Design of a Case-Based Multi-Agent Wave Picking Decision Support System for Handling E-Commerce Shipments

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Abstract--**The emerging trend of e-commerce business poses serious challenges in the field of logistics. To handle e-commerce shipments, warehouses must be able to efficiently handle a large number of stock-keeping units (SKUs), pick and pack small volume orders, and deliver them on time in small parcel shipments to consumers. In this sense, traditional order fulfillment, which encompasses receiving, put-away, picking, and transport through the warehouse, might not be able to fully fulfill the requirements of e-commerce. Considering the fact that order picking in warehouses is one of the most costly activities amongst the logistics operating categories, there is a crucial need to adopt a wave picking strategy to handle e-commerce shipments, an order picking approach that groups the orders for picking at the same time to minimize repeated visits to nearby storage locations. To apply the wave picking strategy properly, decision support for establishing the timing of each wave and the quantity of items to be picked is essential. Therefore, in this paper, a case-based multi-agent wave picking decision support system is proposed to help decision-makers in generating wave picking sequences in order to handle e-commerce shipments, through the integration of case-based reasoning and multi-agent technique. After a pilot study of the proposed system in a third-party logistics service provider, the order-processing efficiency was greatly enhanced.**

I. INTRODUCTION

In the past decade, the online-to-offline (O2O) shopping mode has completely revolutionized our shopping experience. Instead of purchasing their favorite goods in physical retail stores, consumers are enabled to shop online and receive the desired products at home through direct delivery. Such a phenomenon has created a new logistics operating environment to handle these e-commerce shipments, where the order fulfillment process, as well as the delivery process, is entirely different from the conventional one. Under an e-commerce logistics environment, warehouse operations are driven by individual demand from online customers. Warehouses must be able to efficiently pick and pack single items and small volume orders, and deliver them in small parcel shipments at high frequency to consumers. In this sense, traditional order fulfillment, which encompasses receiving, put-away, picking, transport through the warehouse, might not be able to fully fulfill the requirements of e-commerce orders.

While customers are able to order anything, anytime, from anywhere, the pressure is on for supply chains to deliver. To comply with the requirements of e-commerce shipments, the order fulfillment process in the warehouse must be reconstructed and redesigned so that the flow of operations are efficient enough to pick and consolidate small volume orders, and to schedule the delivery sequences of small parcel shipments for frequent delivery of e-commerce shipments directly to end customers. Among the activities involved throughout the order fulfillment process in the warehouse, order picking is found to be the most labor-intensive and costly activity. More than half of the warehouse expenses are incurred from order picking activities [2, 10]. Therefore, it is particularly crucial for logisticians to adopt a proper order picking strategy in an e-commerce operating environment, so as to pick the right volume of orders at the right time.

One of the popular order picking strategies is wave picking, which is defined as an approach that groups orders into batches and a number of batches are picked simultaneously under a single wave [13], so as to minimize repeated visits to storage locations in picking the orders, thereby improving the overall operating efficiency of order handling. However, there are several decisions that need to be made for generating an appropriate wave for picking that is feasible in the real-time situation in warehouses. These include: (i) when to trigger a wave, and (ii) how to group the orders for picking in a number of batches under a single wave. However, SME-type logistics service providers (LSPs), firms that provide outsourced logistics solutions for part, or all of their supply chain management functions, such as warehousing and inventory management, and value-added supply chain activities [21], are unable to afford premium, highly integrated logistics IT solutions with decision support. Such decisions are therefore purely made by experienced warehouse operators who rely on their past experience and practices to generate picking waves.

In view of the essential need for logisticians to improve the operating efficiency in the warehouse under an e-commerce operating environment, this paper proposes a hybrid wave picking decision support system (WP-DSS), incorporating the case-based reasoning (CBR) technique and multi-agent (MA) technology. With WP-DSS, essential order picking information, including (i) the number of batches required in the wave, (ii) the number of SKUs, and (iii) the exact quantity of items to pick under the wave, is provided. Therefore, warehouse operators are able to efficiently group the orders for batch picking under a single wave, which reduces the traveling distances in order picking, and thereby improves the logistics operating performance in handling e-commerce shipments through logistics process automation.

II. LITERATURE REVIEW

This section reviews the typical order processing procedures in warehouses for e-commerce shipments, and highlights the operational issues of handling e-commerce shipments. Following the overview of the existing challenges in warehouses, artificial intelligence (AI) techniques used for decision-making are studied, in order to provide a fundamental understanding of the rationale for developing a system to tackle the identified problems.

A. Warehouse order processing for e-commerce shipments

The warehouse is an essential component within a supply chain of any physical goods to facilitate the on-going logistics processes [15]. The activities in a warehouse can be subdivided into four categories: receiving, storage, picking and shipping [2]. Upon unloading the goods from a truck at the inbound docking area of a warehouse, the receiving activities include inspection of the goods and updating the inventory record. Following the inbound receiving operations, goods are usually stored in assigned locations in the warehouse. Once the delivery notice is received, designated goods are retrieved from storage. The process of picking designated items from their storage locations is called order-picking [2], an operation that is the most costly among all warehousing activities, according to a study in United Kingdom [11]. Subsequently, the picked goods are consolidated as pallets and moved to the outbound docking area for loading on a truck for delivery.

There are a number of warehousing and transportation operations that requires decision-making behind the scenes, such as the stock location assignment of goods, selection of material handling equipment, scheduling operators' tasks, generating the order picking sequence, assigning delivery jobs to the available trucks, planning the routes of the trucks, and so on. The ability to make timely and appropriate decision-making is therefore essential, and greatly affects the operating efficiency as a whole.

In the past decades, the logistics industry has been facing numerous operational challenges. Firstly, the mode of production has been transformed from the traditional mass production into the mass customization production mode to facilitate increasing global market competition [6]. In order to adapt to such change and achieve competitive advantage, warehouses need to be redesigned and automated to achieve higher productivity and throughput, thereby reducing the order processing cost [16]. The adoption of new philosophies, such as Just-In-Time (JIT) and lean production, has brought dramatic changes in the functions and operations of warehouses in minimizing stock with tighter inventory control policies, as well as shortening the response time [15]. Secondly, the emerging trend of e-commerce business also poses serious challenges in the field of logistics. As e-commerce shipments require an entirely new distribution infrastructure to handle online business [5], warehouses must be able to efficiently handle a large number of SKUs, which are of various sizes and weights. Picking and consolidation of single items for individual customers, as well as offering direct delivery to consumers in small parcel shipments within a limited time frame, are of crucial importance under the e-commerce logistics environment. Such mode of operation is completely different from traditional order fulfillment, in which receiving, put-away, picking, and transport through the warehouse or distribution center are not handled in such small lot sizes and a large number of SKUs. With logistics capability being a critical element for superior firm performance in handling e-commerce business [5], it is essential for decision makers to have decision support for making prompt decisions within the warehousing and transportation operations.

B. Case-based reasoning technique

Case-based reasoning (CBR) is a common artificial intelligence technique highlighting knowledge repository information based on past knowledge and experience. A CBR engine organizes past knowledge and experience as "cases". Through the four typical steps in running the CBR engine, namely, case retrieval, case reuse, case revise and case retain, historical cases with the most similar circumstances to the current problem are retrieved from the case library [1]. Selected past cases are then reused to generate solutions for the new problem. These solutions can be reviewed to meet the circumstances of the existing problem. Lastly, the new solution is retained in the case library of the CBR engine for future retrieval. The output of the CBR engine is a set of recommended solutions that is likely to be feasible and applicable in solving a new problem [8].

With the learning ability from real-world decision-making processes, CBR is valuable in environments where decision-making heavily relies on one's knowledge and past practices [4]. In fact, CBR has been extensively applied in various fields for decision support. Zhang *et al*. [26] and Hassanien [17] applied CBR in tackling environmental issues; Woodbridge *et al.* [24] and Sene [22] adopted CBR for providing decision support in the medical industry; Chow *et al.* [6] and Lam *et al.* [19] used CBR for managing resources and mitigating risks in the warehouse operating environment. With the decision-making ability and responsiveness being a critical element under the complex e-commerce logistics environment, the application of CBR is useful for enhancing the operating efficiency of LSPs in handling e-commerce orders.

C. Multi-agent technique

Agent technology provides new concepts and abstractions to facilitate the design and implementation of systems that enables automation of operation and decision support [20, 23, 25]. As suggested by Davidsson *et al*. [9], agent technology is particularly useful and applicable in the context of the logistics and transport industry, therefore the development of agent-based applications in the areas of logistics and transport is promising. The nature of logistics and transportation operations requires processing a large amount of information and data from multiple sources for making timely decisions and perform sequential tasks,. The multi-agent system, which consists of a group of autonomous agents interacting with each other to collectively achieve their goals, has been extensively deployed in the field of supply chains, logistics and the transport industry. In the context of transportation and traffic management, the mainstream literature describes multi-agent technology in various aspects. Brézillon *et al*. [3] developed a support system for rail traffic control. Findler and Lo [12] proposed a system for air fleet control through the integration of agent technology, one of the oldest applications of multi-agent systems. Agent-technology has been integrated into several areas related to warehouse management and production logistics, such as logistics and production planning optimization [18] and solving dynamic logistics process management problems [7]. Multi-agent systems offer such useful features as parallelism, robustness and scalability, which are highly applicable in domains and problems, where integration and interaction of multiple sources of knowledge, the resolution of interest and goal conflicts or time bounded processing of data are required [14, 23]. As warehousing and transportation operations are dynamic and complex, multi-agent technology is considered to be an essential tool that could yield benefits to logistics practitioners in the goal of maximizing operating efficiency.

III. ARCHITECTURE OF THE WP-DSS

To facilitate LSPs in making appropriate decisions in the order picking process, a hybrid wave picking decision support system for handling e-commerce shipments, which incorporates CBR and MA techniques, is proposed. The design and architecture of WP-DSS is shown in Fig. 1. There are two tiers in WP-DSS:

(i) Wave Picking Initiation Tier – for activating the wave picking operations, as well as collecting and processing relevant delivery order details, and
(ii) Wave Picking Formulation Tier – for generating picking waves according to historical similar picking waves which are stored as cases in the case-based reasoning engine.

A. Tier 1: Wave picking initiation tier

Due to the vast number of e-commerce delivery orders that can be received on a daily basis, grouping and consolidating a certain number of orders for further batch processing is necessary. To automate the process of grouping delivery orders, the first tier of WP-DSS involves an autonomous agent, namely the Wave triggering agent (WTA), which is responsible for activating the operating procedures of WP-DSS upon meeting certain pre-defined conditions. WTA is responsible for counting the amount of time the first received order has been awaiting processing, as well as continuously keeping track of the number of orders that have been grouped. Upon meeting either of the conditions, WTA will invoke the Data Collection and Processing Agent (DCPA), another agent in Tier 1 responsible for collecting and processing delivery the order details. Once DCPA is invoked by WTA, DCPA will then assess the database to retrieve the details of all grouped and to-be-processed delivery orders. Upon data retrieval and processing by DCPA, details of these orders are transferred to *Tier 2 – Wave picking formulation tier*. Such information serves as the input of the CBR engine for searching relevant past cases.

With consideration of having urgent or special orders which might require immediate order picking, WP-DSS provides an alternative for LSPs to generate picking waves manually. By inputting the reference number of the orders, DCPA will be initiated to assess the database in order to retrieve and process the details of these special orders. The processed data is then transferred to Tier 2 as usual.

B. Tier 2: Wave picking formulation tier

This tier involves two agents and a CBR engine for knowledge repository and formulation of the wave picking strategy. As processed data are being transferred to Communication and Coordination Agent (CCA) by DCPA from Tier 1, CCA, an agent responsible for communicating and coordinating with other agents within the WP-DSS to facilitate smooth operations, invokes Wave picking knowledge agent (WPKA) to inquire of the CBR engine for retrieval of historical picking solutions which are stored as cases in the case library. The output from Tier 1 serves as the input to the CBR engine in order to search for relevant past cases. Through running the CBR engine, suggested picking solutions for the current to-be-picked delivery orders are provided and transmitted back to WPKA. WPKA then updates the CCA of the picking solutions, so that CCA can display the results to the users in a result output interface. Therefore, LSPs' decisions regarding how to pick the deliver orders are assisted by WP-DSS, with the following information provided:

(i) the number of batches required for picking the orders in this wave,
(ii) items to be picked in each order batch,
(iii) corresponding quantity to be picked for each item under each batch, and
(iv) storage location of each item.

1) Multi-agent technique

In the multi-agent approach embedded in WP-DSS, each autonomous agent has a designated role, mission, and activity to perform. Rules are predefined in the standard agent algorithm for defining the condition of the agent in performing their activities autonomously, as well as for representing the required activities the agent will perform, as shown in Table 1. The standard agent algorithm is expressed below.

TABLE 1. MISSION, CONDITIONS AND ACTIVITIES OF THE AGENTS IN WP-DSS

Name of agent	Mission	Condition	Activity
Wave triggering agent (WTA)	Initiate WP-DSS operations	- Delivery orders received are grouped for processing during a certain period of time, or - Total number of received delivery orders reached a certain quantity	Invoke DCPA to collect delivery order details to be processed
Data collection and processing agent (DCPA)	Collect and process delivery order details	Receive notification from WTA	- Assess database to retrieve order details, and - Transfer processed data to CCA
Wave picking knowledge agent (WPKA)	Generate wave picking solution	Receive notification and processed data from CCA	Activate CBR engine to generate wave picking solution
Communication and coordination agent (CCA)	Central coordination among agents	Receive processed data from DCPA	Invoke WPKA to run CBR engine for generating wave picking solution
		Receive wave picking solution from WPKA	Display wave picking solution for the operator

Agent algorithm:

Agent *<agent_name>*

Mission *<mission_statement>*

Activity$_1$ *<description of the activity>*

Dataset *<data>*

Action *<function>*

…

Activity$_n$ *<description of the activity>*

Dataset *<data>*

Action *<function>*

2) Case-based reasoning engine

The CBR engine organizes past order picking knowledge and experience as "cases", which comprises four sequential procedures: case retrieval, reuse, revise and retain. Cases with the most similar circumstances are first retrieved from the case library according to the similarity value calculated by:

$$S = \frac{\sum_{i=1}^{n} wi \times sim(f)}{\sum_{i=1}^{n} wi} \qquad (1)$$

where w_i is the weight of the attribute and sim(f) is the similarity function between the past case and the newly inputted case. The storage location assignment solution of the past cases with the highest similarity value is used as the solution of the new case. These selected cases are then reused to generate solutions for the new problem. The generated solutions are revised and verified so as to be applicable to the circumstances of the existing problem. Finally, the new solution is retained in the case library for future use. The output of the CBR engine is a set of picking lists for warehouse operators to pick the items accordingly.

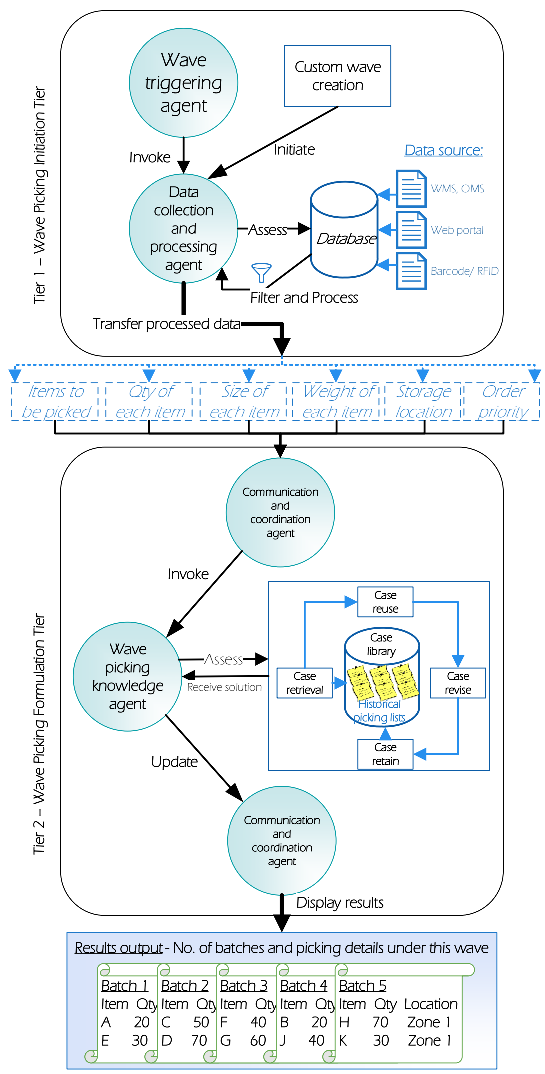

Fig. 1. Architecture of WP-DSS

IV. CASE STUDY

To validate the feasibility of the proposed wave picking decision support system, a prototype of WP-DSS is deployed in a Hong Kong based LSP who handles e-commerce shipments.

A. Company background

ABC Company is a Hong Kong based logistics service provider specialized in providing a wide range of logistics and transportation services for cross-border shipments. With the emerging trend of e-commerce business, ABC Company started handling e-commerce shipments a few years ago. However, due to the great difference in the operating procedures and requirements in handling e-commerce shipments as compared to traditional cross-border shipments, where e-commerce orders are received at a much higher frequency and in smaller lot sizes, ABC is facing the following problems which heavily affect the order handling efficiency:

(i) Difficulty in resource allocation for order picking – Due to the high frequency in receiving delivery orders from e-commerce customers, the company found it difficult to assign human resources to pick the orders. The utilization rate of the warehouse worker is therefore increasing, which gradually becomes a bottleneck in the entire warehouse operations.

(ii) Increase in travelling distance of warehouse workers which is deemed unnecessary – Instead of picking orders in a large batch and shipping large volume orders as single shipment, e-commerce orders are picked, packed and delivered in a smaller volume but at a higher frequency. Therefore, warehouse workers are required to visit the same or nearby storage locations of the warehouse repeatedly over the whole day to pick the orders.

In an attempt to rectify these problems, the prototype of WP-DSS is deployed in ABC Company's warehouse to assist them in handling e-commerce shipments more efficiently by means of developing order picking strategies that group the orders for batch picking and processing.

B. Implementation of WP-DSS

To deploy WP-DSS in the case company, a set of implementation procedures is designed, which involves five phases, as shown in Fig. 2. They are: Phase I – Study of current operational flow in handling e-commerce shipments; Phase II – Data collection such as e-commerce order attributes; Phase III – Construction of a database for data storage and processing; Phase IV – Development of CBR engine; and Phase V – System evaluation.

1) Study of current operational flow in handling e-commerce shipments

The first phase is a comprehensive study of the existing operational flow of the case company in handling e-commerce shipments. Through site visits and interviews of experts, the standard operating procedures (SOP) in warehouses in handling e-commerce orders, including order receiving in the inbound area, put-away process, order allocation and picking, and order consolidation for outbound delivery, are studied. It is an essential implementation phase for constructing a proper database, agent algorithms, as well as a CBR engine that suits the operational parameters and requirements of the case company.

2) Data collection

In the second phase, the data collected, including resource availability, historical demand for outbound delivery and order attributes, serve as fundamental in deciding the triggering condition of WTA. By understanding the delivery order receiving rate and distribution, we can decide on the amount of time accumulated for grouping the unprocessed orders. Taking the resource availability, especially the number of warehouse operators available for order picking into consideration, the maximum allowable quantity of delivery orders to be grouped for batch order picking can also be decided. In this case, according to the data collected in the case company, the amount of time accumulated for grouping the unprocessed orders is set to be 45 minutes, while the maximum allowable quantity of delivery orders to be grouped is 180 SKUs. These two figure indicate that, upon grouping the delivery orders for 45 minutes, the WTA will automatically stop further grouping the orders and will start performing its function, so that WP-DSS can separate these orders into several waves for picking. However, if the quantity of delivery orders grouped reached 180 SKUs, the WTA will stop further grouping the orders, even if the accumulated time does not yet reach 45 minutes. It should be noted that the triggering conditions of WTA depends on the nature of the e-commerce operations, the rate of receiving delivery orders, as well as the types of goods the LSP handles. Therefore, different LSPs could have a very different set of values serving as the triggering condition of WTA.

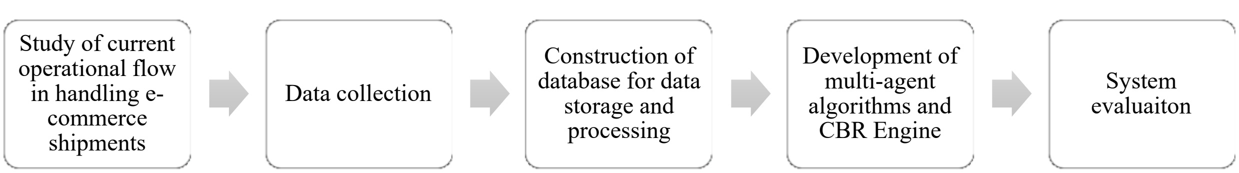

Fig. 2. Implementation procedures of WP-DSS

3) Construction of database for data storage and processing

A relational database is constructed in the third phase for data retrieval, storage and processing. For facilitating the wave picking system operations in WP-DSS, three are three types of static data to be retrieved, as shown in Table 2. They are: (i) General order information – delivery order details such as customer ID, order number and status, delivery mode, date and location; (ii) Product information – this specifies the items and corresponding quantity requested by the customers, and the estimated size and weight of the total packaged shipment; (iii) Storage location information – this specifies the current storage location of each requested item. This information is captured from the internal warehouse management system (WMS) and order management system (OMS). The database built for WP-DSS allows the Data Collection and Processing Agent to assess the database to retrieve all the details of the delivery order. DCPA will then process the data by summarizing the order details of all the grouped orders. Items to be picked, quantity, size, weight and storage location of each item, and order priority are the processed information serving as the input of the CBR engine.

4) Development of multi-agent algorithms and CBR engine

A case library that stores historical picking lists in a tree structure is built in the fourth phase. In the case retrieval process under the CBR engine, the inductive indexing approach is used for browsing and identifying past cases that are found similar to the input parameters, creating a search path in the tree structure of the case library. According to the case company operating requirements and environment, n indexing levels are defined, as shown in Fig. 3. The tree structure of the case library is then developed, as shown in Fig. 4.

5) System evaluation

As the database, multi-agent algorithms and CBR engine are developed, the final phase is system evaluation. Through the evaluation of the performance of WP-DSS, the suitability of the defined rules, such as the triggering conditions set for WTA, can be determined. It also suggests whether the tree structure in the case library is appropriate or not for the effective retrieval of similar past cases. The average order picking time per order and the utilization of human resources for order picking are used as the key performance indicators in this pilot study, for comparing the order picking performance before and after the deployment of WP-DSS.

TABLE 2. DATA STRUCTURE IN DATA WAREHOUSE

	FIELD NAME	DATA TYPE	DESCRIPTION
	<u>*General Order Information*</u>		
*	Customer ID	*Numeric*	A unique customer reference number for tracking
*	Delivery Order number	*Numeric*	A unique delivery order number for tracking
*	Order status	*String*	Current order status, i.e. unprocessed, picking, picked, completed, delivered
	Order priority	*String*	Order priority, i.e. Default, high, urgent
	Delivery Note Type	*String*	Type of the delivery order, i.e. Online individuals, online retailers, offline retailers
	Request Date	*Date*	Date of receiving the delivery order
	Delivery Date	*Date*	Expected date of delivery
	Delivery location	*String*	Eighteen districts in Hong Kong
	Delivery Mode	*Boolean*	Mode of delivery, i.e. Home delivery, Self-pickup
	<u>*Product Information*</u>		
*	Item ID	*Numeric*	A unique production identification number
	Request Quantity	*Numeric*	The quantity of items requested by the customer
	Total Gross Weight	*Numeric*	Estimated total gross weight of the packaged shipment
	Total CBM	*Numeric*	Estimated total CBM of the packaged shipment
	Master A/C	*String*	The manufacturer of the product
	Sub A/C	*String*	The wholesaler of the product
	<u>*Storage location Information*</u>		
	Warehouse number	*Numeric*	A unique identification number for the warehouse
	Zone number	*Numeric*	A unique identification number for the warehouse's zone
	Bin number	*Numeric*	A unique identification number for the zone's bin
*	*Primary Keys*		

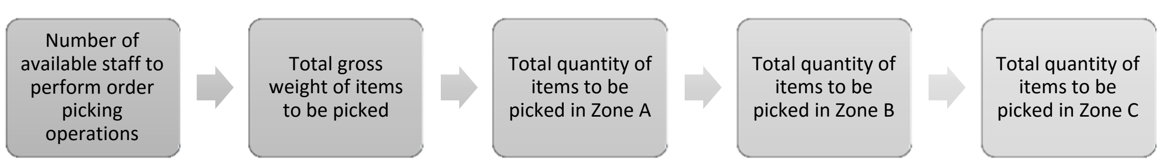

Fig. 3. Five indexing levels in case library

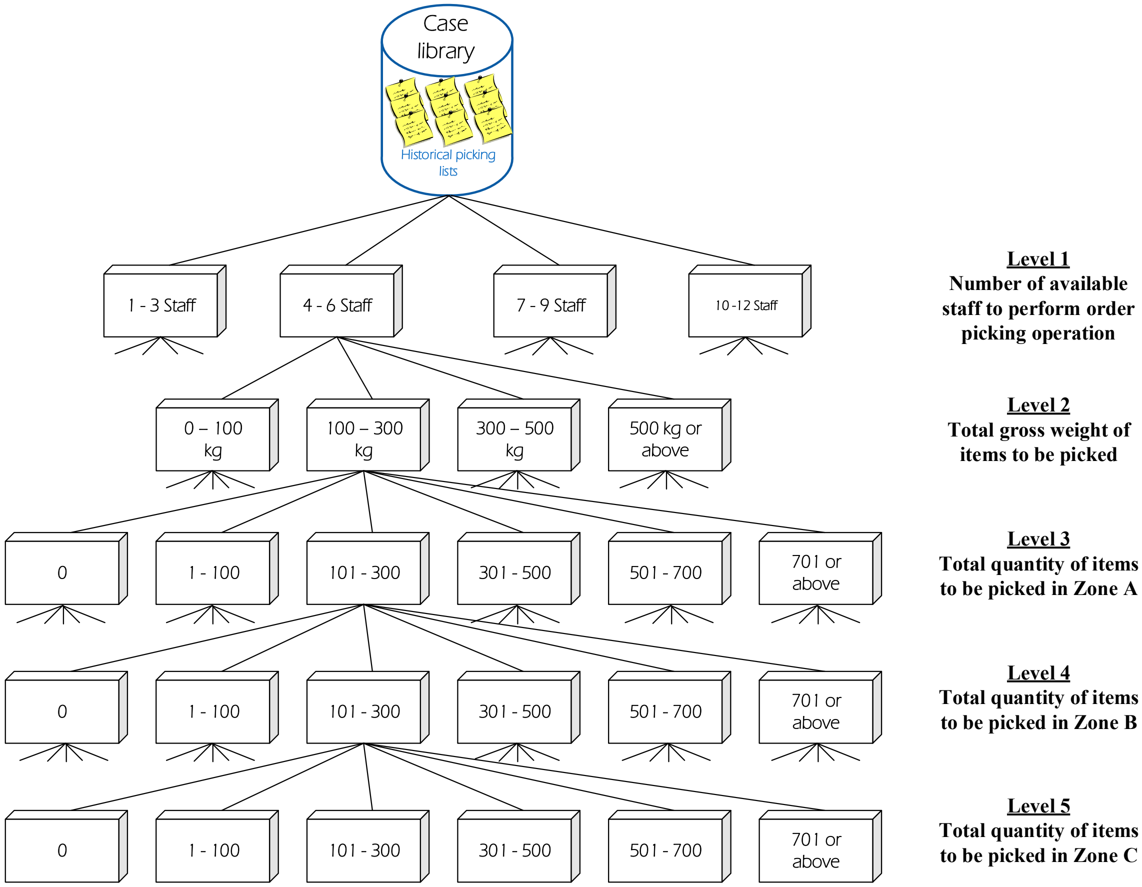

Fig. 4. Tree structure in case library

V. RESULTS AND DISCUSSION

As a pilot run was undertaken in a case company for verification of the feasibility and significance of WP-DSS, this section discusses the results of the pilot run by comparing the operating performance in order picking before and after the implementation of WP-DSS, in terms of two key performance indicators, namely, the average order picking per order and the utilization of human resources for order picking.

A. *Average order picking time per order*

Without the use of WP-DSS, the case company does not deploy any order picking strategy for grouping the delivery orders for picking concurrently. This is due to the difficulty in manually classifying the orders into different waves or batches for picking if grouped for bulk processing. Although there are a few occasions on a daily basis when some orders are unintentionally picked in a batch, as these orders are received simultaneously, most of the orders are picked instantly after they are received. With the use of WP-DSS, it often requires approximately 15 minutes to complete a wave picking operation in which a multiple number of delivery orders are picked under several waves. In terms of the average order picking time per order, each order only require 18 seconds to pick, a significant reduction of the amount of time used for picking an order as compared to the traditional order picking time of 4 minutes, as shown in Table 3.

B. *Percentage of productive hours spent for order picking*

In the absence of decision support for formulating order picking strategies, frequently receiving delivery notification of e-commerce orders indicates that warehouse operators are required to pick the orders all day. In the case of ABC Company, warehouse operators who are assigned to perform order picking operations originally spent over 60% of their productive hours in picking orders. According to the results of the pilot run in the case study, with the use of WP-DSS, warehouse operators spent less than half of their productive hours in picking orders, showing that over 20% of their productive hours is saved, as shown in Table 3. This allows efficient utilization and management of human resources.

TABLE 3. ORDER PICKING PERFORMANCE COMPARISON BEFORE AND AFTER IMPLEMENTATION OF WP-DSS

	Before	After	Percentage of improvement
Average order picking time per order	4 mins	0.3 min	92.5%
Percentage of productive hours spent for order picking	62%	48%	24%

VI. CONCLUSIONS

Order picking is a critical warehouse operation that determines the order handling efficiency of LSPs in both the warehouse and transportation sectors. Following the order picking process, the efficiency of subsequent order processing steps in warehouses, such as labeling, packing and consolidation of goods, are heavily affected by the order picking effectiveness. With tight order handling requirements of e-commerce shipments, challenges are posed to LSPs to timely and accurately process and consolidate goods in warehouses, and then ship the required orders within a limited and specified time frame. Without appropriate decision support throughout the order handling process in the warehouse or distribution center, LSPs find it hard to maintain the quality of their logistics services as well as their operating efficiency, especially in handling e-commerce shipments in such a competitive and time-sensitive warehouse environment. Therefore, in the present paper, an intelligent decision support system, integrating CBR and MA techniques, is designed for aiding the LSPs to make correct decisions during the order-picking process. Incorporating the concept of wave management for order picking in the proposed decision support system, the application of CBR and MA determines the order picking details in each picking wave. This greatly assists LSPs in realizing three essential elements in order picking, namely, the specified time to start picking the goods from the storage location, the quantity of goods to be picked in that picking wave, and the resources required for picking the goods. The proposed system has been validated through a pilot study in a case company, and effectively enhanced the order handling efficiency by reducing the required time of order picking, while avoiding over-utilization of human resources in the order picking operation. In order to further enhance the applicability of WP-DSS in the field of logistics and supply chains under e-commerce operating environment, more case studies for validation would be essential.

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