An Efficient Storage Allocation in Warehouse to Minimize Travel Distance of Pickers

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Abstract

Order picking is the most labor-intensive and costly operation in warehouse. Efficient storage assignment rules enormously affect the order picking efficiency. Warehouse managers are concerned about searching for the most effective way of managing order picking, minimizing the costs involved in terms of travel distance. The purpose of this research is to develop an efficient dedicated storage allocation method utilizing both the principle of group technology (GT) and the cube-per-order index (COI) storage policy in a maintenance environment warehouse. In this method, spare parts required for a particular maintenance work are grouped together on the basis of similarity of usages, even if they are dissimilar in size, shape etc. After that, the groups and parts within each group are assigned according to COI rule. The performance of the method is evaluated using simulation and compared with other sequence, frequency and group based dedicated storage methods. A genetic algorithm is embedded into the simulation program to determine the optimal traveling sequence that will minimize the travel distance. In the simulation study, it is found that the proposed method has the highest reduction in the distance travelled by the pickers.

Keywords
Group Technology, Order picking, Routing, Simulation and Genetic algorithms.

1. Introduction

Warehouse is an important part of any supply chain. The primary roles of a warehouse includes buffering of material flow to accommodate variability caused by product seasonality, consolidation of products from different suppliers for joined delivery to customers, and value-added-processing such as packaging, labeling, and product customization (Gu et al. 2007). All the problems that arises in the warehouse are categorized into two main groups: the design problem and the operational problem. The design problem is concerned about the issues such as the whole structure, dimension and sizing, layout of the departments, selection of equipment, and strategy of operation of the warehouse. On the other hand, the operational problem deals with receiving, delivering, storing and picking orders. Receiving and shipping are the inferences of a warehouse for incoming and outgoing material flow.

Order picking is an operation that refers to the retrieving of items from storage locations in response to specific orders of customers. Order picking has been practiced as the most labor-intensive and expensive operation of most warehouses from long ago. Bartholdi and Hackman (2011) assessed the picking operations cost 55% of the total operating cost of a warehouse roughly. Illogical execution of order picking can cause inadequate service and high operating cost for the warehouse. For these reasons, order picking has become an intent area to warehousing experts for improving efficiency in warehouses. The order picking efficiency could be enhanced by reducing the total

distance traveled by the order pickers**.** For improving the management of order picking four methods are usually applied such as: 1) allocating items to the precise locations; 2) zoning the warehouse; 3) batching of orders; 4) determining a route for picking (Muppani and Adil 2008a). All of these are firmly interdependent to order picking optimization problem, but the researchers only emphasize one or two of these decision areas simultaneously because of computational intractability.

The efficiency of order picking procedure is immensely affected by storage assignment rules (Le-Duc and Koster 2005). The purpose of the storage function is either to capitalize resource utilization in the mean time trying to maximize satisfaction of customers concurrently (Sooksaksun 2012). Three ordinary storage policies are in practice in the warehouse namely dedicated storage, random storage and class-based storage (Hausman et al. 1976). The dedicated storage policy gives a specific location to each product, i.e., this location is reserved even if the product is out of stock. Dedicated storage locations assist to surge the orientation of the order pickers, resulting in larger routing velocity and lesser incorrect picks. Dedicated storage policies permit logical classification of stored items that is frequently helpful for retail warehouses and generally for items with different weight, which can be kept in decreasing weight along the standard picking route, indicating a decent stacking order (Eckrot et al. 2017). However, the drawback of this policy is the lowest space utilization amongst all storage policies. Volume-based storage assignment is a particular type of dedicated storage assignment scheme in which items are assigned to storage positions depending on their pick volume; typically high pick items are placed nearest to the input/output point (I/O point). The randomized storage policy defined as allocating all received products into a place that is determined arbitrarily from empty positions. The advantages of this policy are the even uses of the storing spaces and decreases pathway blocking. However, this policy consumes huge travel time because the pickers must navigate the entire warehouse. In class-based storage, items are allocated into a number of classes and reserve a region for each class. This policy incorporates the features of both the dedicated and random storage (Gu et al. 2007). Heskett (1963) introduced the cube-per-order index (COI) assignment policy to allocate items close to the I/O point with the lowest ratio of the required space to the order frequency. Petersen et al. (2004) studied the development of order picking effectiveness by forming classes on basis of grouping parts with alike COI values in a manual order picking warehouse. The performances of class-based storage are compared to both random and volume-based storage. Jane and Laih (2005) developed a clustering algorithm for allocation of item by harmonizing the workload among all order pickers so that the utilization of the picking system is upgraded. De Koster et al. (2007) introduced family grouping, where the products are classified according to relations or resemblances between products or orders. Mantel et al. (2007) introduced a new storage allocation approach called Order Oriented Slotting (OOS), where items that appear together in orders are stored close with respect to each other. Muppani and Adil (2008b) developed a branch and bound algorithm to create classes and distribute storage space and to make a comparison with a benchmark dynamic programming algorithm. Their study showed that class-based policy has shorter travel distance in comparison with the dedicated policy. Bindi et al. (2009) established different storage allocation laws based on the implementation of original similarity co-efficient and clustering methods. Xiao and Zheng (2010) studied storage assignment problem that is correlated by considering the production bill of material (BOM) information where relatively stable order frequency is found. Chiang et al. (2011) introduced an adaptive approach, a Data Mining-based Storage Assignment approach (DMSA), to find the optimal storage allocation for newly delivered items that need to be put away when there is available space in a distribution center. Accorsi et al. (2012) presented a systematic hierarchical top-down method that permits the merging of successive decision steps concerned with allocation and assignment issues. Bottani et al. (2012) studied genetic algorithm for optimization of item allocation with the intention of reducing travel time of pickers.

The goal of routing policies is to sequence the items on the pick list to ensure a decent route through the warehouse. A lot of policies have been recommended that range from basic heuristics to ideal algorithm to accomplish this purpose. This issue is a warehouse-specific Traveling Salesman Problem (TSP), where the picking/storage area of an item is given. The issue where there are several probable areas for the retrieval or capacity of an item is more complex and few research results are available, in spite of the fact that usually found practically speaking. The TSP in the warehouse is exceptional due to the aisle structure of the possible travel paths. Roodbergen (2001) considered the routing method as traveling salesman problem and recommended six routing strategies such as: S-shape, return, mid-point, largest gap, combined and optimal. Hwang et al. (2004) exhibited analytical expressions for return, S-shape and midpoint routing methods. They consider COI based storage policies for their study. Ene and Ozturk (2012) developed a quicker genetic algorithm to form optimal batches and optimal routes for order pickers. The fundamental preferred standpoint of this algorithm is the quick response and can be applied to any sort of warehouse layout. Kulak (2012) proposed a novel tabu search algorithms integrated with a novel clustering algorithm to solve

the picker routing problems jointly for multiple-cross-aisle warehouse systems. The routing problem of pickers was modeled as a classical TSP. They proposed efficient Nearest Neighbor+Or-opt and Savings+2-Opt heuristics to meet the specific features of the problem. Grosse et al. (2014) studied the joint order batching and routing problem in conventional multi-parallel-aisle picker-to-part order picking systems. They formulated a mathematical model and developed a simulated annealing algorithm to batch orders and to determine pick tours. Cheng (2015) proposed an efficient hybrid algorithm for solving picker routing problem. The particle swarm optimization (PSO) and the ant colony optimization (ACO) algorithms are composed in this hybrid algorithm.

It is evident from the above discussion, most of the researchers focus on distribution centers or retail warehouses, where order can be changed dynamically. For this reason, they use similarity coefficient to identify correlations between items. On the other hand, maintenance environment warehouse is very similar to production warehouse where order structures are limited. In maintenance environment spare parts required for a particular type of maintenance is heterogeneous but they are similar in the sense that they are used for a specific maintenance purpose. For this reason, most of the time a particular maintenance requires spare parts from a predefined set of spare parts. So, it should be better approach to apply group technology which is an approach that seeks to identify those attributes of a population that permit its members to be collected into groups, sometimes called families. The members of each particular group possess attributes that are similar. If it is possible to group spare parts on the basis of similarity of usages and locate near each other, then the retrieval of parts will be easier and less time consuming. Again, the COI rule has been considerably studied in the literature and proved that it is optimal in minimizing the material handling cost in dedicated storage. So, it will be efficient if the groups with minimum COI are assigned near to the I/O point.

The rest of the paper is organized as follows. In next section, we propose an efficient group formation method and COI based storage allocation for maintenance environment warehouse. In third section, we develop a simulation model to evaluate the performance of the proposed method. In fourth section, we run the simulation program and compare the results of the proposed storage method with the other three different dedicated storage methods. The conclusion and discussion on the potential research direction is presented in the last section.

2. The proposed storage method

2.1 Problem description

The problem that is considered for this study is a maintenance type warehouse. Spare parts are stored and retrieved for maintenance purposes in a maintenance type warehouse. In such an environment, allocation of space and assignment of spare-parts is a vital problem for smooth operation in a warehouse. Miss-allocation of spare-parts takes huge time to retrieve specific parts. The demand for spare parts for a particular maintenance work depends upon the type of maintenance work. So, the spare parts required for a maintenance work is a sub set of a super set. This super set can be determined by obtaining the list of all the spare parts required for the particular maintenance work. This super set is defined as spare part set in this study. For instance, spare parts essential for maintenance of injection pump and engine head of internal combustion engine might be dissimilar in type and in amount. The spare part set for these two types of maintenance work hardly have common intersection. If it is possible to identify spare part set required for a particular type of maintenance work, then the set of parts with lowest COI can be kept in one region closest to the I\O point so that the searching and retrieval time can be minimized. The following assumptions (Lee 1992) are made in this study:

(1) A single-sided storage rack with 42 storage locations, as shown in figure 1 is considered in which the I/O point is located at the extreme lower left-hand corner.
(2) Each storage location (or shelf) is uniform in size (2ft × 2ft × 2ft) and reserved for a specific type of spare parts i.e., dedicated storage.
(3) The storage or retrieval (S/R) device can travel simultaneously in both the vertical and the horizontal directions at constant velocity.

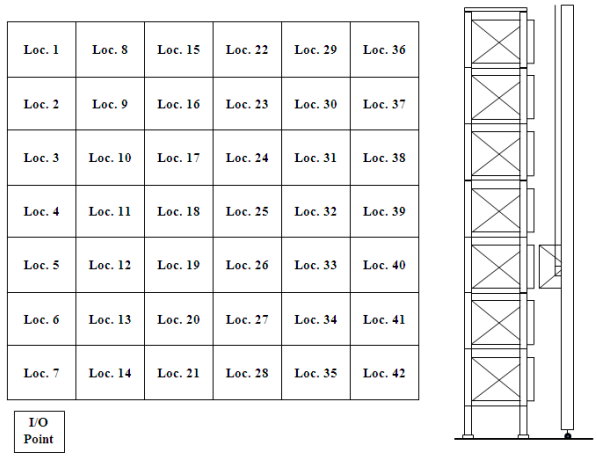

Figure 1. Front view and side view of the warehouse rack (Malmborg et al. 2000)

2.2 Storage method

The proposed storage method consists of five following stages as shown in figure 2.

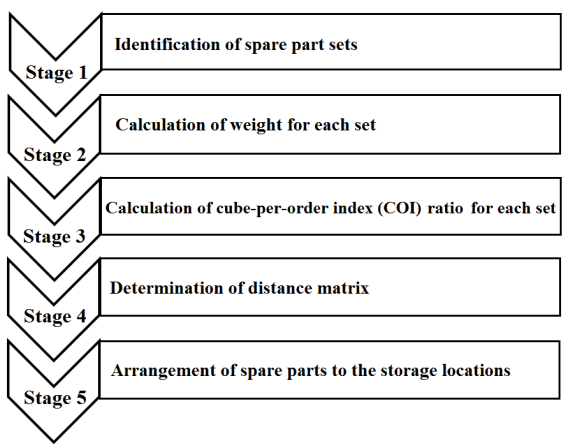

Figure 2. Methodology of proposed storage allocation

Stage 1: Identification of spare part sets

The demand for spare parts for a particular type of maintenance can be found from the issue register of the warehouse. Let us assume that

m = type of maintenance, $m = 1, 2, 3, \ldots, M$

t = time of maintenance, $t = 1, 2, 3, \ldots, T$

D_{mt} = the demand set is the set of spare parts demanded for maintenance type 'm' at time period 't'

S_m = set of spare parts for maintenance type 'm'

From these past demand sets, the sets of spare parts can be determined with the following formula:

$$S_m = \bigcup_{t=1}^{T} D_{mt}$$

Here, if a part is appeared in more than one group then the part will be in the group where the demand frequency is higher.

Stage 2: Calculation of weight for each set

The weight is used to identify a set as fast moving or slow moving. As the fast moving sets are used more frequently so these sets should be kept near to the issues counter as opposed to the slow moving sets. A simple way to determine the weight of a set could be the sum of annual usage frequency of all parts in the set. Let,

N_m= Total number of spare parts in set 'S_m'

f_{im}= Annual usage frequency of spare part 'i' in set S_m, i= 1, 2, 3, …, N_m

So, the weight of set 'S_m' will be,

$$W_m=\sum_{i=1}^{N_m} f_{im}$$

Stage 3: Calculation of cube-per-order index (COI) value for each set

As per our assumption, each spare part is stored into a specific shelf. So, the total number of shelves required for a set is equal to the number of spare parts in the set. Let, the volume of a shelf is 'v'. Therefore, the total volume required for a set will be,

$$V_m= N_m \times v$$

Now, cube-per-order index (COI) value for a set 'S_m' will be,

$$COI_m= \frac{V_m}{W_m}$$

Stage 4: Determination of distance matrix

Let us assume that, the distance between I/O point and the most nearest shelf is 3 meter and the distance between any two adjacent shelves is 2 meter. According to the assumption, the S/R device can travel to the vertical and the horizontal directions simultaneously. So, the distance between any two locations i and j (including the I/O point) in two dimensional co-ordinate is given by the following formula:

$$d_{i,j}= |x_i - x_j| + |y_i - y_j|$$

Finally, the distance values are stored in a distance matrix. For example, the distance between I/O point and location 33 (see figure 3) is,

$$d_{0,33}= 8+7= 15 \text{ ft.}$$

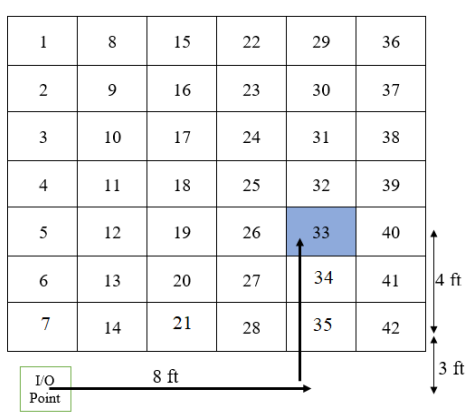

Figure 3. Distance between I/O point to location 33

Stage 5: Arrangement of spare parts to the storage locations

Here, the sets are assigned to storage locations according to COI policy. Since each type of parts occupies the same amount of space, the frequency rule will be the same as the COI rule. So, the spare parts within each set are arranged in descending order of frequency. The proposed storage algorithm is given below:

Step 1. Arrange the shelf numbers in ascending order of distance from I/O point (name this list as *A*).
Step 2. Arrange the sets in ascending order of COI value (name this list as *B*).
Step 3. Take a set from the top of the list *B*.
Step 4. Arrange the parts of this set in descending order of frequency.
Step 5. Assign the parts into the shelves from the top of the list *A*.
Step 6. Continue steps 3 to 5 until the list *B* is empty.

3. Development of simulation model

A single-sided storage rack is considered for the experiment to evaluate the performance of the proposed storage method. The storage rack is considered due to its simplicity and to avoid the computational complexity. The simulation model assumes the pattern of a Monte Carlo process. Furthermore, it is assumed that there are 7 types of maintenance works and all the spare parts are required by these maintenance works. Total number of parts in each spare part set varied from 4 to 8. The usage frequency of a spare part for a particular maintenance work is varied from 8 to 72 in a year. Table 1 represents the assumed sets of spare parts and the corresponding frequency sets. The frequency set shows the annual usage frequency of each part in the set. The weight of a set is the sum of usage frequency of all parts in the frequency set. In the simulation model a maintenance type is selected according to the weight. Table 2 shows the random number generation scheme for selecting the types of maintenance. Similarly, spare parts from a set are selected according to their demand frequency. Table 3 shows the random number generation scheme for selecting spare parts from the set S_1 related to type-1 maintenance.

Table 1. Weight and COI calculation of each set of spare parts

Maintenance type, *m*	Spare part set (1-42), S_m	Frequency set	Weight (W_m)	COI_m
1	[6,7,15,28,36,42]	[8,47,52,30,21,38]	196	0.245
2	[9,14,16,18,22,24,32]	[62,19,50,54,36,57,9]	287	0.195
3	[5,21,25,34,41]	[23,32,65,27,47]	194	0.206
4	[1,11,13,26,31,35]	[53,58,26,32,14,41]	224	0.214
5	[2,3,4,8,10,17,20,40]	[18,52,43,16,20,23,25,34]	231	0.277
6	[12,19,29,33]	[21,26,15,30]	92	0.348
7	[23,27,30,37,38,39]	[72,26,53,41,58,30]	280	0.171

Table 2. Random number generation scheme for selecting types of maintenance

Maintenance type, *m*	Weight	Probability	Cumulative	Range
1	196	196/1504=0.130	0.130	0<R≤0.130
2	287	0.191	0.321	0.130<R≤0.321
3	194	0.129	0.450	0.321<R≤0.450
4	224	0.149	0.599	0.450<R≤0.599
5	231	0.154	0.753	0.599<R≤0.753
6	92	0.061	0.814	0.753<R≤814
7	280	0.186	1	0.814<R≤1

Table 3. Random number generation scheme for selecting spare parts from the set S_1

Spare part No.	Demand frequency	Probability	Cumulative	Range
6	8	8/196=0.041	0.041	0<R≤0.041

7	47	0.240	0.281	0.041<R≤0.281
15	52	0.265	0.546	0.281<R≤0.546
28	30	0.153	0.699	0.546<R≤0.699
36	21	0.107	0.806	0.699<R≤0.806
42	38	0.194	1	0.806<R≤1

Four dedicated storage allocation methods including the proposed storage method are considered for the comparative analysis. The first one is sequence based storage, in which the spare parts are stored according to part number sequence i.e., alphanumeric order without regard to order frequency, size, weight etc. This method is often used due to its simplicity. The second one is frequency based or volume based storage, in which spare parts are stored according to the annual usage frequency of each part. In this method, the parts with the largest demand are kept closest to the I/O point. The third one is group based storage, in which spare parts are stored according to the group or similarity of usage. This method only consider the total order frequency of each group, not their space occupation, for the assignment to storage locations. The fourth one is group and COI based storage, which is the proposed method developed in this research. The proposed method consider both the demand frequency and the space occupation of each group. These four storage allocation methods (see figure 4) are simulated for the single-sided storage rack to investigate the performance of the proposed storage method in terms of average travel distance of order pickers.

1	8	15	22	29	36
2	9	16	23	30	37
3	10	17	24	31	38
4	11	18	25	32	39
5	12	19	26	33	40
6	13	20	27	34	41
7	14	21	28	35	42

(a) Sequence based storage

19	27	5	10	31	29
40	37	39	13	6	8
7	33	28	36	2	32
11	15	42	21	14	17
24	3	16	22	20	34
9	18	38	41	26	12
23	25	1	30	4	35

(b) Frequency based storage

36	28	15	33	19	29
6	42	7	41	21	12
10	2	8	25	34	5
40	20	17	1	26	31
14	3	4	11	35	13
18	16	32	38	37	39
9	24	22	23	30	27

(c) Group based storage

13	33	19	12	29	8
1	26	31	4	17	2
14	11	35	3	40	10
24	16	32	28	36	20
9	18	22	15	42	6
38	37	27	21	34	7
23	30	39	25	41	5

(d) Group and COI based storage

Figure 4. Four dedicated storage allocation methods

Travel distance refers to the distance between the I/O point from where the S/R device has to start travel to collect parts from the shelves and come back to that point. To collect 'n' numbers of parts from the rack with minimum travel distance is a traveling salesman problem (TSP). We assumed that the S/R device picks only one order at a time. The total distance traveled to collect 'n' parts of an order is given by the following formula:

$$d = d_{0,i} + d_{i,j} + d_{j,k} + d_{k,l} + \ldots\ldots\ldots + d_{(n-1),n} + d_{n,0}$$

Figure 5 shows how to determine the distance travelled by the picking device to collect spare parts 5, 21, 25, 34, 41.

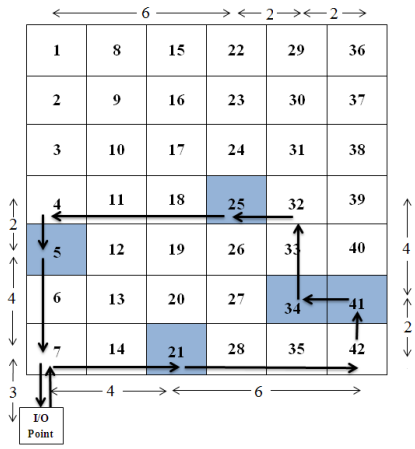

Figure 5. Sample travel distance calculation

So, the total distance travelled, d = 3+4+6+2+2+4+2+6+2+4+3 = 38 ft.

Finally, to solve the TSP of each tour, the well-known genetic algorithm is used which is a very good global search technique. The algorithm is embedded into the simulation program to estimate the optimal traveling sequence to minimize the total travel distance to collect all the parts of a demand. For this purpose, we incorporate the distance matrix of the locations into the algorithm. At first, the algorithm generates a preset number of random tours and then improves the population until a stop condition is satisfied and the best tour is returned as the solution. Order crossover technique (Wang et al. 2016) is used in this algorithm, illustrated in figure 6. In this technique, one segment from parent 2 is selected randomly and copied into child 1 in the same position. The rest portion of the child 1 will be filled from parent 1 sequentially except the elements which have already occupied. Similarly, child 2 will be generated in the same manner. Moreover, exchange mutation operation (Larranaga et al. 1999) has been applied in the genetic algorithm, described in figure 7. In this operation, two randomly selected elements in the child are swapped with each other. We also initialize the population size according to the number of locations to be traveled.

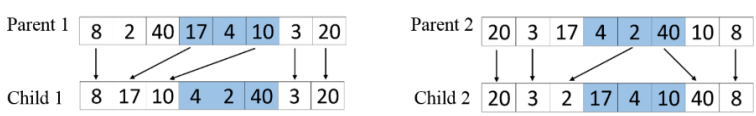

Figure 6. An example of Order Crossover

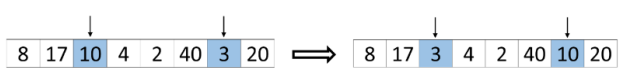

Figure 7. An example of Exchange Mutation

The pseudo code of the genetic algorithm is given below:

(1) Generate initial population with a number of random travel routes;
(2) **For** each route (chromosome)
(3) Evaluate its fitness value (length of travel);
(4) **Next**
(5) Select the best fit routes for reproduction;
(6) Perform crossover operation with probability of 0.80 to generate new route;
(7) Perform mutation operation with probability of 0.01;
(8) Update population for the next generation;

(9) **For** each modified route
(10) Evaluate its fitness value;
(11) **Next**
(12) **If** the stop condition is not reached **then**
(13) return to step (5);
(14) Terminate and return the optimal route and its length for a demand;

The pseudo code of the simulation program is given below:

(1) **Input** the total number of travels *N*;
(2) **For** travel no. = 1 to *N*
(3) Randomly generate a maintenance type '*m*' according to their weight;
(4) Randomly generate number of parts '*n*' required for the maintenance work according to uniform probability distribution;
(5) Randomly select the '*n*' number of parts one by one from the set of spare parts according to their demand frequency;
(6) Find the optimal traveling sequence and distance by using genetic algorithm for different storage methods;
(7) **Next**
(8) Evaluate average travel distance for different storage methods;
(9) Terminate the simulation;

4. Simulation results

The computer simulation program for the experiment was coded in C programming language. C language is much easier than any other language in implementing complex algorithms. The simulation program performs on the basis of randomly generated data as per our assumption. The simulation terminates once a user-defined number of iterations (travels) has been completed. The iteration number of the simulation is significantly large enough due to the stochastic nature of the process. The data are generated from uniform probability distribution within specified limits. At first, we run the simulation program with the length of 100 travels performed on the randomly generated maintenance types. Table 4 shows the resulting average travel distance from each travel for the proposed method of storage.

Table 4. Simulation result for the storage with proposed method

No	Maintenance type, *m*	Number of spare parts required, *n*	Spare parts to be picked	Traveling sequence by Genetic algorithm	Travel distance (ft)	Average travel distance (ft)
1	4	5	1 35 11 26 31	11 35 31 26 1	34	34.0
2	2	5	24 9 16 14 22	22 16 14 24 9	30	32.0
3	7	3	23 39 37	23 37 39	18	27.3
4	5	4	40 2 17 3	3 2 17 40	46	32.0
5	4	6	11 13 1 26 35 31	13 1 26 31 35 11	38	33.2
6	2	3	16 18 22	16 22 18	26	32.0
7	6	2	33 29	29 33	46	34.0
8	4	3	11 35 1	1 11 35	34	34.0
9	7	1	23	23	6	30.9
10	4	4	26 1 13 35	13 1 26 35	38	31.6
11	6	2	29 33	33 29	46	32.9
12	1	4	7 28 36 15	15 28 36 7	38	33.3
13	5	4	40 2 10 17	17 2 10 40	46	34.3

. . .	. . .	. . .	. . .	. . .	. . .	. . .
96	6	3	29 33 19	29 19 33	46	30.9
97	2	4	18 32 16 22	22 32 16 18	26	30.8
98	3	1	34	34	26	30.8
99	4	5	35 11 1 26 31	1 26 31 35 11	34	30.8
100	2	6	18 22 24 9 16 14	9 24 14 16 18 22	30	30.8

It can be seen from figure 8, the average travel distance of picking device for all the storage methods become almost stable. It also shows that, the storage method proposed in this research has the lowest average travel distance which is 30.80 feet. On the other hand, the average distances travelled for sequence, frequency and group based storages are 42.36, 36.96, and 32.56 feet respectively.

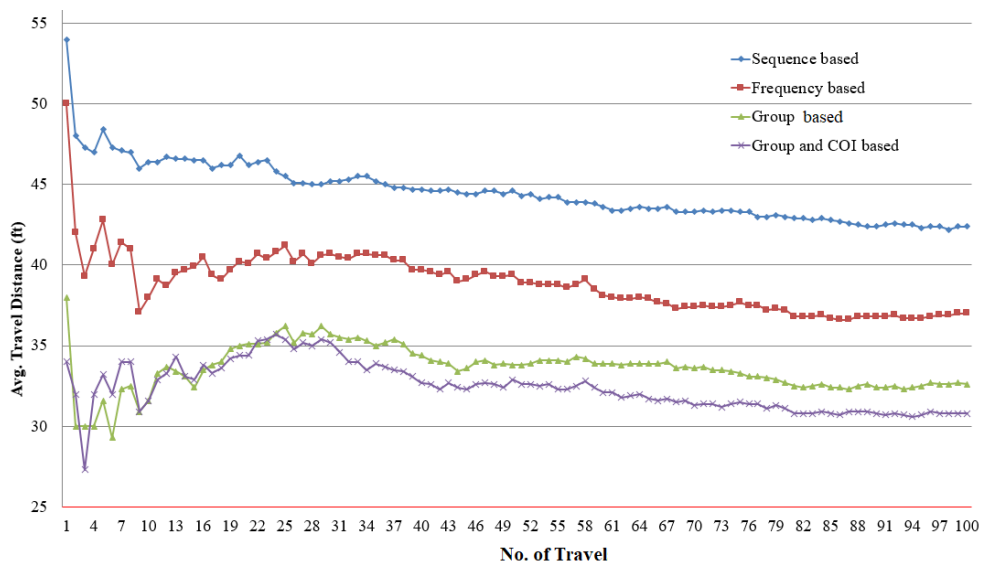

Figure 8. Comparison of average travel distance for various storage methods

Finally, we run the simulation program for ten times with the length of 1000 travels each, which is very large enough to ensure that the results depend on the given probability distribution rather than the choice of random numbers. The average execution time needed to run this length is 53.34 second. In this case, the result shows that the proposed storage allocation method has the highest reduction in the travel distance for each replication. Table 5 represents the percentage of travel distance reduction of proposed storage method with respect to other storage allocation methods. It has around 24.59% reduction in travel distance with respect to sequence based storage. Similarly, it has 18.07% and 2.96% reduction with respect to frequency and group based storage respectively.

Table 5. Simulation results for 10 independent replications

Replication	travel distance reduction (%) of proposed storage method with respect to		
	Sequence based	Frequency based	Group based
1	25.58	17.98	3.47
2	24.97	17.89	2.90
3	25.14	18.06	3.70
4	22.94	17.38	2.16
5	24.62	18.18	2.61

6	25.23	18.63	3.43
7	23.98	17.47	2.35
8	23.35	18.73	3.38
9	25.39	18.34	3.17
10	24.70	18.07	2.43
Average Reduction (%)	24.59	18.07	2.96

5. Conclusions and scopes for future research

Warehouse managers are concerned about searching for the most effective way of managing order picking, minimizing the costs involved in terms of travel distance. For maintenance environment warehouse, it is possible to group spare parts according to the type of maintenance works. The group with the lowest COI ratio can be kept closest to the I\O point. Moreover, the parts of a group can be arranged according to their usage frequency. In the simulation study, it is found that the proposed method has the highest reduction in the distance travelled by the picking device in the warehouse compared to the other storage methods. So, the proposed storage method can be applied to any production warehouse where the order structures are limited. On the other hand, the storage method will be easy to implement and simple to understand by a warehouse manager when it is adopted.

For this research, we consider a single-sided storage rack only. Therefore, the developed storage allocation model can be extended for multi rack warehouse system and figuring out the effects on the order picking efficiency. It is also suggested to considering different warehouse layout and incorporating more realistic issues that would be very interesting but challenging problem.

References

Accorsi, R., Manzini, R., and Bortolini, M., A hierarchical procedure for storage allocation and assignment within an order-picking system. A case study. *International Journal of Logistics Research and Applications*, vol. 15, no. 6, pp. 351-364, 2012.

Bartholdi, J.J., Hackman, S.T, Warehouse and distribution science, Release 0.94. Retrieved July, 28, 2011.

Bindi, F., Manzini, R., Pareschi, A., and Regattieri, A., Similarity-based storage allocation rules in an order picking system: an application to the food service industry. *International Journal of Logistics Research and Applications*, vol. 12, no. 4, pp. 233-247, 2009.

Bottani, E., Cecconi, M., Vignali, G., and Montanari, R., Optimisation of storage allocation in order picking operations through a genetic algorithm. *International Journal of Logistics Research and Applications*, vol. 15, no. 2, pp. 127-146, 2012.

Cheng, C. Y., Chen, Y. Y., Chen, T. L., and Yoo, J. J. W., Using a hybrid approach based on the particle swarm optimization and ant colony optimization to solve a joint order batching and picker routing problem. *International Journal of Production Economics*, vol. 170, pp. 805-814, 2015.

Chiang, D. M. H., Lin, C. P., and Chen, M. C., The adaptive approach for storage assignment by mining data of warehouse management system for distribution centres. *Enterprise Information Systems*, vol. 5, no. 2, pp. 219-234, 2011.

De Koster, R., Le-Duc, T., and Roodbergen, K. J., Design and control of warehouse order picking: A literature review. *European Journal of Operational Research*, vol. 182, no. 2, pp. 481-501, 2007.

Eckrot, A., Geldhauser, C., and Jurczyk, J., A simulated annealing approach to optimal storing in a multi-level warehouse. arXiv preprint arXiv:1704.01049, 2017.

Ene, S., and Ozturk, N., Storage location assignment and order picking optimization in the automotive industry. *The international journal of advanced manufacturing technology*, vol. 60, no. 5, pp. 787-797, 2012.

Grosse, E. H., Glock, C. H., and Ballester-Ripoll, R., A simulated annealing approach for the joint order batching and order picker routing problem with weight restrictions. *International Journal of Operations and Quantitative Management*, vol. 20, no. 2, pp. 65-83, 2014.

Gu, J., Goetschalckx, M., and McGinnis, L. F., Research on warehouse operation: A comprehensive review. *European journal of operational research*, vol. 177, no. 1, pp. 1-21, 2007.

Hausman, W. H., Schwarz, L. B., and Graves, S. C., Optimal storage assignment in automatic warehousing systems. *Management science*, vol. 22, no. 6, pp. 629-638, 1976.

Heskett, J. L., Cube-per-order index-a key to warehouse stock location. *Transportation and distribution Management*, vol. 3, no. 1, pp. 27-31, 1963.

Hwang, H., Oh, Y. H., and Lee, Y. K., An evaluation of routing policies for order-picking operations in low-level picker-to-part system. *International Journal of Production Research*, vol. 42, no. 18, pp. 3873-3889, 2004.

Jane, C. C., and Laih, Y. W., A clustering algorithm for item assignment in a synchronized zone order picking system. *European Journal of Operational Research*, vol. 166, no. 2, pp. 489-496, 2005.

Kulak, O., Sahin, Y., and Taner, M. E., Joint order batching and picker routing in single and multiple-cross-aisle warehouses using cluster-based tabu search algorithms. *Flexible services and manufacturing journal*, vol. 24, no. 1, pp. 52-80, 2012.

Larranaga, P., Kuijpers, C. M. H., Murga, R. H., Inza, I., and Dizdarevic, S., Genetic algorithms for the travelling salesman problem: A review of representations and operators. *Artificial Intelligence Review*, vol. 13, no. 2, pp. 129-170, 1999.

Le-Duc, T., and De Koster, R. M. B., Travel distance estimation and storage zone optimization in a 2-block class-based storage strategy warehouse. *International Journal of Production Research*, vol. 43, no. 17, pp. 3561-3581, 2005.

Lee, M. K., A storage assignment policy in a man-on-board automated storage/retrieval system. *The International Journal of Production Research*, vol. 30, no. 10, pp. 2281-2292, 1992.

Malmborg, C. J., and Al-Tassan, K., An integrated performance model for order picking systems with randomized storage. *Applied Mathematical Modelling*, vol. 24, no. 2, pp. 95-111, 2000.

Mantel, R. J., Schuur, P. C., and Heragu, S. S., Order oriented slotting: a new assignment strategy for warehouses. *European Journal of Industrial Engineering*, vol. 1, no. 3, pp. 301-316, 2007.

Muppani, V. R., and Adil, G. K., Efficient formation of storage classes for warehouse storage location assignment: a simulated annealing approach. *Omega*, vol. 36, no. 4, pp. 609-618, 2008a.

Muppani, V. R., and Adil, G. K., A branch and bound algorithm for class based storage location assignment. *European Journal of Operational Research*, vol. 189, no. 2, pp. 492-507, 2008b.

Petersen, C. G., Aase, G. R., and Heiser, D. R., Improving order-picking performance through the implementation of class-based storage. *International Journal of Physical Distribution & Logistics Management*, vol. 34, no. 7, pp. 534-544, 2004.

Roodbergen, K. J., Layout and routing methods for warehouses (No. EPS-2001-004-LIS), 2001.

Wang, S., Lu, Z., Wei, L., Ji, G., and Yang, J., Fitness-scaling adaptive genetic algorithm with local search for solving the Multiple Depot Vehicle Routing Problem. *Simulation*, vol. 92, no. 7, pp. 601-616, 2016.

Sooksaksun, N., Pareto-based multi-objective optimization for two-block class-based storage warehouse design. *Industrial Engineering and Management Systems*, vol. 11, no. 4, pp. 331-338, 2012.

Xiao, J., and Zheng, L., A correlated storage location assignment problem in a single-block-multi-aisles warehouse considering BOM information. *International Journal of Production Research*, vol. 48, no. 5, pp. 1321-1338, 2010.

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