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A knowledge-based logistics operations planning system for mitigating risk in warehouse order fulfillment

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ABSTRACT

Customer orders with high product varieties in small quantities are often received by the logistics service providers with requests for customized value-added services and timely delivery, so the warehouse has to plan its logistics strategy in such a way that it can effectively maintain the quality of its services. In addition, they have to pay attention to the possible risks that may occur during the logistics operations so as to prevent loss if they fail to deal with the problems and risks properly. 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 logistics service providers. The system makes use of Radio Frequency Identification technology to collect real-time logistics data. Analytical hierarchy processes and case-based reasoning are integrated into the system. These help to categorize the potential risk factors considered by customers and formulate the logistics operations strategy, respectively, as the different product characteristics and order demands are taken into consideration. The searching performance in case-based reasoning is enhanced by the iterative dynamic partitional clustering algorithm. After conducting a trial run in the case company, the result shows that there is significant improvement in case retrieval time and in solution formulation.

1. Introduction

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. Since the decision making process is one of the most complicated processes involved in warehouse operation, the fulfillment of customer orders in the warehouse is challenging as it is necessary 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 by the possible risks that may occur during the logistics operations. Thus, 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. However, only a small number of research studies are reported to have taken risk control into consideration during the decision making process in the area of warehouse operations.

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 the quality of customer service. 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. Bias and subjective judgment may result in an inaccurate decision. The lack of a resources allocation strategy may mean that no suggestions regarding the allocation of resources are provided on how to handle the order when a possible risk occurs. This might result in improper use of resources and loss of customer satisfaction.

The 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 Radio Frequency Identification (RFID) technology and artificial intelligence techniques, i.e. analytical hierarchy process (AHP) and case-based reasoning (CBR), to collect real-time warehouse data and relevant logistics data for providing knowledge support in decision making when

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operational 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. This paper is organized as follows. In Section 2, the literature related to risk and warehouse management, RFID, AHP and CBR technique is studied. Section 3 presents the system architecture of K-LOPS. In Section 4, a case study is presented to demonstrate the implementation procedures of the system. In Section 5, the results of implementing the system are discussed and a conclusion is drawn in Section 6.

2. Literature review

2.1. Warehouse operations and risk management

Risk is defined as an exposure to the possibility of negative 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 (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 increase in 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 aim at minimizing, monitoring and controlling the probability and impact of unfortunate events (Carole and Olivier, 2012). Responses are given to mitigate the effect of or prevent the occurrence of risk.

The warehouse operations involve a number of processes which increase the complexity of effective planning. Depending on the type of warehouse and product to be handled, the attention paid and the customer requirements are also different. Warehouses handling general cargo may focus on the efficiency of order fulfillment, while providing good quality control is important for a warehouse where special goods that are sensitive to temperature are handled. Thus, product characteristics may sometimes impose constraints and uncertainties on warehouse operations planning. Concerning sustainable development of a business, it is very important to implement risk management that assesses risks faced by the organization and develop contingency plans to mitigate the consequences 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 relativity of risk, and acceptability of risk. 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 those assessing the risk may lack sensitivity when estimating the probability of possible outcomes induced by the risks. In some cases, an organization may tend to focus on critical performance rather than risk outcomes. Therefore, it is very important for a company to adopt a risk management model and approach with a quantitative model and qualitative plans to assess risks.

2.2. Artificial intelligence techniques in decision support

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 result in different rankings (Ishizaka and Labib, 2011). With the developed hierarchy, the company can 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. (2008a) proposed an integrated AHP–DEA approach to evaluate the risks of bridge structures so as to determine the maintenance priorities of the bridge. To sum up, AHP is able to assess the defined alternatives effectively, based on various decision support criteria by conducting pair-wise comparisons. Therefore, it is useful to prioritize risk factors in a systematic way when making use of the quantitative approach which can increase the accuracy of the assessment.

Case-based reasoning (CBR) is one of the well-known knowledge repository and learning techniques that are widely adopted in decision making based on previous experience. It makes use of a similar previous experience to provide decision support to a new problem instead of an intuitive estimation approach (Wang et al., 2008b). By using CBR, the solution obtained in a past case is expected to be useful in solving a new problem (Craw et al., 2006). The CBR cycle comprises four processes: retrieve, reuse, revise and retain where case retrieval is an important step to search for appropriate similar cases (Aamodt and Plaza, 1994). Clustering is one of the retrieval methods that can reduce searching time by grouping the related information into the same cluster (Kang et al., 2007). With the use of the clustering approach, the performance of the retrieving process is increased in terms of time, efficiency and effectiveness (Can et al., 2004). Given that the clustering result is sensitive to 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 a near-optimal cluster result to be produced. The results show that the GA k-means clustering method can improve segmentation performance compared with other typical clustering algorithms (Kim and Ahn, 2008).

2.3. Automatic data capturing technologies

Furthermore, to enhance the speed and accuracy of information sharing, automatic data capturing technologies are required to increase the visibility of the operation. Two commonly used data capturing technologies in use today, i.e. the bar-code system and the Radio Frequency Identification (RFID) system, are introduced. In the last decade, the barcode was a popular technology that was 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. Although barcode technology is considered fully developed, there are still problems and limitations when using the barcode system (Jones et al., 2004). Resulting from the increasing complexity of data and information required in the operation process, the barcode system is no longer adequate as its storage capacity is limited. 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. Because of the limitations of the bar-code system, a number of research papers have been published advocating the adoption of Radio Frequency Identification (RFID) technology instead of the bar-code system for data capturing (Wyld, 2006). 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 the 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). Regarding RFID in the warehousing industry Chow et al. (2007) proposed an RFID-multi-agent based process knowledge-based system which has the ability to solve dynamic logistics process management problems according to the real-time process status collected. Wang et al. (2010) integrated RFID technology into the warehouse management system to improve operation efficiency and enhance the utilization of warehouse capacity in the tobacco industry. Lao et al., 2012 applied RFID when capturing real-time data to facilitate the food safety control activities in receiving areas of warehouses. The result showed an improvement in efficiency and timeframe needed for the actions.

To summarize, to provide quality services and maintain customer satisfaction, logistics companies not only need to manage the warehouse operations in a knowledgeable and effective manner, but should also take into consideration the potential risks that may have a negative impact on the warehouse. Therefore, in order to fulfill customers' demands and provide an ability to capture real- time data, assess risk factors, and use the knowledge gained for 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.

3. Knowledge-based logistics operations planning system

In this section, 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. Fig. 1 shows the system architecture of 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 the AHP 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.

3.1. 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 from the transmission of radio signals. A RFID tag is attached to each SKU to record its identity and exchange data with the RFID reader. The reader with 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 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. The warehouse has to handle various types of SKU so the type of data required varies accordingly. So, the settings of the RFID equipment are adjusted 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 are stored in the tag during the inbound operations such as SKU number, type of SKU, physical dimension of SKU and quantity. This type of data is usually captured by passive tags. 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, and hence they are captured by semi-passive RFID tag with temperature and humidity sensors. With such information, the storage conditions for each SKU can be detected in real-time.

In summary, by adopting RFID technology in the Real-time Data Collection Module of K-LOPS, 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. Besides, it should be noted that 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.

3.2. Warehouse Risk Assessment Module (WRAM)

Due to the uncertainty and rapidity of changes in the business environment, the performance of warehouse operations is affected by the logistics strategy planning process. It is also necessary to pay attention to the possible risks that may occur during the logistics operations. Effective risk management brings the advantage of improved efficiency to the warehouse, improves financial performance and increases competitive advantage. It enables the warehouse managers to handle risk efficiently despite higher

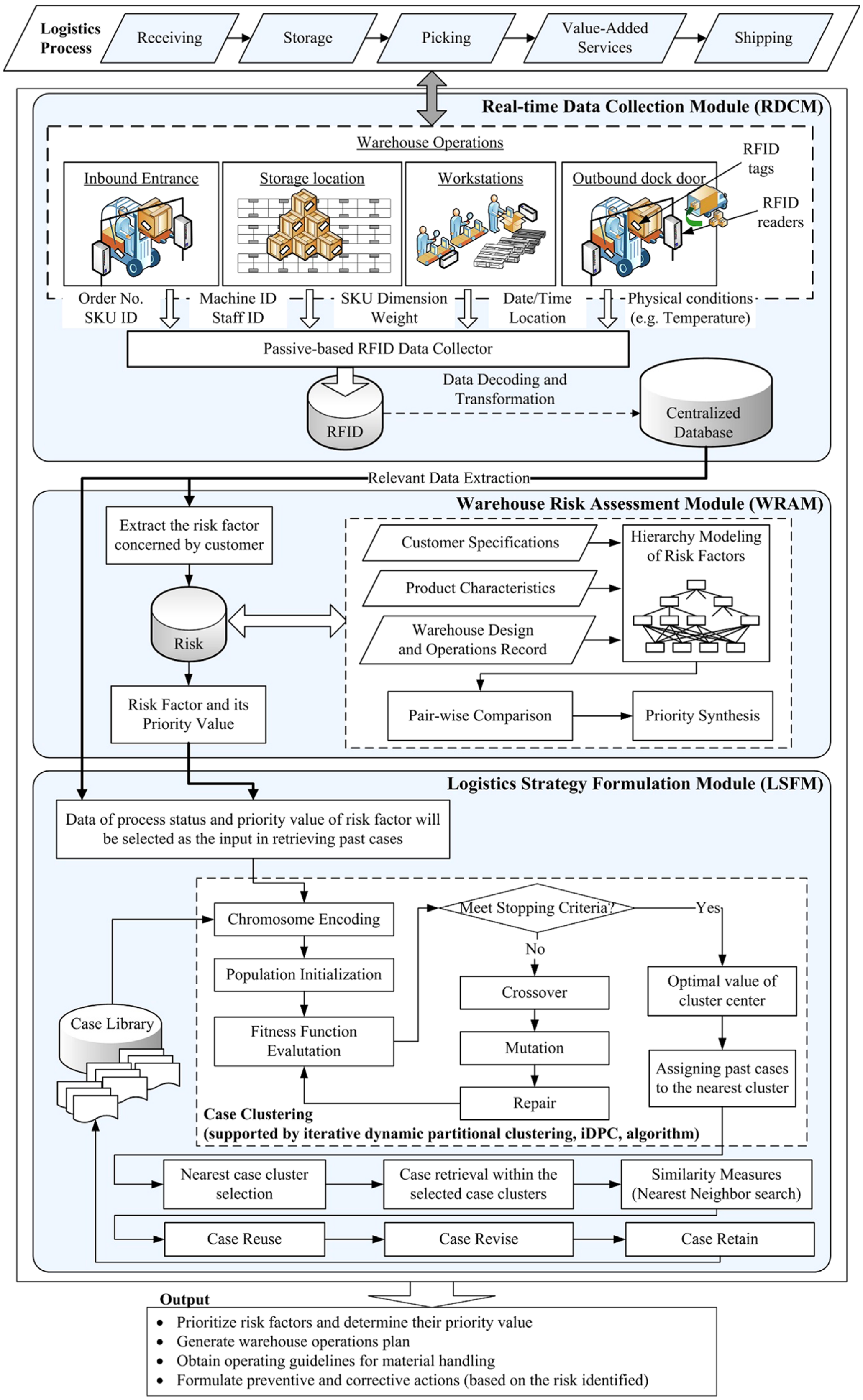

Fig. 1. System architecture of K-LOPS.

severity of risks, and to recover rapidly after a disruption. 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 when planning warehouse operations.

In this module, the risks that may affect warehouse operations are analyzed in order to identify the major types of risk that are of concern to 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 disruption 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, a discussion is conducted by the warehouse management team to identify the possible risks that the warehouse may encounter and to share experience in managing 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 consequences of disruption in the warehouse and determine the importance of risk factors and sub-risk factors. With such information, AHP is adopted to determine the weights of the risk factors.

In summary, the AHP model is used to evaluate the type of risks that concerned by the customer and the warehouse representatives. In fact, as different products have their own characteristics, the risk factors concerned when handling each product may vary. The risk factors are first defined according to the product characteristics, customer specifications and warehouse reliability. After that, the system would prioritize the type of risks of concern to both the warehouse manager and customer in handling a specific type of product. Then, the AHP process is performed once when the customer confirmed the service requirement with warehouse representative. The process is carried out once which provides a comprehensive approach for the service provided. On the hand, the type of risk factors can be adjusted from on the list of potential risks, which provides flexibility to the customers and warehouse representatives when formulating appropriate logistics operations.

3.3. 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 dynamic approach in considering multiple features at the same time, the developed iDPC algorithm is adopted 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. Fig. 2 shows the mechanism of the iDPC in LSFM and the details of the iDPC algorithm can be referred to Lam et al. (2012).

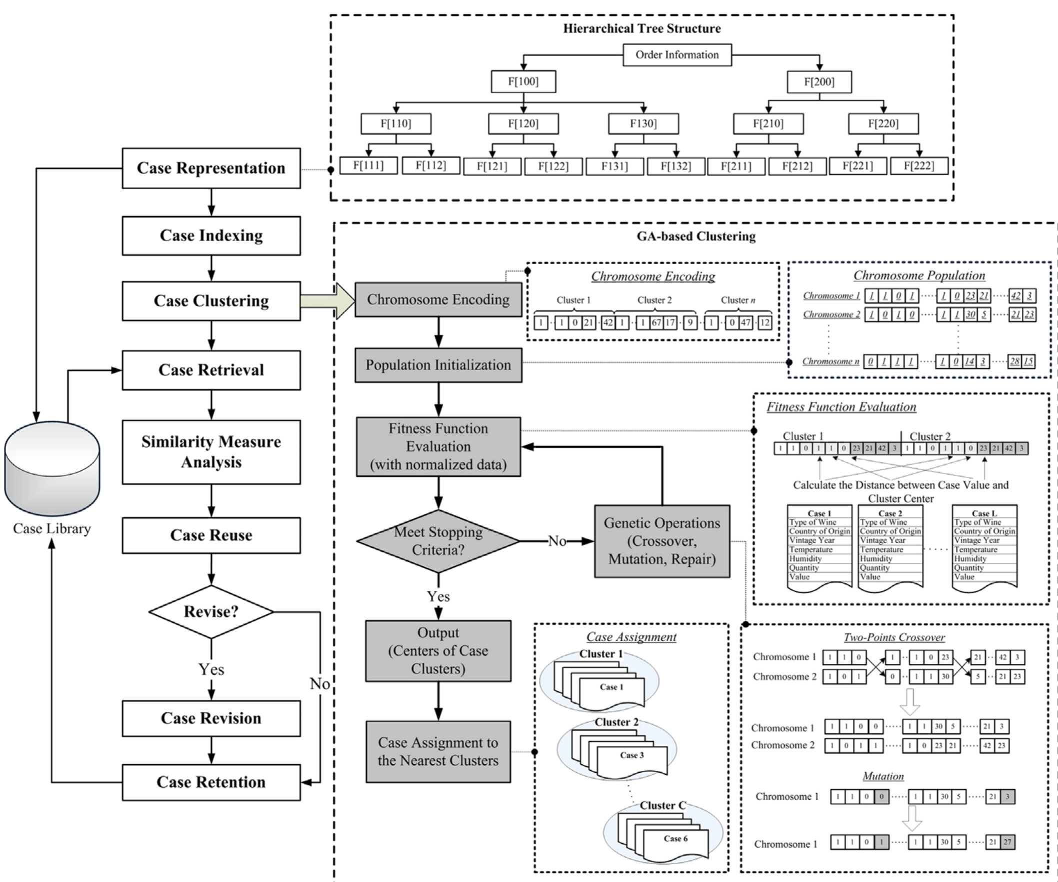

Fig. 2. Mechanism of iDPC in LSFM.

3.3.1. Case representation and indexing

The process starts by representing the past problem and its solution in a structural form. Key attributes and parameters in the warehouse operations process are identified after retrieving the past case. The key attributes identified are then represented by the construction of a hierarchical tree structure, as shown in Fig. 3. The structural representation of the order cases enables the relationship between dimensions and attributes to be presented so that the corresponding dimensions are known when making decisions.

$F_{[x_1x_2\ldots x_l]}$ is the generic form that represents all the case features included in the tree structure, while $V_{[x_1x_2\ldots x_l]}$ is the generic form that represents all the parameter values of the corresponding case feature, where F is the function of case feature in the hierarchical decision tree; V is the function of parameter value of the corresponding case feature; l is the lth hierarchy levels in the decision tree, $\forall l \in H$; x_l is the number of case attributes in the lth level of the hierarchical decision tree that belongs to the factor $F_{[x_1x_2\ldots x_{l-1}0\ldots0]}$, $\forall l \in H$.

3.3.2. Case clustering by iDPC algorithm

The iDPC algorithm is adopted in the case clustering process for classifying past cases into appropriate case groups. The development of the iDPC algorithm is based on the GA approach, so the chromosome is first encoded to represent the initial center of the case clusters. The length of the chromosome depends on the type and number of features present in the hierarchical decision tree. In fact, more than one tree structure can be used in representing the past cases. The generic form of the chromosome is shown as follows:

$$\left[\left[\bar{f}_{[x_1x_2\ldots x_H]}\bar{v}_{[x_1x_2\ldots x_H]}\right]^i\right]^j$$

where $\bar{f}_{[x_1x_2\ldots x_H]}$ and $\bar{v}_{[x_1x_2\ldots x_H]}$ are the value of attributes in the case-feature (F) region and parameter-value (P) region of the cluster respectively, i refers to the ith case cluster in the gene matrix, $\forall i \in M$ while j is the jth chromosome in the gene matrix, $\forall j \in N$.

Based on the generic form of the chromosome, the steps for classifying past cases into clusters using iDPC algorithm are as shown below

Step 1 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 adjusted distance error (ε'_{ik}) between the past case k and the cluster center i, $\forall k \in P, i \in M$ where $\varepsilon'_{ik} = \varepsilon_{ik} \times A_s$. 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. The amendment factor A_s is included to adjust the combination effect with an increased number of case attributes when more than one case attribute is considered at the same time.
Step 4 Compare the calculated distances (ε'_{ik}) 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 $\left(\varepsilon'^{\min}_{ik}\right)$.
Step 6 Calculate the fitness value for the chromosome by summing the minimum adjusted distance error for all cases, Minimize$\lambda = \sum_{i \in M}\sum_{k \in P} \varepsilon_{ik} \times A_s \times z_{ik}$.
Step 7 Repeat Step 2–6 after the renewal of the mean values of cluster centers.
Step 8 Stop the process when the termination criteria is reached.

3.3.3. Case retrieval and reuse

After the case-clustering processes, the case cluster that best fits the needs of the new problem is retrieved. The potentially useful cases in the cluster are then compared with the new problem using the nearest neighbor approach. Given that a case consists of textual and numeric feature information, the similarity measures for textual features are determined by the construction of similarity tables while the similarity measures for numeric features are calculated based on the distance of numeric attributes between past cases and a new order. Thus, the cluster retrieval priority index, I_{CR}, for retrieving a similar case cluster is calculated

$$I_{CR} = \frac{\sum_{l \in H} w_{[x_1x_2\ldots x_l]} \times sim(Z_i, T_{new})}{\sum_{l \in H} w_{[x_1x_2\ldots x_l]}}, \ \forall i \in M$$

where $w_{[x_1x_2\ldots x_l]}$ is a weighting factor that indicates the importance of the case attribute $F_{[x_1x_2\ldots x_l]}$; sim is the similarity function; Z_i is the center of the ith case cluster; and T_{new} is the attributes of the new case.

The weighting factor, $w_{[x_1x_2\ldots x_l]}$, considers the importance of the case attribute in searching for useful past cases. The case attribute with a higher value of weighting factor shows the attribute has higher preference for being 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 $\bar{f}_{i[x_1x_2\ldots x_l]} = 0$,

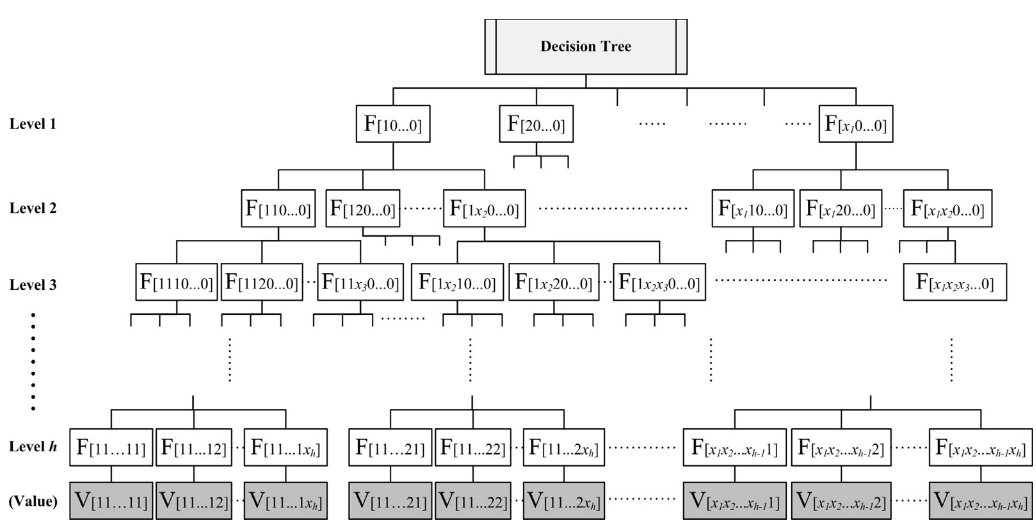

Fig. 3. The generic structure of a hierarchical decision tree.

which concludes that the case attribute $F_{[x_1 x_2 \ldots x_l]}$ is not included as the center of cluster i.

In the retrieved ith cluster, potential past cases are ranked in descending order according to the priority index I_P. I_P measures the similarity between the kth past case in the cluster i and a new case. The case with the 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 solving the new problem. All the past cases in the retrieved case cluster are then ranked in descending order based on their similarity with the new order. The past case which has the highest similarity value is then retrieved and reused as the solution of the new problem. The content of the solution includes suggested workflow, guidance and KPIs for measuring the performance of warehouse operations which can be further modified to suit the needs of the current situation.

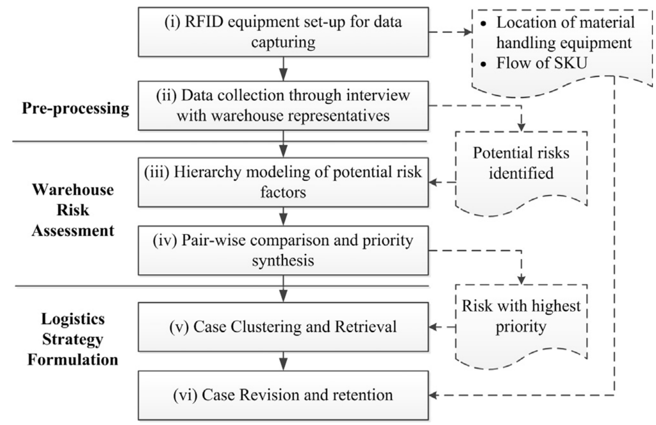

Fig. 4. Implementation procedure of K-LOPS in KY Logistics Ltd.

4. Case study

The logistics industry is one of the four pillars that support the economy of Hong Kong. In 2012, according to the Hong Kong Census and Statistics Department, Trading and logistics accounted for 25.5% of GDP in terms of value-added in 2010. In the last decade, there has been a dynamic change in business logistics requirements. Traditionally, the logistics hubs of Hong Kong mainly handle mainland China's import/export business, especially the Pearl River Delta area. Following rapid economic development, Hong Kong has gradually developed itself to a premier international transportation and logistics hub for the Asia-Pacific region. With internationalization, global competition, cost inflation and higher customer expectation, Third-party logistics providers (3PL) play a crucial role in the logistics development of Hong Kong.

KY Logistics Ltd. is a global third-party logistics service provider with its headquarters based in Hong Kong. It aims at providing the best logistics solutions with high reliability and flexibility to make customers successful by creating value for them. Its core business activities include integrated logistics, international freight forwarding and supply chain solutions. With more than 2000 employees, a transport fleet of over 300 vehicles and logistics facilities of about 650,000 m^2, KY Logistics Ltd. is serving more than 500 companies in Hong Kong. The target market segments are electronics and technology, fashion and lifestyle, food and beverage, and, fast moving consumer goods (FMCG). As the company is required to handle large amount of orders for diversified products, any wrong decision made in logistics operations would affect the warehouse performance and the quality of customer service. Therefore, KY Logistics Ltd. has decided to adopt the K-LOPS to assist the planning process for handling outbound operations.

The implementation procedure of the K-LOPS in KY Logistics Ltd. is presented in Fig. 4. The six steps are (i) RFID equipment is set-up for data capturing, (ii) data is collected through interviews 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. The details of each step have been presented from Section 4.1–4.6. Through the data collected by the RFID equipment, the location of material handling equipment and the flow of SKUs can be obtained. This information will be further used to revise the solution of a case based on a real-time situation in the warehouse. After that, risks faced by the customers, with respect to the type of product to be handled, are identified. These are taken into consideration when generating new solution plans.

4.1. RFID equipment set-up for data capturing

To cope with the implementation of the K-LOPS in the warehouse of KY Logistics Ltd., RFID equipment, including RFID tags and readers, has to be set up to capture the real-time data during the operations. In this study, passive tags are used to capture the static data. Firstly, passive RFID tags are stuck onto each carton when they arrive at the warehouse, which records the item ID, product information and its storage location. Besides, the SKUs to be handled are general good which do not require special care on temperature and humidity and hence, no dynamic data capturing is required. The tags are also attached to the material handling equipment, i.e. forklifts, to identify them and their working locations. Fig. 5 shows the passive RFID tags on the cartons and forklift. Then, the passive RFID readers are mounted in major passage ways to keep track of the movement of cargo and material handling equipment. As shown in Fig. 6, the passive RFID readers are mounted at the entrance to the dock door and to 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 pallets are transmitted to the reader when the pallets pass through the warehouse entrance and the dock door. Warning is given if any carton is incorrectly packed or loaded on the container.

4.2. Data collection through interview with warehouse representatives

In order to have a better understanding about the current situation of the warehouse, interviews with the customers and representatives of the warehouse of KY Logistics Ltd. 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 causes of the risks and solutions, are prepared for warehouse representatives. Table 1 shows a description of the risk factors of concern to the warehouse and to 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.

Fig. 7 summarizes the possible risks and their sub-risk factors identified through the interviews. Take the information inaccuracy in operations risk as an example, information inaccuracy occurs

Fig. 5. Passive RFID tags on cartons and forklift.

Fig. 6. Passive RFID reader on the dock door and on the entrance of the warehouse.

Table 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)	This refers to poor managerial skills of senior management and insufficient conceptual skills to solve the problems and complex situations related to the warehouse
Physical environment risk (C)	The physical environment such as natural disasters would affect warehouse operations resulting in interruption of service, damage to cargo and to warehouse facilities
Human risk (D)	Warehouse labor/staff with insufficient knowledge to carry out the logistics services
Security risk (E)	Security concerns such as anti-theft facilities and security of IT system are important to protect the customers' goods, especially high value goods, and ensure the safety of confidential customer information
Financial risk (F)	This 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 change in regulations and policy would bring pressure and risk when the warehouse tries to fit in with the new environment
Operations risk (I)	This results from the breakdown of internal procedures, systems and people, when the factors directly affect the process of internal warehouse operations

mainly due to human error during manual data entry. Warehouse operators have to ensure the warehouse operations such as delivery time, order quantity and goods are correct before the warehouse process starts. As the data is entered manually, the occurrence of transaction information inaccuracy, inventory information inaccuracy or ordering information inaccuracy may lead to time consuming in correction and delay in warehouse operation.

4.3. Hierarchy 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 of disruption without any specific details of the risk and because the description of risk factors is extensive, only consequence/severity is considered as a criterion to estimate the impacts. Fig. 8 shows the 3-level hierarchical structure for determining the importance of the risk factors.

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. Fig. 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 show the details considered that are related to the factors of operations risk.

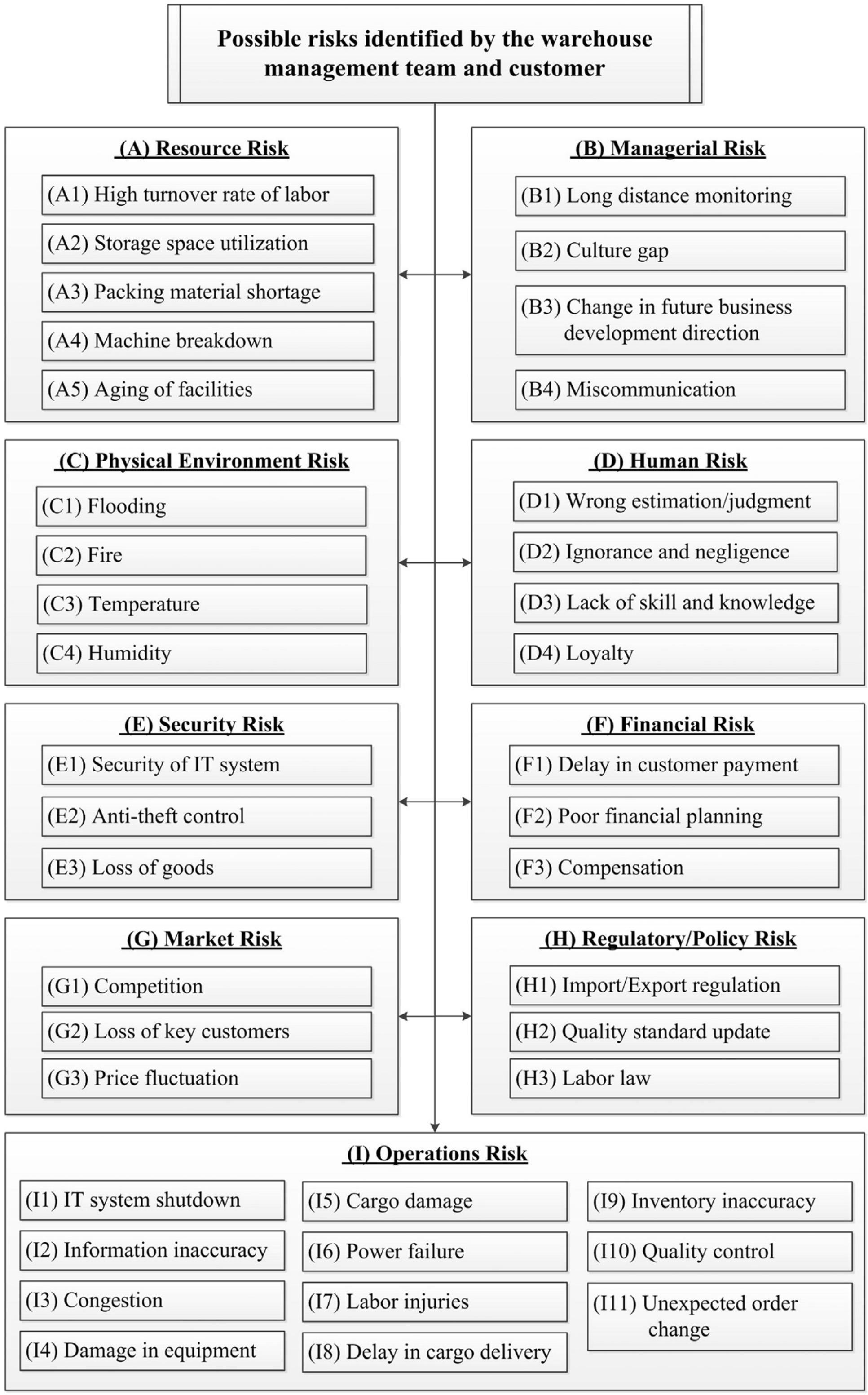

Fig. 7. Possible risks and sub-risk factors identified through interviews.

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. This 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 during which 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.

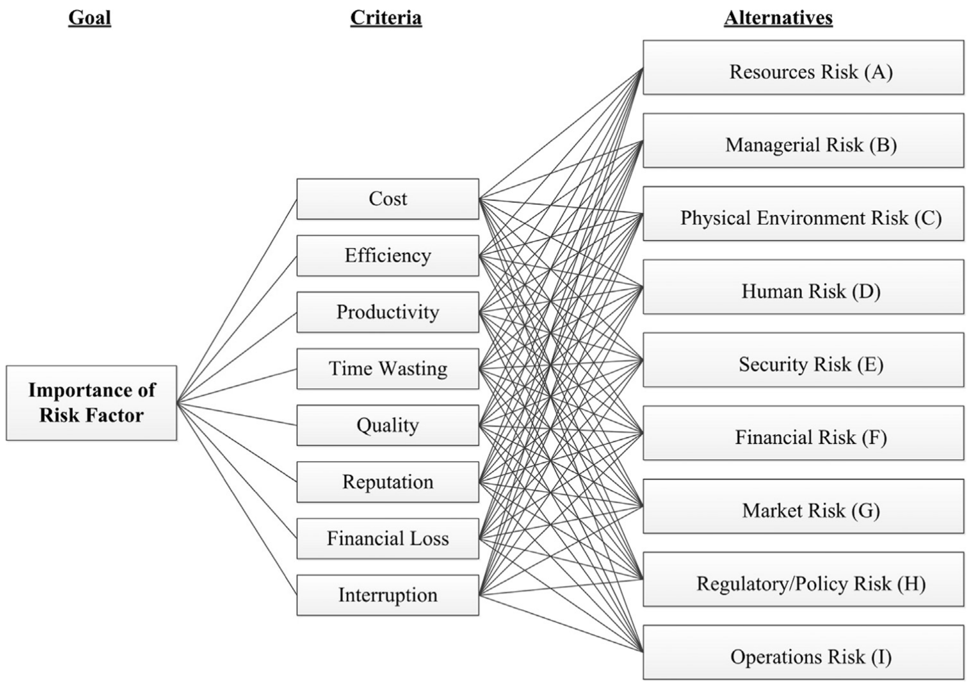

Fig. 8. Hierarchy structure for determining the importance of risk factors.

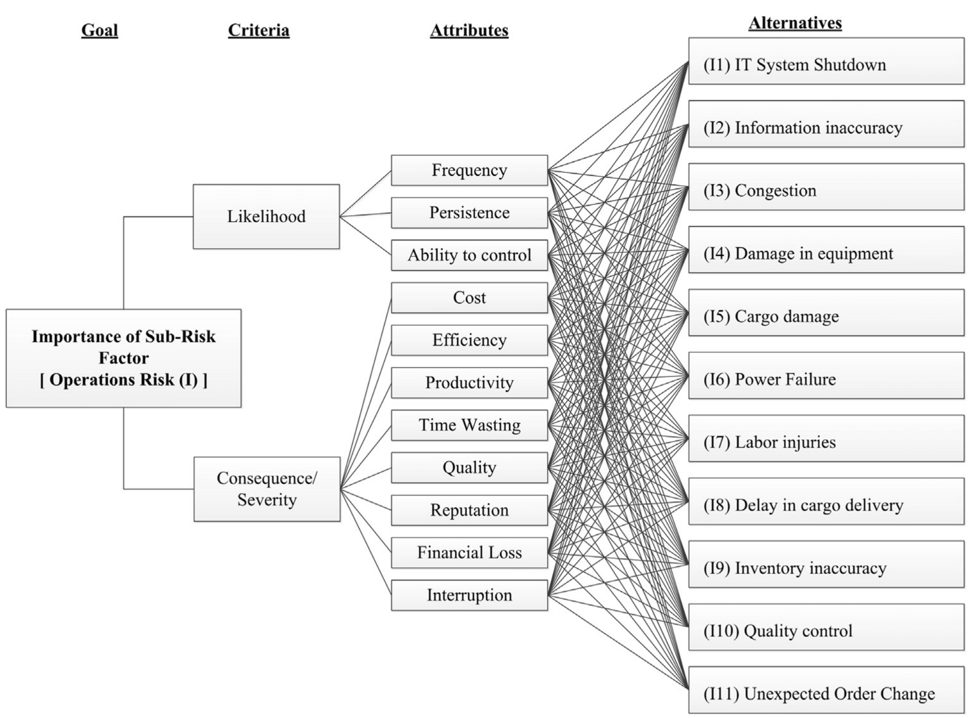

Fig. 9. Hierarchical structure for determining the importance of sub-risk factors.

4.4. Pair-wise comparison and priority synthesis

Based on the opinion of the customers and representatives of the warehouse of KY Logistics Ltd., a list showing all potential risks are prepared. Pair-wise comparison is then conducted once the customer confirmed the order specifications with the warehouse manager. They have to compare each alternative based on the criteria of likelihood and consequence/severity, and assign the rating for the importance of each risk factor afterward. The importance of each risk factor is determined by the rating given for two criteria in pairs. Fig. 10 shows an example of pair-wise comparison for all risk factors, based on the criteria of cost. Take the first record as an example, a rating of “3' is given to financial risk than human risk, which indicates that, based on the criteria of cost, the financial risk is slightly important than the human risk. That is, when there is a fluctuation on cost, KY Logistics Ltd. would pay more attention to the financial risk that may affect the company performance than the human risk which mainly focuses on staffing issue of the company.

After comparing all the risk factors based on the defined criteria, the result of priority synthesis is obtained. Fig. 11 shows the result of priority synthesis for the importance of risk factors.

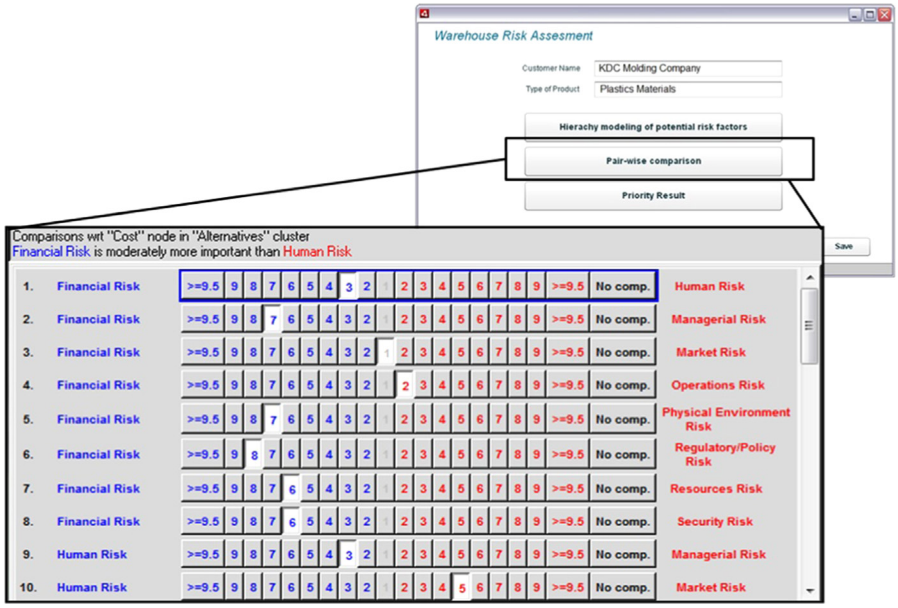

Fig. 10. Example of pair-wise comparison for all risk factors based on cost.

Referring to Fig. 11, it is found that the consistency ratio is 0.0906, which is smaller than 0.1, to ensure the consistency of subjective perception and accuracy of the relative weights. The eight criteria are ranked in descending order according to their weightings. After that, the overall results on importance of risk factors are obtained. The priority vector of the criteria is analyzed to find out the criteria that may have a 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 for 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 to the operation efficiency for maintaining customer satisfaction. As the criteria of cost, financial loss and efficiency have a higher impact when evaluating the risk factors, the priority vector of the risk factors is further investigated based on these criteria.

Among the criteria of cost, 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 is different, except that the operations risk has the highest weighting for all three criteria. Based on the individual analysis results, the warehouse management team of the warehouse of KY Logistics Ltd. should provide a continual improvement plan for mitigating the high potential risks according to the corresponding criteria. To obtain the overall result of the importance of the risk factors, the nine risk factors are compared using the criteria of cost, efficiency and financial loss. The results show that operations risk has the highest average weight of 23.2%. This 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. Fig. 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%.

4.5. Case clustering and retrieval

According to 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. 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. After the number of clusters is defined, 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. Fig. 13 shows the interface for retrieving case clusters based on order information. As shown in Fig. 13, details related to order information, risk considerations, product information and service requirement are input to the system for searching the past similar records. The system will then retrieve the case cluster with the highest similarity value based on the proposed iDPC algorithm. 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. 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.

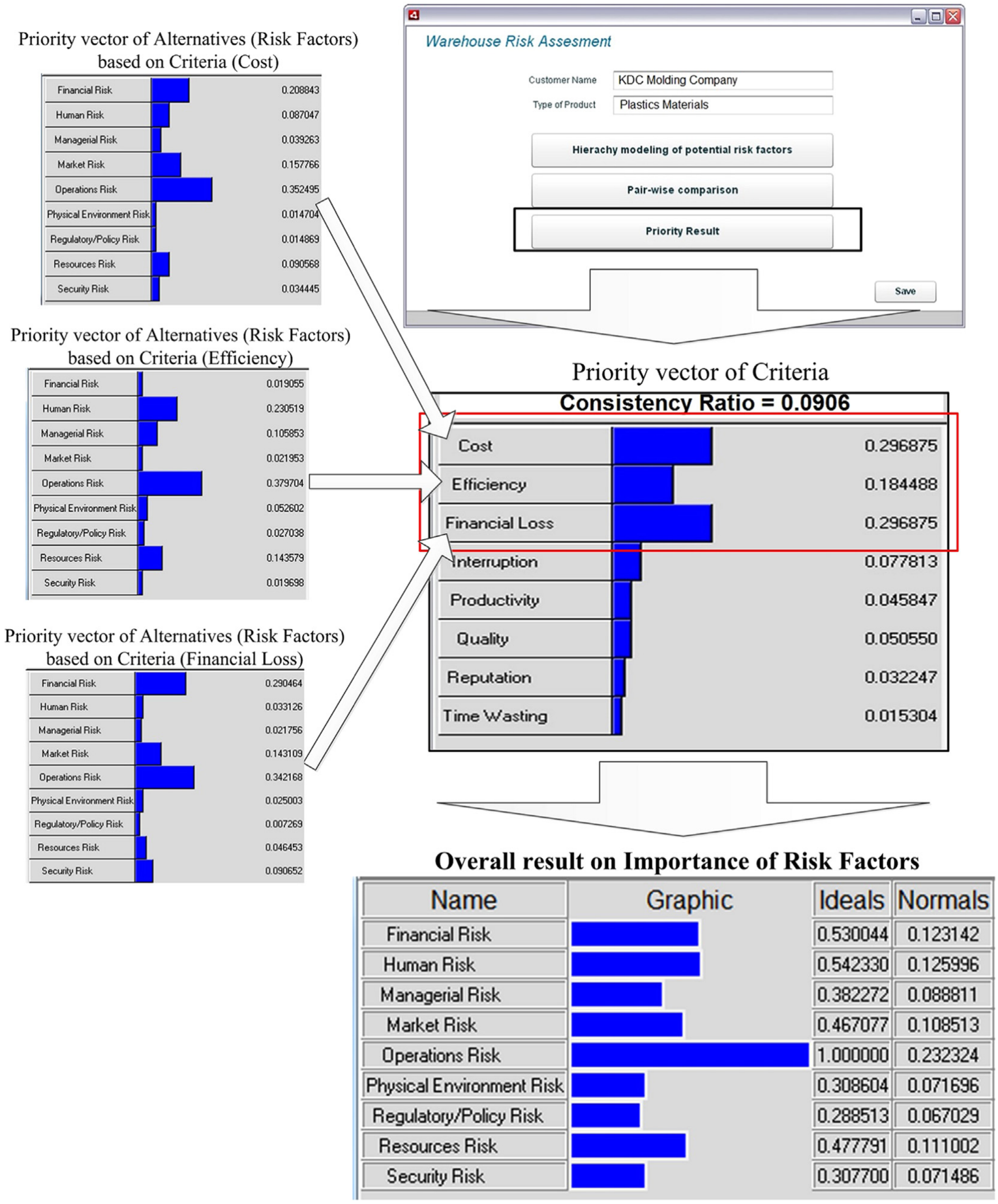

Fig. 11. Result of priority synthesis for the importance of risk factors.

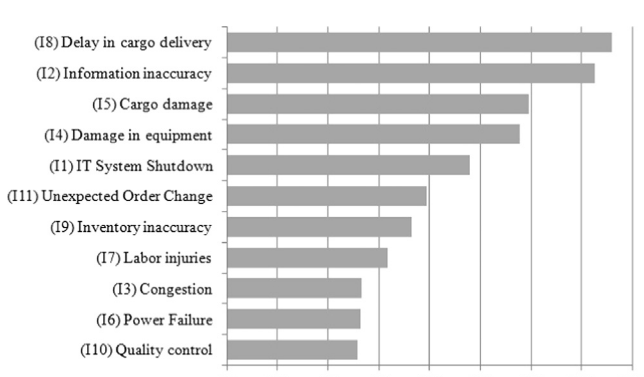

Fig. 12. Priority syntheses for the sub-risk factors of operations risk.

4.6. Case revision and retention

The solution of the past case with the highest similarity value is adopted for the current situation. It is possible for details of the solution to be modified according to the specific needs of the customer. The solution content includes the type of key performance indicators (KPIs) 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 them into the container. Once

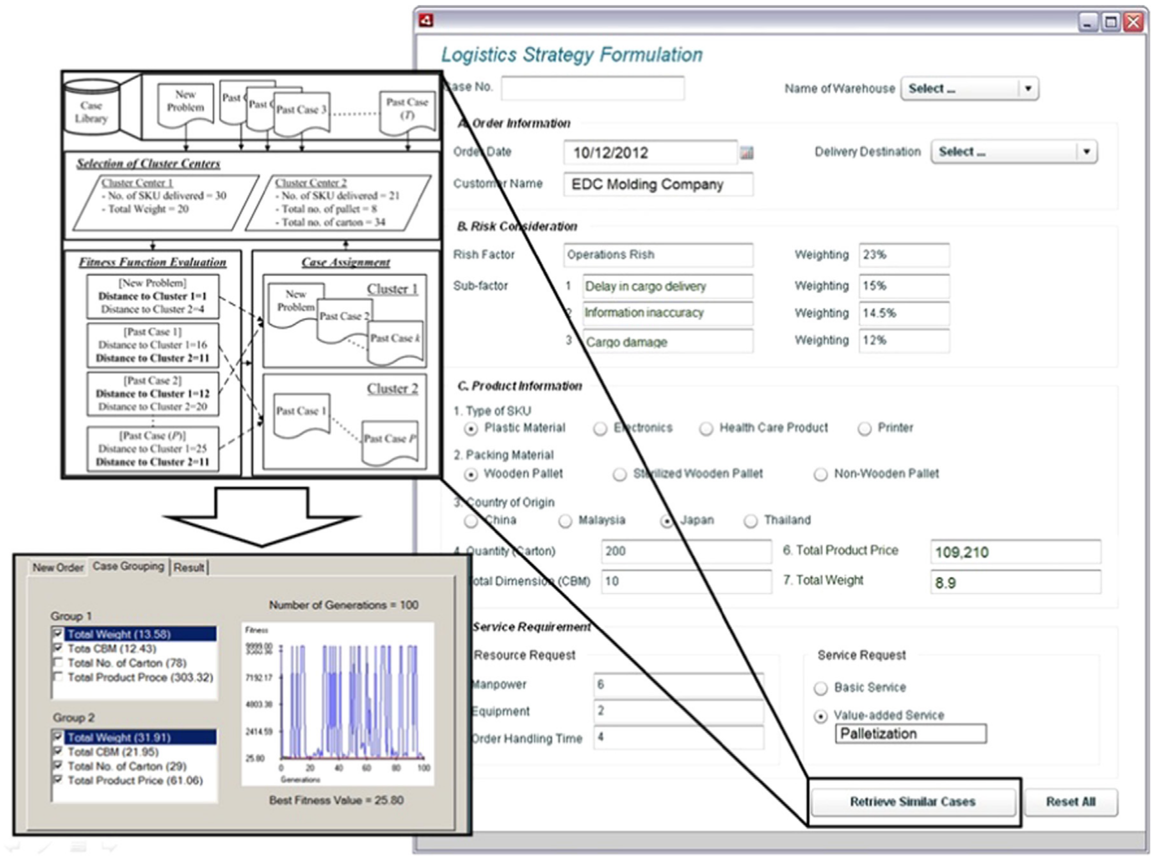

Fig. 13. Interface for retrieving case clusters based on order information.

the delivery truck is ready for loading, the forklift carries the pallet through the warehouse entrance and puts it onto the container. However, to fulfill specific cross border orders, KY Logistics Ltd. would like to pack the same type of product onto 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. Fig. 14 shows the logistics strategy formulation process based on the performance of the past case. By viewing the performance value, logistics strategy and workflow of past similar cases generated by the system, the warehouse should assign 6 labors to perform the task. The materials required and allocation of labors are specified as a reference to current situation. 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.

In summary, through the results obtained after launching the system in the case study, overall planning and operating efficiency were shown to be improved which proves the feasibility and usefulness of K-LOPS in actual warehouse operations environments, showing the relevance of the system to solve related industrial problems.

5. Results and discussion

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 expectations. 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. In this section, the results of adopting K-LOPS in the case company are first discussed to validate its feasibility and advantages. After that, the case retrieval time and fitness value between simulated annealing (SA) and iDPC algorithm are compared to examine the system performance.

5.1. Results of K-LOPS in the case company

5.1.1. Performance of K-LOPS in solution formulation

In order to measure the performance of K-LOPS in formulating an operations strategy based on past reference cases, a survey was designed to collect the feedback from selected customers and the system users, i.e. the 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 the 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 of acceptability before, and after, the implementation of the system, it allows the 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 when the retrieved past cases are

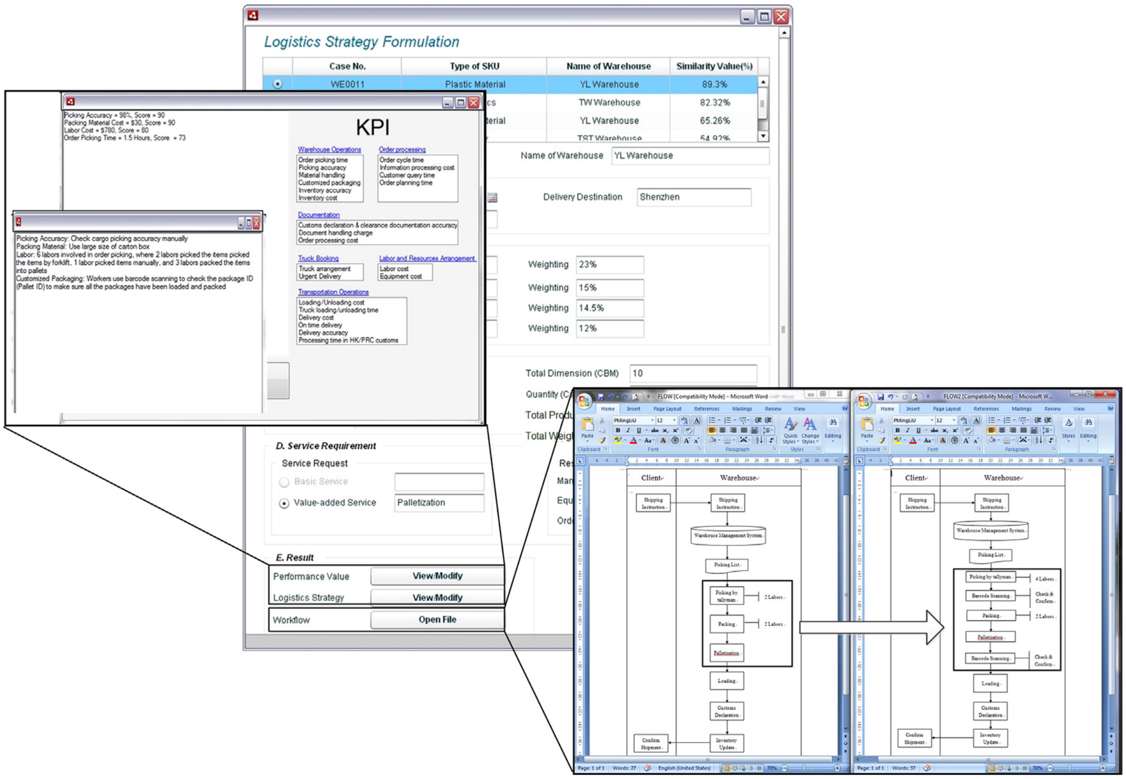

Fig. 14. Logistics strategy formulation based on the performance of a past case.

Table 2
Performance of K-LOPS in solution formulation.

	Before	After (with K-LOPS) (%)
Acceptability of logistics strategy suggested = *Number of orders 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 the strategies of which are adapted to the new order (without any change)/Total number of new order input*	–	45
Degree of customer satisfaction in the order fulfillment	68%	87

used directly for the new order, i.e. without any modification. Table 2 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%.

5.1.2. Performance in warehouse operation effectiveness

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 result of improvement in warehouse operation effectiveness is shown in Table 3. 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 3
Improvement in warehouse operation effectiveness.

	Before	**After (with K-LOPS)**	**Percentage of improvement (%)**
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

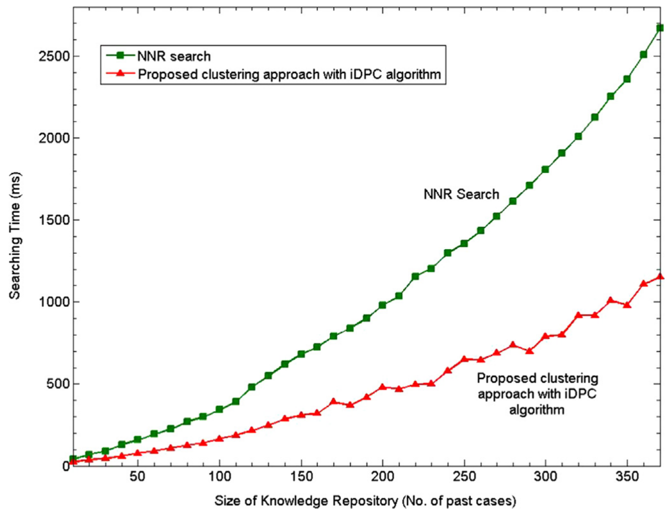

Fig. 15. Comparison of case retrieval time between NNR search and proposed case clustering approach with iDPC algorithm.

5.2. Discussion on system performance

5.2.1. 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. Fig. 15 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 a 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 the 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. This 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.

To summarize, the result of the experiment shows that the retrieval approach using an 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 time is reduced which shortens the decision making time in K-LOPS.

5.2.2. 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. For the clustering approach with SA, a cooling rate of 0.9 and 0.99 is used in performing the experiment. Fig. 16 shows the comparison of fitness value between SA and iDPC algorithm. 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 either approach after running for 800 generations.

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 Fig. 16, 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 that 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.

6. Conclusion

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. K-LOPS has been developed as a new framework to provide a decision support function in logistics strategy formulation by considering practical needs of LSPs. 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 is 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. In addition, there are various kinds of risks

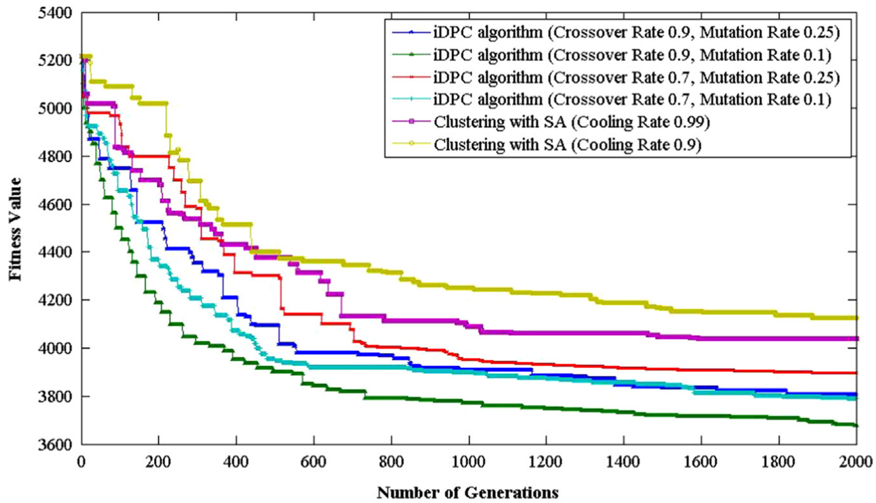

Fig. 16. Comparison of fitness value between SA and iDPC algorithm.

faced by the warehouse. There is no doubt that logistics companies would suffer losses if they are failed to tackle risks properly. To sustain the competiveness in warehousing industry, it is necessary to consider risks when planning logistics strategy. 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 needs to be formulated to fulfill the demand for high efficiency and quality in logistics services.

The proposed K-LOPS collects, analyzes and supports the logistics operation planning using RFID technology, AHP and CBR techniques respectively. Firstly, RFID technology is adopted to collect real-time data, and to monitor the real-time inventory status and physical storage conditions in a warehouse. It is the basis for providing the data for the other two modules. Secondly, the identified potential risk factors are categorized and presented in a hierarchical structure using AHP model. The model with procedures is considered suitable for warehouse risk assessment. Lastly, the risk with the highest importance level is included as an input parameter of CBR to formulate the logistics operations strategy. It is the key module in the system. RFID, AHP and CBR interactively monitor and optimize the operations flow in a logistics system. In addition, the mechanism of the newly designed iterative dynamic clustering (iDPC) algorithm with GA is also presented to enhance the searching performance of the case retrieval process. This unique feature of K-LOPS provides a value-added function to support and improve the logistics operations performance in the warehouse practically; thus customer satisfaction can be enhanced.

From the literature review, it is found that research related to the integration of these techniques to solve the strategy formulation problems while considering possible risks in a warehouse is extremely limited. This research study provides a feasible solution to improve the performance of an existing system by adopting hybrid techniques. To conclude, the major contribution of this paper 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. However, in the matter of performing a pair-wise comparison using AHP, a nine-point scale is used to reflect the customer expectation on the risk factor with respect to the criteria concerned based on their subjective judgment. To enable a comparison between variable types of parameters, future research will be focused to apply a fuzzy logic approach for comparing the importance with the fuzzy linguistic terms which are easily understandable by users. In addition, the proposed K-LOPS would be useful to those LSPs having similar needs, i.e. the need to improve planning process for handling outbound operations with large amount of orders for diversified products. However, the key characteristics and application of K-LOPS in managing the warehouse operations should be fine-tuned so as to its current situation. 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.

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