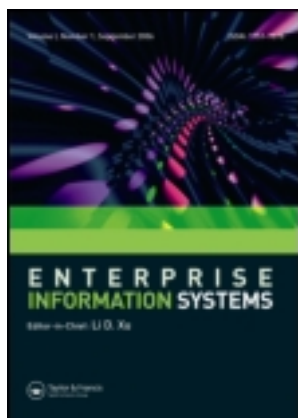


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## The adaptive approach for storage assignment by mining data of warehouse management system for distribution centres

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Among distribution centre operations, order picking has been reported to be the most labour-intensive activity. Sophisticated storage assignment policies adopted to reduce the travel distance of order picking have been explored in the literature. Unfortunately, previous research has been devoted to locating entire products from scratch. Instead, this study intends to propose an adaptive approach, a Data Mining-based Storage Assignment approach (DMSA), to find the optimal storage assignment for newly delivered products that need to be put away when there is vacant shelf space in a distribution centre. In the DMSA, a new association index (AIX) is developed to evaluate the fitness between the put away products and the unassigned storage locations by applying association rule mining. With AIX, the storage location assignment problem (SLAP) can be formulated and solved as a binary integer programming. To evaluate the performance of DMSA, a real-world order database of a distribution centre is obtained and used to compare the results from DMSA with a random assignment approach. It turns out that DMSA outperforms random assignment as the number of put away products and the proportion of put away products with high turnover rates increase.

**Keywords:** enterprise information systems; business planning and logistics; warehousing; storage assignment; order picking; data mining; association rules

### 1. Introduction

Due to the rapidly changing preferences of customers, customer orders increasingly exhibit characteristics of higher product variety, smaller order size and reliably shorter response time (Li 2007). Such changes to order patterns challenge the efficiency of warehousing order fulfilment processes in today's highly competitive market. Major warehousing activities include receiving, putting away, storing, order picking, sorting and shipping. Among these activities, order picking is the most labour-intensive operation in warehouses with manual systems (Koster *et al.* 2007) and normally accounts for 55% of warehouse operating expenses (Tompkins *et al.* 1996). In addition, the service level at a warehouse is also directly relevant to the operation of order picking. Due to the labour-intensive and highly changeable nature of modern warehouse operations, order picking may become a bottleneck for satisfying customer orders in a timely manner. Hence, improving picking efficiency

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may achieve a higher service level by creating a shorter picking distance, a lower labour cost by employing fewer pickers, or both.

In previous studies, four methods were used to reduce the pickers' travel time or distance: (1) determining the order picking route appropriately; (2) zoning the warehouse; (3) assigning products to suitable storage locations; (4) assigning orders to batches (Roodbergen and Koster 2001). Although different approaches can be applied to achieve the objective, storage assignment plays an essential and important role in warehousing activity, and it also tremendously affects the performance of order picking. A storage assignment (or product allocation) policy consists of a set of rules used to assign products to storage locations (Koster *et al.* 2007). Pickers can skip some aisles in a picking route to reduce travel time and distance if storage assignment is appropriate. In spite of some rule-of-thumb policies used, some previous researchers have focused on allocating products to different zones according to the turnover rates of products such that products with a high turnover rate or picking frequency are placed nearer to the outbound exit of the picking area to reduce the travel distance. Relatively few researchers (van Oudheusden *et al.* 1988, Frazelle and Sharp 1989, van Oudheusden and Zhu 1992) have proposed correlated storage assignment approaches in which products that are frequently ordered together should be assigned locations that are close to each, causing the travel distance and number of stops of picking tours to be significantly reduced. However, both the frequency and the properties of the order relationships have an influence on storage assignment. For example, the pair of products should be allocated far apart from each other if the relationship between them is substitutive.

With the rapid advance in information technology, order data, product data and customer data can be automatically and constantly saved in enterprise information systems, such as warehouse management systems (WMSs), electronic order systems (EOS), product development systems (PDS) and enterprise resource planning (ERP) systems. These abundant data can bring great value to the enterprise and help it improve operational efficiency, provided that appropriate techniques are used to extract knowledge from them for decision support (Shu and Wang 2007, Staley and Warfield 2007, Xu *et al.* 2007, Gao *et al.* 2008, Wu *et al.* 2009, Beheshti and Beheshti 2010). Data mining techniques are developed to extract useful information from the bulk of data, and among them, association rule mining can be used to identify the relationship of products, i.e. to discover which products commonly appear in customer orders simultaneously. The information of product association can be utilised to generate storage assignment rules for improving warehousing efficiency.

In addition, past research has devoted efforts to locating entire products from scratch. Instead, this study intends to propose an adaptive approach, the Data Mining-based Storage Assignment (DMSA) approach, to find the optimal storage assignment for newly delivered products requiring putting away. In DMSA, a new index, the association index (AIX), is developed to evaluate the fitness between the available storage locations and products being put away by applying association rule mining. With AIX, the storage location assignment problem (SLAP) can be formulated as a binary integer programming. By using DMSA, the pair of products that most frequently appear in the same customer orders are more likely to be allocated to the same aisle. Therefore, DMSA can reduce the number of times a picker enters aisles and the number of stops in a tour of order picking, greatly improving picking efficiency. In addition, the resulting storage assignments can adapt to the change in patterns of customer orders by applying our adaptive

approach. Furthermore, almost no additional costs are incurred to apply our proposed approach for storage assignment because only the rules for allocation of product locations need to be revised in the WMS.

Our article is organised as follows. Section 2 briefly reviews previous studies on storage assignment policies. In Section 3, the proposed heuristic storage assignment approach based on association rule mining is introduced. The proposed approach is then implemented in a real case study of a distribution centre, as illustrated in Section 4. Finally, some conclusions based on our observations are made in Section 5.

## 2. Literature review

The essential functions of a warehouse are receiving, storing and retrieving products. A storage assignment (or product allocation) policy consists of a set of rules used to assign products to storage locations in a warehouse (Koster *et al.* 2007). The way to assign products to storage locations enormously affects the utilisation of space and the efficiency of order picking. Because the labour costs and service levels of warehouses are limited by the performance of order picking, more studies have focused on improving order picking performance through sophisticated storage assignment rather than on the utilisation of the storage facility.

The literature related to storage assignment policies can be classified into three categories: rule-of-thumb policy, class-based policy and family grouping policy (Koster *et al.* 2007). This taxonomy is conceived based on a detailed use of information. The rule-of-thumb policy is a straightforward approach that only utilises information about availability at current storage facilities. The most prevalent rule-of-thumb policies include random location assignment, closest open location, farthest open location and longest open location (Gu *et al.* 2007). Random assignment policy allocates products to available locations with respect to probability. Assigning the nearest available location from the outbound exit to the product is the so-called closest open location policy, whereas assigning the farthest one is the farthest open location policy. The longest open location policy selects an available location with the longest unoccupied time for the product under assignment. In this category of policies, storage assignment proceeds without using any product information. The major benefits of these policies consist of higher space utilisation, congestion prevention and better allocation convenience. However, the lack of consideration for the subsequent activities of warehousing and product information ultimately downgrades the efficiency of the whole warehousing cycle. With the development of a WMS, the product properties, such as turnover rate and order frequency, can be constantly recorded such that the class-based policy can be applied to storage assignment. The class-based storage policy stems from inventory control and divides various product classes according to product characteristics such as the turnover rate. The basic idea is that assigning a product with a higher turnover rate to locations nearest the outbound exit can enhance the efficiency of order picking. Thus, a product class is assigned to a dedicated zone based on some properties of product class, such as turnover rate or order frequency, and in each zone, products are randomly allocated to shelves. The class-based assignment policy is intended to reduce picking distance and maximise space utilisation at the same time Heskett (1963, 1964) proposed an index named the cube-per-order index (COI) and carried out a storage assignment procedure based on COI in a numerical

experiment. COI is the ratio of the product's unit storage space requirement to its order frequency. The products with higher COI are placed nearer to the outbound exit of the warehouse by using the assignment procedure. Kallina and Lynn (1976) used COI as a measurement to classify products in their class-based policy. Most previous studies used the turnover rate as the basis to classify the products. Through simulation of an automated storage/retrieval system (AS/RS), Hausman *et al.* (1976) compared the closest open location and the turnover-based and class-based assignment approaches in terms of the travel time and turnover distribution of products. Graves *et al.* (1977) extended the work in Hausman's study by additionally considering the dual command of depositing and picking in AS/RS. On the other hand, a heuristic storage assignment method based on the stochastic model is developed by Jarvis and McDowell (1991). This heuristic method minimises the expected travel distance through the allocation of products to aisles according to picking frequency. van de Berg (1996) also used dynamic programming to solve a class-based allocation problem for the single command situation. Subsequently, Larson *et al.* (1997) took into account the storage space on different floors and proposed a class-based heuristic approach for storage assignment. The effects of various factors in the class-based assignment were explored in Manzini *et al.* (2007) by running a set of design experiments. Their results indicated that the number of products in each class and the number of products in the picking list do not have a significant impact on picking distance. Muppani and Adil (2008a) applied simulated annealing to solve a complex binary integer model, which simultaneously assigns products to a class and a storage location. Muppani and Adil (2008b) also formulated the class-based allocation problem as a nonlinear integer programming model and developed a branch-and-bound algorithm to solve the problem. However, the turnover rate or order frequency of products is not the only characteristic that can be gathered from WMS and EOS to improve the product allocation. Additional valuable information can also be obtained for decisions after the details of customers' orders are further analysed. One observation may reveal that the products in different classes may have certain relationships. For example, some products are commonly ordered together by customers, and thus they have a higher association. Such relationships between products may not be explicitly presented to decision-makers, but they can be discovered by further analysing the order database. In addition, the manner of random allocation within a class amplifies the difficulty of order picking in a manual system.

Finally, the family grouping policy considers the product relationships, which are described as the frequency of products ordered together. The basic idea is that products frequently ordered together should be stored closer to each other for improving the efficiency of order picking (van Oudheusden and Zhu 1992). Frazelle and Sharp (1989) proposed a correlated assignment policy by using the statistical correlation that is the ratio of the number of orders in which two products appear together to the number of all orders. They proposed that storage locations should be assigned pairwise to products in descending order with statistical correlation, and then the layout of racks should be designed according to the turnover rate of the rack. van Oudheusden *et al.* (1988) further developed a pairwise interchange procedure based on the distance and closeness between products to allocate spare parts in the warehouse of a steel mill. In their work, closeness is defined as the number of times that two parts are retrieved together. By interchanging parts iteratively, the parts with a higher closeness are allocated nearer to each other. Next,

van Oudheusden and Zhu (1992) considered the recurrent orders in AS/RS and proposed a storage assignment approach with respect to contact frequency, which counts the number of times that two products are ordered together. They formulated the SLAP as a set-partitioning problem by considering the contact frequency, which can be resolved by a heuristic method. Lee (1992) formulated the SLAP as a generalised assignment problem by minimising the total picking time. In Lee's method, the items' propensity was used to classify similar products into groups and assign the storage locations by using the COI of each group. The items' propensity is the relative frequency with which two items are requested together in customer orders. According to order patterns of products, Rosenwein (1994) defined the distance between products and formulated the clustering problem as a  $p$ -median binary integer programming (BIP). Brynzér and Johansson (1996) employed the product structures to classify the parts into variant groups. The variant groups were stored next to each other according to concurrent demand, which is similar to the statistical correlation (Frazelle and Sharp 1989). Liu (1999) took into account the quantity of items ordered and measured the similarity coefficient with the probability that the pair of items appears in the same order. Liu formulated SLAP as a BIP with the correlation of products and correlation of customers. A bill of material (BOM)-oriented, class-based storage assignment method was designed by Hsieh and Tsai (2001). In Hsieh and Tsai's method, the materials are allocated according to the attributes recorded in BOMs. The concept of a family grouping policy was applied in a synchronised-zone order-picking system by Jane and Lai (2005). They defined a similarity measurement regarding order requests and developed a corresponding heuristic to solve  $p$ -median cluster problems. The statistical correlation proposed by Frazelle and Sharp (1989) was adopted by Manzini (2006). To generate product families, three algorithms were proposed in Manzini's study. Xiao and Zheng (2010) also used the BOM information to deal with SLAP, which was formulated as complex BIP to minimise travel distance. In their multi-stage heuristic, the similarity of parts was measured by the frequency with which a pair of parts is presented together in all BOMs. In the abovementioned studies, the frequency with which the pair of products appears together was used to capture the relationships between products in the similarity measurements, which are used to group the products. Next, the information about product groups was used to allocate products. However, the property of relationships between products (i.e. complementary or substitutive) is not taken into account when family grouping policy is applied. Different properties of relationships should correspond to different assignment logics. In the complementary relationship, products should be allocated closer for the convenience of order picking, and vice versa. To catch different properties of relationships, association rule mining is applied in this study. Association rule mining cannot only reveal useful information from huge databases, but can also extract the implicit properties of relationships between products, such as complementary, substitutive and independent relationships. Thus, this article intends to extend the research of family grouping to propose a new approach of storage assignment based on a data mining technique of association rule mining. A new index, namely, the association index (AIX) will be further developed to measure the fitness between the stocked products and the unassigned storage locations by applying association rule mining. The SLAP can be formulated as a generalised assignment model with AIX. The detailed procedure of our proposed approach will be discussed in the next section.

### 3. The proposed DMSA approach

As we mentioned in Section 1, our proposed storage assignment approach, DMSA, is designed to determine the optimal storage assignment for the newly delivered products needed to be put away when there is empty shelf space in a distribution centre. In practice, allocating newly delivered products to the unoccupied shelves of the picking area is a more realistic and cost-effective approach compared to allocating entire products in the DC. The other benefit of partial reallocation is that storage assignment can be adjusted in a timely manner to adapt to the change of order patterns revealed by association rule mining. The proposed DMSA approach consists of three stages that are illustrated in Figure 1. First, association rule mining is used to calculate the support count, which represents the relationship between products. Second, our proposed AIX is developed to evaluate the fitness between the newly delivered products and the available storage locations based on the convenience of order picking. AIX considers not only the turnover rate of a single product and the distance between location and exit but also order relationships between products. Third, a BIP is formulated and solved to determine the optimal storage assignment for order picking. Each stage is detailed in the following three subsections.

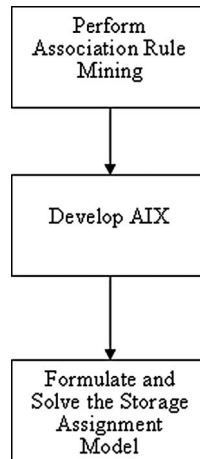


Figure 1. The framework of proposed DMSA approach.

#### 3.1. Stage 1: perform association rule mining

Before introducing the DMSA approach, notation is defined in Table 1. The proposed DMSA approach employs association rule mining to discover the relationships between products. In the first stage, the order data are analysed by using the apriori algorithm (Agrawal *et al.* 1993, Srikant and Agrawal 1997, Han and Kamber 2001), which is an efficient algorithm for mining association rules. The characteristics of the discovered rules are generally described by three indexes: support, confidence and lift (Agrawal *et al.* 1993, Srikant and Agrawal 1997, Han and Kamber 2001). Support, defined as  $P(Y \cup Z)$ , evaluates the popularity of a rule. Confidence, defined as  $P(Y|Z)$ , measures the certainty of a rule, and lift, defined  $P(Z|Y)/P(Z)$  or  $P(Y \cup Z)/P(Y)P(Z)$ , illustrates the property of relationships



Table 1. Notation.

Parameters	
$I$	The location set which contains $m$ locations $I=\{1, 2, \dots, m\}$
$K$	The product set which contains $l$ locations $K=\{1, 2, \dots, m\}$
$L_i$	The set of products already allocated within the aisle of location $i$
$T_k$	The turnover rate of product $k$
$D_i$	The distance between location $i$ and the outbound exit
$wsupc_{pq}$	The weighted support count between product $p$ and $q$ ; it is positive when lift value is greater than 1; negative when lift value is less than 1; and 0 when lift value equal to 1
Decision variable	
$X_{ik}$	$= \begin{cases} 1, & \text{if product } k \text{ is allocated in location } i \\ 0, & \text{otherwise} \end{cases}$

between products. The concept of support is similar to the statistical correlation (e.g. Frazelle and Sharp 1989, Manzini 2006).

Due to the hundreds of product items stored in a warehouse, the huge combinations among products and numerous daily orders may lead to relatively small support values. Therefore, the support count, the frequency that products appear in the same order, is adopted in our index for easy computation and avoiding the round-off error. The support count is similar to the statistical correlations defined in Frazelle and Sharp (1989) and Manzini (2006). However, the property of relationships cannot be described by only using the support count or statistical correlations. Hence, the lift value is used to consider the properties of relationships in this proposed approach. For instance, a complementary relationship between two products (lift > 1) increases the fitness for allocation of the two products in the same aisle. In contrast, the substitutable relationship (lift < 1) decreases the fitness. Consequently, the support count is transformed to be a weighted support count, which is positive if the lift value is great than 1, negative if the lift value is less than 1 and 0 if the lift value is equal to 1. The weighted support count will be further integrated with the turnover of products to form the AIX in the second stage.

### 3.2. Stage 2: develop association index (AIX)

The AIX is developed to measure the fitness between the available storage locations and newly delivered products being put away. The fitness is measured by three factors: the association between product  $k$  being allocated to location  $i$  and products (i.e.  $k'$ ) already allocated to the aisle of location  $i$ , the turnover rate of product  $k$ , and the distance between location  $i$  and the outbound exit.  $AIX_{ik}$  is used to represent the fitness value if product  $k$  is allocated to location  $i$ , and it takes the form of

$$AIX_{ik} \left[ \sum_{k' \in L_i} wsupc_{kk'} \right] \times \frac{T_k}{D_i} \quad (1)$$

The first term is the summation of all weighted support counts of product  $k$  and the products already allocated to the aisle of location  $i$ . The weighted support count, which can handle the property of relationship, is generated by association rule

mining. The concept behind the first term is based on the family grouping policy discussed in Section 2. If product  $k$  is more often ordered together with those products already allocated to the same aisle, the first term of AIX is higher, and AIX increases. The second term is the ratio of turnover of product  $k$  ( $T_k$ ) to the distance between location  $i$  and the outbound exit ( $D_i$ ). The concept behind the second term corresponds to the class-based policy discussed in Section 2. The second term is higher, and AIX increases while allocating products with higher turnover rates to the locations nearer to the outbound exit. The previous studies mentioned above only took turnover or the order relationship between products (i.e. support value) into consideration, or both, but the property of product relationships (i.e. lift value) was ignored. In this article, the turnover rate, the frequency and the properties of order relationships are considered to allocate the products by adopting AIX.

The example presented in Figure 2 is used to demonstrate how to calculate in detail the AIX between available locations and newly delivered products needing to be put away. In this example, there are 10 locations in an aisle ( $i_1$  to  $i_{10}$ ) and 10 products ( $k_1$  to  $k_{10}$ ). Six storage locations ( $i_1$ ,  $i_2$ ,  $i_5$ ,  $i_6$ ,  $i_7$  and  $i_8$ ) have already been occupied by products ( $k_1$  to  $k_6$ ), so only four locations are available for allocation ( $i_3$ ,  $i_4$ ,  $i_9$  and  $i_{10}$ ). Two products ( $k_7$  and  $k_8$ ) need to be put away in the aisle. Table 2 summarises the weighted support count between the products needing to be put away and the products already allocated to the aisle. Let the turnover rate of products  $k_7$  and  $k_8$  be 3.5 and 2.0, respectively. The distance from empty locations  $i_3$ ,  $i_4$ ,  $i_9$ , and  $i_{10}$  to the outbound exit are 8, 4, 4 and 2 m, respectively. Table 3 presents the AIX values for different products allocated to different locations.  $AIX_{10,7}$  (21) is greater than  $AIX_{10,8}$  (4), and it implies that product  $k_7$  is more suitable to be allocated to location  $i_{10}$  than product  $k_8$  if two products compete for the same location  $i_{10}$ .

To evaluate the fitness of every product allocated in all available storage locations, the  $AIX_{ik}$  between the products being put away and the available locations should be calculated in advance. In the next subsection, the mathematical model of storage assignment is then formulated to assign the unoccupied locations to the best suitable products.

### 3.3. Stage 3: formulate and solve the storage assignment model

With all the association indices between the products being put away and the available locations generated in Stage 2, the SLAP is formulated as a generalised

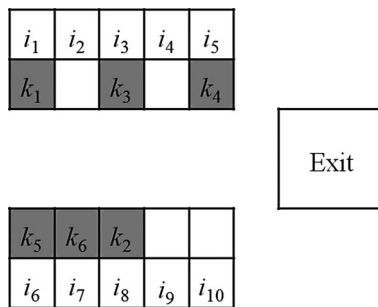


Figure 2. A simple example for demonstrating calculation of AIX.

Table 2. The weighted support count between products.

	Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
Product 7	-3	4	5	5	-3	4
Product 8	1	3	3	-2	2	-3

Table 3. The AIX between available locations and products need to allocate.

	Location 2	Location 4	Location 9	Location 10
Product 7	5.25	10.50	10.50	21.00
Product 8	1.00	2.00	2.00	4.00

assignment problem. Lee (1992) used the generalised assignment model to solve SLAP. Different from the objective function and the similarity measurement applied in Lee (1992), the proposed association index, AIX, is embedded into the objective function (2) in the model described to maximise the summation of AIXs between the products needing to be put away and available locations. The model can be formulated as

$$\text{Max } \sum_i \sum_k X_{ik} \times \text{AIX}_{ik} \quad (2)$$

$$\sum_i X_{ik} = 1 \quad \forall k \quad (3)$$

$$\sum_k X_{ik} \leq 1 \quad \forall i \quad (4)$$

$$X_{ik} \in \{0, 1\} \quad (5)$$

In this model, Constraint set (3) ensures that each product is assigned to a storage location. Constraint set (4) limits a single storage location at most to be assigned with a product. Constraint set (5) guarantees the binary solution for storage assignment.

The implementation of our approach is presented in the next section through a case study of a grocery distribution centre.

#### 4. Experimental design and analysis

In this section, the proposed DMSA approach is implemented with a real dataset from a grocery distribution centre in Taiwan. The dataset contains order records of 12 months extracted from the information system of the distribution centre. First, 30 products with the highest turnover rate are used to evaluate the improvement of

travel distances in the distribution centre by adopting our proposed approach. Next, an experimental design is applied to investigate the performance of DMSA when both the products with high and low turnover rates are reallocated. The characteristics of the dataset and data preprocessing are detailed in Subsection 4.1, and the experimental settings are described in Subsection 4.2. The experimental results are analysed in Subsection 4.3.

#### **4.1. Dataset**

The dataset is extracted from the order database of a distribution centre, which belongs to the logistics group of a company in Taiwan. The distribution centre we studied supplies the grocery stores' daily orders in the north of Taiwan. Our proposed DMSA approach is suitable for improving efficiency in this kind of storage facility because the orders from grocery stores consolidate the customers' repeated purchasing behaviours. Because the order pattern is recurrent in this database, products in the orders usually have more stable association relationships. To avoid traffic congestion near the stores, the time for replenishment of grocery stores is usually at night or early morning. Therefore, the distribution centre is most often congested with orders in the evening. All order pickings need to be accomplished in a very short time frame. In addition, the customer orders are often small in size and high in variability, such that the order picking in the picking area of the manual system becomes much more labour intensive. In this kind of storage facility, the time saved for order picking is more valuable than the time for allocating products.

The dataset includes 338,113 daily orders from all served grocery stores in 1 year. There are 1308 products recorded in the order transaction list, but only 787 products are stocked in the picking area. To evaluate the performance of our proposed DMSA approach, the dataset is divided into two parts. The first 312,665 transaction records from January to November are used to generate support counts, and the remaining 25,448 records from December are considered incoming orders.

#### **4.2. Experimental settings**

The experimental settings are described as follows:

- The distribution centre has a rectangular shape with 800 storage locations. There are 21 aisles and 20 shelves. Each shelf is two-sided and has 20 locations within 1 layer on each side. Figure 3 presents the layout of the distribution centre.
- The 787 products need to be allocated within the picking area.
- The length of an aisle is 32 m. The width of a single-sided shelf is 1.5 m and the width of a two-sided shelf is 3 m.
- Each product is only stored in one storage location.
- There is an entrance and an outbound exit in the distribution centre.
- A picking tour follows an S-shape strategy (Hall 1993). The picker will not enter an aisle, if there is no product item in the aisle that needs to be picked.
- Orders are picked by using the first-come-first-served policy. Order batching is not applied at this distribution centre.
- A single command is adopted.



factors impact the performance of DMSA. The number of newly delivered products needing to be put away is the first factor, Factor A. In general, the average number of products needing to be put away is around 40 items, and the maximum and minimum numbers are 60 and 20, respectively. The second factor is the proportion of products with a higher turnover rate for all put away products, Factor B. Based on the company's practice, the products with the first 273 highest turnover rates (approximately the top 30% of the 787 products) are defined as high-turnover products, and the rest are treated as low-turnover products. Three levels of proportions are chosen, 30, 60 or 90%. Therefore, nine experimental setups are used to obtain the travel distances. The factor settings are illustrated in Table 4. The products in each experimental setting are randomly selected from the high- and low-turnover items, according to the proportion of products with a higher turnover rate. Each setting is run four times. For example, the settings of Factor A as 20 and Factor B as 30% means that the sample of 20 products consists of 6 high-turnover rate products and 14 low-turnover rate products.

Table 5 summarises the results of the 36 experiments in nine settings. The range of improvement varies from 0.4 to 2.8%. To justify how the two factors affect the reduction of travel distance, a two-factor ANOVA is used to further analyse these results.

In the two-factor ANOVA, the assumptions of normality, consistency and randomisation are tested, and they are acceptable. Table 6 presents the results of ANOVA. Apparently, the main effect of Factor A, the main effect of Factor B, and the interaction effect between Factors A and B all have significant effects on the improvement of travel distances ( $\alpha=0.01$ ). Figure 4 illustrates that the travel distance decreases as the number of products needing reallocation (Factor A) and

Table 4. The experiment settings.

Factor	Level 1	Level 2	Level 3
Factor A	20	40	60
Factor B	30%	60%	90%

Table 5. The result of the 36 experiments.

Setting <sup>a</sup>	The average moving distance in four repeat trails (m)	Average improvement comparing with random assignment (7,229,087 m), %
20–30	7,199,807	0.4050
20–60	7,195,551	0.4639
20–90	7,183,279	0.6337
40–30	7,191,903	0.5144
40–60	7,146,287	1.7893
40–90	7,108,831	1.6635
60–30	7,151,375	1.0750
60–60	7,099,087	2.1137
60–90	7,022,495	2.8578

Note: <sup>a</sup>The number in front of each dash presents the level of Factor A and the number after the dash presents the level of Factor B.

Table 6. The ANOVA table of the experiments.

Source	Sum of squares	DF	Mean square	F value	p value
Model	1.107E + 011	8	1.384E + 010	23.72	<0.0001
A	6.269E + 010	2	3.135E + 010	53.71	<0.0001
B	3.493E + 010	2	1.747E + 010	29.92	<0.0001
AB	1.312E + 010	4	3.279E + 009	5.62	0.0020
Pure error	1.576E + 011	27	5.837E + 008		
Total	1.265E + 011	35			

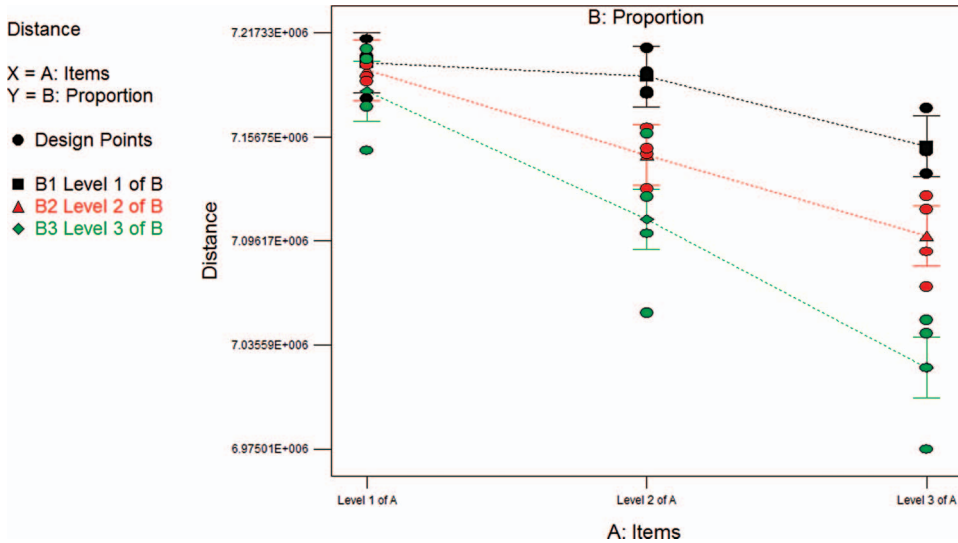


Figure 4. Interaction graph.

the proportion of high-turnover products in the restocking list (Factor B) increase. In terms of the main effect, the increased number of products needing reallocation leads to more available locations such that a better storage assignment can be conducted with a more flexible arrangement. On the other hand, the high-turnover products are ordered and picked more often than the low-turnover ones. Consequently, as more high-turnover products are involved in re-assignment processes, the total travel distance is reduced. In terms of the interaction effect, the improvement of distance reduction is better[0] while both Factors A and B are set to the higher levels. In such a setting, more products of a high-turnover rate reallocated to more available locations can achieve greater distance reduction.

The experimental results also demonstrate how the efficiency of order picking can be improved by using DMSA to re-assign newly delivered products to the storage locations without incurring any additional pickers or picking facilities. The proposed DMSA approach can greatly reduce the likelihood of entering an aisle for picking one product as well as the number of stops for picking, which results in shorter travel distances. Because the AIX is partially generated from order data, our approach can be easily adapted to accommodate the variation of order patterns. In most practices of logistic firms, enhancing order picking may require employing more pickers, purchasing superior equipment or applying new operation processes, which leads to

more investment and costs. However, our proposed DMSA approach only requires minor modification of the storage assignment programme in WMS. Therefore, DMSA can both achieve a higher service level with shorter picking distances and save labour costs by employing fewer pickers. In addition, the CPU time to solve the assignment model is very short (commonly less than 2 seconds). The support count in association rule mining does not need to be re-generated daily if the order patterns do not significantly change from day to day.

## 5. Conclusion

To face the challenges of varying customer demands and a highly competitive marketplace, distribution centres need to become more effective and more efficient. Both service level and cost should be considered and balanced to enhance the performance of distribution centres. Under the progress of information technology, order transaction data can be utilised not only to record daily transactions but also to assign product locations for improving picking efficiency. This article proposes a heuristic approach for storage assignment, the DMSA, to improve the efficiency of order picking. DMSA is used to allocate the newly ordered products needing to be put away in warehouses. A new index, AIX, is also developed to evaluate the fitness between the available storage locations and products being put away by applying association rule mining. With AIX, the SLAP is formulated and solved as a binary integer programming model to allocate the products with high frequency appearing in the same customer order in the same aisle.

The proposed DMSA approach has the following advantages. First, AIX both considers the prevalence and property of relationship between products by using association rule mining. The proposed DMSA approach applies association rule mining to integrate the turnover rate of products and the distance between location and exit in AIX. Second, the likelihood of entering an aisle for picking items and the number of stops are both reduced, which results in shorter travel distance. Third, AIX is partially generated from order data such that the storage layout may be changed with the variation of order patterns automatically. The allocation of products is dynamically adjusted with respect to the ordering patterns so as to take seasonality into consideration. Fourth, almost no additional cost is required because the implementation of DMSA simply requires revising the storage assignment programme in the WMS. Thus, DMSA can both achieve a higher service level with shorter picking distance and save labour costs.

In spite of the advantages mentioned above, DMSA still has some limitations. First, DMSA can not be used to assign brand-new products without historical order data. This is a general limitation of the family grouping policy. Further developing the approach to allocate the new products is a worthy enterprise. Second, DMSA is an adaptive approach and designed to reallocate only the quantity of products that need re-stocking for cost-effective consideration. Thus, the improvement of DMSA may be restricted by partial reallocation. In future work, DMSA can be extended to reallocate all products in a distribution centre.

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