Enhancing Order-picking Efficiency through Data Mining and Assignment Approaches

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Abstract: Using data mining techniques, this study attempts to explore how a proper layout zoning following class-based storage enhances order picking efficiency over randomized storage. Association web statistics and association rule mining examines the relative intensity levels among various product categories. These findings serve as the layout for zoning of the storage area of α company, a pharmaceutical industry master distributor. A class-based assignment policy is then proposed. Finally, by transforming accumulated orders into Pallet-Case-Broken case (PCB) data and adopting batch picking, this study compares random assignment policy with zoning and class-based assignment policy. The results conclude that zoning and class-based assignment policy decreases travel distances by 24% and improves picking times by 21%.
Key- Words: order picking, storage assignment, data mining, association rule, layout zoning, class-based assignment

1. Introduction

A distribution center (DC) supplements the commercial activities of upstream and downstream businesses by performing receiving, storage, order picking, and shipping functions. Under the high pressure of e-commerce, time-based competition emphasizes quick and reliable responses to customer requirements [1-3]. Managers must reduce product or material moving times to increase operational performance [4-6] and enhance customer service quality. However, the huge numbers of products and the time pressure of order processing limit operational efficiency, while most Taiwanese distribution centers still depend on manpower that accounts for 55% to 65% of total operating costs. In an attempt to increase productivity, managers tend to emphasize order picking operations as the highest-priority area [7,8].

Goetschalckx and Ashayeri (1989) [9] pointed out that the characteristics of warehouse operation systems, such as mechanization, informatization, and layout structure, all affect order picking efficiency. Routing policy, batch policy, storage assignment policy, and storage area zoning also affect order picking efficiency [1,9-12]. Compared with investments in technology and information techniques, storage assignment has the most direct effect on picking time and travel distance [1,4,13,14].

The primary goal of storage assignment is to dispatch products to their specific locations. In terms of convenient storage, retrieval, and space utilization, storage assignment can adopt random storage, dedicated storage, and class-based storage [14,15,16]. Random assignment is applied within an area; dedicated storage reserves a fixed location for each product according to its characteristics; but due to its emphasis on product characteristics and the ease of combining dedicated and random assignment, class-based storage assignment is the most popular policy [16-19].

Storage assignment problems are related to the zoning issue. Zoning is a part of facility design and operation planning that improves order picking costs and balances workloads across zones [14,20-24]. The zoning process specifies different storage zones within a storage area and assigns products to the specified zones. Although it is also an important factor in order picking, relatively few studies examine this topic [2,20,25].

Most past studies of manual order picking systems only discuss unit-load storage and retrieval in low level racks [7,26]. Previous researchers emphasize differences between multi-parameters using mathematical models and algorithms [12,19,20,28,29] but have not observed real operation styles, Pallet-Case-Broken case (PCB) picking to multiple-tier racks, or applications involving real databases [7,26].

The purpose of this study is to develop a flexible and efficient storage assignment policy and demonstrate how it contributes to the manual order picking system of α company. By using real transaction data of α company, this study explores the layout zoning rules for storage areas and incorporates PCB operation styles into order picking system design. Association web statistics and association rule mining identifies the probability and frequency of product co-occurrence in the layout zoning foundation of a storage area. A class-based assignment policy is developed to assign products to the multiple-tier racks. Furthermore, the experiment uses Pallet-Case-Broken case calculations with synchronous forklift and manual picking.

This study is organized into five sections. In Section 2, relevant literature is reviewed. Section 3 describes the case problem and develops a location assignment strategy. The results are reported in Section 4. Finally, Section 5 offers conclusions to this study.

2. Literature review

2.1 Assignment policy and zoning in order picking efficiency

The goals of storage assignment are to reduce travel distance, cut order picking time, fully utilize rack/shelf space, and reduce material handling costs [25,30]. Managers should consider product characteristics and the distance between picking locations and the In/Out (I/O) point in developing an appropriate storage assignment strategy. Under a random assignment policy, managers do not class the storage area, and assign all incoming products to any available location to maximize space utilization. If the number of classes equals the number of products, this policy is called dedicated assignment. Class-based assignment allows managers to group products into classes. Each class is then assigned to a dedicated area of the warehouse. Item storage within a class area is random [16,17].

As for the class criteria, managers can classify products based on shipping frequencies, turnover rates, and cube-per-order (COI) values [31]. The reason for considering the turnover rate is to reduce the time that products stay in a warehouse, as this decreases the carrying costs of inventory management. Managers apply COI values to achieve full space utilization. For picking efficiency improvement, managers should set shipping frequency as the class criteria [7,15,32].

As for the number of classes, Hausman et al. (1976) [16] showed the ideal number is three. Therefore, managers tend to divide products into ABC groups. Dekker et al. (2004) [17] studied a multiple-parallel-aisle warehouse and found that adjusting the number of classes can cut the travel distance by 30%. However, the literature contains no hard rules regarding how to determine the best class numbers for multi-aisle and multi-pick-per-route situations [2,11,12,17].

Managers should consider storage area zoning issues in conjunction with class-based assignment and zoning prior to location assignment [26]. Dividing the storage area into several areas benefits the picking activities of high-frequency items [2,7]. For example, organizing the storage area into a forward area and reserve area improves order picking efficiency [33]. In practice, zoning is partially based on product properties such as size, required temperature, and safety requirements [2]. However, previous studies about facility layout show that shipping frequency and associate rules are also important factors in zoning a storage area [23,25]. Considering limited warehousing space and the properties of various products, this study adopts shipping frequency and association analysis results, which includes association web statistics and association rule mining, as the foundation of zone storage.

2.2 Order analysis and association rule mining

Due to the high number of products and busy receiving and shipping operations in a distribution center, its transaction database can accumulate huge amounts of operational data. By considering appropriate operation styles, warehouse managers can make accurate deductions regarding the storage assignments required to improve order picking efficiency [34].

Because of shipping information reflects customer demands. The huge amount of accumulated order data in a transaction database should be carefully analyzed to control operational characteristics and increase operational efficiency [31,39]. Order analysis includes the total order volume, the total item numbers, item shipping frequencies, and item shipping volumes. Combined with the ABC analysis method, these criteria can reveal the most valuable customers [41], the operation style of order picking [31], and the key commodities [38]. Scholars have recently developed a storage assignment policy that reveals the relationships among products or customers through cluster analysis [32,40] and association rule mining [1,42,43,44]. However, since many managers do not fully comprehend data mining techniques, the useful knowledge hidden in databases remains hidden and unused in their managerial practices [30].

Data mining is a knowledge extraction process that retrieves meaningful models and patterns from large databases. Fayyad (1997) [45] defined the data mining of databases as an invisible procedure for constructing efficient, novel, implicit, and previously unknown but meaningful patterns or rules. Association web statistics present the frequency of pair-wise items that occur in a transaction database. Association rule mining can discover interesting relationships in a large dataset [42,43].

The Apriori algorithm is extensively applied in support of business decisions. Consider an itemset I containing k transactions, a k-itemset, presented as $\mathrm{I} = \{i_1, i_2, i_3 \cdots, i_k\}$. The Apriori algorithm can find all candidate itemsets that have transaction support above the minimum support defined by the user, called ‘large k-itemsets.’ To find ‘large k-itemsets,’ a set of ‘candidate k-itemsets’ is generated by joining ‘large k-1 itemsets’ with itself [42,43]. D stands for a set of transactions in a database, where each transaction T is a set of items such that $T \subseteq I$. Each itemset T is a non-empty sub-item set of I ($T \neq \phi$). A unique identifier, namely TID, is associated with a set of some items in I. The association rule is an implication of the form $\mathrm{X} \rightarrow \mathrm{Y}$, where $\mathrm{X} \subset \mathrm{I}$, $\mathrm{Y} \subset \mathrm{I}$ and $\mathrm{X} \cap \mathrm{Y} = \phi$. The association rule means the occurrence of itemset X in a TID infers that itemset Y also occurs (i.e., there is a synchronous relationship between items or features). The association rule holds in the transaction set D according to two measure standards - support and confidence. Support (denoted as $Support(X, D)$) represents the rate of transactions in D containing the item set X. Therefore, the rule $\mathrm{X} \rightarrow \mathrm{Y}$ has $Support(X \cup \mathrm{Y}, D)$, which represents the ratio of transactions in D containing $X \cup Y$. The higher the support value, the more important the transaction set D is. Confidence (denoted as $Conf(X \rightarrow Y)$) represents the rate of transactions in D that contain X, the chance that also contains Y. In other words, $\mathrm{Conf}(\mathrm{X} \rightarrow \mathrm{Y}) = Support(X \cap Y) / Support(X, D)$. The confidence measure is then used to evaluate the level of confidence in the association rules $\mathrm{X} \rightarrow \mathrm{Y}$. An analyst must determine the threshold of minimum support (called $Min\sup$) and minimum confidence (called $Minconf$) to ensure that the mining results will be useful. Therefore, association rules must satisfy two conditions: $Support(X \cup \mathrm{Y}, D) \geq Min\sup$ and $Conf(X \rightarrow \mathrm{Y}) \geq Minconf$.

Market basket analysis is a famous application of association rule mining. By mining basket data, a marketer can find sets of products that are frequently bought in the same transaction. Association rules are useful to marketers if support and confidence measurements meet both minimum support and minimum confidence thresholds. The results of association rule mining contribute to product-mix [43,46-48] and shelf-space adjacency policies [43-45], product design and brand extension [42,46], manufacturing quality improvement [30], personnel selection [48], and order batching analysis in distribution centers [1,37].

This study adopts the association web statistic and the association rule mining results from the Apriori algorithm to develop a zoning adjacency and a storage assignment policy. Analysis results are applied to the storage area of α company and productivity performance tests are made in batch picking.

3. Research Method

3.1 Business comprehension and data preparation

α company, a distributor of foreign pharmaceuticals, imports over 90% of its medicines and medical devices, and organizes the inventory control, sales promotion, and distribution service for foreign clients. Providing medical supplies to downstream customers in the right condition at the right time is a key requirement for α company to satisfy its customers and remain competitive. To ensure quick and effective response to customers, managers strive to reduce picking time and travel distance when designing a manual order picking system. The implementation of the National Health Insurance scheme and a global budget system in Taiwan also forced upstream clients and domestic healthcare institutions to decrease their expenses, resulting in profit compression for medical distributors.

Similar to most Taiwanese distribution centers, α company processes orders through a manual order picking system in a small storage area. Random assignment is the easiest policy for managers to implement if a distribution center is limited to a small-sized storage area and has quick product turnover rate [14]. α company does not zone the storage area and adopts random assignment policy. Pickers search for items in a back-and-forth manner and this increases order picking time.

To accommodate order picking operations to products, managers must ensure that internal picking activities can quickly respond to customer requirements [34]. α company sales data shows that August, September, and October are busy months. October is the peak period for shipping frequency, shipping items, and overall sales volume. However, February, November, and December are slow months, and February has the lowest operational results. Therefore, the picking system should be designed to satisfy the load requirements in October, and operational adjustments should be executed in February, if necessary.

The storage area of α company is a rectangle shape. The storage area contains an I/O point and five picking aisles run parallel to one front-end central aisle. The rectangular layout has two symmetrical sections equipped with 12 columns and 4 horizontal shelves, containing 360 compartments. A cool-storage area includes a cold-room designed to for reagent and indicator (RI) storage and is considered separate from other space in developing a storage assignment policy. Each compartment can contain 3 EURO pallets, creating 1,080 pallet spaces.

The data used in this study consists of a product master file, supplier transaction data, purchasing files, and sale records. To streamline data analysis, this study extracted the operation manner from the October sales records. The storage area is divided into 10 zones for 10 product categories based on shipping data from August to October. The association algorithm identifies the probability of different categories appearing in identical order, and the association web calculates the relational frequencies of pair-wise categories. A combination of busy-season and off-season data is used to confirm the efficiency of batching order.

3.2 Data transformation and knowledge extracting

This study transferred the product transaction data from August to October into ten categories and an association web was used to count the relative pair-wise category frequencies among the ten categories. Table 1 summarizes the association web results. The Apriori algorithm found nine association rules, as shown in Table 2.

Table 1. Association web statistic results for various product categories (August ~ October)

Relation Class	Linked Frequency	Category I	Category II
Strong	2001	POM	SS
Middle	780	PHDN	SS
	305	PHDN	POM
	104	POM	PON
Weak	59	MI	MIC
	40	PHDN	GS
	39	PON	SS
	39	SS	GS

Note: No association relationship rule exists among PA, PM or RI.

POM: post-operation medication
PON: post-operation nutrition
PHDN: post-hemodialysis nutrition
SS: surgical substitutes
GS: Gifts and samples
PA: patent articles
MI: medical instruments
MIC: medical instrument components
RI: Reagents and indicators
PM: Patent medicines

This study zones the storage area on the basis of two association analysis results to match the storage layout and equipment constraints. Furthermore, the zone space requirement of each product category is adjusted according to product capacity and volume analysis of product master and transaction data files.

Table 2. Association rule mining results

Rules	Consequence	Antecedent	Support	Confidence
1	POM	SS	78.65%	76.99%
2	SS	POM	91.99%	68.42%
3	SS	PHDN	70.84%	64.50%
4	PHDN	SS	78.65%	60.52%
5	POM	PON	52.24%	67.97%
6	MI	MIC	41.58%	64.50%
7	SS	PON	42.24%	56.74%
8	POM	PHDN	70.84%	55.66%
9	MIC	MI	44.11%	55.55%

Note: For abbreviations see Table 1.

The modules layout is based on the association web results of Table 1. The more linked the frequencies, the closer the product categories are placed. Figure 1 shows the initial module layout. In Section 3.3 the constraints of layout space, equipment, product capacity, volume, and non-associated categories are merged into the zoning plan. The relative module position and space requirements are adjusted according to the results in Table 2.

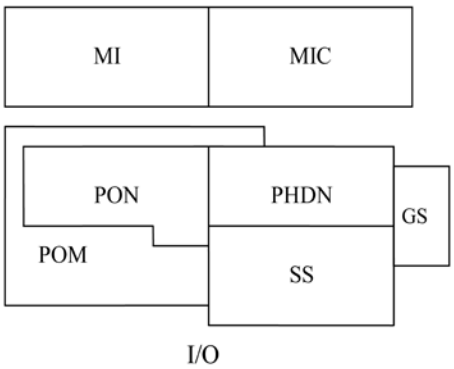

Fig. 1 The initial module layout of the storage area.

Note: The initial module layout was based on the relationship requirements but ignored space and building constraints. For abbreviations see Table 1.

3.3 Knowledge application- Storage area zoning and storage assignment

The storage area of α company is segmented into areas ABC based on the picking distances from the I/O point and the installed rack layout. Furthermore, the zone space requirement of each product category is adjusted according to the product capacity and volume analysis of product master and transaction data files.

As Table 1 shows, product categories with high linked frequency means that the association relationship is strong or the probability of a products appearance in the database simultaneously is also high. Products with higher association relationship also reflect that those products have higher shipping frequency and should be assigned closer to the I/O point [1,42,49]. Therefore, post-operation medication (POM) and surgical substitutes (SS) are assigned to area A, and post-operation nutrition (PON), post-hemodialysis nutrition (PHND) are assigned to area B. Area C contains a fixed cool-room where reagents and indicators (RI) are stored. Area C is designed to store other products with the lowest shipping frequency also. The final storage area planning and category zoning is illustrated in Figure 2.

After zoning and assigning the categories in the storage area, the Pareto method is used to rank the shipping frequency of products in each category and classify the products into three groups in areas A and B. Both within-aisle and across-aisle policies are simultaneously applied to storage assignment [43]. The 6th and 8th rack columns store products with the highest shipping frequency in each category. Product groups with a medium shipping frequency are assigned to the 4th, 5th, 9th, and 10th rack columns. The remaining locations in areas A and B are reserved for products with the lowest shipping frequency in each category. Because Area C is prepared for products with special product properties (i.e. size and refrigeration requirements) and very low shipping frequency, a random assignment policy in area C is implemented.

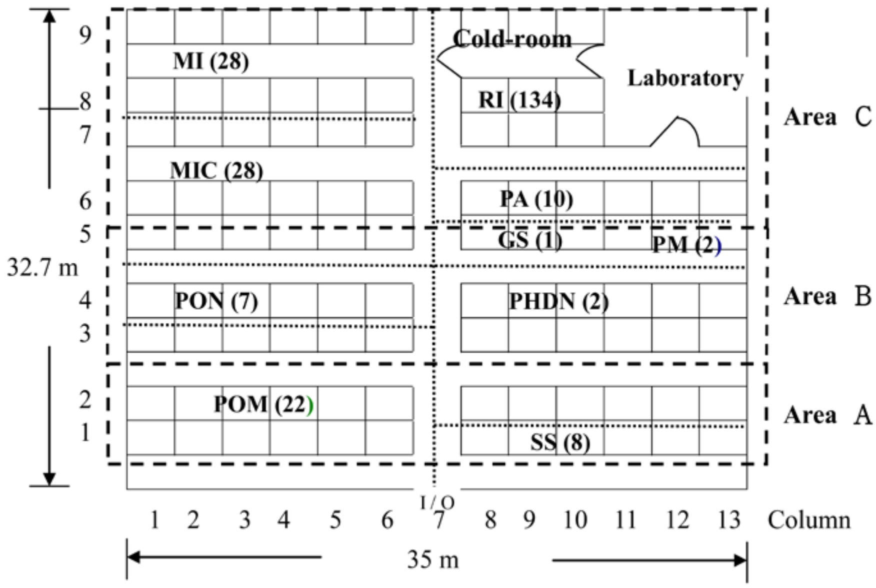

Fig. 2 Storage area zoning based on product categories.

Note: To match the layout for rack installment, this study adjusted GS location to accommodate the placement of PA, PM, and RI. For abbreviations see Table 1.

4. Experimentation and findings

4.1 Experimentation method and model development

This study uses batch picking compares the picking efficiency of random assignment policy to a zoning and class-based assignment method. The experimentation is executed based on the real operations in the distribution center of α company. The information on random storage location assignment is based on the year-end stocktaking list of the same year.

There are an average of 30 to 40 orders in the off-season and an average of 40 to 60 orders in the busy season every day. The average accumulated orders in a month are about 1,000. A picker performs order picking in the storage area only 2 or 3 times daily. Although storage racks have four levels, order picking is only performed at the first and the second levels. A picker retrieves products from the first level with the case and broken case method and accompanies a manual pallet truck. A forklift performs pallet picking from the second level in the whole storage area, excluding the cold room in area C. The experimental procedure is shown in Figure 3 and is described below.

A picking list is released when 10, 15, and 20 orders have accumulated in the off-season. In the busy season, batch picking is performed when 15, 20, and 30 orders have accumulated. For greater statistical reliability, each batch picking is performed 30 times. Therefore, 1,350 orders in the off-season and 1,950 orders in the busy season are used according to their arrival sequence to perform

180 batching comparisons.

As Figure 4 shows, this study organized the bilateral layout into areas A1, A2, B1, B2, C1, and C2, divided into 64 locations. A picker follows the return policy from the I/O point to area A1, B1, C1, C2, B2, A2, and back to the I/O point. This study assumes both the manual pallet truck and the forklift truck have sufficient capacity for each batch picking. The velocity of a picker is about 5 km/hr; a forklift is about 15 km/hr.

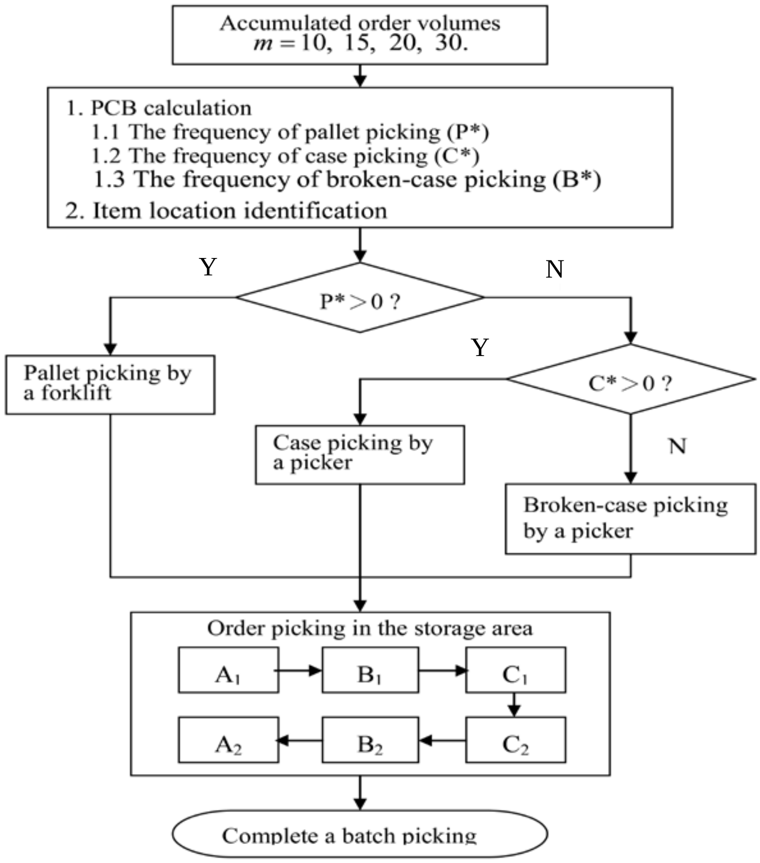

Fig. 3 Experiment procedure- Order processing.

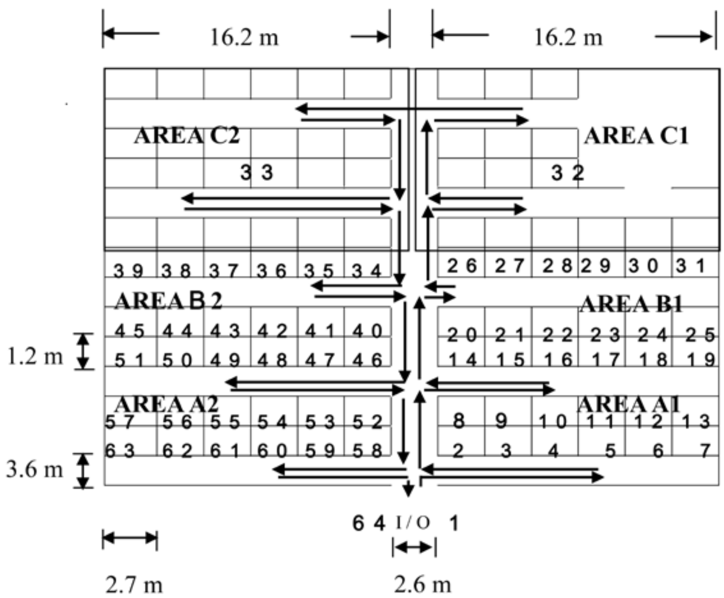

Fig. 4 Layout- location coding and routing policy for the experimental batch picking

Next, this study converts the accumulated volumes of each batch into PCB picking units for each picking product. This step allows managers to determine whether to dispatch the forklift and to figure out the operational time of one picking tour by summing the pallet, case and broken-case picking times. The PCB conversion methods are shown in equation 1, 2, and 3.

$$P^* = \left\lfloor \frac{\sum_h \sum_m \sum_u O_m^h I_u}{PI_u} \right\rfloor \quad (1)$$

$$C^* = \left\lfloor \frac{\sum_h \sum_m \sum_u O_m^h I_u - P^* \times PI_u}{\mathrm{C}I_u} \right\rfloor \quad (2)$$

$$B^* = \sum_h \sum_m \sum_u O_m^h I_u - P \times PI_u - C^* \times CI_u \quad (3)$$

The total travel distances and total picking times that describe the various batch pickings according to the PCB conversion parameters are shown in model 4 and model 5.

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij} X_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{n} d_{ij}^{p} X_{ij} \quad (4)$$

$$Minimize \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij} X_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij}^{p} X_{ij} + \sum_{i=1}^{n} \sum_{j=1}^{n} t_{ij}^{cb} X_{ij} \quad (5)$$

Subject to $\sum_{i=1}^{n} X_{ij} = 1, \quad j = 1,\ 2,\ \ldots\ , n.$

$$\sum_{j=1}^{n} X_{ij} = 1 \quad i = 1,\ 2,\ \ldots\ ,\ n.$$

Where,

$$T_i - T_j + nX_{ij} \le n - 1 \quad i,\ \ j = 2, \ldots, n.\ \ i \ne j.$$

$$X_{ij} = 0, 1 \quad i,\ j = 1,\ 2, \ldots , n.$$

$$T_i = \begin{cases} 1, \text{ if the batch routing exists between location } i \text{ and location } j, \\ 0, \text{ otherwise.} \end{cases}$$

$$T_i = \begin{cases} 1, \text{ if } X_{ij} = 1, \\ 0, \text{ otherwise.} \end{cases}$$

Table 3 summaries the relative notations. Table 4 and Table 5 contain the real parameters to compute picking time and travel distance.

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