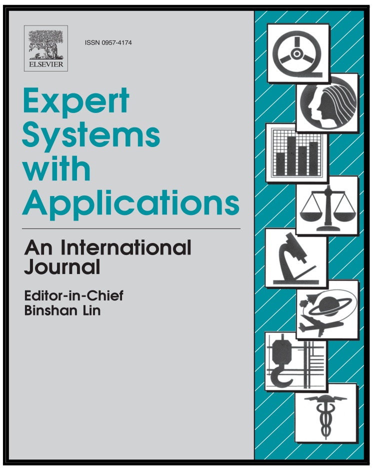
Accepted Manuscript



A B2C E-commerce Intelligent System for Re-engineering the E-Order Fulfilment Process

K.H. Leung , K.L. Choy , Paul K.Y. Siu , G.T.S. Ho , H.Y. Lamm ,
Carman K.M. Lee

PII: S0957-4174(17)30628-0
DOI: 10.1016/j.eswa.2017.09.026
Reference: ESWA 11547

To appear in: *Expert Systems With Applications*

Received date: 30 May 2017
Revised date: 25 July 2017
Accepted date: 9 September 2017

Please cite this article as: K.H. Leung , K.L. Choy , Paul K.Y. Siu , G.T.S. Ho , H.Y. Lamm , Carman K.M. Lee , A B2C E-commerce Intelligent System for Re-engineering the E-Order Fulfilment Process, *Expert Systems With Applications* (2017), doi: 10.1016/j.eswa.2017.09.026

Highlights

- The e-commerce internal order processing flow is streamlined and re-designed.
- A GA-rule-based system for efficient e-commerce order fulfillment is proposed.
- An optimal order processing plan is generated by genetic algorithm technique.
- A system implementation shows a significant order processing time reduction.

A B2C E-commerce Intelligent System for Re-engineering the E-Order Fulfilment Process

K.H. Leung
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: eric.kh.leung@connect.polyu.hk

K.L. Choy*
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: kl.choy@polyu.edu.hk

Paul K.Y. Siu
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: paul.ky.siu@connect.polyu.hk

G.T.S. Ho
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: george.ho@polyu.edu.hk

H.Y. Lam
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: cathy.hy.lam@polyu.edu.hk

Carman K.M. Lee
Department of Industrial and Systems Engineering,
The Hong Kong Polytechnic University, Hunghom, Hong Kong
Email: ckm.lee@polyu.edu.hk

*Correspondence Address:
Dr K.L. Choy
Department of Industrial and Systems Engineering
The Hong Kong Polytechnic University
Hung Hom, Kowloon
Hong Kong
Email: kl.choy@polyu.edu.hk
Tel: (852) 2766 6597
Fax: (852) 2362 5267

ABSTRACT
In today's world of digitization, the rise of the e-commerce business around the globe has brought a tremendous change not only in our purchasing habits, but also to the entire retail and logistics industry. Given the irregular e-commerce order arrival patterns, limited time for order processing in e-fulfilment centers, and the guaranteed delivery schedules offered by e-retailers, such as same-day or next-day delivery upon placing an order, logistics service providers (LSPs) must be extremely efficient in handling outsourced e-commerce logistics orders. Without re-engineering the order fulfilment processes, the LSPs are found to have difficulties in executing the order fulfilment process due to the tight handling requirements. This, in turn, delays the subsequent processes in the supply chain, such as last-mile delivery operations, consequently affecting customer satisfaction towards both the retailer and the LSP. In view of the need to improve the efficiency in handling e-commerce orders, this study aims at re-engineering the fulfilment process of e-commerce orders in distribution centers. The concept of warehouse postponement is embedded into a new cloud-based e-order fulfilment pre-processing system (CEPS), by incorporating the genetic algorithm (GA) approach for e-commerce order grouping decision support and a rule-based inference engine for generating operating guidelines and suggesting the use of appropriate handling equipment. Through a case study conducted in a logistics company, the CEPS provides order handling solutions for processing e-commerce logistics orders very efficiently, with a significant reduction in order processing time and traveling distance. In turn, improved operating efficiency in e-commerce order handling allows LSPs to better align strategically with online retailers, who provide customers with aggressive, guaranteed delivery dates.

Keywords e-commerce logistics, O2O retailing, order fulfilment, business process re-engineering, warehouse postponement applications, expert systems

1. INTRODUCTION

The e-commerce business is rapidly expanding around the globe. To increase physical presence, online retailers are using brick-and-mortar stores for the display of their products (referred to as "showrooming") while enabling customers to make purchases online. The rise of such online-to-offline (O2O) retailing and e-commerce business has revamped the entire order fulfilment process along supply chains (Lekovic & Milicevic, 2013). A recent study by Forrester Research (2016) indicated that the total online retail revenues in China, Japan, South Korea, India, and Australia will nearly double from US$733 billion in 2015 to US$1.4 trillion in 2020. While the emerging e-shopping trend is expected to continue, bringing billions of transactions to every corner of the world, order fulfilment along supply chains has been identified as one of the major bottlenecks affecting the development of the global e-business and end consumers' online purchase experience (Cho et al., 2008; Wang et al., 2014). On the one hand, logistics service providers (LSPs) attempt to grasp the blooming market segment of e-commerce in a wider business perspective. On the other hand, however, at the operational level, they are struggling with the problem of e-commerce order handling inefficiencies in warehouses or distribution centers (Lang & Bressolles, 2013). Though the bottlenecks of e-order fulfilment process, as illustrated in Figure 1, have received greater concern by both industry practitioners and researchers in recent years, the increased complexity and dynamism of the handling requirements of e-commerce orders, i.e. orders being purchased via the Internet using computers or smartphones, have worsened the logistics industry's headaches. This phenomenon is largely attributed to the difference between e-commerce orders and traditional orders, as shown in Table 1 (Leung et al., 2016).

Table 1. A comparison between the nature of traditional logistics orders and e-commerce orders (Leung et al., 2016)

Order characteristics	Traditional logistics orders	E-orders placed by end customers electronically
Order arrival	Regular	Irregular
Order nature	Mostly stock replenishment	Fragmented, discrete
Size per order	In bulk	In small lot-size
SKUs involved in each order	Very few or even identical	Many
Number of orders pending for processing	Less, relatively easy to predict	More and unlimited, relatively difficult to predict
Time availability for fulfilment	Less tight	Very tight
Delivery schedule	Relatively more time buffer	Next-day or even same-day delivery

Traditionally, logistics orders processed in warehouses are mainly initiated from retailers who require stock replenishment for specified physical stores. In contrast to these traditional orders, generally involving only a few types of stock-keeping units (SKUs), but in large quantity, the business-to-consumer (B2C) e-commerce orders, which are placed by end consumers, are significantly more wide-spread in terms of delivery location and involve a large number of SKUs, but with each SKU demanding only a very small quantity. Adding the requirement of same-day or next-day delivery for e-commerce orders, the e-commerce logistics business model is now more complex and dynamic than we could have imagined. The typical order fulfilment process under the B2C e-commerce business environment is illustrated in Fig. 1. Previous studies have already addressed the difficulty of managing warehouse operations and last-mile order fulfilment, without strategic and operational transformation, by logistics service providers (LSPs) (Hultkrantz & Lumsden, 2001; Cho et al., 2008; Lang & Bressolles, 2013). Therefore, LSPs, who capture the e-commerce logistics business, can no longer follow the conventional order fulfilment process to handle e-commerce orders. Without the order fulfilment process being re-engineered for today's e-business, there are two significant problems in the existing operations, as shown in Fig. 1; they are:

(i) A lack of mechanism for data pre-processing of e-commerce orders

In the case of Hong Kong, being a global transhipment hub, LSPs are shifting their business to an e-commerce orientation owing to the fast growing trend of e-business in Asia. Most of the logistics practitioners, however, lack an effective mechanism for e-commerce order pre-processing, as their operations are still manual and without IT support. E-commerce orders are handled in the conventional way to that of traditional logistics orders.

(ii) Inefficiency of e-commerce order handling due to frequent and discrete arrival of orders

The frequent and discrete arrival of e-commerce orders, one of the biggest differences as compared to the traditional logistics orders, has resulted in e-commerce order handling in e-fulfilment centers being inefficient. There is a lack of lightweight, cost effective IT solutions that are specifically designed to handle e-commerce orders which are received from the Internet. The core reason for this is the lack of domain know-how by IT solution developers in the e-commerce supply chain field, thereby being unable to identify the B2C e-commerce order handling difficulties currently faced by the logistics practitioners.

Consequently, the absence of a mind-set in the managerial perspective and an effective mechanism in the operational perspective for order pre-processing has created barriers for logistics practitioners to engage in the e-commerce logistics business. Further, not only does the internal incapability of efficient e-order handling become the major obstacle in business expansion, but is also a bottleneck in the entire e-commerce supply chain which affects the efficiency of e-fulfilment of the downstream supply chain partners. This explains why the last-mile delivery in e-commerce, the final leg of the complete journey of a parcel before it reaches the customer, is regarded as one of the biggest challenges in today's e-commerce business. In view of the necessity of logistics process re-engineering under the emerging e-commerce logistics business environment, this paper presents a cloud-based e-order fulfilment pre-processing system (CEPS), which integrates the concept of warehouse postponement, an operational strategy of "grouping pending logistics orders for processing in batch" (Leung et al., 2016). Through the incorporation of the genetic algorithm (GA) approach for e-commerce order grouping decision support, a rule-based inference engine for generating operating guidelines and suggesting the use of appropriate handling equipment, LSPs are able to consolidate pending, discrete e-commerce orders for batch release and processing, thereby improving the effectiveness in e-order handling and meeting the same-day delivery requirements of e-commerce orders, even in the case of receiving a large number of orders simultaneously. The contributions of this paper are twofold. First, this study contributes to a wider body of the literature, which has rarely addressed the operating issues and bottlenecks specifically in handling e-commerce orders. A majority of the expert systems proposed in previous studies in the domain of warehousing and transportation process improvement, such as Oliveira et al. (2015), Patriarca et al. (2016), Gu et al. (2016), Yang et al. (2015), Accorsi et al. (2014), Lam et al. (2011), Poon et. al. (2011), Yao et al. (2010), Zacharia & Nearchou (2010), Taniguchi & Shimamoto (2004), Chan et al. (2009), and Chen et al. (2008), focus on tackling a specific operational issue in warehouses or distribution centers in handling general logistics orders. However, without consideration of the differences in the nature and handling requirements between e-commerce orders and conventional logistics orders, previous expert systems might not be applicable to the scenario of today's e-commerce order handling process. Therefore, this paper fills this gap in the literature by proposing a decision support system for streamlining e-order fulfilment, thereby providing insights for future research in logistics business process re-engineering under the era of e-commerce. Second, the proposed hybrid solution, which integrates GA and rule-based inference engine, groups the orders for picking at the same time to minimize repeat visits to nearby storage locations. This streamlines the order picking operations of items in their storage locations in warehouses or distribution centers, one of the costliest activities amongst the various logistics operating categories, i.e. receiving, storage, pick-and-pack, and delivery.

The rest of this paper is organized as follows. Section 2 presents a literature review of the existing research and theories related to the topic. The CEPS model design is presented in Section 3, followed by a case study to demonstrate the implementation procedures of the model in Section 4. The results and findings are discussed in Section 5. Finally, Section 6 contains the conclusion of the study and directions of future research.

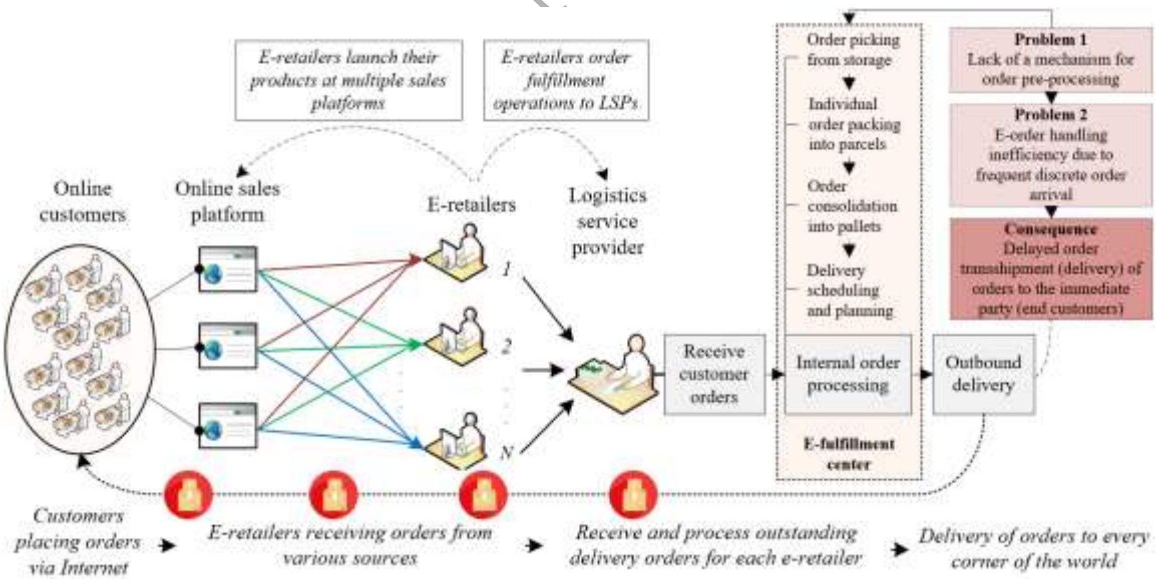


Fig 1. Order fulfilment under B2C e-commerce business environment

2. LITERATURE REVIEW

In a traditional supply chain, goods are processed in a multi-level supply chain in order to transport the goods from the factory to physical retail stores. End consumers make purchases and receive the products at physical stores. In today's Omni-channel retailing, the buying process of the end consumer involves various sources, from online to offline. End consumers' orders can be received anytime and anywhere by the e-retailer. As orders are placed via the Internet, the downstream of the e-commerce B2C supply chain consists of a large number of unknown destinations spread around the world, requiring direct home delivery or consumer-direct delivery. The underlying fulfilment operations for e-commerce shipments, also called e-fulfilment (Agatz et al., 2008), is a crucial driver of e-commerce growth (Morganti et al., 2014; Maltz et al., 2004). While logistics and distribution play essential roles in the e-commerce sector (Chen & Lin, 2013, Esper et al., 2003), logistics practitioners engaged in e-business have been facing a variety of challenges in fulfilling online B2C customer orders due to the e-fulfilment process being fundamentally different from the traditional shipments handling process in terms of the order nature and handling requirements, inventory management, warehouse design and management, last-mile delivery, and returns management (Agatz et al., 2008; De Koster 2003; Fernie & McKinnon, 2009; Leung et al., 2016; Maltz et al., 2004).

The order fulfilment process in traditional warehouses includes four major aspects: order receiving, order storage, order picking and packing, and order delivery. Amongst the four categories of order handling operations, order-picking is the most labour intensive operation in the warehouse and induces the highest warehouse-associated costs (Accorsi et al., 2014). In e-fulfilment, the operating categories in warehousing and distribution are common with respect to traditional order fulfilment. However, order-picking operations in e-fulfilment centers are initiated by end consumers who placed orders requiring the e-retailers or the logistics service providers to fulfil the orders accordingly. Such a demand-driven distribution model in the era of e-commerce further increases the complexity of order picking operations, as the order arrival pattern in more difficult to predict, comparing to conventional large lot-sized logistics orders for weekly or bi-weekly stock replenishment of designated retail stores. Therefore, the importance of logistics capability and outsourcing is likely to increase, requiring an entirely new fulfilment infrastructure to handle e-commerce shipments (Morganti et al., 2014; Xing et al., 2011; Chan et al., 2012; Cho et al., 2008).

A range of research activities regarding warehousing and transportation activities can be found in the mainstream literature, and a summary is shown in Table 2, for the areas specifically related to the design and process improvement in warehouses. Concerning the warehouses and distribution operations, streamlining the traditional order fulfilment process through providing decision support for logistics practitioners has become one of the active research areas. Poon et al. (2011) integrated radio frequency identification (RFID) technology with the genetic algorithm (GA) technique for generating pick-up and delivery route plans for small batch replenishment orders. Lam et al. (2011) proposed a decision support system integrating the case-based reasoning (CBR) technique for supporting managers in making appropriate order fulfilling decisions. Though various aspects of the warehousing and transportation sector have been widely examined, previous research activities focused on traditional warehousing operations or transportation operations, and the attention paid by researchers in consideration of today's e-commerce order fulfilment in the warehousing and transportation sector is very limited.

The used of knowledge-based techniques in solving a range of decision-making problems in manufacturing and logistics activities is common nowadays (Tana et al., 2006; Ho et al., 2008). The genetic algorithm technique, one of the popular artificial intelligence (AI) techniques in tackling real-world problem without requiring huge computational effort, has been proven to excel in solving combinatorial optimization problems (Ho et al., 2008). The GA operation is based on the principles of genetic and natural evolution through random selection and the reproduction of offspring (Renner & Ekárt, 2003; Lee et al., 2016). A nearly optimal solution generated by the GA technique is in a form of chromosome, which involves a string of genes. Two basic operators in GA, the crossover operator and mutation operator, create new offspring from the parent chromosomes by selecting a pair of chromosomes for matching, and performing a random adjustment of some values of the genes in a chromosome, respectively. The generated chromosomes are then being evaluated through a defined fitness function. A number of GA applications have been found in the domain of manufacturing, warehousing and distribution, showing the use of GA for solving scheduling-related problems. Lin et al. (2014) developed a genetic algorithm-based optimization model for managing green transportation operations. Mendes et al. (2009) integrated GA with heuristics rules for tackling the joint replenishment problem in warehouses. Lee et al. (2016) provided a comprehensive quality assurance scheme in the garment industry through optimizing the fuzzy rules using a genetic algorithm.

Numerous intelligent systems and approaches for providing order-handling decision support in warehouses have been developed. However, there is a scarcity in the literature on B2C e-commerce order fulfilment in distribution centers, which takes the e-order handling process and requirements into consideration. Only a limited range of papers related to B2C e-commerce can be found in the literature, such as assessing the level of B2C trust in e-commerce (Akhter et al., 2005), developing a negotiation model for B2C ecommerce (Huang et al., 2010), a prototype of e-commerce portal with a set of services provided by intelligent agents (Castro-Schez et al., 2011), and an evaluation model for ranking B2C websites in e-alliance (Yu et al., 2011). Hence, in this paper, an e-order fulfilment pre-processing system is proposed, which highlights the importance of using the genetic algorithm approach as the core means of tackling the common operational bottlenecks found in e-fulfilment centers, with an integration of a rule-based inference engine for further providing a more comprehensive solution to assist e-commerce order fulfilment operations.

Table 2. A summary of the literature related to warehousing and transportation activities

Scope	Researchers
Warehouse layout design	Yao et al., 2010; Hassan, 2002; Caron et al., 2000; Önüt et al., 2008
Storage location assignment in warehouses	Yang et al., 2015; Pan et al., 2015; Chew & Tang, 1999; Jane, 2000; Muppani & Adil, 2008
Order picking time reduction	de Koster et al., 2007; Petersen, 2000; Bindi et al., 2009
Resource management in warehouses	Chow et al., 2006
Design of warehouse scheduling system	Zacharia & Nearchou, 2016; Chan & Kumar, 2009; Park et al., 1996
Transportation routing and scheduling	Zegordi et al., 2010; Chen & Lee, 2008; Geismar et al., 2008; Taniguchi & Shimamoto, 2004

3. CLOUD-BASED E-ORDER FULFILMENT PRE-PROCESSING SYSTEM

In order to meet the tight delivery requirements of e-commerce orders, the outsourced e-order fulfilment process must be executed efficiently. This requires warehouse process re-engineering by the logistics service providers. Therefore, a cloud-based e-fulfilment planning system (CEPS) is proposed, for streamlining and re-engineering the flow of e-order fulfilment operations. Through the use of CEPS, the decision support provided by the proposed system enables logistics operators to postpone order fulfilment process execution in their e-fulfilment centers by effective consolidation and planning of incoming e-orders for later batch processing, instead of conventionally processing each e-order individually, as illustrated in Fig. 2. CEPS is a web application (or web app) which comprises two modules, namely (i) E-order information collection and sorting module, and (ii) E-order grouping and resource allocation module. Fig. 3 depicts the architecture of CEPS.

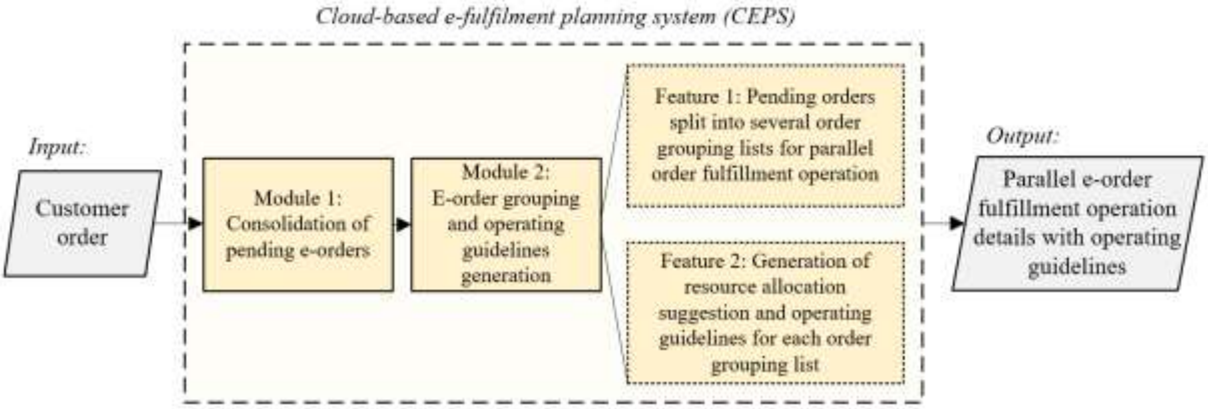


Fig. 2. E-order fulfilment process with CEPS

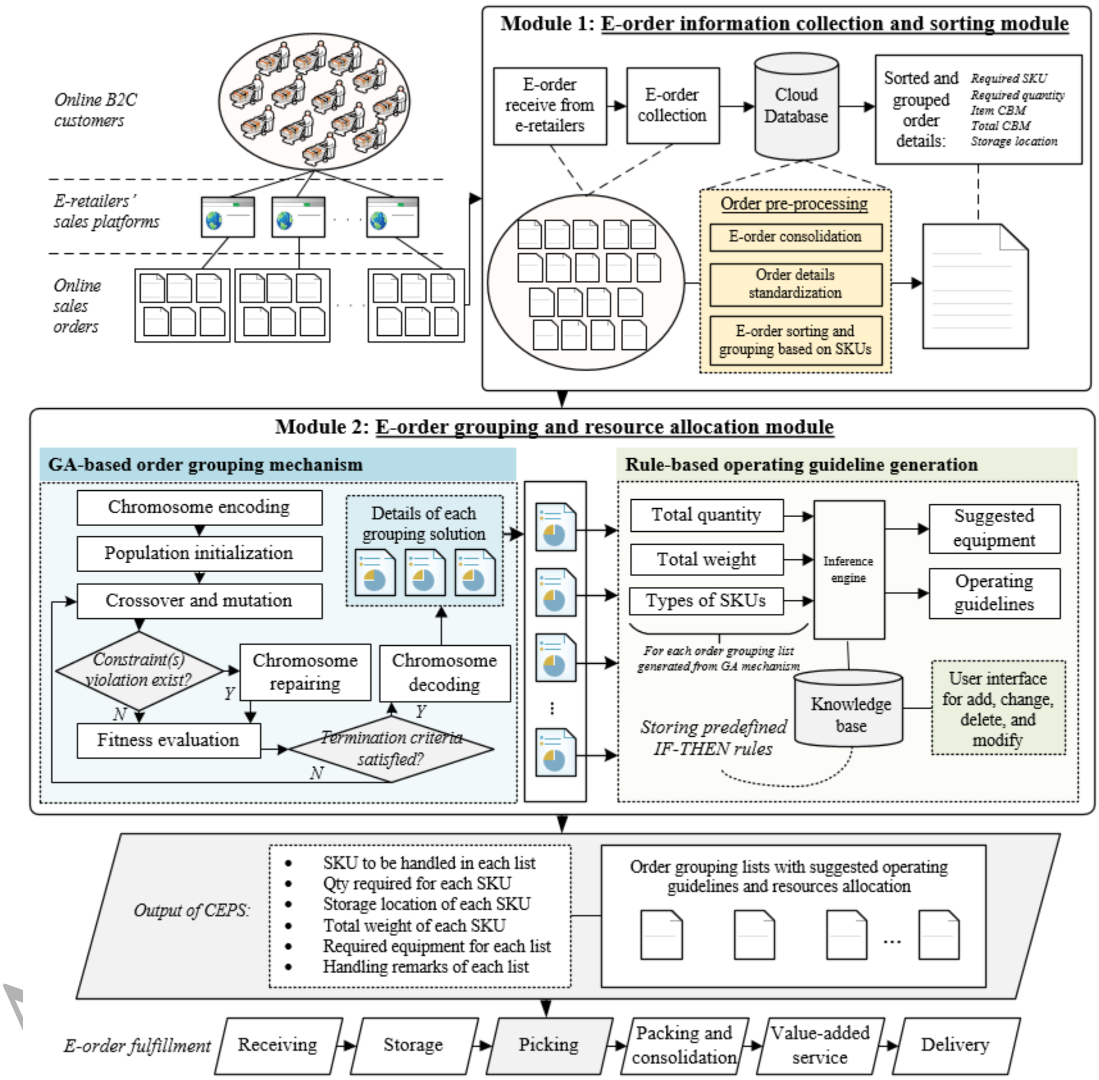


Fig. 3. Architecture of cloud-based e-order fulfilment pre-processing system specifically designed for e-commerce order handling

3.1 E-order information collection and sorting module

In the era of the e-commerce business, delivery orders placed by end consumers are retrieved from the Internet. Efficient retrieval and consolidation of an order therefore requires a cloud database integrated into a web app for real time data retrieval and processing. The front-end of this module involves a user interface (UI) in the CEPS's web app, allowing users, typically the customer service (CS) staff in a logistics company, to retrieve the details of e-orders pending for further processing and confirmation, and to manually update them if necessary. The web app, which consists of a series of web pages, is constructed by Hypertext Mark-up Language (HTML). Any action made by the users on the web pages would trigger an update on the cloud database of CEPS. The database of CEPS is the information repository for collecting, storing and sorting two types of data: (i) delivery order details, which are received in real time via the Internet either from e-retailers or directly from end consumers, and (ii) the basic settings of e-fulfilment center, which are static information preliminarily stored in the cloud database for retrieval. The details of these two major types of data stored in the cloud database are displayed in Table 3.

The major data processing operations in this module includes database query processing, data sorting and display. For database query processing, essential data as shown in Table 3 for insert, view, edit, delete and update can be performed in the UI of the CEPS through a set of structure query language (SQL) statements designed and stored in the SQL database. For data sorting and display, the operation is done automatically in the back-end of the database so that all retrieved e-orders are aggregated and sorted by stock-keeping units (SKUs), disregarding which particular SKUs are fulfilling which customer order. An illustration is shown in Fig. 4. With the rearranged order information, a list of items to be processed in e-fulfilment center is displayed in the UI of the CEPS, which serves as the input of the subsequent module for e-order grouping and resource allocation decision support.

Table 3. Generic details of the information stored in CEPS's cloud database

Types of data:		
(i) Customer order details		
Details	*Data type*	*Data source*
Ordered item (presented as SKU no.)	*Numeric*	Real time retrieval from retailers of end consumers
Item quantity	*Numeric*	
Item weight	*Numeric*	
Order time	*Date*	
Estimated time of delivery (ETD)	*Date*	
Delivery location	*String*	
Order number	*Numeric*	
Order priority	*String*	
Customer ID	*Numeric*	
(ii) Initial setting of e-fulfilment centers		
Storage location setting (Zone and bin level)	*String*	Initial input as part of the construction of the cloud database
Travel distance between each bin location	*Numeric*	
Storage location of each SKU	*String*	
Equipment master	*String*	

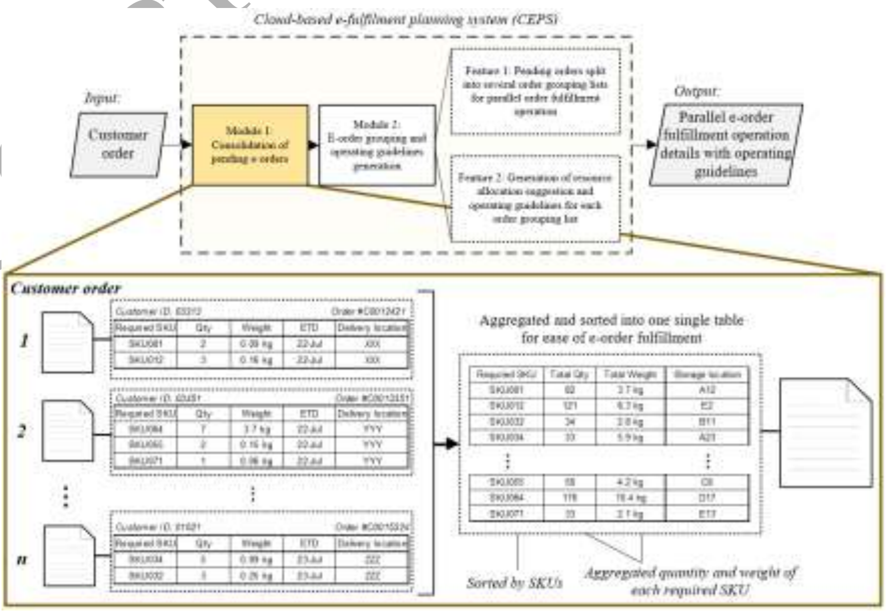


Fig. 4. Consolidation and sorting of customer e-order in CEPS

3.2 E-order grouping and resource allocation module

The sorted order details and storage location of SKUs pending to be picked are the inputs of this module. The grouping of e-orders using the GA mechanism starts with encoding the proposed order grouping model into a chromosome. An initial population of e-orders grouping solution is then formed, followed by the fitness of each chromosome being evaluated with the adoption of a quantitative model that includes constraints as the representation of the order grouping criteria. Prior to reaching the termination criteria, crossover and mutation operations are repeatedly performed to generate different sets of solutions. Upon fulfilling the termination criteria, the chromosome with smallest fitness value is selected as the near-optimal solution, which will then be decoded and transformed into a complete e-order grouping plan with resource and operating guidelines generated for each order grouping list. An overview of the procedures in module 2 of CEPS is shown in Fig. 5.

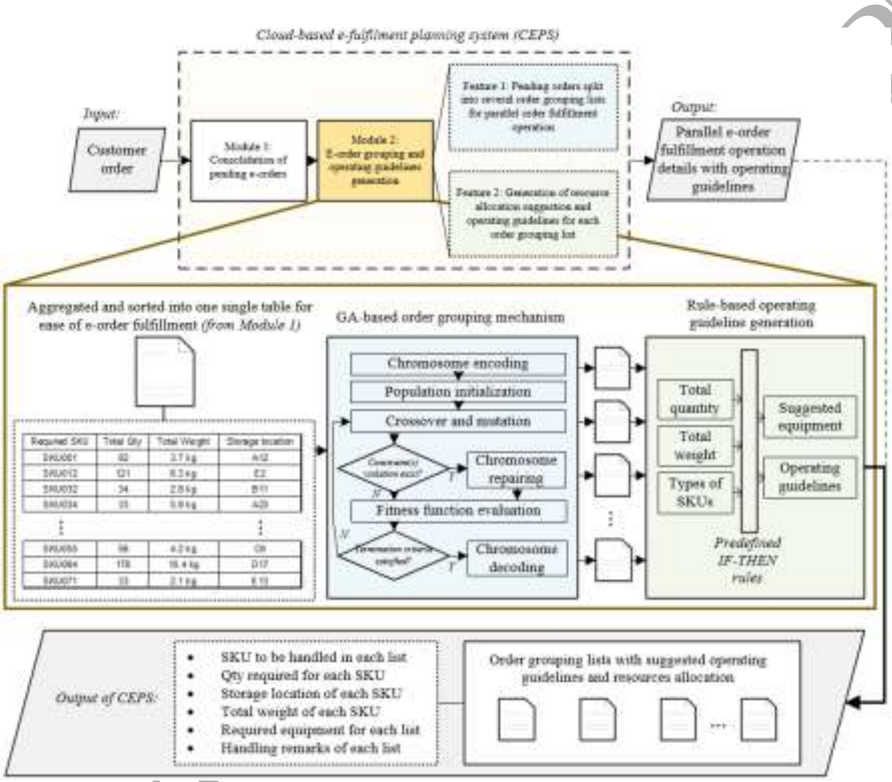


Fig. 5. E-order grouping and operating guidelines generation in CEPS

3.2.1 Chromosome encoding

The chromosome in the CEPS is a solution for identifying the nearly optimal combinations of SKUs to be picked under the same order grouping list. Several order grouping lists will be formed and presented in the chromosome. As shown in Fig. 6, the generic format of a chromosome is divided into two areas: order grouping region, and parameter region. For the order grouping region, the basic idea of the chromosome encoding scheme of this region comes from Lin et al. (2014). The value of each gene is a real number, where “0” represents the depot, and other values indicate the storage bin location. Take the chromosome in Fig. 6 as an example, a chromosome “112 114 145 0 243 231 212 321 0 410 412 413 415 0” can be interpreted as 0-112-114-145-0, 0-243-231-212-321-0, and 0-410-412-413-415-0, which implies that a total of three order grouping lists are generated, with the storage location under each order grouping list specified in the chromosome. For example, the order grouping list with chromosome “0-112-114-145-0” denotes that three storage bin locations, i.e. 112, 114 and 145, are to be travelled to when operator in the e-fulfilment center follows this order grouping list in executing e-order fulfilment operations.

The parameter region can further be classified into three different areas: total weight, total quantity and required equipment. The genetic operations will be performed only in the order grouping region, as the parameter region displays the corresponding total weight (W), total quantity (Q) and types of SKUs involved (S) in each order grouping list based on the order grouping solutions generated in the chromosome genes in the order grouping region. The information provided in the parameter region serves as the input of the rule-based inference system, which generates operating guidelines and suggests the required equipment based on the pre-defined rules. As shown in Fig. 6, the corresponding total weight, total quantity and required equipment for the order grouping list 1, i.e. chromosome gene B_{1j}, where j = 1, 2, …, N, are denoted as W_1, Q_1, S_1 respectively. The length of the chromosome in the parameter region depends on the number of order picking lists generated for the current problem.

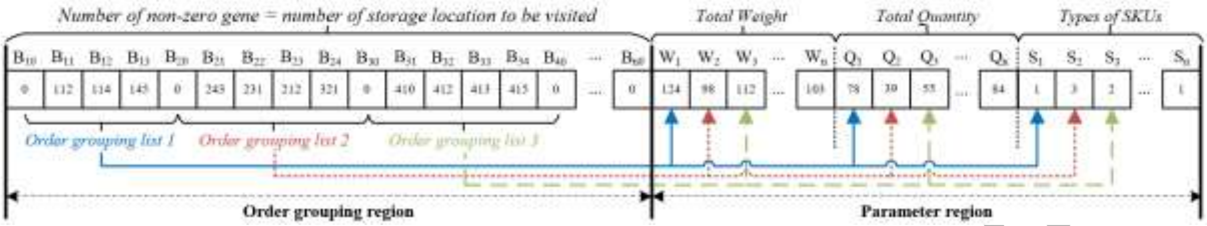


Fig. 6. The generic format of a chromosome

3.2.2 Population initialization, fitness evaluation, and genetic operations

Due to a large number of required storage locations to be visited in an e-fulfilment center for order picking of various items ordered by different online customers, the long length of a chromosome suggests that a large population size is required for generating a considerable number of possible combinations in crossover and mutation operations in the GA mechanism. A fitness function that minimizes the one-dimensional travel distance between two adjacent nodes, i.e. storage bin location, is used to evaluate the fitness of each chromosome. Considering the placement and alignment of a series of pallet racks in parallel as a common facility layout in the storage area of e-fulfilment centers, warehouses and distribution centers, a distance matrix that calculates and indicates the inter-bin distances among each storage bin is proposed, instead of a conventional computation of the distance between two adjacent nodes i and i+1 with coordinates (x_i, y_i) and (x_j, y_j) using $D_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$. The preparation of an inter-bin distance matrix is considered to be a more rational and appropriate approach, in comparison to a simple calculation of the distance between two adjacent nodes using their x,y coordinates, due to the fact an operator who is about to visit two storage bin locations, say bin A1 and bin B1 in Fig. 7, must be either picking route 1 or route 2 as illustrated in Fig. 7. A distance matrix that illustrates the shortest possible travel distance among each bin therefore achieves a better accuracy for fitness function evaluation. The shortest inter-bin travel distance ($D_{i,j}$) for bin i and j is calculated by Eq. 1:

$$D_{i,j} = \min\,[X_i + X_j, (L - X_i) + (L - X_j)] + N_s \times S + N_A \times A \qquad (1)$$

where X_i is distance between the x-coordinate of storage bin i and the starting position of the aisle (the origin), L is the total length of an aisle, N_A and N_s are respectively the number of aisles and storage bins vertically travelled across, and A and S are respectively the widths of an aisle and a storage bin.

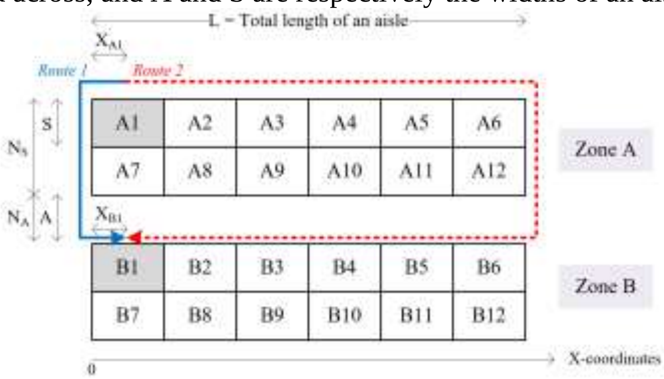


Fig. 7. An example of the shortest inter-bin travel distance calculation between two storage bins

For each order grouping problem, n out of N storage bins are required to be visited to pick up the items ordered by online customers, where N is the total number of storage bins, and n ≤ N. With the N×N distance matrix that contains all inter-bin shortest travel distances in the e-fulfilment center, the inter-bin distances among n out of N storage bins are required to be extracted from the parent distance matrix, by filtering out the inter-bin distances of all storage bins that will not be visited in this order fulfilment wave. This allows the GA mechanism to evaluate the fitness of each chromosome by only coping with the inter-bin distances of the n storage bins concerned in the current problem using the n×n distance matrix extracted from the original N×N distance matrix. The quantitative format of CEPS for e-order grouping is presented below. The notations are depicted in Table 4. Eq. (2) determines the shortest travel distance of all generated chromosomes. Constraint (3) ensures that the order grouping list includes the visiting storage bin location j immediately after storage bin location i. Constraints (4) and (5) ensure that each travel path only has one order grouping list and each storage bin location is included in only one single order grouping list. Constraints (6) and (7) respectively specify the volume and weight limit of an order grouping list. Constraint (8) ensures the continuity of path.

$$Minimize \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{g=1}^{G} D_{ij}x_{ijg} \tag{2}$$

$$x_{ijg} = \begin{cases} 1, & \text{if order grouping list g includes visiting bin location j just after i} \\ 0, & \text{otherwise} \end{cases} \quad \forall g \in G \tag{3}$$

$$\sum_{i\in N}\sum_{g\in G} x_{ijg} = 1, \qquad \forall\, j \in N \tag{4}$$

$$\sum_{j\in N}\sum_{g\in G} x_{ijg} = 1, \qquad \forall\, i \in N \tag{5}$$

$$\sum_{i\in N}\sum_{j\in N} v_i x_{ijg} \leq V_g, \qquad \forall\, g \in G \tag{6}$$

$$\sum_{i\in N}\sum_{j\in N} w_i x_{ijg} \leq W_g, \qquad \forall\, g \in G \tag{7}$$

$$\sum_{\substack{j\in N \\ j\neq i}} x_{ijg} = \sum_{\substack{j\in N \\ j\neq i}} x_{jig}, \qquad \forall\, i \in N, \forall\, g \in G \tag{8}$$

Table 4. Notation table for quantitative model of CEPS

Notation	Definition
G	Index set of all order grouping lists, G={1,2,…,g}
N	Index set of all storage bin location, N={1,2,…,n}
g	Index for order grouping list
i, j	Index for storage bin location
$\boldsymbol{v_i}$	Volume of items to be picked at storage bin location i
$\boldsymbol{w_i}$	Weight of items to be picked at storage bin location i
$\boldsymbol{V_g}$	Volume limit of order grouping list g
$\boldsymbol{W_g}$	Weight limit of order grouping list g
$\boldsymbol{D_{ij}}$	Shortest inter-bin distance between storage bin location i and j
$\boldsymbol{x_{ijg}}$	Binary variable indicating whether order grouping list g∈G travels storage bin location i and j

Through the typical genetic operations in GA, including crossover, mutation, and repairing operations, the GA iteration process is stopped once the maximum number of iterations has been reached. The best chromosome is then selected as the near-optimal solution and decoded into a readable format of order grouping solutions. This allows users to obtain the suggested number of order grouping lists required, and the details of each order grouping list, including the storage bin locations sequence to be visited in each order grouping list, and the corresponding items with quantity information to be handled at each storage bin location.

3.2.3 Rule-based operating guidelines decision support

Rule-based operating guidelines decision support is generated in addition to the order grouping solutions. As the operating procedures and equipment selections vary depending on the nature of an order, the total weight and quantity of each order grouping list, as indicated in the parameter region of the chromosome, along with the product categories handled in each order grouping list, serve as the antecedents, i.e. the if-part of a rule, of a set of "IF-THEN" rules pre-defined in CEPS, whereas the required equipment and a set of suggested operating procedures are the consequent, the then-part of a rule. Among the two broad kinds of inference engines used in rule-based systems, forward chaining and backward chaining systems, the former one, that is, a data-driving reasoning strategy, is adopted in CEPS, so as to process the known parameters given in the parameter region of the chromosome to keep using the "IF-THEN" rules to suggest an appropriate set of operating procedures and handling equipment.

With the order grouping decision support and knowledge support through suggesting an appropriate set of operating procedures and equipment, the e-commerce order processing flow in the e-fulfilment center is reengineered, as the top management of e-fulfilment center can flexibly consolidate pending a large number of discrete, small lot-sized online customer orders and release the jobs in waves with clear instructions of how these jobs are to be handled.

4. CASE STUDY

In order to validate the performance, the CEPS is implemented in a case company. The case company is a medium-sized Hong Kong-based logistics service provider that has specialized in B2C e-commerce logistics and distribution services in recent years. As China continues to drive cross-border growth, and its share of the online cross-border market is expected to grow from 27% in 2015 to 40% in 2021 (Forrester Research, 2016b), the developing trend of e-commerce in China has created a golden opportunity in recent years for logistics practitioners in Hong Kong and within the Pearl River Delta region to grasp a large part of the e-commerce pie by transforming their traditional B2B logistics businesses into e-commerce logistics businesses. This can be achieved by providing total e-logistics solutions so that e-retailers can concentrate on their core business by outsourcing the entire e-order fulfilment, including e-commerce last-mile delivery operations, to logistics service providers.

However, logistics service providers face enormous challenges in the e-commerce logistics business not only due to the tight handling requirements of e-commerce orders, in which it is becoming popular for e-retailers to guarantee 24-to-48-hour delivery to customers, but is also affected by the internal inefficiency of e-order handling and processing. The challenges are generic and are also faced by the case company, including the heavy workload of warehouse operators in fulfilling the orders in a timely manner and the increasing frequency of picking and packing wrong items. These typical challenges result from the irregular arrival of e-orders as online customers can place orders at any time via the Internet. Another reason is due to the fact that each B2C customer order involves a relatively large number of various types of SKUs, although in small quantities, which results in a higher chance of inaccurate order fulfilment considering the large number of fragmented e-orders that are required to be fulfilled within a limited time. In view of the operating inefficiency in managing their e-commerce business, the CEPS is implemented in the case company with an implementation roadmap as illustrated below, which highlights the essential stages of development for the proposed system to work on a production environment.

4.1 Implementation of the cloud-based e-fulfilment planning system

The implementation procedures can be divided into four phases: (i) Cloud database development, (ii) Customization of GA mechanism and rule-based inference engine, and (iii) Front-end user interface development.

4.1.1 Cloud database development

E-order consolidation and sorting in the cloud database is one of the most crucial functions of the CEPS for the purpose of logistics process re-engineering in the e-commerce business. Table 5 summarizes the essential functions of the centralized cloud database for data storage across various e-logistics activities in the case company. The cloud database collects e-orders and displays the collected e-orders pending processing. The logistics order processing flow is re-engineered by allowing users to control when pending orders are ready for batch release to the warehouse department so as to perform the order fulfilment operations. The centralized relational database also sorts the received orders by SKUs, so that the SKUs to be handled in the e-fulfilment centers are grouped for ease of actual processing. Figs. 8 and 9 show respectively the storage area of the e-fulfilment centers of the case company where order picking operations take place, and the computer terminal for the display and consolidation of e-orders.

Table 5. Database construction for various e-logistics activities

Related department	Logistics activities	Functions of the cloud database
Customer service department	Customer order inquiry	Create log for track and trace of order inquiry history
	E-order collection	Retrieve new orders and stores information in the database
	Documents for order processing	Prepare required documents and import and export, update the documentation completion status of each order
	Shipment notification to customers	Generate shipment notification templates for notifying customers of their orders ready for delivery
Warehouse department	Order fulfilment in e-fulfilment centers	Follow the tables for order receiving, put-away, pick-and-pack, and delivery operations
	Order status update	Update the status of e-order for order visibility and transparency
	Inventory update	Cross-checking and updating of inventory in database and in storage areas of e-fulfilment centers

Fig. 8. Order picking operations in storage bin locations of e-fulfilment centers

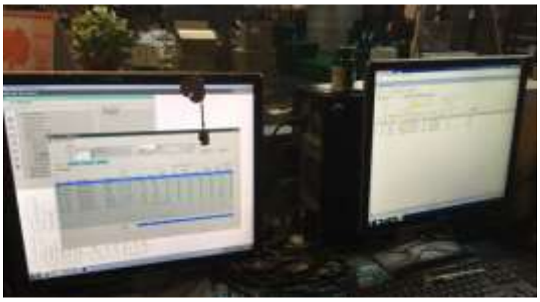


Fig. 9. Computer terminal for e-order consolidation and generating order grouping list

4.1.2 Customization of the Genetic Algorithm mechanism and rule-based inference engine

(i) GA mechanism and the distance matrix

To govern the e-fulfilment operational flow, decision support for grouping SKUs with similar storage locations in e-fulfilment centers, and suggesting an appropriate set of handling remarks and handling equipment, is developed through the construction of the proposed GA mechanism. Storage bin locations of the e-fulfilment centers are decoded into real numbers for formulating a valid chromosome encoding scheme. A Microsoft Excel spreadsheet is used for the back-end algorithm development, and Evolver, a software developed by the Palisade Corporation, is adopted to minimize the fitness function using Eq. (2) in order to search for the best global solution of order grouping. Fig. 10 shows the order grouping decision support development using an MS Excel spreadsheet. A distance matrix that calculates all the inter-bin distances among each storage bin is proposed. A distance matrix is prepared for the case company based on the layout design of the storage bin locations in the e-fulfilment center, as shown in Fig. 8. For each order grouping problem, the pending e-orders only involve part of the total number of SKUs stored in the storage areas. Therefore, using the parent distance matrix, that includes all inter-bin distances, is unnecessary. In this regard, a sorting algorithm, which is developed using Visual Basic for Applications (VBA), a programming language that automate tasks in MS Excel, is built for extracting the required inter-bin distances from the parent distance matrix to form a child distance matrix. The programming code for the sorting algorithm is depicted in Fig. 11.

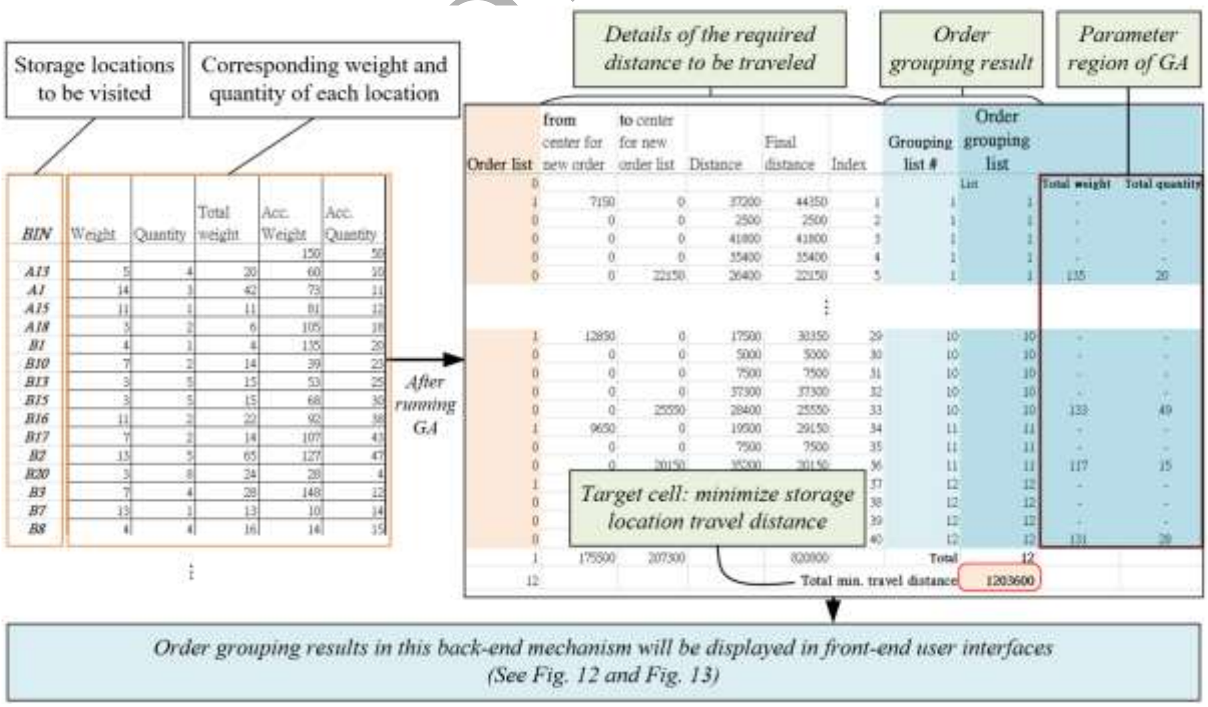


Fig. 10. Order grouping decision support development using GA

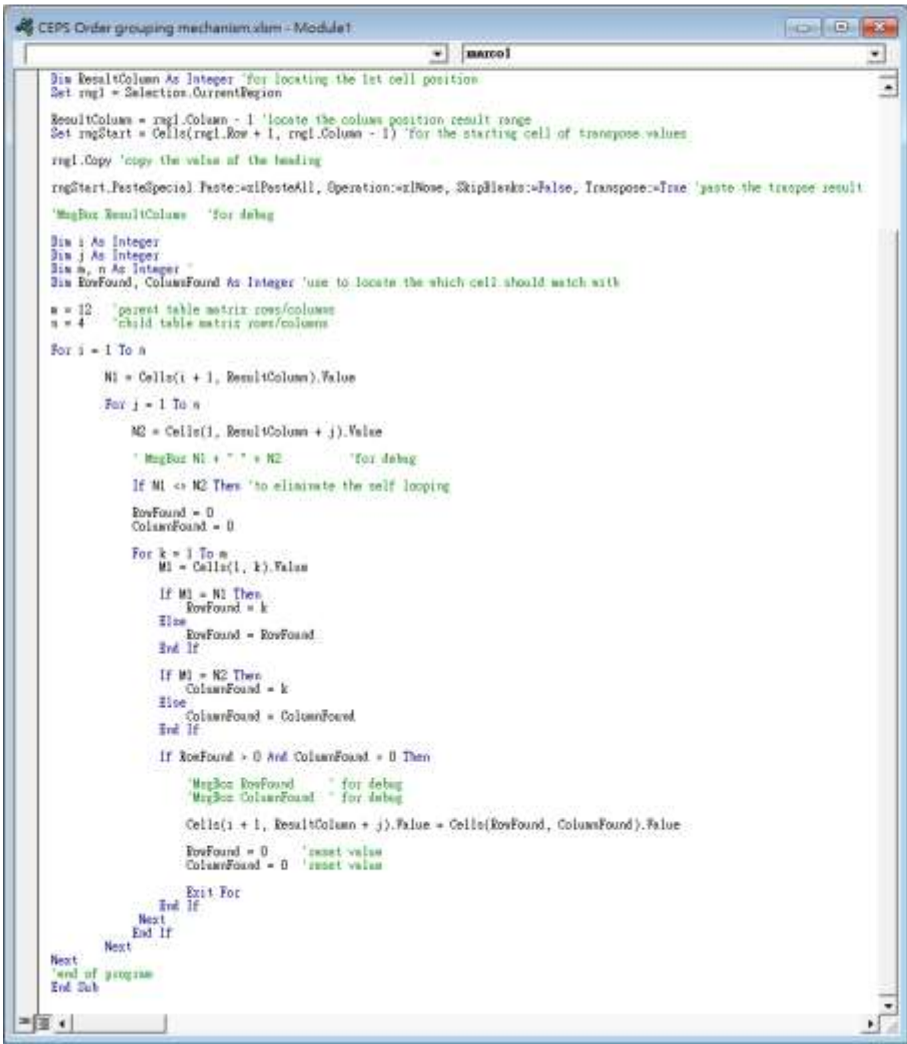


Fig. 11. Codes for distance matrix sorting

(ii) Rule-based inference engine

An appropriate set of operating guidelines and order handling equipment are suggested through a rule-based inference engine for each of the e-order grouping solutions generated from the GA mechanism. A rule-based inference engine is adopted for ease of storing and manipulating human knowledge to interpret order grouping information in a useful way. The engine is customized for the case company based on the current throughput volume and resource availability for e-order fulfilment operations in the e-fulfilment center. Three parameters are identified as the factors that influence the operating procedures and equipment selection: total quantity, total volume of the order grouping list, and the types of SKUs involved in the order grouping list. An example of the "IF-THEN" rules are presented in a decision table format in Table 6. In the CEPS, the warehouse manager has the access right to preview all active rules, and add, change, and delete a rule whenever appropriate or necessary. Any change in the database which stores the "IF-THEN" rules is subject to an internal checking by the system itself for ensuring there is no violation or contradiction among the rules.

Table 6. Example rules applied in the case company

"IF" condition	**"THEN" Action**
Example rules for operating guidelines	
Quantity is more than 50	Double check if the quantity picked for each SKU is correct at the end of operation
Volume is more than 20 kg	Reserve lower space for heavier item
Types of SKUs is more than 5	Pick up item separation tool for separating different SKUs;
Example rules for equipment selection	

Volume is <u>26-50 kg</u>	Use Multi-Storey Trolley for separation of different SKUs
Volume is <u>more than 50 kg</u>	Use Lifter

4.1.3 Front-end user interface development

A front-end user interface (UI) serving as the presentation and interaction tier for users is designed, as shown in Figs. 12 and 13. It integrates the cloud database, back-end GA mechanism and rule-based inference engine, so that users are able to conveniently view the newly received e-orders which are retrieved from the Intranet and stored in the cloud database; obtain decision support from the GA mechanism regarding how the required SKUs from the pending e-orders are to be grouped for batch processing in e-fulfilment centers; and receive suggestions from the rule-based inference engine regarding the equipment and handling procedures of each order grouping list generated in the GA mechanism. The CEPS is a web-based application so that users can login onto the system via the Internet. The Customer Service department can decide when to stop the consolidation of e-orders and start initiating the CEPS so as to generate order grouping suggestions, as shown in Fig. 12. The suggested outputs can then be exported to other formats for modification or printed for the warehouse department to execute accordingly. The warehouse department can, on the other hand, modify or add various information to the CEPS, including the available material handling equipment, operating guidelines for different types of e-orders and the storage location of SKUs, so that the database is up-to-date, and the decision support provided by CEPS is feasible.

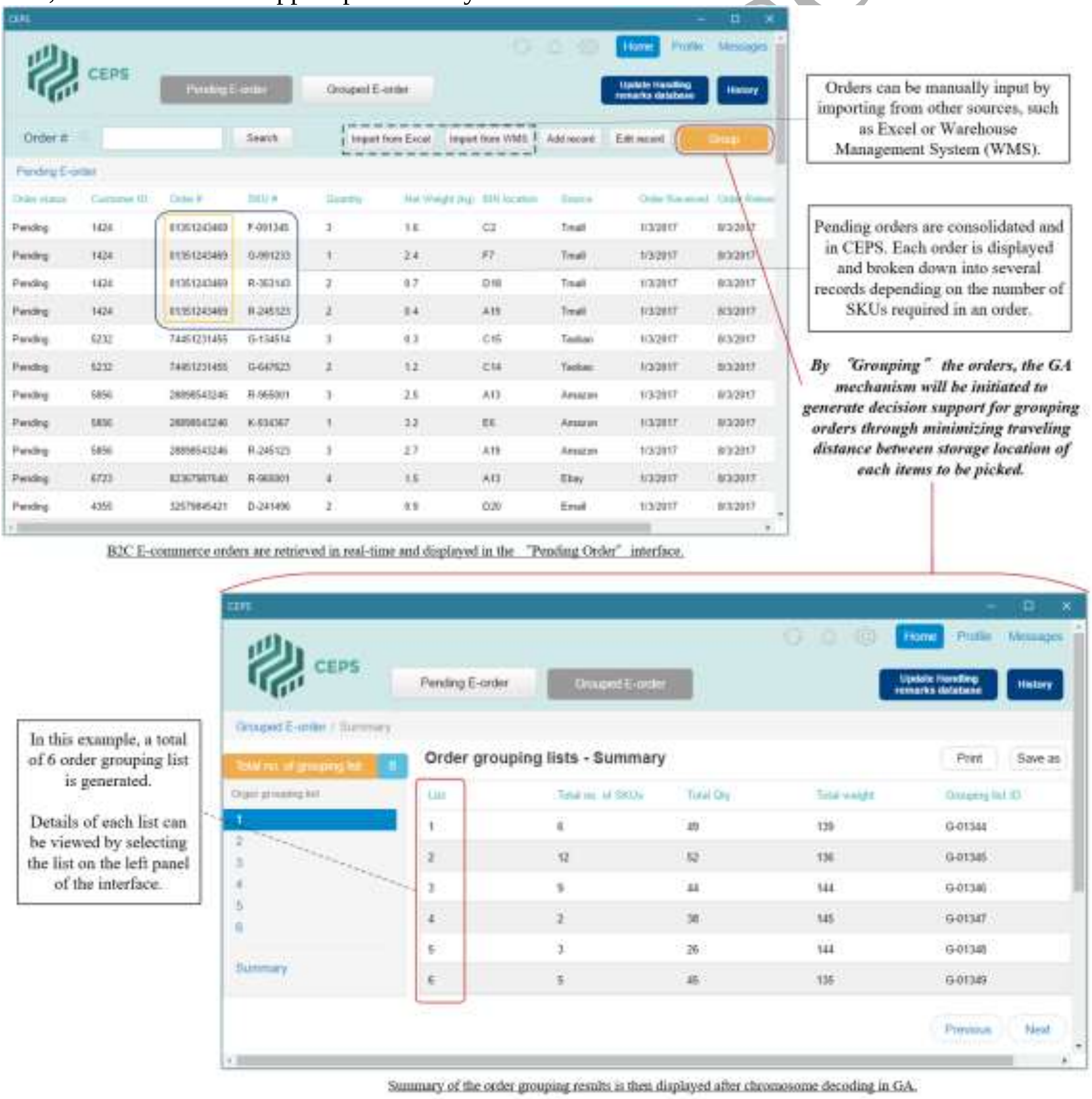


Fig. 12. User interfaces of CEPS – Order consolidation and grouping

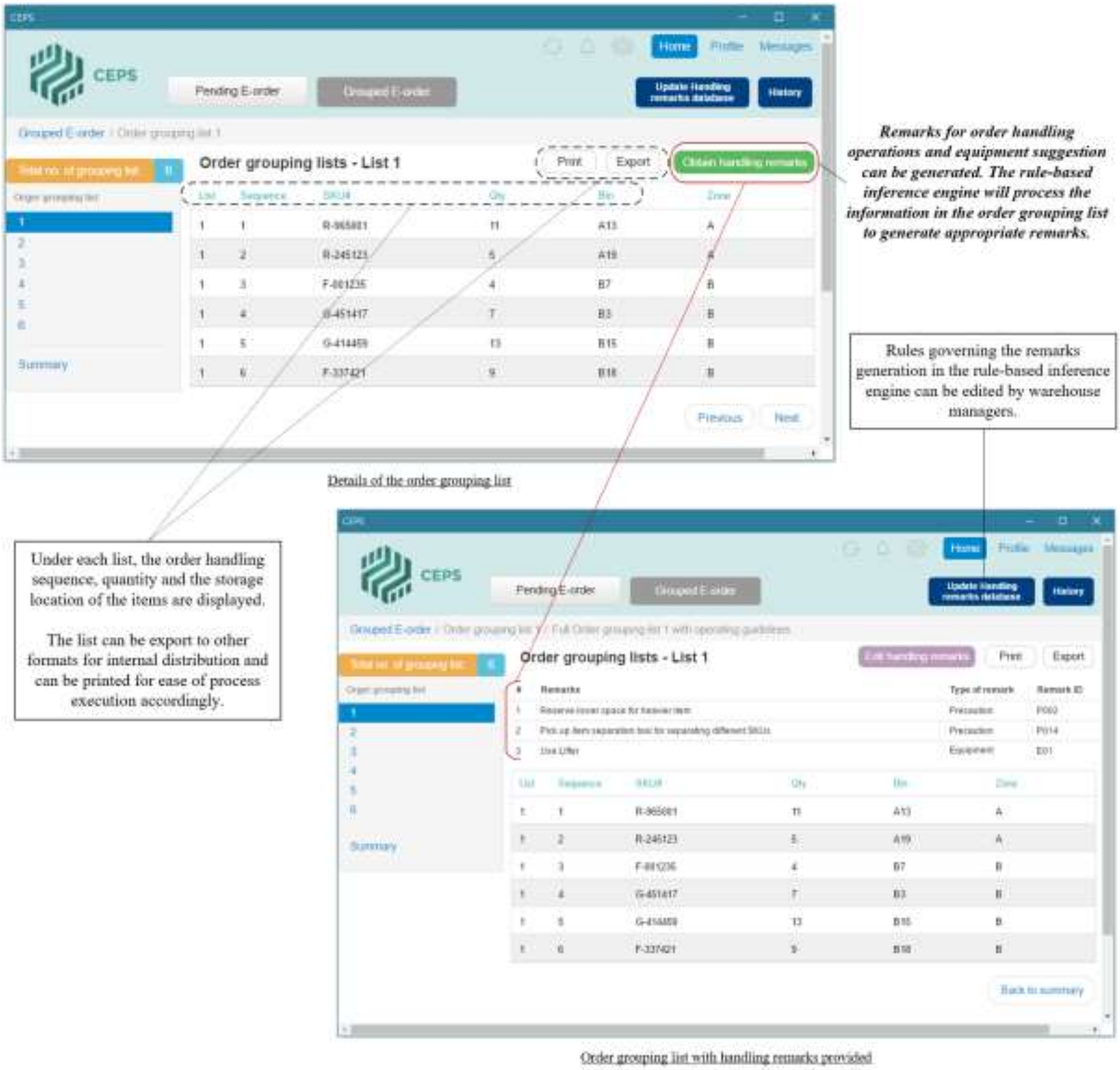


Fig. 13. User interfaces of CEPS – Details of order grouping list and generating operating guidelines

5. RESULTS AND DISCUSSION

With CEPS, the e-fulfilment process in warehouses or distribution centers is re-engineered. Logistics service providers no longer perform e-order fulfilment operations immediately after orders are received online. Instead, e-orders, which are placed by B2C customers from various online sales platforms, and usually small in lot-size, are consolidated in a cloud database for further order grouping. In addition to the order grouping decision support by separating pending to-be-picked SKUs into several order grouping lists based on storage locations dissimilarity, the operating procedures and appropriate material handling equipment are further suggested for ease of e-order fulfilment process execution. The improvement is not only beneficial to the case company, but also its downstream logistics service providers along the supply chain. In this section, the GA optimal parameter setting is first reported, followed by an analysis of the key performance improvement areas found in the case company. Finally, the implications to the e-commerce logistics business are discussed in depth.

5.1 Parameter settings of the Genetic Algorithm

The GA parameter settings are required to be defined prior to implementation in an actual production environment. Specifically, a crossover rate and a mutation rate, ranging from 0 to 1, are defined by the users. A trial-and-error approach is used to determine an appropriate crossover and mutation rate that best suits the GA mechanism developed. In this case study, a crossover rate of 0.7

and 0.9, and a mutation rate of 0.1 and 0.25, are selected for testing under a population size of 2000 and with the number of generations set to be 50,000. Using different combinations of crossover and mutation rate as specified in Table 7, it is found that, after pair-wised executing for 10 times, a GA parameter setting with a crossover rate of 0.9 and a mutation rate of 0.1 gives the lowest fitness value, as summarized and shown in Fig. 14. The more storage locations to be visited, a greater number of trials is preferred, so as to obtain a better nearly-optimal solution.

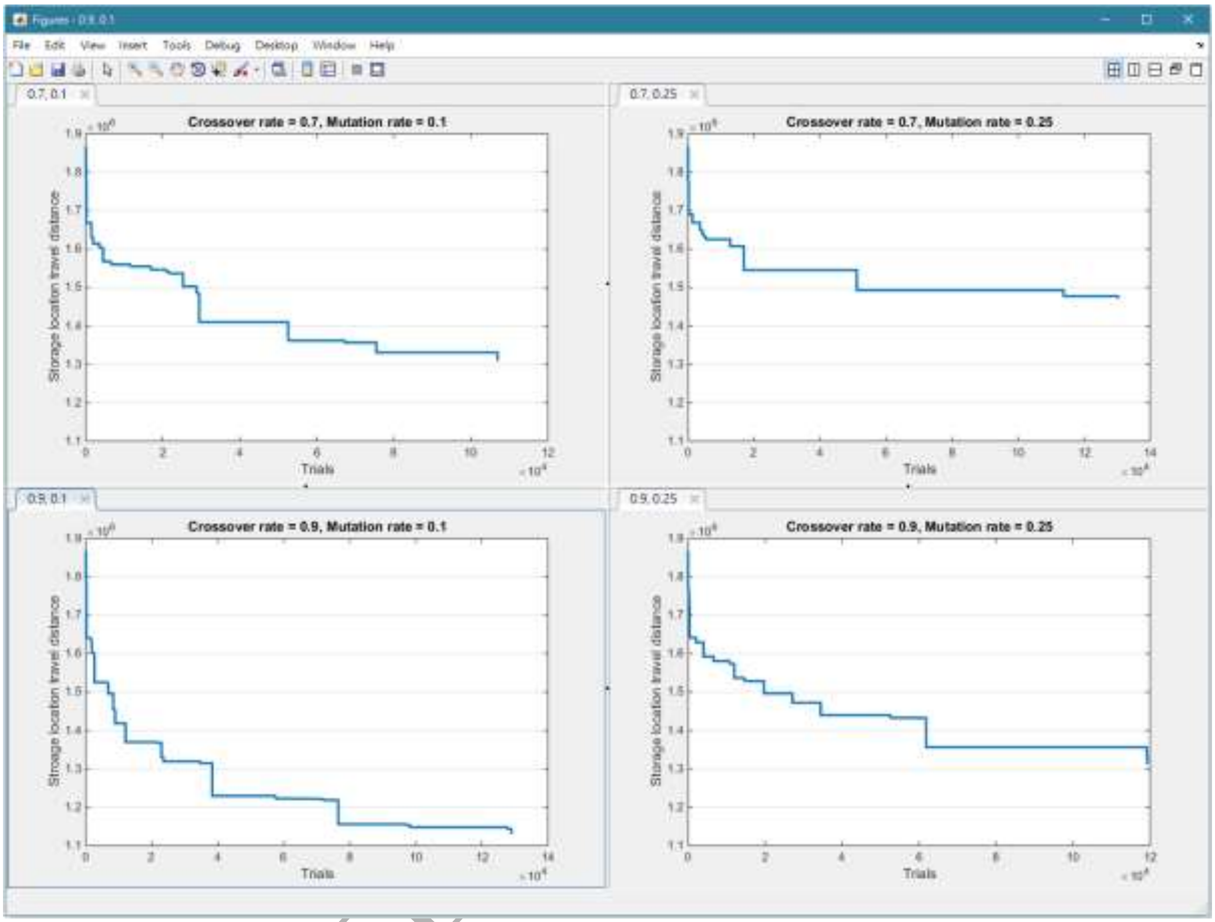


Fig. 14. Graphical comparison of the results under different combinations of GA parameter setting

Table 7. GA parameter settings

Parameter	**Settings**
Crossover rate	0.7/0.9
Mutation rate	0.1/0.25
Population size	2000
Termination criteria	Stops if: (1) the number of generations reach 50,000; or (2) the target cell has an improvement of less than 0.01% in the last 10,000 trials.

5.2 Key operating performance improvements

The performance improvement in the order fulfilment operations in e-fulfilment centers can be found in terms of two measurable areas, they are: (i) Reduction of total order processing time, and (ii) Reduction of total traveling distance of a customer order.

(i) Reduction of total order processing time

The total order processing time in handling an e-order in e-fulfilling centers involves the following sequential operations: I. Order planning – Consolidate e-orders and print relevant documents for warehouse operators to execute accordingly; II: Picking - Travel to storage locations and pick the required items; III. Packing – Allocate the picked items to the designated customer order and pack the items in a carton box; IV. Labeling – Print and stick required label(s) on the packed carton box.

Before the implementation of CEPS, e-orders were processed individually without any grouping of orders in advance for future batch processing. Therefore, the order processing operation does not consist of any order planning operation that consolidate e-orders before process execution. E-orders are immediately picked by assigning a worker to travel to the specified storage locations to pick up the required items. After the picked items are inspected, the items are loaded onto a carton box at the packing area, followed by placing the shipping and precaution labels on the packed carton box. According to a previous time measurement conducted by the case company, the total e-order processing time of an order, which involves the operations as mentioned above, is 9.33 minutes on average, as shown in Table 8.

With the implementation of CEPS, the e-orders are consolidated before processing in a batch. On average, each batch consist of 30 individual online customer orders. Through time measurement over a 3-month period, for a batch order processing operation, it takes 13.5 minutes for order planning operations, followed by 37 minutes for picking the grouped e-orders by visiting the storage locations once, 52 minutes for allocating the required items to the customers and packing the 30 carton boxes, and 10 minutes for labelling all the packed boxes. On a per-order basis, the total e-order processing time is 2.68 minutes on average, showing a 70% reduction of the total processing time as compared to the performance before the implementation of the proposed system. A graphical comparison of the time spent on each order processing operation is shown in Fig. 15.

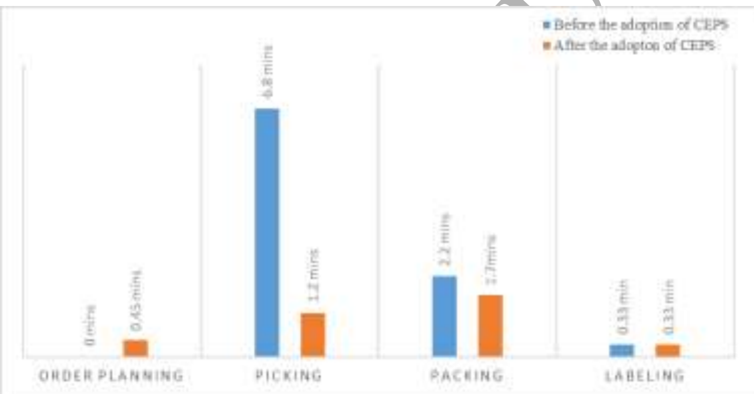


Fig. 15. Improvement in terms of order processing time

Table 8. Order processing time before-and-after comparison

Operation	Before	After	After (per batch)	Difference
Order planning	*0 min*	*0.45 mins*	*13.5 mins*	-
Picking	*6.8 mins*	*1.2 mins*	*37 mins*	-82.4%
Packing	*2.2 mins*	*1.7 mins*	*52 mins*	-22.7%
Labeling	*0.33 min*	*0.33 min*	*10 mins*	0%
Total	***9.33 mins***	***2.68 mins***	*112.5 mins*	-71.3%

(ii) Reduction of total traveling distance of a customer order

The total travelling distance is another noticeable improvement area. The adoption of CEPS has reduced the traveling distance of an e-order as storage locations are visited only once for a batch of consolidated customer orders, instead of conventionally visiting storage locations repeatedly throughout the working hours for each particular customer order. Before the re-engineered order fulfilment operations, the items purchased in an e-commerce order were picked by visiting the storage locations once, which, on average, requires a travel distance of 68 meters. With the implementation of CEPS, a batch, which consists of 30 individual online customer orders on average, requires a total travel distance of 397 meters. In other words, only a travel distance of 13.2 meters is required for an order, yielding a 81% reduction of total traveling distance of handling a customer order. In the long run, the re-engineered e-order process reduces the workload of employees working in e-fulfilment operations. The saved time for repeated visits to storage locations enables managers to flexibly reallocate the human resources to handle other operations such as put-away and cargo loading or unloading operations.

5.3 Managerial implications

The rise of e-commerce, O2O retailing, and direct-to-consumer last-mile delivery has positioned e-fulfilment distribution centers at the very heart of what end consumers perceive as good service. Aggressive, guaranteed delivery dates are often provided for addressing customer demands. The increasing convenience of online shopping has redefined the way we shop; the customer demands, on the other hand, are reshaping e-fulfilment. In the e-commerce marketplace, customer segmentation is a known market opportunity enabling retailers to reach a wider customer base. However, it is also one of the biggest challenges in e-commerce. The e-order fulfilment of logistics service providers has to be very efficient in handling e-orders, which are received from the internet at any time, and are to be delivered to a vast number of locations worldwide before the guaranteed delivery dates. In the absence of decision support systems facilitating the e-order internal processing operations in e-fulfilment centers, logistics practitioners, especially those SME-sized organizations that often handle orders without comprehensive IT support, experience obstacles in maintaining the same level of efficiency as they had in handling traditional orders in warehouses or distribution centers.

The evolution of information and communication technology (ICT) services with cloud computing and mobile technologies has offered enterprises not only more sales channels and effective formulation of target marketing strategies through big data analytics, but also better internal and external information and communication management solutions for integration into daily business for operational excellence. However, with the slow pace of new technology adoption and innovation in the logistics and distribution sector (Evangelista & Sweeney, 2006; European Commission, 2012), logistics practitioners manage e-orders in a conventional flow of operations, which affects their e-order handling capability and prolongs the e-fulfilment lead time. The results from the case study indicates that light-weight IT applications, which integrate artificial intelligence techniques and the state-of-the-art cloud computing technologies, enable logistics practitioners to improve their internal order processing cost effectively. Software and solution providers should take e-fulfilment requirements into consideration when designing and developing competitive ICT solutions, with the integration of artificial intelligence techniques for providing decision support and e-commerce logistics process re-engineering and automation.

6. CONCLUSIVE REMARKS AND FUTURE WORK

The capability of logistics service providers in e-order fulfilment is one of the key factors affecting the growth of the online retail business. This paper develops a cloud-based e-order fulfilment pre-processing system, which integrates the genetic algorithm technique and the rule-based inference engine, so that logistics service providers are able to effectively plan for the upcoming internal processing operations of received orders before actual process execution. By so doing, any warehouse postponement strategy can be realized and supported by the proposed system, as presented in this paper. Through consolidating pending e-orders using a cloud database, justifying an optimal internal order processing plan by the genetic algorithm approach, and providing essential operating guidance through the rule-based inference engine for order processing execution, logistics service providers no longer have to process discrete e-orders immediately after they are received. The e-commerce internal order processing flow is therefore streamlined and re-designed. The improved e-order handling capability of logistics service providers eventually reduces the processing time in e-fulfilment centers, thereby meeting the ever tighter delivery requirements of online customers. Ultimately, the intelligent system presented in this paper contributes to the development of the e-commerce business environment from the perspective of the interconnected parties. Logistics service providers become more capable in capturing the logistics of the e-commerce business; retailers can build brand images and loyalty by satisfying the consumers' needs and expectations, especially considering the timeliness of the last-mile e-order delivery, one of the most critical e-fulfilment processes; and end consumers can receive their purchased items without a long waiting time.

This research provides a systematic way of managing a large number of discrete, small lot-sized e-orders in distribution centers, which is a phenomenon that commonly exists in today's order fulfilment operations. While the GA mechanism with the support of rule-based inference engine proposed in this paper effectively groups e-orders for further batch processing, decision makers are still required to manually determine the cut-off points for releasing the grouped e-orders, in terms of, for example, the maximum time for grouping e-orders, or the maximum allowable number of e-orders to be grouped. It is recommended that more research is undertaken on determining "when to group" in order to improve the feasibility of the decision support system.

ACKNOWLEDGMENT
The authors wish to thank the Research Office of The Hong Kong Polytechnic University for supporting the project (Project Code: RU5T and G-UA7Z).

REFERENCES

Agatz, N.A., Fleischmann, M., & Van Nunen, J.A. (2008). E-fulfillment and multi-channel distribution: a review. *European Journal of Operational Research*, 187, pp. 339–356.

Accorsi, R., Manzini, R., & Maranesi, F. (2014). A decision-support system for the design and management of warehousing systems. *Computers in Industry*, 65(1) pp. 175-186.

Akhter, F., Hobbs, D., & Maamar, Z. (2005). A fuzzy logic-based system for assessing the level of business-to-consumer (B2C) trust in electronic commerce. *Expert Systems with Applications*, 28(4), 623-628.

Bindi, F., Manzini, R., Pareschi, A., & Regattieri, A. (2009). Similarity-based storage allocation rules in an order picking system: an application to the food service industry. *International Journal of Logistics Research and Applications*, 12(4), pp.233-247.

Caron, F., Marchet, G., & Perego, A. (2000). Optimal Layout in Low-Level Picker-to-Part Systems. *International Journal of Production Research*, 38, 101-117.

Castro-Schez, J., Miguel, R., Vallejo, D., & López-López, L. (2011). A highly adaptive recommender system based on fuzzy logic for B2C e-commerce portals. *Expert Systems with Applications*, 38(3), 2441-2454.

Chan, F., & Kumar, V. (2009). Hybrid TSSA algorithm-based approach to solve warehouse-scheduling problems. *International Journal of Production Research*, 47(4), 919-940.

Chan, H., He, H., & Wang, W. (2012). Green marketing and its impact on supply chain management in industrial markets. *Industrial Marketing Management*, 41(4), 557-562.

Chen, B., & Lee, C. (2008). Logistics scheduling with batching and transportation. *European Journal of Operational Research*, 189(3), 871-876.

Chen, X., & Lin, H. (2013). Research on e-commerce logistics system informationization in chain. *Procedia-social and behavioral sciences*, 96, 838-843.

Chew, E. P., & Tang, L.C., 1999. Travel time analysis for general item location assignment in a rectangular warehouse. *European Journal of Operational Research*, 112, 582–597.

Cho, Jay Joong-Kun, Ozment, J., & Sink, H. (2008). Logistics capability, logistics outsourcing and firm performance in an e-commerce market. *International Journal of Physical Distribution & Logistics Management*, 38(5), 336 – 359.

Chow, Harry K.H., Choy, K.L., Lee, W.B., & Lau, K.C. (2006). Design of a RFID case-based resource management system for warehouse operations. *Expert Systems with Applications*, 30(4), 561-576, 2006.

De Koster, R.B.M. (2003). Distribution strategies for online retailers. *IEEE Transactions on Engineering Management*, 50, pp. 448–457.

De Koster, R., Le-Duc, T., & Roodbergen, K. (2007). Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, 182(2), pp.481-501.

Esper, T. L., Jensen, T. D., Turnipseed, F. L., & Burton, S. (2003). The last mile: an examination of effects of online retail delivery strategies on consumers. *Journal of Business Logistics*, 24(2), 177-203.

European Commission, (2012). Report of the High Level Group on the Development of the EU Road Haulage Market. Brussels.

Evangelista, P., & Sweeney, E. (2006). Technology usage in the supply chain: the case of small 3PLs. *The International Journal of Logistics Management*, 17(1), 55-74.

Fernie, J., & McKinnon, A. (2009). The development of e-tail logistics. In Fernie, J. and Sparks, L. (eds), *Logistics and Retail Management, Emerging Issues and New Challenges in the Retail Supply Chain*. London: Kogan Page, 207–232.

Forrester Research, (2016a). eCommerce Trends and Outlook In Australia, China, India, Japan, And South Korea.

Forrester Research, (2016b). Forrester Research Online Cross-Border Retail Forecast, 2016 To 2021 (Global).

Geismar, H., Laporte, G., Lei, L., & Sriskandarajah, C. (2008). The Integrated Production and Transportation Scheduling Problem for a Product with a Short Lifespan. *INFORMS Journal On Computing*, 20(1), 21-33.

Gu, W., Foster, K., & Shang, J. (2016). Enhancing market service and enterprise operations through a large-scale GIS-based distribution system. *Expert Systems with Applications*, 55, 157-171.

Hassan, M.M.D. (2002). A framework for the design of warehouse layout. *Facilities*, 20(13/14), 432-440.

Ho, G.T.S., Lau, H.C.W., Chung, S.H., Fung, R.Y.K., Chan, T.M., & Lee, C.K.M. (2008). Fuzzy rule sets for enhancing performance in a supply chain network. *Industrial Management & Data Systems*, 108(7), 947-972.

Huang, C., Liang, W., Lai, Y., & Lin, Y. (2010). The agent-based negotiation process for B2C e-commerce. *Expert Systems with Applications*, 37(1), 348-359.

Hultkrantz, O., & Lumsden, K. (2001). E-commerce and consequences for the logistics industry. In *Proceedings for Seminar on "The Impact of E-Commerce on Transport."*. Paris.

Jane, C.C. (2000). Storage location assignment in a distribution center. *International Journal of Physical Distribution & Logistics Management*, 30(1), 55-71.

Lam, Cathy H.Y., Choy K.L., & Chung, S.H. (2011). A decision support system to facilitate warehouse order fulfillment in cross-border supply chain. *Journal of Manufacturing Technology Management*, 22(8), 972 – 983.

Lang, G., & Bressolles, G. (2013). Economic Performance and Customer Expectation in e-fulfillment Systems: a Multi-Channel Retailer Perspective. *Supply Chain Forum: An International Journal*, 14(1), 16-26.

Lee, C.K.H., Choy, K.L. Ho, G.T.S., & Lam, C.H.Y. (2016). A Slippery Genetic Algorithm-Based Process Mining System for Achieving Better Quality Assurance In The Garment Industry. *Expert Systems with Applications*, 46, 236-248.

Lekovic, S., & Milicevic, N. (2013). The importance and characteristics of logistics in electronic commerce.

Leung, K.H., Cheng, W.Y., Choy, K.L., Wong, W.C., Lam, H.Y., Hui, Y.Y., Tsang, Y.P., & Tang, Valerie (2016). A Process-Oriented Warehouse Postponement Strategy for E-Commerce Order Fulfillment in Warehouses and Distribution Centers in Asia. In Patricia Ordóñez de Pablos (Eds.), *Managerial Strategies and Solutions for Business Success in Asia* (pp.21-34). Hershey, PA: IGI Global.

Lin, C., Choy, K.L., Ho, G.T.S., & Ng, T.W. (2014). A Genetic Algorithm-based optimization model for supporting green transportation operations. *Expert Systems with Applications*, 41(7), 3284-3296.

Maltz, A.B., Rabinovich, E., & Sinha, R. (2004). Logistics: the key to e-retail success. *Supply Chain Management Review*, 8, 48–54.

Mendes, J. J. M., Gonalves, J. F., & Resende, M. G. C. (2009). A random key based genetic algorithm for the resource constrained project scheduling problem. *Computers and Operations Research*, 36, 92–109.

Morganti, E., Seidel, S., Blanquart, C., Dablanc, L., & Lenz, B. (2014). The Impact of E-commerce on Final Deliveries: Alternative Parcel Delivery Services in France and Germany. *Transportation Research Procedia*, 4, 178-190.

Muppani Muppant, V., & Adil, G. (2008). Efficient formation of storage classes for warehouse storage location assignment: A simulated annealing approach. Omega, 36(4), 609-618.

Oliveira, R., Cardoso, I., Barbosa, J., da Costa, C., & Prado, M. (2015). An intelligent model for logistics management based on geofencing algorithms and RFID technology. *Expert Systems with Applications*, 42(15-16), 6082-6097.

Önüt, S., Tuzkaya, U. & Doğaç, B. (2008). A particle swarm optimization algorithm for the multiple-level warehouse layout design problem. *Computers & Industrial Engineering*, 54(4), 783-799.

Pan, J., Shih, P., Wu, M., & Lin, J. (2015). A storage assignment heuristic method based on genetic algorithm for a pick-and-pass warehousing system. *Computers & Industrial Engineering*, 81, 1-13.

Park, J., Kang, M., & Lee, K. (1996). An intelligent operations scheduling system in a job shop. *International Journal of Advanced Manufacturing Technology*, 11(2), 111-119.

Patriarca, R., Costantino, F., & Di Gravio, G. (2016). Inventory model for a multi-echelon system with unidirectional lateral transshipment. *Expert Systems with Applications*, 65, 372-382.

Petersen, C.G. (2000). An evaluation of order picking policies for mail order companies. *Production and Operations Management*, 2000, 9(4), 319-335.

Poon, T.C., Choy, K.L., Chan, F.T.S., Ho G.T.S., Gunasekaran, A., Lau, H.C.W., & Chow, H.K.H. (2011). A real-time warehouse operations planning system for small batch replenishment problems in production environment. *Expert Systems with Applications*, 38(7), 8524-8537.

Renner, G., & Ekárt, A. (2003). Genetic algorithms in computer aided design. *Computer-Aided Design*, 35(8), 709-726.

Tana, K.H., Limb, C.P., Plattsc, K. and Koay, H.S. (2006). An intelligent decision support system for manufacturing technology investments. *International Journal of Production Economics*, 104, 179-90.

Taniguchi, E., & Shimamoto, H. (2004). Intelligent transportation system based dynamic vehicle routing and scheduling with variable travel times. *Transportation Research Part C: Emerging Technologies*, 12(3-4), 235-250.

Wang, X., Zhan, L., Ruan, J., & Zhang, J. (2014). How to Choose "Last Mile" Delivery Modes for E-Fulfillment. *Mathematical Problems in Engineering*, 2014, 1-11.

Xing, Y., Grant, D., McKinnon, A., & Fernie, J. (2011). The interface between retailers and logistics service providers in the online market. *European Journal of Marketing*, 45(3), 334-357.

Yang, P., Miao, L., Xue, Z., & Ye, B. (2015). Variable neighborhood search heuristic for storage location assignment and storage/retrieval scheduling under shared storage in multi-shuttle automated storage/retrieval systems. *Transportation Research Part E: Logistics and Transportation Review*, 79, 164-177.

Yao, A., Paik, S., & Wedel, T. (2010). Developing an Efficient Warehousing Operation System: An Expert System Approach. Journal of Management Information and Decision Sciences, 13(1), 19-30.

Yu, X., Guo, S., Guo, J., & Huang, X. (2011). Rank B2C e-commerce websites in e-alliance based on AHP and fuzzy TOPSIS. *Expert Systems with Applications*, 38(4), 3550-3557.

Zacharia, P., & Nearchou, A. (2016). A population-based algorithm for the bi-objective assembly line worker assignment and balancing problem. *Engineering Applications of Artificial Intelligence*, 49, 1-9.

Zegordi, S., Abadi, I., & Nia, M. (2010). A novel genetic algorithm for solving production and transportation scheduling in a two-stage supply chain. *Computers & Industrial Engineering*, 58(3), 373-381.