Proceedings of the International Conference on Industrial Engineering and Operations Management
Washington DC, USA, September 27-29, 2018

Warehouse Storage Assignment by Genetic Algorithm with Multi-objectives

Chi-Bin Cheng
Department of Information Management
Tamkang University
New Taipei City, Taiwan
cbcheng@mail.tku.edu.tw

Yu-Chi Weng
Department of Information Management
Tamkang University
New Taipei City, Taiwan
emily091131027@gms.tku.edu.tw

Abstract

Order picking operation is one of the major sources of operating costs of a distribution center. The proper assignment of storages to stocks prior to their picking is critical to reduce such costs. Appropriate storage assignments can also shorten storing time, improve storage utilization, and facilitate inventory management. The storage assignment problem can be modeled as a quadratic assignment problem, which appertains to an NP-Complete problem, and hence creates difficulties in solving large scale problems. This study develops a genetic algorithm to solve the problem with three objectives: minimizing the routing length of storing stocks, maximizing the future chance of adjacent stocks to be picked together, and minimizing the storage distance to the access point for popular stocks. This study devises a genetic algorithm to find feasible solutions and uses a method to determine the final storage assignment from a set of Pareto solutions. Performance of the proposed approach is evaluated via a computer simulation based on historical orders of the case-study distribution center.

Keywords
Storage assignment problem, Distribution center, Genetic algorithm, Multi-objective decision making, Order picking.

1. Introduction
Distributions centers are an integral part of the order fulfillment process, and play an ever important role in the logistic process as B2B or B2C e-commerce growing at full speed. Order picking is the process to retrieve items from storages in response to customer orders, and is one of most laborious and costly activities in a distribution center. The cost of the picking task accounts for up to 55% of the total warehouse operating costs (Tompkins et al. 2010). An investigation also showed that the labor hours consumed by the order picking activities share 60% of the total hours of the distribution center (Chen 1995).

Several operational decisions closely relate to the performance of the order-picking process, e.g. warehouse layout, picking policies, routing methods, and storage assignment (Coronado 2015):

- Warehouse layout is a tactical decision. It concerns the layout of various departments of receiving, picking, storage, sorting and shipping, warehouse blocks, storage space, and paths (Dukic and Opetuk 2012).
- Picking policies are operational decisions. They determine how orders are picked by the order picker, such as discrete picking, batch picking, and zone picking. Among which, discrete picking is perhaps the most commonly used picking method, where one order-picker picks one order, one line at a time (Wheeler 2014).
- Routing methods are operational decisions to determine the route of an order picker as they travel through the warehouse, as well as the sequence of items to be picked. There are numerous routing strategies, such as the S-shape routing, the largest gap routing, optimal routing, and hybrid procedures (Coronado 2015).

- Storage assignment is both tactical and operational decisions. It is a rule to determine the storage location of an item. Common storage assignment policies include random storage, full-turnover storage, and class-based storage (Roodbergen 2012).

The aim of this study is to improve the efficiency of the order picking of a distribution center under the constraints of its current layout, routing method, and picking policy. The case study distribution center is an auto parts seller who owns a few warehouses where facility layout was just renovated. The distribution center adopts a discrete picking policy and strictly follows a first-in-first-out rule that for the same items the earliest stored ones are always picked first. The S-shape routing strategy is used when picking an order. This strategy leads to a route in which the aisles to be visited are totally traversed while aisles without items to be picked are skipped, as shown in Figure 1 (Material handling Forum 2018). The order picker thus enters an aisle from one end and leaves the aisle from the other end. This strategy is frequently used due to its simplicity and explicitness.

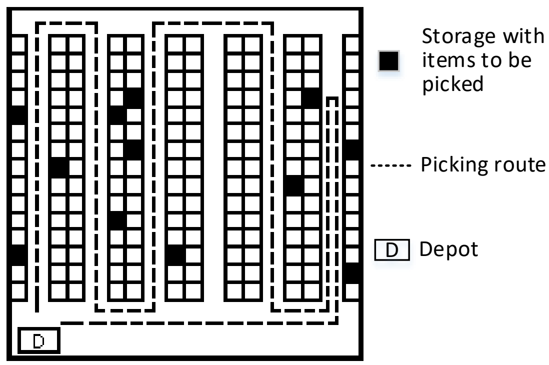

Figure 1. The S-shape routing strategy (Material handling Forum 2018)

With the above constraints imposed by the current operations of the distribution center, this study focus on the design of the storage location assignment method to improve the order picking efficiency of the distribution center. This is also the intention of the distribution center for its current storage location assignment method has been creating inefficiency to the order picking process. The current storage assignment method of the distribution center is similar to a random storage policy. A typical random storage policy assigns incoming items to a location in the warehouse that is selected randomly from all eligible empty locations with equal probability. An additional rule by the case study distribution center is that receiving items are assigned to storage frames where the same items have been stored previously, if such storage locations are available; otherwise, to save space, the receiving items are assigned to other storage frames with different items in a random fashion. The storage frames used by the case study distribution center are similar to those shown in Figure 2.

Figure 2. Storage frames[1]

[1] The photos were not taken from the case study distribution center, but from http://www.xn--0vq11a773c.tw/pro5/pro14a.jpg and http://lcdoor.en.easthardware.net/product-detail-142880.html

Random storage policy is used often in practice for its simplicity. This storage policy, in the long run, makes the probability of an item to be needed from any location being equal. However, in many cases, the demand frequencies of items are not unique but often vary greatly among them. Thus, the use of random storage policy inevitably creates inefficiency in the future order picking operations. With this consideration, this study attempts to solve the storage assignment problem by taking into account the demand frequencies of items; that is, the frequently demanded items ought to be stored near the depot. Furthermore, since the case study distribution center adopts a discrete picking policy where the items in the same order are picked together, we also consider the possibility that the receiving item will be picked with certain items in the future and prioritize their locations for storing the receiving item. Finally, the items are received in batch and generally the receiving amount exceeds the available capacity of a single storage frame, and thus, it is required to seek multiple available storage frames in such a case. This study also considers the traverse distance among the storage frames when assigning storage locations for the receiving item. Consequently, the storage assignment model of this study has three objectives: minimizing the distance from the storage location to the depot, maximizing the possibility of the item to be picked with items in its adjacent locations, and minimizing the traverse distance among storage frames when storing the item.

2. Storage Assignment Rules

Typical storage policies include: (1)dedicated location that assigns specific storage locations for each item, (2)Random location that assigns incoming products to a location selected randomly, (3) class-based storage that divides the products into a number of classes, and each class is then assigned to a dedicated area, and (4)utility location that allows different items to share a storage location.

Storage policies are just general guidelines and have to couple with assignment rules to determine the practical operations of item storing. Commonly used assignment rules include:

- Turnover-based: items are ranked based on their turnover rates, and items with higher turnover are stored nearer to the depot.
- Correlation-based: items that are highly correlated are often ordered together and thus are stored at adjacent locations.
- Complementary-based: items that are complementary to each other are stored at adjacent locations, thus they can substitute each other when one of them is out of stock.

More complicated methods have also been used to determine storage locations, such as cube-per-order index (CPOI) and entry-item-quantity (EIQ) analysis. CPOI was proposed by Hesket (1963) with the consideration of storage space and demand frequency of the item as below:

$$\text{CPOI} = \frac{R}{F} \tag{1}$$

where R denotes the required storage space of the item, and F is the number of orders of the item in a predefined period. The items with smaller CPOIs are stored nearer to the depot. The definition of CPOI implies that products that are demanded frequently ought to be stored near to the depot to reduce moving distances, and the storage area near to the depot is retained for as many as possible the frequently-ordered products and thus large items are stored in deeper area of the warehouse.

EIQ analysis was proposed by Suzuki (1985) to identify the characteristic of a distribution center and discover important customers and frequently-ordered products, based on the analysis of three logistics factors of a distribution center, which are E (order entry), I (item), and Q (quantity). This analysis result can be used to determine storage locations of items.

Mathematical programming with heuristics have been also employed to solve the storage assignment problems. Dekker et al. (2004) and Le-Duc and De Koster (2005) both used 2-opt exchange procedures to solve the storage location assignment problems. Pan et al. (2015) presents a genetic algorithm for storage location assignment in a single-aisle multi-item picking system. Muppani and Adil (2008) introduced a branch-and-bound method to determine storage locations for unit load warehouses with multi-aisle and single-item picking. Ene and Öztürk (2011) modeled the storage location decision by integer linear programming, where travel time is approximated by a weighting factor for different storage classes.

3. Storage Assignment with Multiple Objectives

As described in the first section, the receiving items the case study distribution center are assigned with priority to storage frames where the same items have been stored previously, and if such storage locations are not available, the receiving items are assigned to other storage frames which may be empty or contain different items. Furthermore, the items are received in batch and generally the receiving amount exceeds the available capacity of a single storage frame, and thus, it is required to seek multiple available storage frames. Considering the operational characteristics of the distribution center, this study proposes three objectives for the storage assignment operations of the case:

- Maximize the correlation between the receiving item and the items in the assigned storage frame. This objective is to reduce the potential moving distance in the future when picking orders by keeping the items that may be picked together in the same storage frame.
- Maximize a frequency-distance index based on the concept of CPOI. The idea is to store the frequently-demanded items nearer to the depot to reduce the potential moving distance.
- Minimize the moving distance among the assigned storage frames. Since we generally need to find multiple storage frames to store the receiving items, this objective intends to find a set of storage frames which are closer to each other.

Though the above three objectives are all related to moving distances, the first two distances are not known at the moment items are received until the order picking operations. Estimates of such distances based on probability distributions of orders might be performed to obtain an expected measure; however, such estimates are difficult for the great uncertainties of future orders and the great varieties of items. Thus, we consider it is simpler to determine the storage assignment via optimizing the indexes we suggest in the three objectives.

3.1 Formulation of the Three Objectives

The three objectives are formally defined as follows.

3.1.1 Correlation of items

The correlation between two items is measured by computing the support of the two items from historical orders. Let c_{ij} denote the correlation measure of items i and j, then

$$c_{ij} = \frac{n_{i\cap j}}{N} \tag{2}$$

where $n_{i\cap j}$ is the number of orders that contain both items i and j, and N is the total number of orders. Suppose item i is assigned to storage frame k, the correlation between the item and the frame, f_{ik}, is defined as

$$f_{ik} = \frac{\sum_j c_{ij} q_{jk}}{\sum_j q_{jk}} \tag{3}$$

where q_{jk} is the amount of item j in storage frame k. The objective is to maximize an overall correlation index, CI, over all the storage frames assigned for item i:

$$CI = \sum_{k\in K} f_{ik} \tag{4}$$

where K is the set of storage frames assigned for item i.

3.1.2 Frequency-distance index

Similar to the concept of CPOI, the items demanded more frequently are stored nearer to the depot, while items demanded less frequently are stored farther away from the depot. Let $FI\in[0, 1]$ be an index that reflect the above intention, and the greater the FI the more satisfaction of the intention. The extreme cases of FI can be observed from Table 1, in which the highest frequency is represented by a number 1 and the lowest frequency by 0, while the farthest distance is represented by 1 and the nearest by 0. Treating these numbers as truth values, the relations between FI and the frequency and the distance are identical to the logic operation XOR. Based on this observation, we attempt to design the FI index by XOR operation. However, XOR can be applied only to {0, 1} values, and thus a modification on the traditional XOR is required to accommodate non-binary values. Such a need motivates us to use the fuzzy XOR which generalizes the traditional XOR to continuous logic. The fuzzy XOR introduced by Mela and Lehmann (1995) is adopted by this study:

$$FI = \overline{\phi_i} + \overline{d_i}^{\max} - 2\overline{\phi_i} \cdot \overline{d_i}^{\max} \tag{5}$$

where $\overline{\phi_i} \in [0,1]$ is the normalized demand frequency of item i and is computed by

$$\overline{\phi_i} = \frac{\overline{\phi_i} - \phi^{\min}}{\phi^{\max} - \phi^{\min}} \tag{6}$$

with $\phi^{\min}$ and $\phi^{\max}$ being the minimum and the maximum among the demand frequencies of all items; $\overline{d_i}^{\max} \in [0,1]$ is the normalized distance of the farthest storage frame assigned for item i and is obtained by

$$\overline{d_i}^{\max} = \frac{d_i^{\max} - d^{\min}}{d^{\max} - d^{\min}} \tag{7}$$

with $d_i^{\max}$ as the distance (to depot) of the farthest frame that stores item i, and $d^{\min}$ and $d^{\max}$ and the smallest and the greatest distances among all frames in the warehouse to the depot, respectively.

Table 1. Extreme cases of *FI*

Demand frequency	Distance to depot	*FI*
highest (1)	farthest (1)	worst (0)
highest (1)	nearest (0)	best (1)
lowest (0)	farthest (1)	best (1)
lowest (0)	nearest (0)	worst (0)

3.1.3 Traverse distance among frames

The receiving item often requires multiple storage frames to accommodate the entire batch. This objective is to find a set of storage frames that minimize the distance required to visit these frames. To compute the traverse distance of a sequence of storage frames to be visited, the information regarding the distance between every pair of frames have to be known in advance. Due to the storage layout and aisle structure, the distance between two frames is a Manhattan distance. There are numerous routes to reach a storage frame from another one. Here, we apply the Dijkstra shortest path algorithm to determine the distance between two storage frames. The traverse distance t among a set of storage frames assigned for item i is again normalized by

$$T = \frac{t - t^{\min}}{t^{\max} - t^{\min}} \tag{8}$$

where $t^{\max}$ is the possibly longest distance predetermined based on experience, and $t^{\min}$ is the possibly shortest distance, i.e. $t^{\min} = 0$ when the entire batch of item i is stored in a single frame.

3.2 Genetic Algorithm

When one item is assigned to one and only one storage location, the storage assignment becomes a quadratic assignment problem, which has been proved as NP-complete (Gary and Johnson 1979). This study considers assigning a batch of the item to multiple storage locations that is more complicated than one-to-one assignment, and thus we propose a genetic algorithm instead of an exact solver to solve the problem.

3.2.1 Solution encoding

The solution to the problem is a sequence of storage frames to be visited and store the item. A chromosome is used to represent such a sequence as shown in Figure 3, where each cell of the chromosome indicates the frame number. The frames are visited by the orders of cells and the traverse distance among frames is thus computed. The chromosomes are generated randomly or through genetic operations. Unlike regular GA, the length of chromosome is not fixed in our algorithm. If the chromosome is not long enough to accommodate the entire batch, it is discarded; otherwise, it is truncated if too long. For example, suppose the batch is 100 units, and the available capacities of the frames in the chromosome of Figure 3 are 50, 20, 15, 25 and 30 units in turn, then the last cell is discarded since the first four frames are abundant already to take the entire batch.

2_5#4	3_5#1	2_2#1	2_6#2	3_4#3

Figure 3. An exemplar chromosome

3.2.2 Fitness function

Desirability function (Harrington 1965, Derringer and Suich 1980) is a classical approach for solving multiple objective optimization problems by combining individual objectives into a single index/measure. The desirability function approach requires the specification of weights associated with objectives, and relies upon prior information regarding the objectives, which could be difficult because *a priori* knowledge of objective values is often unavailable. To overcome the difficulties of the desirability function approach, Lu et al. (2012) suggested obtaining a set of Pareto optima and then choosing the best solution from the set according to a pre-determined criterion; the obtaining of the Pareto set is referred to as the Pareto optimization approach, and the method of choosing the best solution from the Pareto set is referred to as the Pareto decision analysis approach.

A simple way to find the Pareto front is to vary the weights of objectives in the desirability function approach. For the weighted sum method, which is a particular and popular desirability function approach, if all weights are positive the optimization of the weighted sum of all objectives provides a sufficient condition for Pareto optimality, i.e. the solutions obtained by such optimization are always Pareto optimal (Zadeh 1963, Goicoechea et al. 1982). However, the weighted sum method does not guarantee the finding of all Pareto optimal points. Though it is not easy or possible to obtain the complete Pareto optimal curve by the weighted sum method, the method is able to provide an approximate of the Pareto front. Thus, this study adopts the weighted sum method to approximate the Pareto front, where the weighted sum of the three objectives serves as the fitness function of the posed GA and is defined as:

$$FT = w_{CI} \cdot CI + w_{FI} \cdot FI + w_T \cdot (1\text{-}T) \tag{9}$$

where w_{CI}, w_{FI} and w_S are weights of the three objective respectively and $w_{CI} + w_{FI} + w_T = 1$. After the Pareto frontier is obtained or at least approximated, the final solution is selected within the set represented by the Pareto frontier using the empiric rule suggested by Bortolini et al. (2016):

$$\max_p \{\frac{CI_p}{CI^*} \cdot \frac{FI_p}{FI^*} \cdot \frac{(1-T_p)}{(1-T^*)}\} \tag{10}$$

where CI_p, FI_p and T_p are the p-th Pareto solution, and CI^*, FI^* and T^* are the respective single objective optimal solutions.

3.2.3 GA operations

GA operations include reproduction, crossover and mutation. Two types of reproduction are both used in our GA: roulette wheel selection, and tournament selection. Roulette wheel selection is the most frequently used selection strategy in GA. It is a proportional and stochastic selection analog to a roulette wheel. Tournament selection is also a frequently-used selection strategy which selects individuals based on their competitiveness. The basic idea of this strategy is to select the individual with the highest fitness value from a certain number of individuals randomly chosen from the population. A comparison of the two selection strategies can be found in Zhong et al. (2005).

The purpose of crossover is to generate new chromosomes that we hope will retain good features such as with higher fitness from the previous generation. This procedure is carried out by selecting pairs of parent chromosomes with a probability equal to a given crossover rate. A chromosome is chosen for crossover when the random number generated for it is less than or equal to the crossover rate. A basic crossover operation called one-cut-point method is commonly used. This method sets a crossover point on the chromosome strings randomly and two parent chromosomes are interchanges at this point. As mentioned earlier, the length of chromosomes of our GA are not fixed, and hence the regular one-cut-point method cannot be directly applied. Alternatively, we suggest a one-cut-ratio which randomly chooses a ratio of the chromosome length and finding the corresponding cut-point based on that ratio. The example in Figure 4 demonstrates such a method, where the length of the first chromosome is 5 and that of the second one is 3. Suppose the randomly generated one-cut-ratio is 0.45, which is between the second and the third cells of the first chromosome, i.e 5×0.45=2.25; similarly, the ratio is between the first and the second cells of the second chromosome. Thus, the second cell of the first chromosome and the first cell of the second chromosome are used as cut-points for crossover.

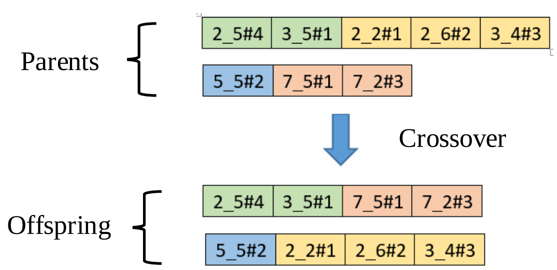

Figure 4 An example of crossover by one-cut-ratio

The operation of mutation creates a new chromosome which is very different from the current gene pool; therefore, it can provide a new search direction and prevent the population from converging to a local optimum prematurely. This operation is carried out by randomly changing a cell of the chromosome. A cell is chosen to change according to a predefined mutation rate. To prevent from harming the original gene pool, the change is not arbitrarily random; instead, we control the random range within a predetermined circumference of the chosen cell.

3.3 Solution procedure

The solution procedure to determine the storage assignment for a receiving item is illustrated in Figure 5. The procedure begins with a setting of the weight vector used in the fitness function (9). This fitness function is sent to the GA to obtain a storage assignment solution. The solution is recorded to approximate the Pareto frontier of the multi-objective problem. If all the weight vectors have been enumerated, the algorithm determine the final solution based on Equation (10).

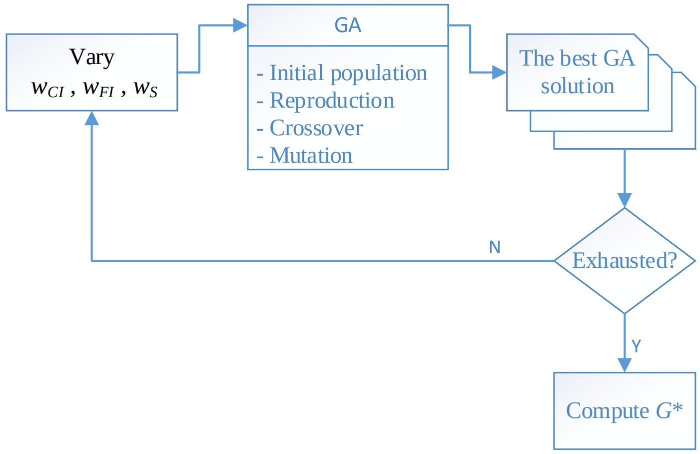

Figure 5 Solution procedure

4. Performance Evaluation

To evaluate the performance of our method, we simulate the procurement decision and customer order arrival of the case study distribution center based on its inventory policy and historical orders. Performance evaluation is carried out by comparing the storage assignment decisions for receiving items by the principle of current operations and by the proposed method. The reorder point of new items is determined by the following rule:

$$s = L \cdot AVG + z_{1-\alpha} \cdot STD \cdot \sqrt{L} \tag{11}$$

where L is the lead-time, *AVG* and *STD* are the mean and deviation of demand respectively, and $z_{1-\alpha}$ is the score of standard normal distribution under service level α. The procurement amount is determined based on the economic order quantity (EOQ):

$$Q = \sqrt{\frac{2 \cdot O \cdot AVG}{h}} \tag{12}$$

with O being the fixed cost of each procurement and h the unit holding cost. Order arrival is simulated based on real orders of three months which contains 332 orders with 1818 items. The simulation was run for three months.

The parameters of GA are set as the follows: population size 50, reproduction rate 0.7, crossover rate 0.7 and mutation rate 0.2. The weights used in the fitness function (9) are changed from 0 to 1 with an increment of 0.1, which results in 66 sets of weights. Part of the computational results are shown in Table 2. The individual best value of single objective is 0.76 for (1-T), 0.541666 for *CI*, and 0.6285714 for FI. From the approximate Pareto frontier we find G^*= 0.8749984. It is noted that at G^* it is also the best solutions for the two objectives, T and *CI*. The moving distance produced by G^* is compared to that by the current operations. Figure 6 shows the comparison, where our method outperforms the current method for both item storing and order picking.

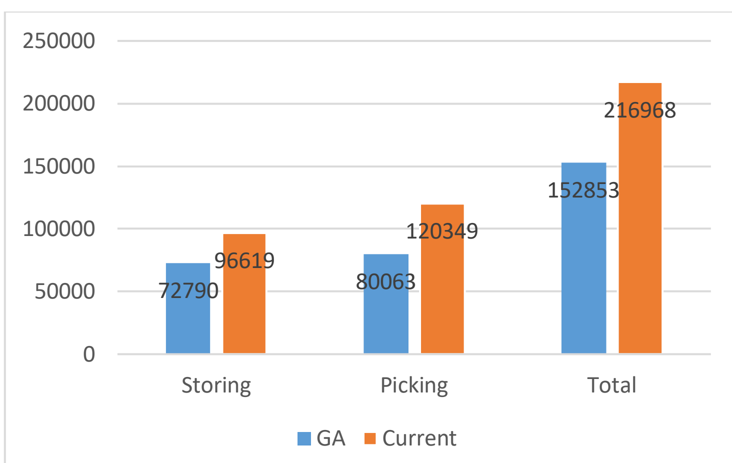

Figure 6 Comparison of moving distances of different types of moving by two methods

Table 2 Computational results of GA

w_T	w_{CI}	w_{FI}	1-*T*	*CI*	*FI*	*G*
0	0	1	0.534	0.407333333	0.617857143	0.519372488
0	0.1	0.9	0.578	0.5	0.617857143	0.690057968
0	0.2	0.8	0.538999	0.5	0.582142857	0.606299482
0	0.3	0.7	0.506	0.408	0.617857143	0.492944939
. .						
0	1	0	0.681	0.538461538	0.475	0.673123991
0.1	0	0.9	0.657	0.397142857	0.628571429	0.633820706
. .						
0.2	0.3	0.5	0.682	0.464285714	0.592857143	0.725469925
0.2	0.4	0.4	**0.76***	**0.541666***	0.549999	**0.8749984***
0.2	0.5	0.3	0.665	0.435333333	0.607142857	0.679256993
. .						
0.3	0.1	0.6	0.618	0.355	0.625	0.529903156
0.3	0.2	0.5	0.629	0.432142857	**0.6285714***	0.660286293
0.3	0.3	0.4	0.64	0.466428571	0.549999	0.634492774
. .						
0.9	0.1	0	0.754	0.466428571	0.621428571	0.844592789
1	0	0	0.729	0.399285714	0.546428571	0.614673317

5. Concluding Remarks

This study proposes a method to assist the storage assignment decisions of a distribution center. Unlike most previous studies focus on the minimization of potential order picking moving distances in the future, this study suggests optimizing three indexes associated with storage assignment that may improve order picking efficiency in the future. Our formulation results in a multi-objective optimization problem. Considering the computational complexity of the problem, this study formulate a solution procedure that contains a genetic algorithm. The proposed method is evaluated through a simulation of item receiving and order picking of the case study distribution center, and its performance is compared with the current operations of the distribution center. The result shows that our method is able to reduce the moving distance by 40%.

Acknowledgements

The authors are grateful for the assistance of the case study distribution center in collecting data of this study.

References

Bortolini, M., Faccio, M., Ferrari, E., Gamberi, M., and Pilati, F., Fresh food sustainable distribution: cost, delivery time and carbon footprint three-objective optimization. *Journal of Food Engineering*, vol. 174, pp. 56-67, 2016.

Brynzer, H. and Johansson, M. I., Storage location assignment: using the product structure to reduce order picking times, *International Journal of Production Economics*, vol. 46–47, pp. 595-603, 1996.

Coronado, V., Warehouse and distribution center: order-picking optimization, Available: https://www.linkedin.com/pulse/warehouse-distribution-center-order-picking-victor-coronado/, June, 2018.

Dekker, R., de Koster, M.B.M., Roodbergen, K.J., and van Kalleveen, H., Improving order-picking response time at Ankor's warehouse, *Interfaces*, vol. 34 (4), pp. 303-313, 2004.
Derringer, G., and Suich, R. Simultaneous optimization of several response variable, *Journal of Quality Technology*, vol. 12, pp. 214-219, 1980.
Dukic, G. and Opetuk, T., Warehouse layouts, in *Warehousing in the Global Supply Chain: Advanced Models, Tools and Applications for Storage Systems*, Manzini, R. (ed.), Springer-Verlag, London, 2012.
Ene, S., and Öztürk, N., Storage location assignment and order picking optimization in the automotive industry, *Int. J. Adv. Manuf. Technol*., vol. 60, no. 5-8, pp. 787-797, 2011.
Gary, M. R., and Johnson, D. S., *Computers and Intractability: A Guide to the Theory of NP-completeness*, WH Freeman and Company, New York, 1979.
Harrington, J., The desirability function. *Industrial Quality Control*, vol. 21, pp. 494-498, 1965.
Goicoechea A, Hansen, D. R., Duckstein, L., Multiobjective Decision Analysis with Engineering and Business Applications, Wiley, New York, 1982.
Heskett, J. L., Cube-per-order index‒a key to warehouse stock location. *Transportation and Distribution Management*, vol. 3, pp. 27-31, 1963.
Suzuki, S., EIQ graph represents the order picking character, *Proceedings of the 6th International Conference on Automation in Warehousing*, pp. 197–208, Stockholm, Sweden, 1985.
Le-Duc, T., De Koster, R.B.M., Travel distance estimation and storage zone optimization in a 2-block class-based storage strategy warehouse, *Int. J. Prod. Res*., vol. 43, no. 17, pp. 3561–3581, 2005.
Lu, L., Anderson-Cook, C. M. and Robinson, T. J., A case study to demonstrate a Pareto frontier for selecting a best response surface design while simultaneously optimizing multiple criteria, *Applied Stochastic Models in Business and Industry*, vol. 28, pp. 206-221, 2012.
Material handling Forum, Routing strategies, Available: https://www.erim.eur.nl/material-handling-forum/research-education/tools/calc-order-picking-time/what-to-do/routing-strategies/, June, 2018.
Mela, C. F. and Lehmann, D. R., Using fuzzy set theoretic techniques to identify preference rules from interactions in the linear model: an empirical study, *Fuzzy Sets and Systems*, vol. 71, pp. 165-181, 1995.
Muppani, V.R., and Adil, G.K., A branch and bound algorithm for class based storage location assignment, *Eur. J. Oper. Res*. 189 (2), 492-507, 2008.
Pan, J. C.-H., Shih, P.-H., Wu, M.-H., and Lin, J.-H., A storage assignment heuristic method based on genetic algorithm for a pick-and-pass warehousing system, *Comput. Ind. Eng*., vol. 81, pp. 1-13, 2015.
Roodbergen, K. J., Storage assignment for order picking in multiple-block warehouses, in *Warehousing in the Global Supply Chain: Advanced Models, Tools and Applications for Storage System*s, Manzini, R. (ed.), 2012, Springer-Verlag, London, 2012.
Tompkins, J. A., White, J. A., Bozer, Y. A., and Tanchoco, J. M. A., *Facilities planning*, John Wiley & Sons, 2010.
Wheeler, C., The 8 best order picking methods (including batch picking), Available: https://www.newcastlesys.com/blog/bid/348476/order-picking-methods-and-the-simplest-ways-to-minimize-walking-infographic, June, 2018.
Zadeh, L. A., Optimality and non-scalar-valued performance criteria, *IEEE Trans Automat Control*, AC-8, pp. 59–60, 1963.
Zhong, J., Hu, X., Gu, M., and Zhang, J., Comparison of performance between different selection strategies on simple genetic algorithms, *Proceedings of the 2005 International Conference on Computational Intelligence for Modelling, Control and Automation, and International Conference on Intelligent Agents, Web Technologies and Internet Commerce* (CIMCA-IAWTIC'05), 2005.

Biographies

Chi-Bin Cheng received his B.S. in industrial engineering from Chung Yuan Christian University, Taiwan, and Ph.D. in industrial and manufacturing systems engineering from Kansas State University, USA. He is a Professor of Information Management with Tamkang University, Taiwan. His main research interests are in the fields of soft computing, group decision-making, machine learning, and supply chain management. His work has appeared in Fuzzy Sets and Systems, European Journal of Operational Research, Computers and Mathematics with Applications, among others.

Yu-Chi Weng received both her B.S. and Master degree in information management from Tamkang University, Taiwan. She is currently in charge of the development of an ERP system for a manufacturer in Taiwan. Her research interests are in production processes and system development.