conducted. It is used to compare the performance of using SA and the iDPC algorithm in the case clustering process. The fitness value, which measures the total distance error between each past case and the case cluster, is the indicator that reflects the performance of these two approaches. In this experiment, 300 past cases in the knowledge repository are divided into five clusters using the SA approach and the iDPC algorithm separately. The population size and the number of generations are set as 200 and 2000 respectively. For the iDPC algorithm, the two-point crossover method with different crossover rates (0.7 and 0.9) is used to compare their effect on the generated result. Meanwhile, to control the genetic diversity of the solution, two mutation rates, 0.1 and 0.25 are used to generate the result respectively. For the clustering approach with SA, a cooling rate of 0.9 and 0.99 is used in performing the experiment. Table 6.1 shows all the parameter settings for the iDPC algorithm and the SA approach where 8 sets of tests are conducted with different parameter settings. The sample results for each setting are shown in Figures 6.2 to 6.9. It is obvious that both the fitness value of the SA approach and the iDPC algorithm decrease significantly with an increasing number of generations and reach their minimum value after 2000 generations. However, no significant improvement is observed in both approaches after running for 800 generations.

Table 6.1 Parameter settings for iDPC algorithm and SA approach in the experiment

	iDPC algorithm	**SA approach**
(1)	Crossover Rate = 0.7, Mutation Rate = 0.1	Cooling Rate = 0.9
(2)	Crossover Rate = 0.7, Mutation Rate = 0.25	Cooling Rate = 0.9
(3)	Crossover Rate = 0.7, Mutation Rate = 0.1	Cooling Rate = 0.99
(4)	Crossover Rate = 0.7, Mutation Rate = 0.25	Cooling Rate = 0.99
(5)	Crossover Rate = 0.9, Mutation Rate = 0.1	Cooling Rate = 0.9
(6)	Crossover Rate = 0.9, Mutation Rate = 0.25	Cooling Rate = 0.9
(7)	Crossover Rate = 0.9, Mutation Rate = 0.1	Cooling Rate = 0.99
(8)	Crossover Rate = 0.9, Mutation Rate = 0.25	Cooling Rate = 0.99

According to the results generated, it is found that the iDPC algorithm has a better performance than the SA approach in dividing past cases into clusters. In the Figure 6.2 to 6.9, it can be observed that a lower fitness value can be obtained using the iDPC algorithm. In the SA approach, the range of decrease in fitness value is smaller, compared to the iDPC algorithm. Although the performance of the SA approach with a cooling rate of 0.99 performs better than a cooling rate of 0.9, the best fitness value generated is worse than for the iDPC algorithm. For the iDPC algorithm, the fitness value improves continuously and finally a better result can be obtained. On the other hand, it is found that the fitness value generated with the crossover rate of 0.9 and a mutation rate of 0.1 in the iDPC algorithm gives the best performance among all the other settings.

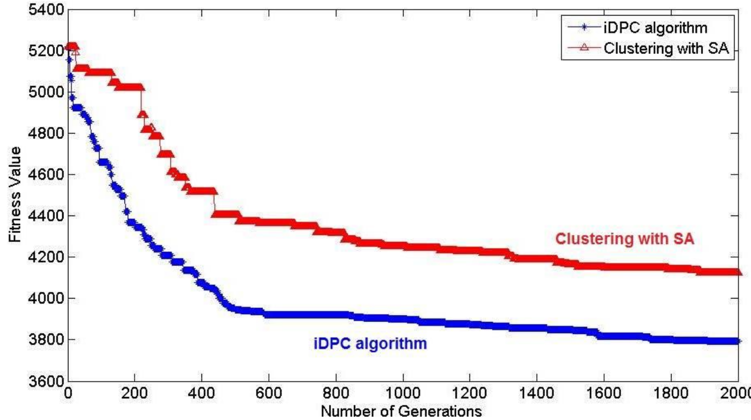


Figure 6.2 Fitness value at crossover rate=0.7 (for iDPC), mutation rate=0.1 (for iDPC) and cooling rate=0.9 (for SA)

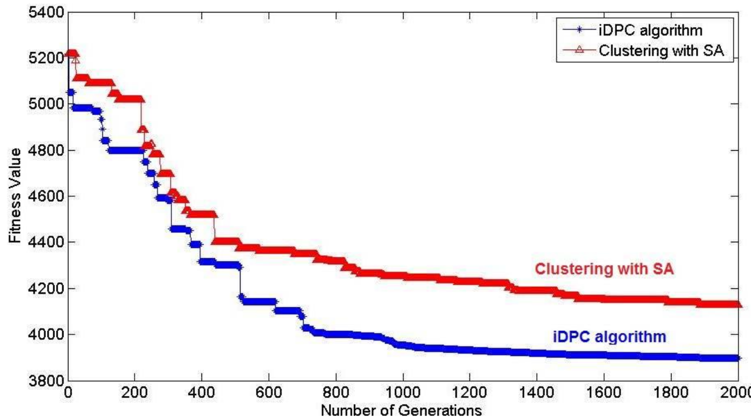


Figure 6.3 Fitness value at crossover rate=0.7 (for iDPC), mutation rate=0.25 (for iDPC) and cooling rate=0.9 (for SA)

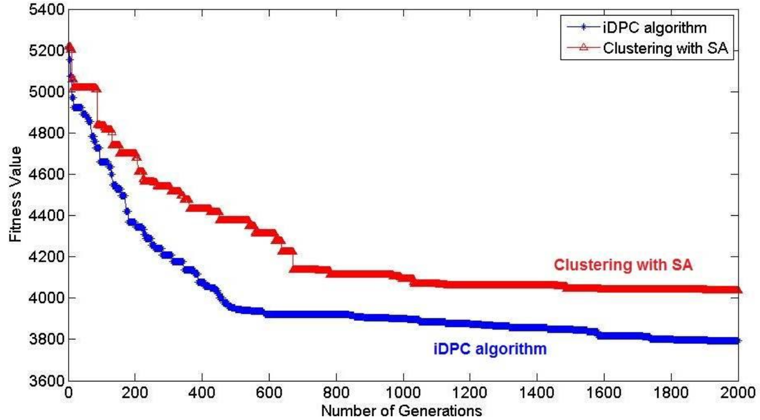


Figure 6.4 Fitness value at crossover rate=0.7 (for iDPC), mutation rate=0.1 (for iDPC) and cooling rate=0.99 (for SA)

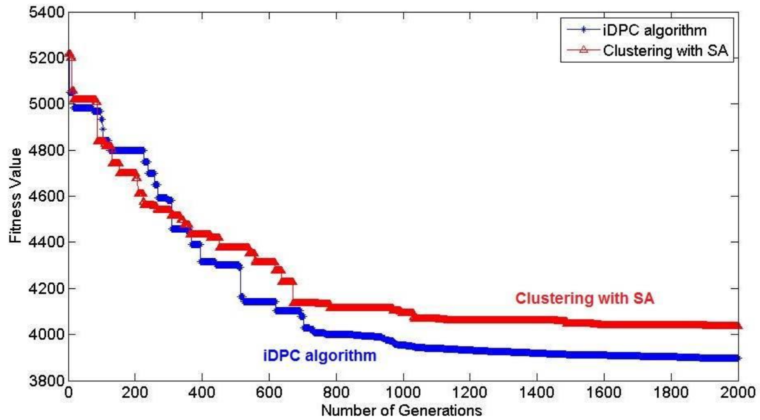


Figure 6.5 Fitness value at crossover rate=0.7 (for iDPC), mutation rate=0.25 (for iDPC) and cooling rate=0.99 (for SA)

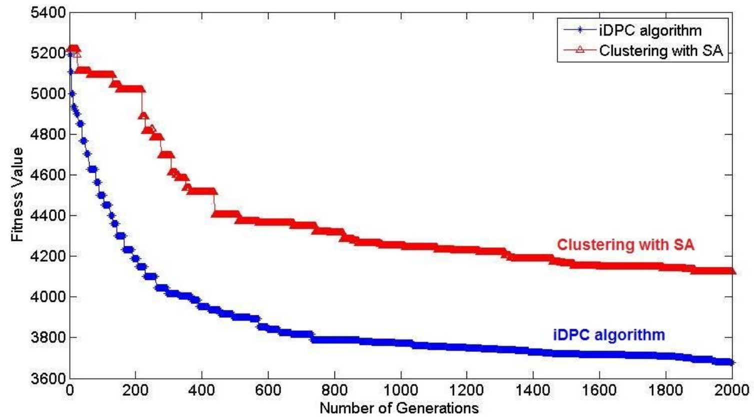


Figure 6.6 Fitness value at crossover rate=0.9 (for iDPC), mutation rate=0.1 (for iDPC) and cooling rate=0.9 (for SA)

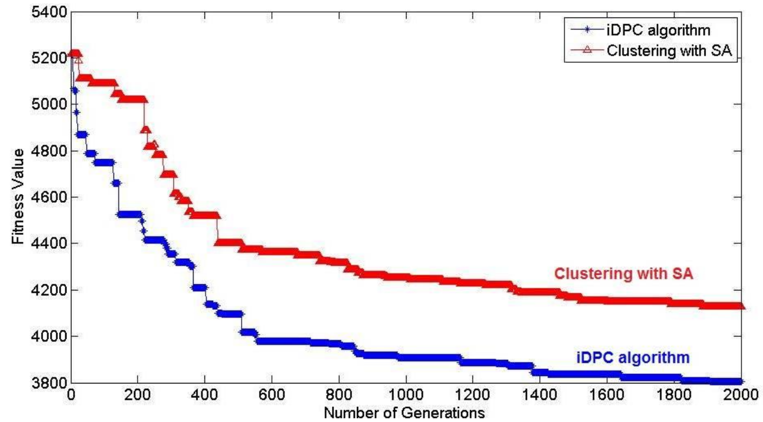


Figure 6.7 Fitness value at crossover rate=0.9 (for iDPC), mutation rate=0.25 (for iDPC) and cooling rate=0.9 (for SA)

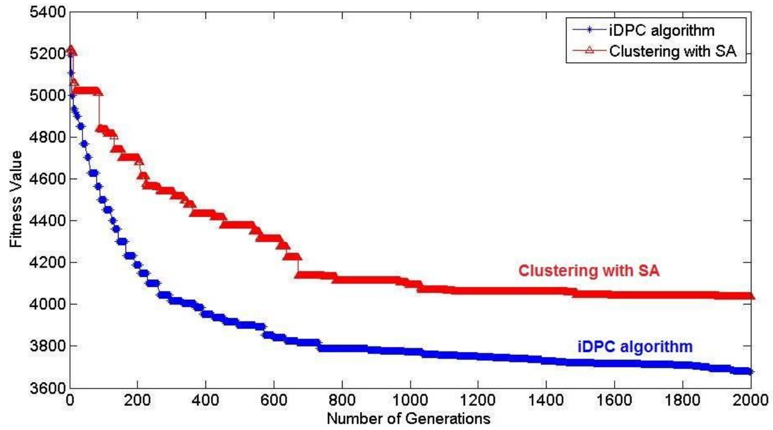


Figure 6.8 Fitness value at crossover rate=0.9 (for iDPC), mutation rate=0.1 (for iDPC) and cooling rate=0.99 (for SA)

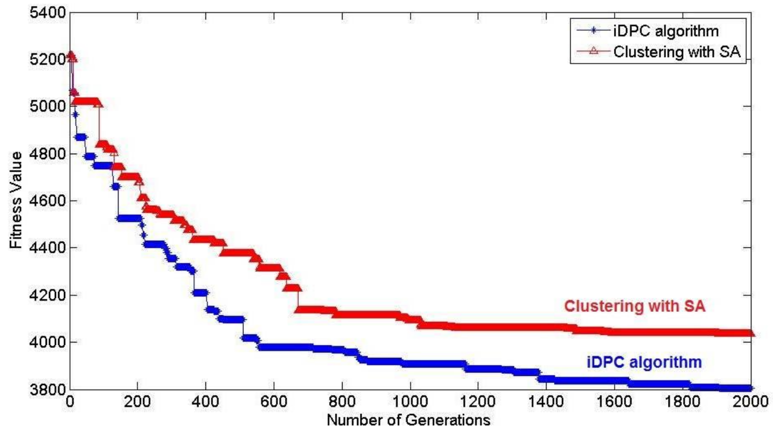


Figure 6.9 Fitness value at crossover rate=0.9 (for iDPC), mutation rate=0.25 (for iDPC) and cooling rate=0.99 (for SA)

(iii) Comparison of different parameter settings for iPDC algorithm

Given that the change of parameter settings in the iDPC algorithm would bring different results for the problem, a number of tests are performed to determine a suitable setting when implementing the proposed system. Table 6.2 shows the test settings for the iDPC algorithm. The result in the previous experiment suggests that the iDPC algorithm provides the best performance with a crossover rate of "0.9" and mutation rate of "0.1". Therefore, in this experiment, different sets of cluster number, number of generations, and population sizes are tested, while the crossover rate and mutation rate remain constant.

Table 6.2 Different parameter settings for iDPC algorithm

Parameter	**Settings**
Crossover rate	0.9
Mutation rate	0.1
Number of clusters	3 / 5/ 7
Number of generations	1000 / 2000 / 3000
Population size	100 / 200 / 400

The objective of the test is to conduct a comparison of the performance of different parameter settings for the iPDC algorithm, which is determined by the fitness value. A knowledge repository with 100 past cases is used to conduct this experiment. Ten independent runs are generated for each setting. The results are compared based on the average value, lowest value, and standard deviation of the distances between the cases and their corresponding cluster centers. The running time of each setting is also considered as a criterion in the searching. The summaries of the simulation results using different parameter settings are shown in Tables 6.3 to 6.5.

Table 6.3 Fitness values for three clusters

Population	**Number of Generations**	**Average Value**	**Lowest Value**	**Convergence**	**Standard Deviation**	**Running Time (Seconds)**
100	1000	89.79	84.06	6.4%	7.7	23
	2000	82.61	80.34	2.7%	2.33	40
	3000	82	79.85	2.6%	3.27	61
200	1000	82.83	79.91	3.5%	2.91	38
	2000	81.29	79.8	1.8%	0.87	79
	3000	80.87	79.8	1.3%	1	127
400	1000	81.37	79.97	1.7%	1.02	67
	2000	80.28	79.82	0.6%	0.52	151
	3000	80.14	79.8	0.4%	0.47	228

Table 6.4 Fitness values for five clusters

Population	**Number of Generations**	**Average Value**	**Lowest Value**	**Convergence**	**Standard Deviation**	**Running Time (Seconds)**
100	1000	55.21	51.36	7.0%	3.58	27
	2000	53.52	48.63	9.1%	7.48	45
	3000	52.32	50.18	4.1%	3.01	67
200	1000	52.3	48.79	6.7%	2.54	41
	2000	50.8	48.58	4.4%	2.15	81
	3000	50.75	48.56	4.3%	2.25	130
400	1000	51.67	50.54	2.2%	1.16	75
	2000	50.31	48.56	3.5%	1.56	156
	3000	49.86	48.21	3.3%	1.14	231

Table 6.5 Fitness values for seven clusters

Population	Number of Generations	Average Value	Lowest Value	Convergence	Standard Deviation	Running Time (Seconds)
100	1000	51.45	44.3	13.9%	5.99	27
	2000	47.4	43.51	8.2%	5.02	53
	3000	46.34	42.09	9.2%	4.38	82
200	1000	47.16	43.19	8.4%	2.92	65
	2000	46.65	43.18	7.4%	1.98	101
	3000	44.9	42.72	4.9%	2	145
400	1000	46.91	43.95	6.3%	2.03	97
	2000	46.09	42.04	8.8%	1.94	216
	3000	43.22	41.77	3.4%	1.47	286

In general, the settings with a larger number of clusters, number of generations, and population size provide a smaller number of average values and standard deviations. Compared with the result obtained by dividing the past cases into 3 clusters, it can be seen that there are more than 35% improvement in average fitness values when 5 clusters are defined. On the other hand, less than 10 % improvements in average fitness values were found by using 7 clusters instead of 5 clusters. The difference in improvement decreases significantly, and it is because more feasible solutions are considered when the number of generations and size increase, which further increases the chance of having a smaller fitness value. Therefore, the setting of dividing past cases into 3 clusters should be ignored as it does not reach an acceptable range of fitness value. In addition, with an increasing number of generations, the improvement of fitness value becomes stable and the range of fitness values generated from the ten independent runs becomes smaller. This finding can be obtained through the standard deviation of the distances between the cases and their corresponding cluster centers. The standard deviation decreases with increasing number of generations and population, which indicates that a more stable reliable solution is generated. On the other hand, the range of distances gradually decreases as the number of clusters generated increases. The findings show that the performance of case clustering improves with increasing number of clusters defined, in terms of the distance error between the past cases and the case clusters. However, the simulation results also show that a larger number of population sizes does not always guarantee the lowest value of distance. In some settings, the lowest values for a population size 200 can be smaller than that found in population size 400. Conversely, the running time increases drastically as the number of clusters, number of generations, and population size increase. In term of convergence to determine the suitable setting, a GA converges when most of the population shares the same value. As the population converges, average fitness value approaches the best. The population is regarded as converged when the average fitness value across the current population is less than 5% different from the best fitness of the current population. Besides, for the case of convergence, less than 0.5% improvement in fitness value should be obtained when the number of generations increases. From the result of Table 6.4 and Table 6.5, although the fitness values obtained using 7 clusters are comparatively smaller than the fitness values obtained using 5 clusters, only the results of 5 clusters with 200 and 400 population sizes give a smaller convergence value, i.e. less than 5%. Meanwhile, less than 0.5% improvement in fitness values are also found with the two settings. To obtain an acceptable result in a reasonable time, settings of population size 200 and 2000 generations with five clusters are selected for the case study.

(iv) Comparison of similarity value by combining different attributes as the cluster center in iDPC algorithm

The case clustering approach using the iDPC algorithm divides past cases stored in the case library into groups by considering multi-dimensional parameters. As a result, the best combination of parameters for the groups is selected. During the clustering process, the iDPC algorithm has to search whether or not the parameters are included as key features in the cluster. Therefore, the number and type of parameters included in each cluster is different. In order to show that the selection of different parameters for each cluster can improve the performance in retrieving past similar cases, a test was carried out to compare the similarity value of cases retrieved the two approaches. Figure 6.10 and Figure 6.11 show examples of the result of five cluster centers where different combinations of parameters and all five parameters, respectively, were considered. The similarity measures for selecting the case cluster with the highest value among the two approaches were calculated. As shown in Table 6.6, it was found that the clusters selected were different for the two approaches. In the first approach that considers different combinations of parameters as the cluster center using iDPC algorithm, cluster 4 is selected with 83.1% similarity by comparison with the new problem. For the second approach that considers all five parameters, cluster 5 is selected with the highest value. In addition, the result also shows that the similarity measures of the five clusters and new case in the second approach are similar in that they range from 69% to 82%. It is difficult to decide whether the cases belonging to the selected cluster are suitable for solving the new problem.

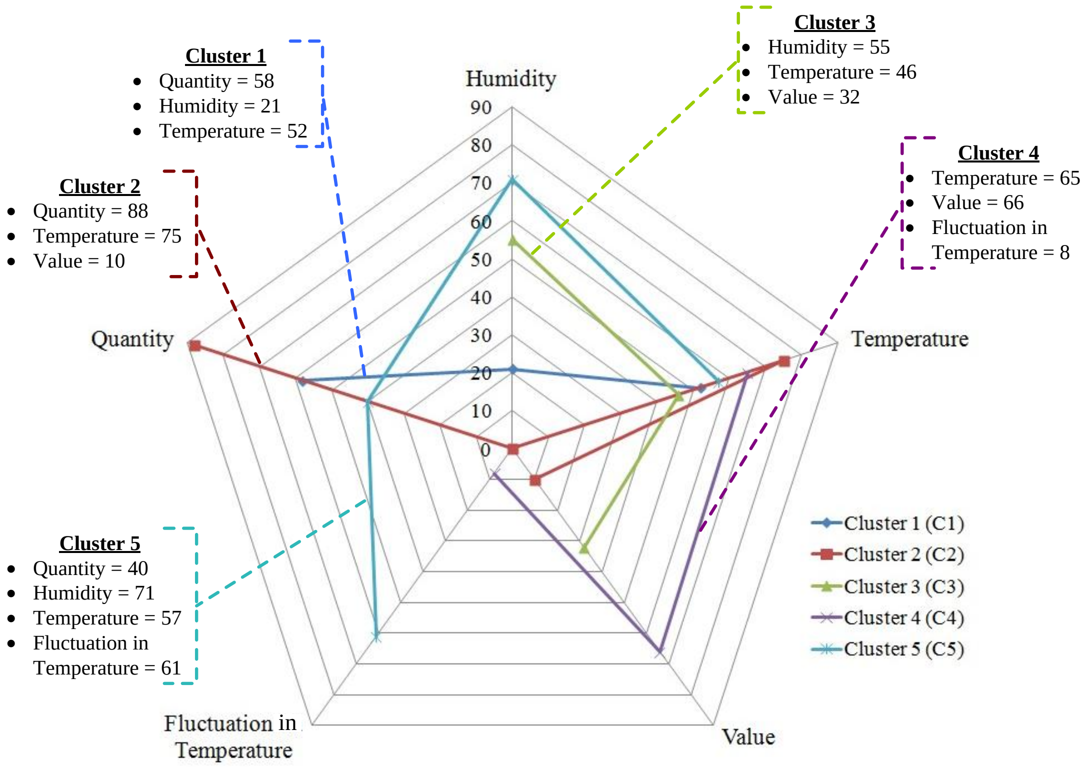


Figure 6.10 Result of five cluster centers by considering different combinations of parameters

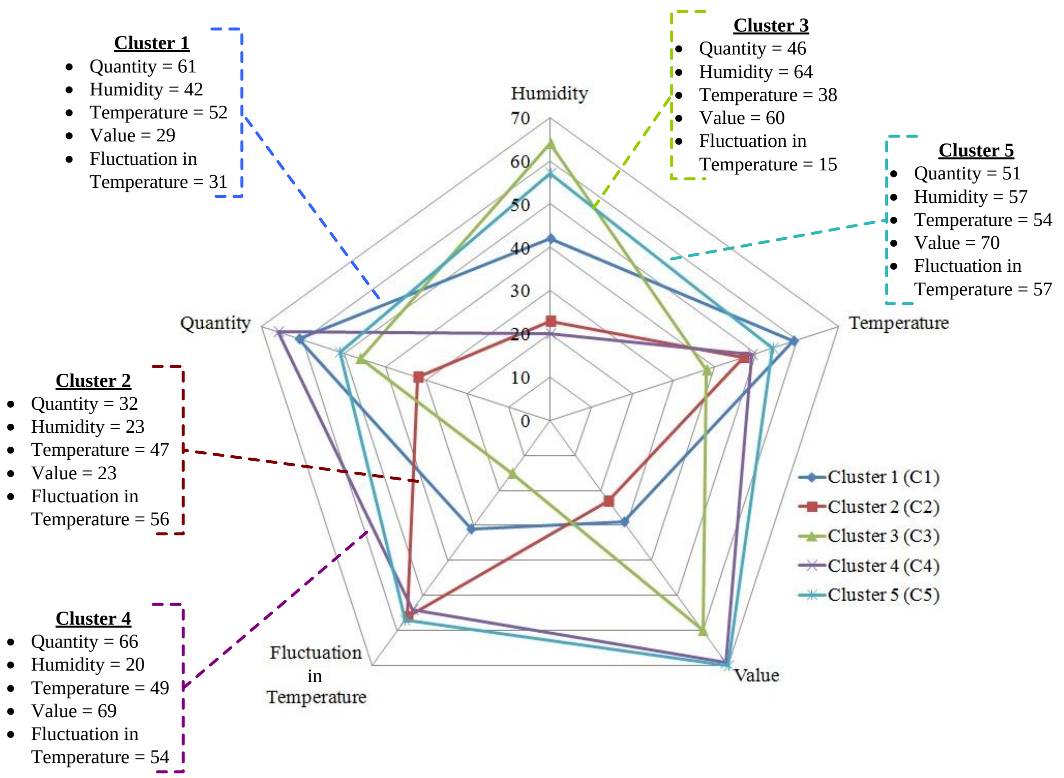


Figure 6.11 Result of five cluster centers by considering all five parameters

Table 6.6 Similarity measures for retrieving case clusters with the two approaches

	Temperature	**Fluctuation in Temperature**	**Humidity**	**Quantity**	**Value**	**Similarity**
Weighting	1	0.5	0.1	0.1	0.5	
New Case	70	25	40	15	73.3	
(i) Considering different combinations of parameters						
Cluster 1	52	-	21	58	-	43.5%
Cluster 2	75	-	-	88	10	52.7%
Cluster 3	46	-	55	-	32	51.7%
Cluster 4	65	8	-	-	66	83.1%
Cluster 5	57	61	71	40	-	60.6%
(ii) Considering all five parameters						
Cluster 1	59	31	42	61	29	81.4%
Cluster 2	47	56	23	32	23	69.5%
Cluster 3	38	15	64	46	60	77.7%
Cluster 4	49	54	20	66	69	79.6%
Cluster 5	54	57	57	51	70	82.3%

Subsequently, the potential cases are ranked in descending order by comparing the similarity between the new problem and the selected case cluster. Figure 6.12 shows the result of a comparison of the case clustering approach with and without considering different combinations of parameters. It is found that the average similarity value with the iDPC algorithm for considering different combinations of the parameters is 88%, while the average similarity value for the second approach is 79%. The past cases retrieved in the case cluster with different combinations of parameters also had higher values compared to that with no selection on the set of parameters. Therefore, the result shows that the performance in retrieving past similar cases by the clustering approach with the consideration of parameters selection for the groups is better than that without parameter selection.

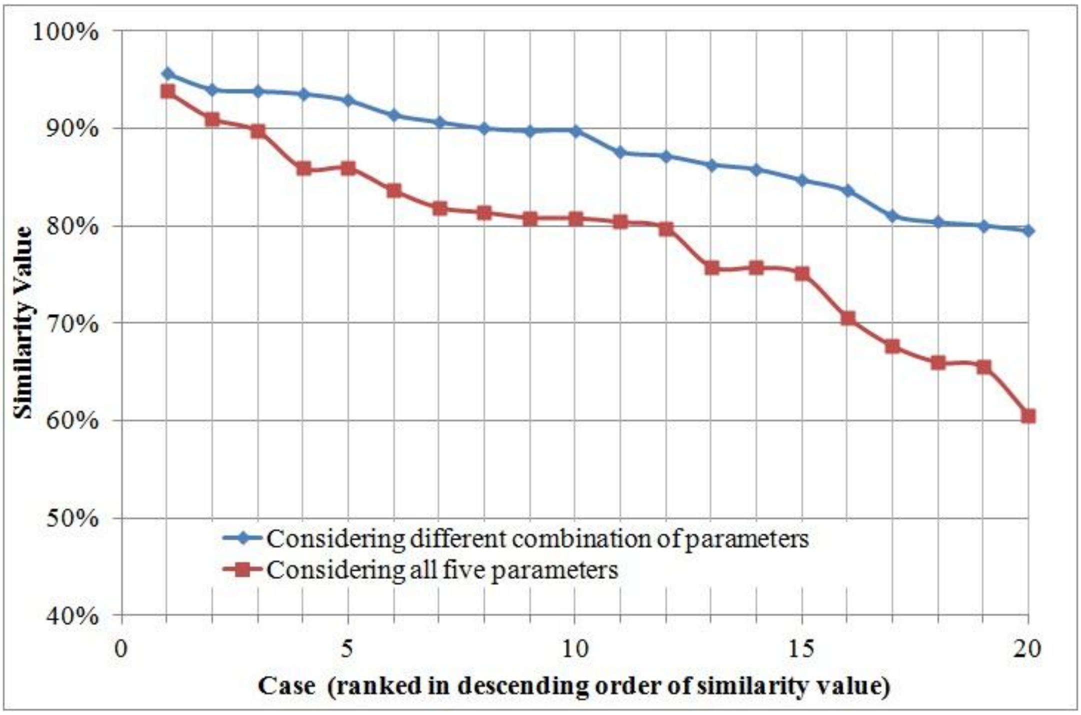


Figure 6.12 Comparison of the case clustering approach with and without considering different combinations of parameters

6.3 Discussion of the Use of K-LOPS in Two Case Studies

In the previous section, the development of prototypes in two case studies was described to validate the feasibility of the proposed K-LOPS. In order to verify the system performance in the logistics companies, quantitative measurements of the K-LOPS are carried out in this section. Comparisons of performance assessment criteria before and after the system implementation are conducted in the two case studies.

6.3.1 Results and Discussion of K-LOPS in EWC Company

In this section, the contributions of the K-LOPS to the EWC Company are examined and presented. By conducting the study in EWC's warehouse that handles daily delivery orders between Hong Kong and China, K-LOPS enhances the performance of warehouse operations process in three categories. They are (i) enabling understanding of customer order practice, (ii) increase in warehouse operation effectiveness, and (iii) increase the effectiveness in warehouse performance monitoring.

(i) Understanding of customer order practice

By adopting the iDPC algorithm in the K-LOPS, past cases and a new order are divided into different customer groups. The grouping result considers multi-dimensional attributes while examining all combinations of the case features. The parameter values of each cluster center are also identified, which allows the warehouse manager to have a better understanding of how the cases are grouped. Based on the parameter values of each case feature, the warehouse manager can further divide customer orders into groups. Special arrangements can be decided and assigned to serve a particular group of customer orders. Thus, customer orders can be fulfilled satisfactorily.

(ii) Increase in warehouse operation effectiveness

Instead of adopting a cross-border operation plan solely by the warehouse manager, the decision-making process becomes a systematic approach with the application of K-LOPS. In adopting this approach, the solution of past cases is applied to incoming new orders. Due to the special requirements in handling cross-border orders, new orders may have different needs. The solution of similar cases can be used again as the solution to the current situation. Therefore, the effectiveness of warehouse operation can be enhanced. The result of improvement in warehouse operation effectiveness is shown in Table 6.7. As the strategy formulation are made by retrieving past cases with similar order handling practice as a reference, the planning time was reduced significantly by 45% with the help of K-LOPS. Furthermore, K-LOPS offers useful information in developing an efficient order selection strategy. With more control on the cross-border requirements (i.e., documentation preparation) during warehouse operations planning, the order can pass through the customs inspection point smoothly. Thus, the chance of late delivery due to failure in presenting the necessary documents is reduced from 7 times to 2 times in a month, which accounts for an improvement of 71.4%. In addition, by adopting the RFID technology, the system can monitor the in-and-out movement and the loading efficiency of forklifts to check whether a particular forklift is able to finish the allocated job on time. If the forklift is behind the planned schedule, immediate action can be taken to increase the working efficiency. In contrast, if the loading efficiency of the forklift increases, the allocated job is expected to finish earlier than the planned time. A further job can be allocated to any forklift that is idle at that time. Thus, the average idle time of material handling equipment is reduced from 22% to 15%, which accounts for an improvement of 31.8%.

Table 6.7 Improvement in warehouse operation effectiveness

	Before	**After (with K-LOPS)**	**Percentage of Improvement**
Consideration of cross-border requirement	No	Yes	
Order planning time	45 min	20 min	45%
Delay in delivery (times per month)	7	2	71.4%
Average idle time of material handling equipments	22%	15%	31.8%

(iii) Increase the effectiveness in warehouse performance monitoring

Instead of making a decision based on the past experience of the planner, the model adopts the CBR engine for retrieving past cases which are similar to the present case in order to decide the strategies to be used for each of the operations. The performance of operational efficiency is measured as a record for future operations. Based on the KPI defined according to the service level set by the top management team and the customer expectation, the warehouse performance can be monitored. It provides measurable operational performance, which allows further evaluation and improvement of the warehouse operational services. After the retrieval and ranking processes, the past case obtaining the highest similarity score with the new case are retrieved for performance comparison. If the strategies listed in the past case are suitable for reuse and do not need revision, the past case solution is then adapted in the new order. If there is amendment required for the new order, modifications are performed based on the information given in the past case generated.

In order to measure the performance of K-LOPS in formulating operations strategy based on past reference cases, a survey was designed to collect the feedback from selected customers and the system users, i.e. logistics supervisor and warehouse manager who have to plan the operating guidelines. Three indicators are defined to measure the performance of K-LOPS in retrieving past cases. They are the acceptability of the logistics strategy suggested, adaptability of the past case solution and degree of customer satisfaction in the order fulfillment. Acceptability of the logistics strategy suggested refers to the percentage of orders, that the logistics strategy suggested is acceptable to the customer without making any change to the total number of new orders that is required for planning. By comparing the percentage between of acceptability before and after the implementation of the system, it allows evaluation of customer satisfaction on the logistics strategy suggested, with consideration of the past performance record. The adaptability of the past case solution refers to the number of past cases retrieved in which the strategies are adapted to the new order without making any changes based on the total number of new order inputs to K-LOPS. This indicator measures the performance of the system on whether the retrieved past cases are used directly for the new order, i.e. without any modification. Table 6.8 shows the result of K-LOPS performance in solution formulation. It is found that 42% of the logistics strategies suggested for the new customer order specifications are accepted by the customers without any change, while 45% of logistics strategies suggested are adapted directly for the new order from K-LOPS. In addition, the degree of customer satisfaction in the order fulfillment is significantly increased from 68% to 87%.

Table 6.8 Performance of K-LOPS in solution formulation

	Before	**After (with K-LOPS)**
Acceptability of logistics strategy suggested = *Number of order that the logistics strategy suggested is accepted by customer (Without any change) / Total number of new order*	15%	42%
Adaptability of the past case solution = *Number of past cases retrieved that the strategies is adapted to the new order (Without any change) / Total number of new order input*	-	45%

6.3.2 Results and Discussion of K-LOPS in KYT Company

In this section, the contributions of the K-LOPS to the KYT Company are examined and presented. During the period of the trial run, previous incident handling records from the past two years are first input into the system as past reference cases. With such preliminary work, the past cases can be classified into a number of groups according to the need for efficient retrieval. Through the case clustering process, multi-parameters for indexing the case were considered to obtain the significant parameters with corresponding values for each case group. It allowed the wine warehouse manager to have better knowledge of the key features of each case group that led to the incidents. With the help of K-LOPS, it is found that there was (i) an improvement in follow-up action formulation, and (ii) an improvement in customer satisfaction and reduction in wine damage are achieved.

(i) Improvement in follow-up action formulation

With the adoption of RFID technology, the incident affected area can be easily located by the RFID tags attached to the wine cartons. Table 6.9 shows the improvement in formulating the follow-up action plan. Compared with the previous practice where electronic sensors are set in fixed places to measure the storage condition for a larger area, the time to locate wine that may be affected by the incident is reduced from 6 minutes to 1 minute, with an improvement of 83.3%. This is because the RFID technology provides such real time information up to the item level so that the wine cartons with abnormal measures can be easily identified. Besides, with the help of the CBR engine in the K-LOPS, the time required to formulate a follow-up plan is reduced significantly from 25 minutes to 8 minutes. An improvement of 68% is made to shortlist the critical control action, identify possible cause of incidents, formulate corrective action steps and propose the compensation cost induced (if any). Thus, the manager no longer needs to spend a lot of time to manually create a shortlist of critical control actions, possible causes of incidents and corresponding actions. Instead, such information can be generated by retrieving past similar cases as a reference.

Table 6.9 Improvement in follow-up action formulation

	Before	**After (with K-LOPS)**	**Percentage of Improvement**
Time to locate the wine that may be affected by the incident	6 min	1 min	83.3%
Time to formulate follow-up plan			
- Shortlist of critical control action	7 min		
- Possible cause of incidents	5 min		
- Corrective action steps	8 min		
- Compensation cost induced (if any)	5 min		
Total	25 min	8 min	68%

(ii) Improvement in customer satisfaction and reduction in wine damage

The K-LOPS allows the real-time storage conditions to be measured and provides an action plan to effectively manage the risk incurred. Table 6.10 shows the improvement in customer satisfaction and reduction in wine damage. Before the launch of K-LOPS, it took longer for the staff to notice the deterioration of wine as there was no control to ensure that the wine was stored in the right storage area until the periodic stock taking process was carried out. On average, more than 15 minutes are required to notify a significant change in storage condition. With the use of K-LOPS, the RFID tag can be used to identify the item and location information. An alert is provided if the wine is placed in the wrong location and if the measured storage condition is out of the allowable range within 10 seconds. Thus, the time to notify a significant change in storage condition is reduced by 98.9%. Meanwhile, with the K-LOPS, corrective actions can be formulated within a short period of time, which lower the chance for the wine to deteriorate due to the inappropriate storage conditions. The wine damage frequency and the number of customer complaints are also reduced by 87.5% and 66.7% respectively. The damage frequency is greatly reduced from 120 cases to 15 cases, which is measured by the number of incidents of deteriorated wine per month. It is because the physical measures in the warehouse environment, including temperature and humidity, are monitored on a real time basis, which eliminates incidents due to inappropriate storage conditions. On the other hand, with the function of formulating a logistics strategy according to the risk of concern to customers, the logistics supervisor is able to prepare any feasible actions as a contingency plan. Therefore, the number of customer complaints due to slow response on the actions to be taken when incident occurs is reduced from 6 to 2 times per month.

Table 6.10 Improvement in customer satisfaction and reduction in wine damage

	Before	**After (with K-LOPS)**	**Percentage of Improvement**
Time to notify the significant change in storage condition	15min	10s	98.9%
Damage frequency (Number of incidents of deteriorated wine per month)	120	15	87.5%
Customer complaints due to slow response (Number of times per month)	6	2	66.7%

6.4 Summary

In this chapter, the results and discussion of the research is presented. Four experiments have been conducted to compare the performance of the proposed case clustering approach which is supported by the iDPC algorithm and other approaches, including the traditional NNR searching method and SA approach. The results show that the proposed iDPC algorithm outperforms the other approaches in terms of searching time and performance of fitness value. It helps to provide the decision support function for the logistics supervisor and warehouse manager in formulating useful operations strategies. In Chapter 7, conclusions of the research are drawn while the limitation of the research is also presented.

Chapter 7 Conclusions

7.1 Summary of Research Work

In today's highly competitive business environment, logistics service providers (LSPs) have changed their strategic goals to achieve shorter order cycle times, lower costs, and better customer service. Customer orders with high product variety and diversified service requirements are often received, with requests for timely delivery. Since the decision-making process is one of the complicated processes involved in warehouse operation for fulfilling various specific customer orders efficiently, the pressure becomes high to complete customer orders with a short delivery lead time. Meanwhile, logistics companies may suffer losses if they fail to deal with customer requirements and the occurrence of possible risks properly. Thus, similar past experience and explicit knowledge become critical for generating effective operations guidelines and a resources allocation plan. However, only a small number of research studies have been reported considering risk control during the decision making process in the area of warehouse operations.

This aim of this research is to propose and develop a knowledge-based logistics operations planning system (K-LOPS) so as to support the decision making process in planning and controlling warehouse operations. K-LOPS makes use of RFID technology and AI techniques, i.e. AHP and CBR, to collect real-time warehouse data and relevant logistics data for providing knowledge support in decision making when operation problems occur. Considerable risks of concern to the customer regarding the product characteristics are identified and become key factors during the planning process of warehouse operations. Due to the necessity to search for similar and useful cases from past explicit knowledge, a newly-designed algorithm, namely the iterative dynamic partitional clustering algorithm (iDPC), is integrated into the CBR engine to improve the performance in retrieving past similar cases. The principle and architectural structure of K-LOPS, which consists of three modules, RDCM, WRAM and LSFM, have been developed and demonstrated, as described in Chapter 3-5, while the implementation results are discussed in Chapter 6.

7.2 Contributions of the Research

This research provides a generic methodology for the development of a knowledge-based logistics operations planning system for the logistics industry to facilitate the decision making process during warehouse operations. This will help the companies to improve the decision making performance in response to particular risks. Therefore, a responsive logistics strategy can be formulated to fulfill the demand for high efficiency and quality in logistics service requirements. The contributions of this research are summarized below.

(i) K-LOPS has been developed as a new framework to provide a decision support function in logistics strategy formulation. Through the analysis of the possible risks concerned when handling customer orders with special needs, the operations strategy can be formulated with consideration of customer expectation. This unique feature of K-LOPS provides a value-added function to support and improve the logistics operations performance in the warehouse, thus customer satisfaction can be enhanced.

(ii) By adopting RFID technology in the Real-time Data Collection module, real-time information on the warehouse environment and the resources status is captured. This helps to enhance the information flow, visualize the instantaneous warehouse operations process, and facilitate decision making in operations assignment and monitoring. With the assistance of RFID technology, the current warehouse environment is fully visualized, thereby effectively facilitating the resources allocation process.

(iii) Although case clustering has been found to be an effective approach in retrieving past cases group-wise, dividing the cases into groups with a similar feature values is still a challenge. In order to enhance the performance in retrieving past explicit knowledge in K-LOPS, a newly-designed iDPC algorithm provides an effective mechanism to search for optimal centers of case clusters. An amendment factor is proposed to adjust the combination effect with increased numbers of case attributes so as to provide a reasonable result when more than one case attribute is considered at the same time. Thus, this algorithm provides a dynamic and comprehensive searching approach in considering multiple features at the same time, and is able to divide the past cases effectively into an appropriate case cluster.

(iv) In K-LOPS, hybrid AI techniques, including AHP and CBR supported by the iDPC algorithm with GA, are used to formulate solutions for enhancing the operations efficiency in the warehouse as well as enhancing customer satisfaction. From the literature review, it is found that research related to the integration of these techniques to solve the strategy formulation problems with the considerations of possible risk in warehouse is extremely limited. This research study provides a feasible solution to improve the performance of an existing system by adopting hybrid techniques.

(v) The K-LOPS has been successfully implemented in a third party logistics company and a wine distribution hub. Through the results obtained after launching the system through the two case studies, overall planning and operating efficiency was shown to be improved which proves the feasibility of K-LOPS in actual warehouse operations environments.

7.3 Limitations of the Research

Although this research makes a number of contributions to both academia and the logistics industry, there are still some limitations in the research which are addressed below.

(i) In this research, the proposed iDPC algorithm focuses on searching for optimal centers of case clusters so as to minimize the distance between past cases and the case clusters. This algorithm provides significant improvement in terms of case retrieval time and similarity value when the number of past cases in the case repository increases. Therefore, it depends on the enterprises and users to collect the case records and store them into the system for future use. If only a limited number of past case records is available, this algorithm may be limited and may increase the computational time in the case clustering process.

(ii) The logistics strategy formulation module is constructed based on the CBR techniques. To ensure the accuracy of the solution provided, it may be demanding and time consuming to convert previous tacit knowledge and operation practice offered by warehouse experts into case format for storage in the case repository.

(iii) The iDPC algorithm divides past cases stored in the case repository into groups by considering multi-dimensional parameters. However, the number of clusters has to be defined prior to the case clustering process. Subsequently, the iDPC algorithm is adopted to search for the optimal center and divides past cases according to the number of case clusters defined. Thus, a number of tests are required in the preparation stage in order to find out a suitable setting on the number of clusters based on the performance of searching time and fitness value obtained.

7.4 Suggestions for Further Work

The future research directions regarding the proposed algorithm and framework are suggested to further improve the capabilities of the system. They are summarized as follows.

(i) In this research, the key characteristics and application of K-LOPS in managing the warehouse operations is presented. Further research on the structural configuration of the system is required in order to further enhance its benefit and extend the approach to the other application areas.

(ii) The proposed iterative dynamic partitional clustering algorithm (iDPC) provides an approach to search for optimal centers of case clusters by minimizing the adjusted distance error between the suggested cluster centers and past cases. By integrating the distance error and amendment factor in evaluating the fitness value, the optimal combinations of parameters and the values of cluster centers can be guaranteed. An extension of the error measurement factor can be considered for enhancing the accuracy of GA mechanism.

(iii) In the matter of performing a pair-wise comparison in the warehouse risk assessment module using AHP, a nine-point scale is used to reflect the customer expectation on the risk factor with respect to the criteria concerned. To enable a comparison between variable types of parameters, the fuzzy logic approach can be applied to compare the importance using the fuzzy linguistic terms which are easily understandable by users.

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Appendices

Appendix A. Questionnaire for Risk Analysis

THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

Department of
Industrial & Systems Engineering
工業及系統工程學系

Survey on identifying potential risk factors in warehouse operations of logistics service provider

Objective: to identify and analyze the potential risk factors in warehouse operations for logistics service providers (LSPs). In order to attract customer and increase profit, it is found that LSPs in Hong Kong have changed the focus of business gradually, which is to provide high value added services to its customer. Thus, large variety of products with difficult requirements is handled by LSPs, which increase the risk to maintain the product quality and their reputation. In order to gain competitive advantages, it is crucial to identify the potential risk factors in warehouse operations within the company when handling customer orders.

Explanation Note:

Please refer to the table below for the scale to rate the importance of risk factors/assessment criteria

Rating	Definition
1	Equal likelihood/consequence
3	Weak likelihood/consequence of one over another
5	Essential or strong likelihood/consequence
7	Demonstrated likelihood/consequence
9	Absolute likelihood/consequence
2, 4, 6, 8	Intermediate values between the two adjacent judgments

Section 1: Company Profile

1. Have your company offer warehousing activities?

   ☐ Yes ☐ No

2. Is your company always involved in handling large variety of products?

Never				**Always**
1	**2**	**3**	**4**	**5**
☐	☐	☐	☐	☐

3. Which location sector is the focus of your company?

   ☐ Hong Kong only ☐ Asia

   ☐ Worldwide

4. Which kind of business is your company's major focus?

   ☐ Textiles and Garments/ Fashion

   ☐ Technology and Electronics

   ☐ Packaging and Paper Products

   ☐ Logistics service

   ☐ Import and Export Trading

   ☐ Others____

5. Please indicate your position in the company

   ☐ CEO

   ☐ Senior Management Team

   ☐ Junior Management Team

   ☐ Operation Team

   ☐ Others____

Section 2 Logistics Risk Factors

Please indicate the relative degree of the importance of the following 9 risk factors when handling customer orders in your company.

(i) Resource

	Insignificant				**Most Critical**
Factors	**1**	**3**	**5**	**7**	**9**
High turnover rate of labor	☐	☐	☐	☐	☐
Storage space utilization	☐	☐	☐	☐	☐
Packing material shortage	☐	☐	☐	☐	☐
Machine breakdown	☐	☐	☐	☐	☐
Aging of facilities	☐	☐	☐	☐	☐

(ii) Managerial

	Insignificant				**Most Critical**
Factors	**1**	**3**	**5**	**7**	**9**
Long distance monitoring	☐	☐	☐	☐	☐
Culture gap	☐	☐	☐	☐	☐
Change in future business development direction	☐	☐	☐	☐	☐
miscommunication	☐	☐	☐	☐	☐

(iii) Physical Environment

	Insignificant				**Most Critical**
Factors	**1**	**3**	**5**	**7**	**9**
Flooding	☐	☐	☐	☐	☐
Fire	☐	☐	☐	☐	☐
Temperature	☐	☐	☐	☐	☐
Humidity	☐	☐	☐	☐	☐

(iv) Human

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
Wong estimation/judgment	☐	☐	☐	☐	☐
Ignorance and negligence	☐	☐	☐	☐	☐
Lack of skill and knowledge	☐	☐	☐	☐	☐
Loyalty	☐	☐	☐	☐	☐

(v) Security

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
Security of IT system	☐	☐	☐	☐	☐
Anti-theft control	☐	☐	☐	☐	☐
Loss of goods	☐	☐	☐	☐	☐

(vi) Financial

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
Delay in customer payment	☐	☐	☐	☐	☐
Poor financial planning	☐	☐	☐	☐	☐
Compensation	☐	☐	☐	☐	☐

(vii) Market

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
Competition	☐	☐	☐	☐	☐
Loss of key customers	☐	☐	☐	☐	☐
Price fluctuation	☐	☐	☐	☐	☐

(viii) Regulatory

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
Import/export regulation	☐	☐	☐	☐	☐
Quality standard update	☐	☐	☐	☐	☐
Labor law	☐	☐	☐	☐	☐

(ix) Operations

	Insignificant				Most Critical
Factors	**1**	**3**	**5**	**7**	**9**
IT system breakdown	☐	☐	☐	☐	☐
Information accuracy	☐	☐	☐	☐	☐
Congestion	☐	☐	☐	☐	☐
Damage in equipment	☐	☐	☐	☐	☐
Cargo damage	☐	☐	☐	☐	☐
Power failure	☐	☐	☐	☐	☐
Labor injuries	☐	☐	☐	☐	☐
Delay in cargo delivery	☐	☐	☐	☐	☐
Inventory inaccuracy	☐	☐	☐	☐	☐
Quality control	☐	☐	☐	☐	☐
Unexpected order change	☐	☐	☐	☐	☐

Section 3 Risk assessment criteria

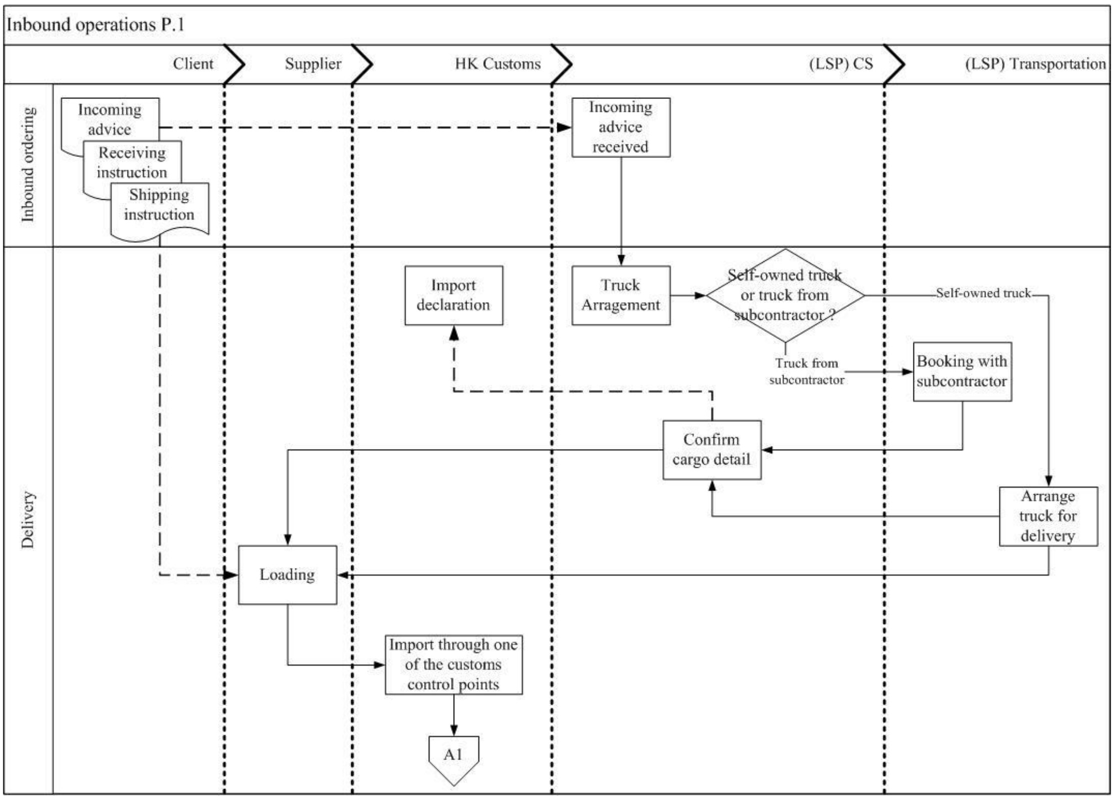
Please indicate the degree of importance of risk assessment criteria when handling customer orders in your company.

Criteria	Absolute Importance		Essential or Strong Importance				Equal					Essential or Strong Importance			Absolute Importance			Criteria
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Efficiency
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Productivity
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Time Wasting
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Quality
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Reputation
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Financial Loss
Cost	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Productivity
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Time Wasting
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Quality
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Reputation
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Financial Loss
Efficiency	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption

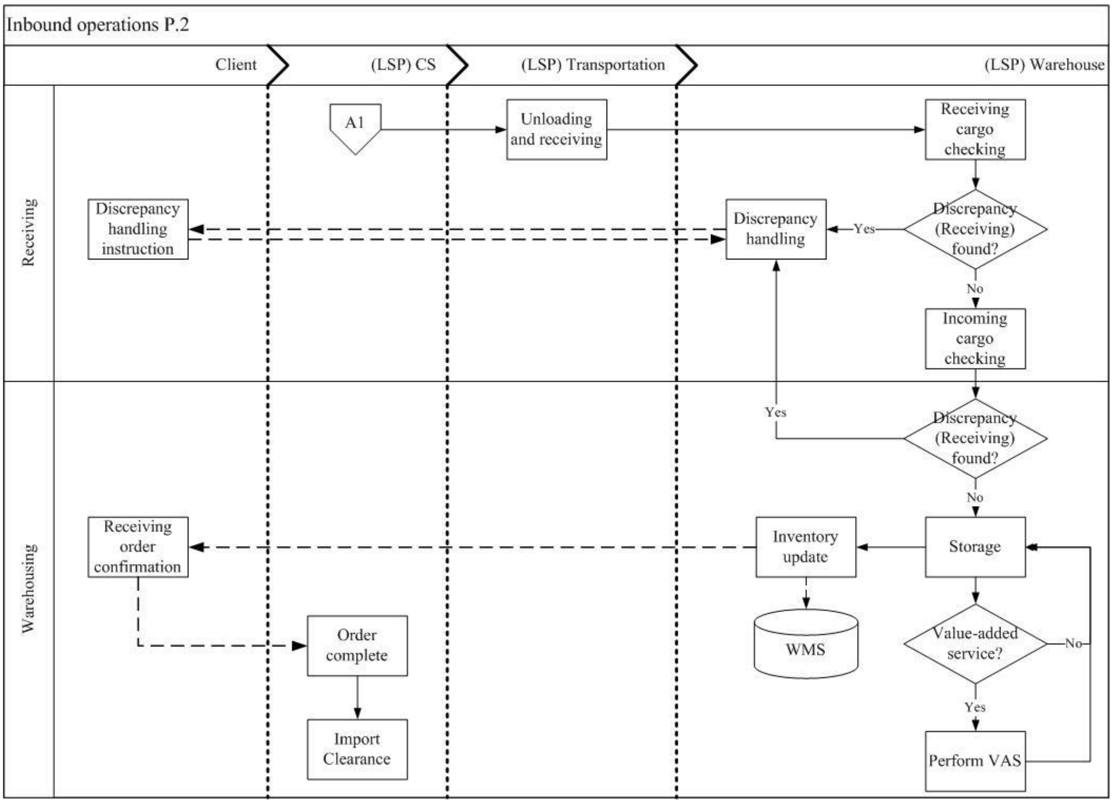
Criteria	Absolute Importance		Essential or Strong Importance					Equal					Essential or Strong Importance		Absolute Importance		Criteria
Productivity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Time Wasting
Productivity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Quality
Productivity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Reputation
Productivity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Financial Loss
Productivity	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption
Time Wasting	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Quality
Time Wasting	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Reputation
Time Wasting	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Financial Loss
Time Wasting	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption
Quality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Reputation
Quality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Financial Loss
Quality	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption
Financial Loss	9	8	7	6	5	4	3	2	1	2	3	4	5	6	7	8	9	Interruption

-------- THANK YOU ---------

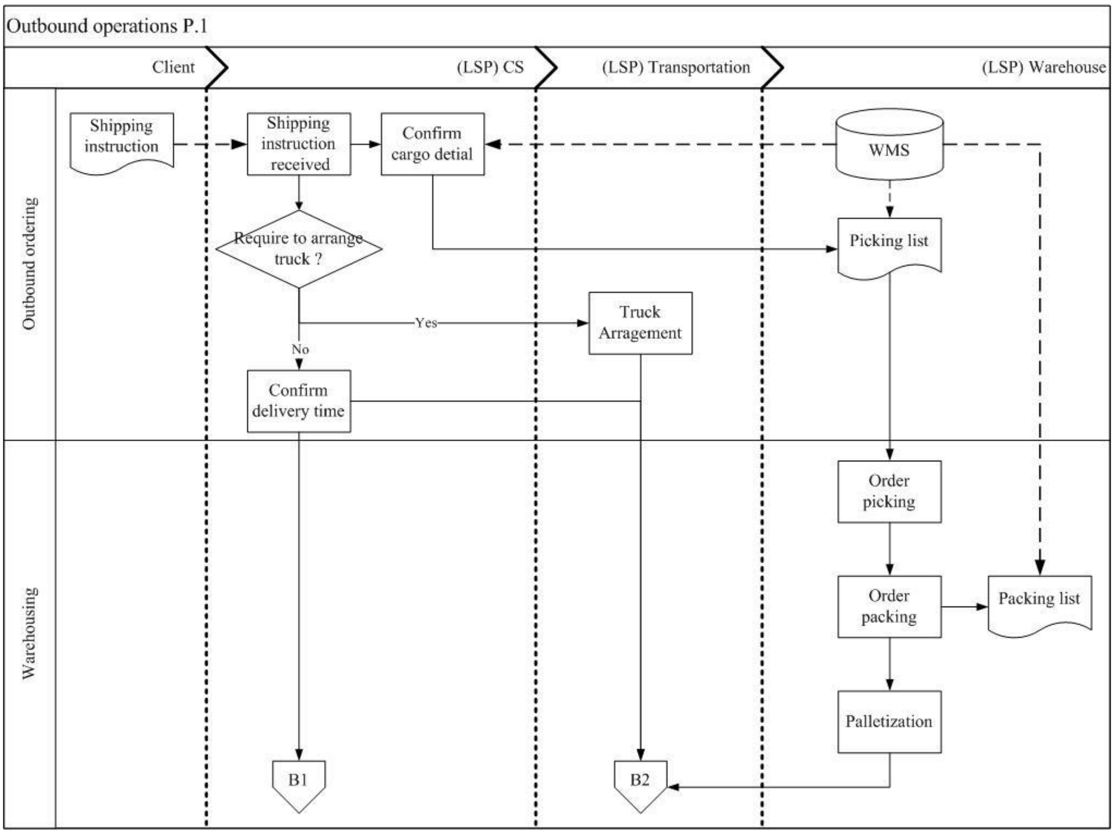
Appendix B. Flow of Inbound and Outbound Logistics Operations



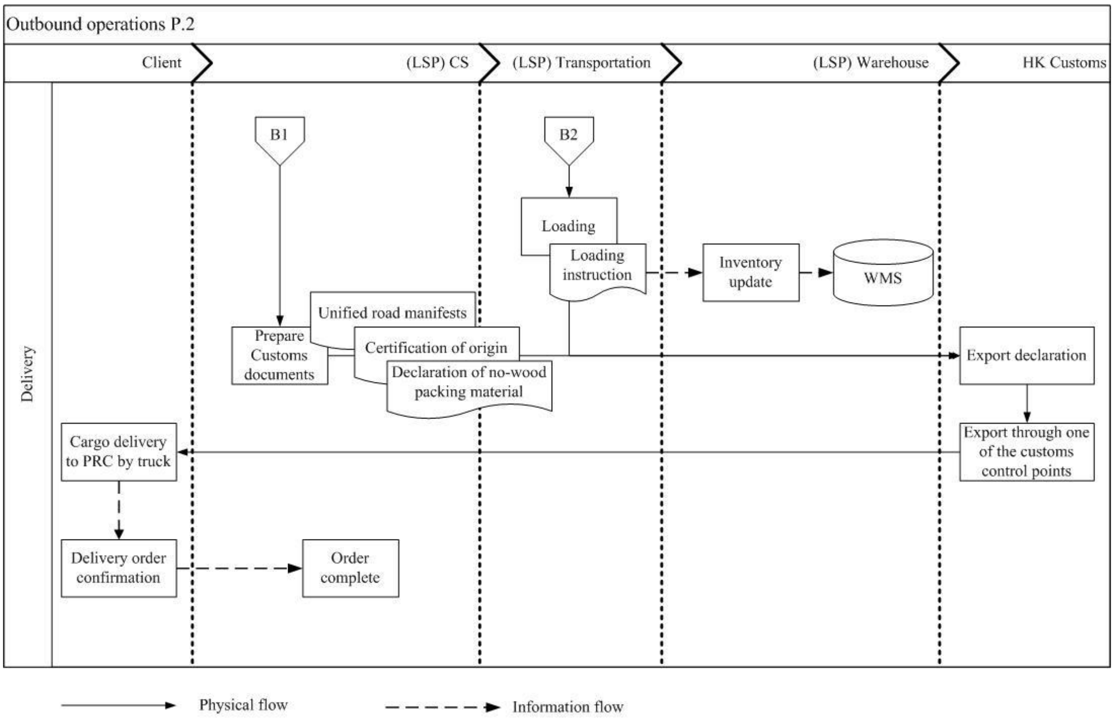
Inbound operations flow – ordering and delivery



Inbound operations flow – receiving and warehousing



Outbound operations flow – ordering and warehousing



Outbound operations flow – delivery