Intelligent Storage Location Assignment in Consideration of Correlation between Items

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Abstract. This study develops Intelligent Storage Location Assignment (ISLA) algorithm in consideration of correlation between items to minimize order picking costs. The correlation between items is defined by the frequency of simultaneous appearance of items in customers' orders. When high correlation items are allocated remotely in the warehouse, order picking costs will increase. Hence, items with high correlation should be allocated in nearby storage locations to reduce order picking costs. Traditionally, Storage Location Assignment Problem (SLAP) is mainly solved by the subjective experience of warehouse managers or class-based storage policies; little research considers the relationship between items. In the proposed ISLA algorithm, a benefit function is developed to evaluate the fitness of storage location. To evaluate the performance of ISLA, a real-world dataset is used to compare order picking costs under different storage location assignment algorithms. Our results show that the proposed ISLA algorithm regularly outperfo rms other methods. When used in a multiple-cross-aisle warehouse, the proposed ISLA can reduce pi cking costs by up to 3%.

Keywords: Correlation between Items; Order Picking Costs; Intelligent Storage Location Assignment; Sto rage Location Assignment Problem

1. INTRODUCTION

Nowadays, in order to quickly respond to customers 'diversified requirements, modern retail industry has to focus on warehousing management to improve warehouse operation efficiency.

Koster et al. (2007) and Tompkins et al. (2003) stated that order picking is the most time-consuming and labor-intensive among all warehousing activities. They noted that order picking itself generally accounts for 55% of warehouse operating expenses. Among the time needed for order picking, the most time-consuming activity is travelling time, which accounts for 50% of an order picker's time.

Roodbergen and Koster (2001) presented four categories of approaches that can help increase the efficiency of order picking activity. The four are below.

1. Determining the appropriate order picking route
2. Zoning the warehouse
3. Assigning products to the right storage locations
4. Assigning orders in batches

Chiang et al. (2011) indicated that although different approaches can be applied to increase the efficiency of order picking activity, storage location assignment has an essential and important role in warehousing activity. A good storage location assignment can have a great effect on the performance of order picking.

Thanks to the development and application of data mining, researchers found some interesting patterns from large amounts of data. For the retail industry, managers can analyze consumers' behavior by exploring the association rules from historical sales data, which can affect the storage location assignment for products. In the warehouse, when high correlation items were allocated remotely, order picking costs will increase. Hence, this paper develops Intelligent Storage Location Assignment (ISLA) algorithm in consideration of correlation between items to minimize order picking costs.

2. LITERATURE REVIEW

In Storage Location Assignment Problem (SLAP), we assign items into storage locations given certain rules in order to achieve planned objectives. In the previous studies, Koster et al. (2007) described five frequently used policies of storage assignment: random storage, closest open location storage, dedicated storage, full turnover storage, and class-based storage. Those five methods only consider the turnover and the space requirement of products, but do not consider the relationships among products.

Swami (1993) first proposed an algorithm to obtain association rule from consumer shopping data. Han and Kamber (2000) stated that data mining is a useful technique to discover interesting rules from large amounts of data. Srikant (1994) proposed an Apriori algorithm to find association rules. Zak, S.Parthasarathy, Ogihara, and Li (1997) proposed an Eclat algorithm to quickly find association rules from once searching. These two algorithms are widely applied till now.

Oudheusden and Zhu (1992) stated that some typical orders were always picked again and again in the warehouse picking activity. In this situation, the structure of these orders would have a significant impact on storage location assignment. The items which often ordered together should be located closer to each other.

Chiang et al. (2011) extended the research of family grouping and proposed the Data Mining-based Storage Assignment (DMSA) approach in order to find the optimal storage assignment for newly delivered products that require being put 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. Chuang et al. (2012) proposed a two-stage Clustering-Assignment Problem Model (CAPM) for the Storage Location Assignment Problem. The first stage of CAPM is to cluster items into groups based on their relationships. The second stage of CAPM is to assign items into storage locations based on their frequency. In their study, the relationship between items is the ratio of the number of orders in which two items appeared simultaneously to the number of orders in which two items appeared respectively. Chiang et al. (2014) developed an association measurement named WSC to consider the relationships between products. In their work, the WSC measure combined the concepts of support and lift value.

Caron, Marchet, and Perego (2000) categorized the rectangular warehouse layouts in previous literature. In this paper, we consider a multiple-cross-aisle warehouse with multiple-layer shelves.

In 1985, David Suzuki, the authority logistics expert in Japan, created EIQ (Order–Item–Quantity) analysis. EIQ analysis includes EQ analysis, IQ analysis, EN analysis, and IK analysis. EQ means the items' volume for each order. IQ means the total volume of each item. EN means the number of types of items in each order. IK means the frequency that each item is ordered. Chiang et al. (2014) stated that EIQ analysis is a method to generate items classes in class-based policies. Chuang et al. (2012) compared their result with random storage and frequency-based method (IK).

3. PROBLEM STATEMENT

The assumptions of ISLA are as follows:

(1) The ISLA method with a pick-by-order policy is employed.

(2) There are no size and quantity limits for items in storage.

(3) There is no temperature control for the storage area.

(4) We can only pick the items from one side of the shelf.

(5) We do not consider the pick-up/deposit time for the operator or machine.

3.1 Notations

The notations are as follows:

Table 1: Model notations

	Indices
$\boldsymbol{n_i}$	item i's storage location
$\boldsymbol{U_n}$	location index of storage location n
$\boldsymbol{A_n}$	aisle index of storage location n
$\boldsymbol{R_n}$	row index of storage location n
$\boldsymbol{D_n}$	side index of storage location n
$\boldsymbol{H_n}$	layer index of storage location n
$\boldsymbol{t_{nn'}}$	distance between storage location n and n'
$\boldsymbol{d_n}$	distance from storage location n to I/O point
$\boldsymbol{f_i}$	order frequency of item i
$\boldsymbol{P(i)}$	number of orders contain item i
$\boldsymbol{P(j)}$	number of orders contain item j
$\boldsymbol{S_{ij}}$	correlation between item i and j
$\boldsymbol{C_{ij}}$	order picking costs for item i and j
$\boldsymbol{C_1}$	order picking costs before the exchange of two items' storage locations

C_2	order picking costs after the exchange of two items' storage locations
B_{ij}	the benefit from the exchange of two items' storage locations

3.2 STORAGE LOCATION AND DISTANCE

Define the storage location by five variables. As shown in Figure 1.

Hence, the storage location n can be defined as $(R_n, A_n, U_n, D_n, H_n)$.

$$D_n = \begin{cases} 1 \\ 2 \end{cases} \quad (1)$$

Here, $D_n = 1$ means the storage location n locates on the left side of the aisle. $D_n = 2$ means the storage location n locates on the right side of the aisle.

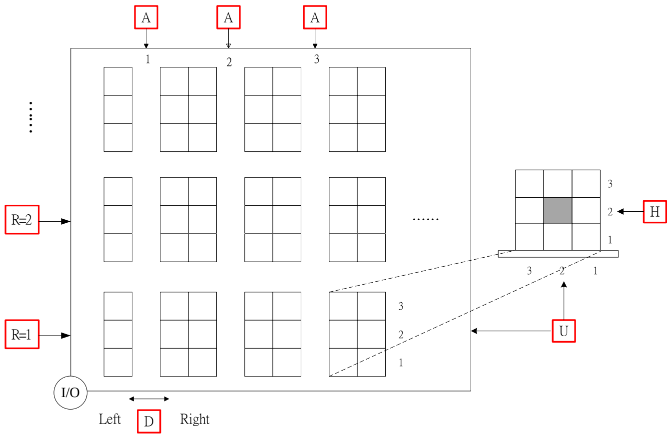

Figure 1: RAUDH coordinate of the warehouse

The distance between storage location n and n' can be divided into two big categories.

When $R_n \neq R_{n'}$, the distance between storage location n and n' as follows. As shown in Figure 2.

$$t_{nn'} = |A_n - A_{n'}| + |R_n - R_{n'}| + |U_n - U_{n'}| + (H_n + H_{n'} - 2) \quad (2)$$

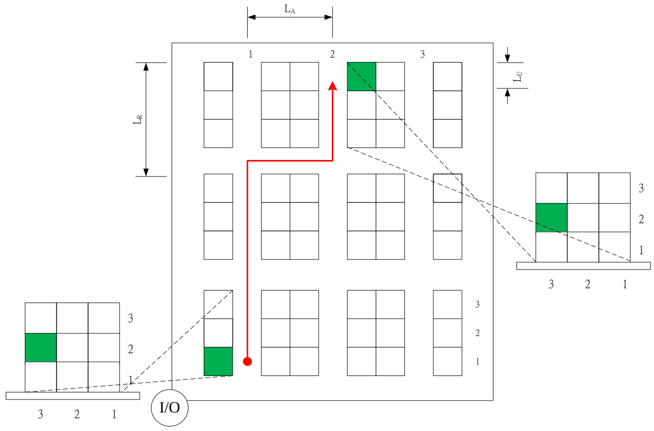

Figure 2: Two storage locations in different blocks

We define the distance from storage location n to I/O point as follows.

$$d_n = L_R(R_n - 1) + L_U U_n + L_A A_n + H_U(H_n - 1) \quad (3)$$

3.3 Correlation between Items

Based on the concept of support in association rule, we define the correlation between item i and j as follows.

$$S_{ij} = \frac{P(i \cap j)}{M} \quad (4)$$

Here, $P(i \cap j)$ is the number of orders in which item i and j appeared simultaneously. M is the total number of customers' orders. When S_{ij} is close to 1, which means item i and j are always ordered together.

$$d_n = (R_n - 1) + U_n + A_n + (H_n - 1) \quad (5)$$

We do EIQ analysis for orders. Ten orders using EIQ analysis is shown in Table 2.

Table 2: EIQ analysis

Order	Item								EQ	EN
	1	2	3	4	5	6	7	8		
1	5	4	3	2					14	4
2	2	1	2					1	6	4
3	1	5		3				2	11	4
4	3	1	1	5				1	11	5
5				4	1	3		1	9	4
6	9			1	2		4	2	18	5
7	4		2	5					16	3
8		3		4	5				16	4
9						5	3	6	14	3
10	7			2	6	4			19	4
IQ	31	14	8	26	14	12	7	13		
IK	7	5	4	8	4	3	2	6		

Chuang et al. (2012) stated that distribution centers always assign items locations by item frequency (IK). IK can be calculated as follows.

$$f_i = \frac{P(i)}{M} \quad (6)$$

Here, $P(i)$ is the number of orders containing item i. M is the total number of customers' orders. When f_i is close to 1, it means that item i is frequently ordered.

3.4 R-A Area Storage Location Assignment

We define the area named R-A area in which the storage locations' aisle indexes and row indexes are all same. The R-A distance from storage location n in R-A area to I/O point is defined as follows.

$$d_n^{RA} = L_R(R_n - 1) + \frac{1}{2}L_R + L_A A_n = L_R\left(R_n - \frac{1}{2}\right) + L_A A_n \quad (7)$$

3.5 Exchange of Items' Storage Locations

On the basis of R-A area storage location assignment, we exchange the storage locations of two items through the exchange rules which contain two parts. The first one is to exchange items' storage locations between different R-A areas. The second one is to exchange items' storage locations within the R-A area. Here, we assume the following.

(1) There is a high correlation between item i and j, a low correlation between item i and k.

(2) Before exchanging items storage locations, item j's storage location can be described as $(R_{n_j}, A_{n_j}, U_{n_j}, D_{n_j}, H_{n_j})$, and item k's storage location can be described as $(R_{n_k}, A_{n_k}, U_{n_k}, D_{n_k}, H_{n_k})$.

(3) After exchanging items' storage locations, item j's storage location can be described as $(R_{n_j'}, A_{n_j'}, U_{n_j'}, D_{n_j'}, H_{n_j'})$, and item k's storage location can be described as $(R_{n_k'}, A_{n_k'}, U_{n_k'}, D_{n_k'}, H_{n_k'})$.

If an order contains item i and j, the cost for picking item i and j can be described as follows.

$$\begin{aligned} C_{ij} = {} & (t_{n_i n_j}^{xy} + d_{n_i}^{xy} + d_{n_j}^{xy}) + (t_{n_i n_j}^{z} + d_{n_i}^{z} + d_{n_j}^{z}) \\ & + (\left|R_{n_i} - R_{n_j}\right| + R_{n_i} + R_{n_j}) \\ & + (\left|A_{n_i} - A_{n_j}\right| + A_{n_i} + A_{n_j} - 2) \end{aligned} \quad (8)$$

The cost function before exchanging items' storage locations can be described as follows.

$$\begin{aligned} C_1 = {} & \sum_g C_{jg} S_{jg} + \sum_l C_{jl} S_{jl} + \sum_g C_{kg} S_{kg} \\ & + \sum_l C_{kl} S_{kl} + (d_{n_j}^{xy} + d_{n_j}^{z} + R_{n_j} \\ & + (A_{n_j} - 1)) f_j + (d_{n_k}^{xy} + d_{n_k}^{z} \\ & + R_{n_k} + (A_{n_k} - 1)) f_k \end{aligned} \quad (9)$$

The cost function after exchanging items' storage locations can be described as follows.

$$\begin{aligned} C_2 = {} & \sum_g C'_{jg} S_{jg} + \sum_l C'_{jl} S_{jl} + \sum_g C'_{kg} S_{kg} \\ & + \sum_l C'_{kl} S_{kl} + (d_{n_j'}^{xy} + d_{n_j'}^{z} + R_{n_j'} \\ & + (A_{n_j'} - 1)) f_j + (d_{n_k'}^{xy} + d_{n_k'}^{z} \\ & + R_{n_k'} + (A_{n_k'} - 1)) f_k \end{aligned} \quad (10)$$

The benefit from exchanging items' storage locations can be described as follows.

$$B_{jk} = C_1 - C_2 \quad (11)$$

Here, $R_{n_l} = R_{n_k}$, $A_{n_l} = A_{n_k}$, $R_{n_g} = R_{n_j}$, $A_{n_g} = A_{n_j}$.

As shown in Figure 3.

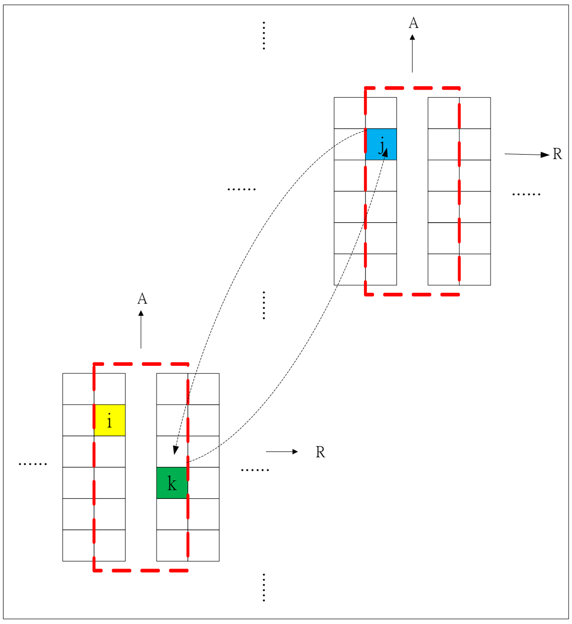

Figure 3: Exchange locations between different R-A area

4. MODEL VALIDATION

In this section, the proposed algorithm, ISLA is implemented with a real online retail data set. The data set is extracted from the database of University of California, Irvine.

We select the top 600 items with highest order frequency in the data set. A total of 1400 historical orders are used to generate items' correlation and the 348 orders for validation. EIQ storage approach is chosen as the benchmark to compare with the performance of ISLA. In implementing EIQ storage approach, items are assigned by their item-frequency (IK). The parameters setting are described as follows:

The warehouse has 648 storage locations. There are 3 row blocks and 6 aisles in the warehouse. Each shelf contains 3 layers. There are 6 locations in one layer on each side of each shelf.

Compared to EIQ storage, the order picking cost generated by ISLA is decreased by approximately 3%. As shown in Table 3.

Table 3: Result

	Total Travel Distance	*Total Order Picking Cost*
EIQ Storage	45304	50115
ISLA Storage	44073	48627
Improvement	2.72%	2.97%

5. CONCLUSION

Nowadays, quickly responding to customers' diversified requirements is an important issue. Therefore, modern retail industry has to focus on warehousing management to improve order picking efficiency.

In this research, we develop an Intelligent Storage Location Assignment (ISLA) algorithm in consideration of correlation between items to minimize order picking costs. When this algorithm is used in a multiple-cross-aisle warehouse containing multiple-layer shelves, the proposed ISLA can reduce picking costs by up to 3% in comparison of the EIQ storage policy. ISLA represent both the order frequency and relationships between items. From this research, we prove that ISLA algorithm can reduce warehouse operation cost and improve operation efficiency. Through numerical analysis, we show that the result is better than EIQ storage policy.

In order to make this algorithm more practical, other factors such as the size of item or the storage environment can be considered in the model in future work.

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