The Optimization of the Location of the Cargo in Three-Dimension Shelf: Employing the FP-Tree and the Artificial Fish Swarm Algorithms

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The allocation issues of the location of the cargo have affected the operational efficiency of retail e-commerce warehouses tremendously. Adjusting the cargo location with the change of the order and the operation of the warehouse is a significant research area. A novel approach employing the FP-Tree and the Artificial Fish Swarm Algorithms is proposed. Firstly, energy consumption and shelf stability are employed for the location-allocation. Secondly, the association rules among product items are obtained by the FP-Tree Algorithm to mine frequent list of items. Furthermore, the frequency and the weight of product items are taken into account to ensure the local stability of the shelf during data mining. Thirdly, another method of the location-allocation is obtained with the objectives of the energy consumption and the overall shelf stability along with the frequent items stored nearby that is conducted by the Artificial Fish Swarm Algorithm. Finally, the picking order distance is obtained through two methods of the location-allocation above. The performance and efficiency of the novel introduced method have been confirmed by running the experiment. The outcomes of the simulation suggest that the introduced method has a higher performance concerning criterion called the picking order distance.

1. Introduction

Based on the newly introduced retail model, buyers have much higher demands for the timely manner of the distribution of online shopping based on the widespread use of it. The directors at the e-commerce warehouse deal with finding the better economical means that try to minimize the costs that are composed of some components, which are called the energy consumption, the distance, and/or time. One of the subsystems of the logistics system, called the sorting, has a key functionality in picking the orders satisfying the expectations of accuracy and being in timely manner. It has been reported that the time of picking the order has accounted for nearly 50% on the average [1], which is the biggest ratio in the operation links of the warehousing composed of both loading and unloading and information crunching. Besides, the travel time accounts for nearly 50% of the order related to some processes such as starting, searching, traveling, and sorting, which is the most time-consuming function requiring the highest labor necessity. Customer satisfaction is one of the critical evaluation measures used in the retail e-commerce by warehouses where the accuracy and timeliness of the orders get the highest attention. Therefore, the optimization of cargo location-allocation taking into account the association rules has affected the management of the warehouse and operations tremendously.

The allocation issue of the cargo location has received higher attention concerning some criteria such as the turnover efficiency of the cargo, the shelf stability, the picking routes, and the storage strategy of the warehouse. Xie et al. [2] proposed an operative method called the Restricted Neighborhood Tabu Search algorithm to resolve the assignment problem of the storage location by using the
Grouping Constraints. Elisa and Cristiano Alexandre [3] studied a class-based storage process employing a cube-per-order index. Li and Ma [4] employed the traditional genetic algorithm combining with a virus coevolutionary genetic algorithm to resolve the problem regarding the cargo location. Yubo et al. [5] constructed an integrated optimization model to minimize the completion time of the command sequence taking into account the influence of assignment of the storage location and sorting the command sequence on the operation time comprehensively. Lei et al. [6] studied the packing of mixed cargo whose location assignment uses the integrated approach. Yang et al. [7] researched the location assignment and sequencing in multishuttle automated storage/retrieval systems under the modified 2nd-command cycle pattern employing the integrated optimization problem. Bortolini et al. [8] studied the so-called unit-load assignment problem for industrial warehouses located in the seismic fields employing a novel integer linear programming model. The optimization outcomes of the PSO, the GA, and the AFSA were compared for the space allocation of cargo problems by Zhang et al. [9]. The findings suggested that the optimization impact of the AFSA was more significant than were the PSO and the GA. This manuscript proposed a method that employs both the AFSA and association rules to optimize cargo location utilizing the distance of order picking as an assessment standard.

Besides, many types of research employing distinct algorithms in this discipline have been utilized to reduce logistics cost and to increase the efficacy of order picking. Homsi et al. [10] investigated the generic routing problem of ships and benchmark suite utilizing the segments of real shipping in maritime logistics, which proposed an exact branch-and-price algorithm and a hybrid metaheuristic to resolve the problem. Lei et al. [11] suggested a two-layer genetic algorithm to resolve an optimization model providing the shortest outbound time of all outbound orders in certain historical periods. Leng et al. [12] constructed a biobjective model, which helps achieve cost saving, energy saving, and emission reduction for the cold chain-based low-carbon location-routing problem that was a simple and efficient framework combining seven well-known multiobjective evolutionary algorithms. Haoxiang et al. [13] put forward an adaptive multiobjective genetic algorithm aiming at reaching the highest efficacy and shelf stability for the efficiency of warehousing. Shang et al. [14] proposed a memetic algorithm incorporating both genetic search and local intensification to attain an optimal/near-optimal solution for realistic sizes within a reasonable period. It was observed that the distribution network size of cargo delivery amplifies when the number of constraints and variables increases drastically. Karaenze et al. [15] employed the available maximizing cardinal utility framework to a retail logistics problem whose outcomes provide the randomized matching mechanisms with an effective tool to reduce waiting times at warehouses. Lam et al. [16] suggested an operation system of order picking to assist devising a plan of order picking and batch handling sequence. Matthews Visagie [17] dealt with the problem of minimizing pickers’ travel distance to pick all orders in this system, which employed a relaxation of this IP formulation to find a lower bound of an optimal solution.

A rule mining has been successfully implemented on several problems in business and engineering such as agriculture, medicine, and computer network. However, a relatively small amount of research on picking a route and the order distance based on data mining can be found in the literature. Zhou et al. [18] combined their well-known methods, which are called the genetic algorithm, the ant colony algorithm, and the cuckoo algorithm, to compute the minimization of the picking path in the form of a fishbone layout. Hossein et al. [19] employed the rule mining to compute the relations between orders concerning their due date. Hence, coming up with a solution procedure of the Traveling Salesman Problem integrated with genetic algorithm was employed to determine the travel path. Chen et al. [20] described the development of an order batching approach based on data mining and integer programming.

Several researchers primarily studied the assignment of the cargo location using the turnover efficiency of the cargo, the shelf stability, and the strategy of the warehouse storage to minimize the total distance. The manuscript has suggested implementing the data mining method to the space issue of the warehouse. Hence, the contributions of it can be articulated as follows:

(1) A new approach employing both the FP-Tree Algorithm and the Artificial Fish Swarm Algorithm was proposed whose objective is to find the best location of cargo in a shelf represented in three dimensions.

(2) Association rule between product items was obtained by the FP-Tree Algorithm to minimize the picking order distance. Specifically, the weight difference of items was taken into account to ensure the local stability of the shelf during data mining.

Then, the manuscript is organized as follows. Section 2 explains the problem. Section 3 deals with the fundamentals of the constructed mathematical model by providing some notations and definitions. The proposed algorithm is explained in Section 4. Section 5 provides the outputs of numerical experiments and analysis. Section 6 gives a conclusion and mentions the future work.

2. The Description of the Problem

Suppose that a retail e-commerce warehouse using a shelf represented in a space composed of three dimensions is depicted in Figure 1. While one dimension called X denotes the depth of the shelf, the other dimension called Y describes the width of it. The last dimension called Z represents the height of it. Some issues can be observed in the allocation of the cargo locations, which are as follows: (1) in the pre-optimization stage, items with the higher frequencies of warehousing are stored in the location near to the input/output (I/O) point. When these stored items are sold out, new items should be sequentially placed to such vacant cargo locations. (2) Concerning the long-term operation of the
warehouse, the shelves will be “heavier on the top, lighter on the bottom” due to the salability of various items changing based on the seasons, and thus the quantity of the product items on the shelf varies widely. It is essential to reassign product items stored on the shelf to the cargo locations in time. (3) The warehouse adopts random storage, which does not take the factor of the association rule into account. (4) The problems of the wrong picking, the missing picking, and the delayed delivery could occur frequently in the process of picking the order, which results in a low timeliness rate and accuracy.

Hence, a multiobjective model to improve shelf stability and to minimize both energy consumption and the distance of frequent items due to warehouse operation is constructed, which aims at choosing an optimal method for allocation of cargo location to minimize the distance of order picking when the local stability of the shelf is satisfied.

3. The Steps of Modeling

3.1. The Assumptions of the Model. To simplify the model, the following assumptions are assumed:

(1) Only one cargo location exists and each item is stored in one cargo location.
(2) Full boxes are used to store items.
(3) The front row is the inbound and outbound points. The zero (0) floor and column of the shelf are located at the bottom left corner in the warehouse zone.
(4) Each cargo location is the same.
(5) The volume of each product item cannot outnumber the storage capacity.
(6) One transaction order corresponds to the product items bought during the visit to the one store.
(7) All order data are acknowledged earlier.
(8) All items are placed into the system.

3.2. The Definitions of the Symbols. The variables of the model are as follows:

The notations of \( h, d, \) and \( w \) are called the height of and the depth of and the width of the cargo, respectively.

\( w_i \): the weight related to the \( i \)th \( (i = 1, 2, \ldots, n) \)
\( p_i \): the frequency related to the \( i \)th during a certain time
\( x \): the \( x \)th row of the shelf \( (x = 1, 2, \ldots, a) \)
\( y \): the \( y \)th column of the shelf \( (y = 1, 2, \ldots, b) \)
\( z \): the \( z \)th layer of the shelf \( (z = 1, 2, \ldots, c) \)
\( \mu \): the friction coefficient
\( g \): the acceleration due to gravity
\( e_{xyz} \): the energy consumption per unit mass from the origin of the item to the location \( (x, y, z) \)
\( N \): the number of frequent itemsets
\( I \): the number of product items in each frequent itemset
\( L \): the distance of center lines of the adjacent shelf passages

3.3. Modeling

3.3.1. The Consumption Model for Energy. The optimization of the cargo location is a readjustment process of the cargo location to lower the energy consumption and the labor cost for items and the warehouse, respectively. The model for energy consumption expands the general formulation of the cargo location-allocation issues by adding \( x \) parity constraint. The following mathematical model is defined:

\[
\min f_1(x, y, z) = \sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} p_i \cdot w_i \cdot e_{xyz}, \quad i = 1, 2, \ldots, n.
\]

The consumption of the energy used for a unit mass of an item from the location to the input/output point is as follows:

\[
e_{xyz} = \mu g \cdot (D_x) + \mu g \cdot w \cdot \left( y - \frac{1}{2} \right) + g \cdot \left( z - \frac{1}{2} \right) \cdot h,
\]

\[
D_x = \begin{cases} 
\frac{x \cdot L}{2}, & \text{if } x \text{ is odd}, \\
\frac{(x - 1) \cdot L}{2}, & \text{if } x \text{ is even}.
\end{cases}
\]

3.3.2. The Stability Model. By optimizing the cargo location, it is essential to ensure the stability of the shelves by storing...
items with a large span of the weight reasonably. In other words, the distance from the center of the gravity point of the shelves to the ground in the z-direction should be minimized. Generally, the heavier items should be stored in the lower location, while the lighter items should be stored in a higher location. The mathematical model is defined by

\[ \min f_z(x, y, z) = \frac{\sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} w_i \cdot (z - (1/2)) \cdot h}{\sum_{x=1}^{a} \sum_{y=1}^{b} \sum_{z=1}^{c} w_i} \]  

(3)

3.3.3. The Frequent Items Model. The optimization of the cargo location means that items are reasonably distributed to the corresponding cargo locations. By doing so, it improves the efficiency of the cargo delivery by reducing the picking distance of the test order.

The strategy of the association storage becomes an essential way to improve the operational efficiency of warehousing and customer satisfaction. The relationships between product items from customer orders can be extracted by employing the association rule mining. The product items with higher support have higher relations. Hence, with higher support they are potentially required to be stored nearby, decreasing the distance and reducing the error probability of the picking process. Higher efficacy can be achieved by employing storing frequent items nearby.

\[ \min f_3(x, y, z) = \sum_{i=1}^{I} d_{i+1} \]  

(4)

Besides, it needs to be ensured that weight difference of frequent items is less than the minimum weight of the two items:

\[ |w_i - w_{i+1}| \leq \min|w_i, w_{i+1}|, \quad i, i+1 \in I. \]  

(5)

3.4. The Target Function Transformation. To deal with all at the same time, this manuscript constructs an evaluation function by using the ideal point method that allows the different targets to be employed. The transformation of the target functions is defined by

\[ \min f(x, y, z) = \left\{ \sum_{i=1}^{3} \alpha_i \left[ \frac{f_i(x, y, z) - f_i^*(x, y, z)}{f_i^*(x, y, z)} \right]^2 \right\}^{1/2} \]  

(6)

where, \[ \sum_{i=1}^{3} \alpha_i = 1, \quad x = 1, 2, \ldots, a, \quad y = 1, 2, \ldots, b, \]  
\[ z = 1, 2, \ldots, c, \]  
when \( x \) is an odd number \( D_x = x \cdot (L/2) \), otherwise, when \( D_x = (x - 1) \cdot (L/2) \).

Besides, \[ |w_i - w_{i+1}| \leq \min|w_i, w_{i+1}| \} (i, i+1 \in I). \]

4. Algorithms

4.1. The FP-Tree Algorithm. In 2000, the proposed FP-Tree Algorithm was called a classic association mining method that was an effective tool to mine the frequent list of items employing an extended prefix-tree structure that helps store the important information about patterns observed frequently titled the frequent-pattern tree (FP-Tree) [21]. When compared with others, namely, the a priori Algorithm and the Tree Projection, the FP-Tree outnumbers them when the high volume of data is a concern [22]. The reason is that the FP-Tree Algorithm only scans the dataset twice no matter what size the dataset would be. This algorithm obtains frequent patterns without generating a lot of candidate sets. It resolves the problem using the a priori algorithm that will generate a higher number of candidate sets. Many types of research available in the literature employing the FP-Tree method extract association rules between items. Lu and Guo [23] suggested an improved association rule algorithm utilizing the FP-Tree to improve the efficacy of the user’s behavior pattern dealing with the extraction of rules in a big-data environment. Syakur et al. [24] examined customer relationships utilizing purchased products. Thus, it presented a discussion for the comparison of time complexity between the FP-Tree Algorithms and a priori algorithms. Yanling and Hongxia [25] employed the FP-Tree Algorithm to attain products that have a high demand utilizing a large number of transaction records. Feng et al. [26] put forward a method in acquiring algorithms by improving the temporally correlated rules of the FP-Tree that are utilized in tracking customers’ behavior. Hence, the FP-Tree Algorithm is adopted to identify the connections between product items herein for the optimization of the cargo location.

Employing the divide-and-conquer mechanism is the key step of the implementation of the FP-Tree composed of three stages. The first stage is the construction of an FP tree using two gradients that are called the entries and the F-Table. The second stage performs the mining recursively on the FP-Tree and generates a frequent list of items. The third stage filters the frequent list of items meeting a given condition. Searching and constructing trees determine the frequent keywords recursively.

The fundamentals of the FP-Tree are as follows:

The input is the database of transaction and the minimum support

The output is the frequent pattern set

How to run the FP-Tree method is summarized as follows:

Step 1: to construct the FP-Tree composed of the following: (1) define the FP-Tree consisting of a root node, the item prefix son tree of the item, and its header table; (2) each node of the item prefix son tree consists of its name, its node count, and its node chain where the node count refers to the nodes numbers and node chain points to the next node with the same item name in the tree; (3) every entry of the item head table includes its name, node chain, and the header pointing to the first node in the tree

Step 2: to mine the FP-Tree that gets the 1-length frequent pattern, to generate its conditional pattern base (a subdatabase), and then to establish its conditional FP-Tree and recursively mine the tree; employing the suffix mode and the frequent pattern from the
conditional FP-Tree, a connection could be achieved for pattern growth.
Step 3: to judge the condition and to discover the frequent 2-itemset satisfying the conditions of the local stability.

4.2. The Artificial Fish Swarm Algorithm. Artificial Fish Swarm Algorithm (AFSA) is an effective method to resolve optimization problems employed for facility location-allocation, traveling salesman problem, and sorting of activities [27–29]. Besides, Wang et al. [28] concluded that the AFSA has a strong global search ability and fast convergence rate and attains a better solution whose performance can be summarized as follows: (1) the fast convergence speed and its applicability to practical problems, (2) quickly attainable outcomes though not having higher precision, and (3) ease of construction of the model. Therefore, the AFSA emerging as a practical method to resolve the assignment of cargo location is proposed. Utilizing Zhang et al. [9], the steps of Artificial Fish Swarm Algorithms are presented as follows:

Step 1: to set \( \text{popsizestepvisual} \), \( \text{numbermax} \), \( \text{gendeta, fishnum} \).
Step 2: to initialize Fish Swarm utilizing \( (x_{11}, x_{12}, \ldots, x_{i0}) \).
Step 3: to calculate the fitness value for each initial Fish Swarm called \( \text{obj.value} (i) \).
Step 4: to record the optimal initial Artificial Fish information.
Step 5: to use preying, swarming, following, and random behavior.
Step 6: to update the Artificial Fish optimal fitness, \( \text{value_gbest} \).
Step 7: to update global optimal Artificial Fish called \( \text{value_zbest} \).
Step 8: to determine whether the termination condition for the condition is met. Then, stop. Otherwise, return to the fifth step.

5. The Simulation

5.1. Data Processing

5.1.1. Data Acquisition and Setting Parameter. In this subsection, we expect to obtain the features of the items of the data including the weights, the amount of goods, and the original locations of each type of goods in the warehouse. Moreover, the warehouse attributes are necessary including the dimensions, the layout, and the distance between the adjacent shelf passages. Lastly, the AFSA is set as follows:

The initial information of the items in the warehouse is shown in Table 1, which mainly includes the initial coordinates of the cargo locations, the quantity of the items, and the frequencies of the items. Besides, the height of each position \( h \) is 1.6 m, the width \( w \) is 1 m, and the depth \( d \) is 1.2 m. The numbers of rows \( a \), columns \( b \), and layers \( c \) on the shelves are 6. The distance between the adjacent shelves \( L \) is 3.7 m. The friction coefficient \( \mu \) is 0.5. The acceleration due to gravity \( g \) is 10.

The parameters called the population size \( N \), \( \text{Maxgen} \), \( \text{Try_number} \), \( \text{Visual} \), and \( \text{Deta} \) are assigned to 60, 500, 100, and 0.8, respectively. When association rule is a concern, \( (\alpha_1, \alpha_2) \) is assigned to \( (0.5, 0.5) \) in the simulation experiment. When it is not, \( (\alpha_1, \alpha_2, \alpha_3) \) is assigned to \( (0.35, 0.35, 0.3) \) in the simulation experiment. Moreover, 10 independent experiments are conducted for each case and the average value of each is computed as the final value to eliminate the effect of randomness.

5.1.2. Determining the Frequent List of Items. Two concepts can be stated for the convenience as follows: many orders are randomly selected from the data of the order of a certain month of the warehouse using the “rand” function to take the samples for data mining, which are called sample orders. Additionally, many orders are randomly selected from the order data of the warehouse in the next month to test the picking distance of ways of cargo location-allocation, which are called test orders.

An illustrative example shown in a python program presents an order database including 60 orders of 50 different items. To obtain the frequencies of items and frequent list of items of the 50 items, we conducted several experiments of data mining for 60 sample orders. Firstly, the information including the data of 60 sample orders and the weight of 50 items are imported into the FP-Tree Algorithm program. Secondly, the “FOR” loop statement is used to accumulate the number of items in the sample order. Hence, the number of items is obtained as the corresponding frequencies of items in and out of the storage. The threshold value \( \text{min_inum_suppport} \) is set to 4. Provided that \( I_1 \Rightarrow I_2 \) support value is higher than the \( \text{min_inum_suppport} \), it implies that product items \( I_1 \) and \( I_2 \) are simultaneously included in order frequently. The FP-Tree Algorithm is implemented to obtain frequent 1-itemset, 2-itemset, and larger itemset, whose counts are greater than or equal to 4. Then, screening out the frequent 2-itemset makes preparations for the association rules simulation of the experiments. Finally, the experiment also set the threshold of the weight difference of frequent items \( \min |m_i - m_j| \leq \min \{m_i, m_j\} \) to ensure the local stability of the shelf. To sum up, the FP-Tree Algorithm obtains the number of times of 50 items out of storage and the frequent 2-itemset of the support degree greater than or equal to 4. In the simulation experiment taking into account the association rules, it is potentially required to take the counts as the frequency of 50 items and take the frequent 2-itemset stored nearby as the third target. By using the FP-Tree Algorithm, the final frequent list of items and corresponding supports are obtained as follows:

\[ \{[2, 8], [4], [9, 17], [5], [15, 10], [7], [123, 31, 4], [26, 5, 4], [37, 35, 4], [42, 16, 16] \} \] (i.e., \( \{[2, 8], [4] \}) \) refers to the number of times that items no. 2 and no. 8 are simultaneously included in the same order is 4. Additionally, the number of times of 50 items acquired by the FP-Tree algorithm is taken as the
frequency of the corresponding items, and it is denoted in Table 1).

### 5.2. Adjusting the Algorithm Parameters

It is a fact that the parameter values have a great impact on the performance of the algorithm, which is a principal challenge for the algorithm affected by the design details. Hence, adjusting parameters for AFSA needs to be done. Two performance measures for parameters are employed, which are called the total objective optimized value and the algorithm convergence rate in general. The total target value refers to the weighted optimal value of objective 1 and objective 2 in the comparative experiment. The parameters of the AFSA are called Fish Swarm size $N$, maximum heuristic times $trynumber$, visual field range $visual$, crowding factor $den$, maximum iteration times $maxgen$, and step size $step$. However, the parameter step size can be ignored since it is

| The number of items | The frequency of items $P_i$ | The weight of items (kg) $W_i$ | The original coordinates of items |
|---------------------|-----------------------------|-----------------------------|---------------------------------|
| 1                   | 1                           | 2.8                         | (3,6,4)                         |
| 2                   | 8                           | 8.6                         | (5,6,6)                         |
| 3                   | 6                           | 4.91                        | (1,5,1)                         |
| 4                   | 2                           | 3.52                        | (1,6,1)                         |
| 5                   | 5                           | 2.81                        | (2,6,1)                         |
| 6                   | 5                           | 3.16                        | (6,2,1)                         |
| 7                   | 1                           | 4.25                        | (1,5,2)                         |
| 8                   | 5                           | 5.13                        | (3,5,2)                         |
| 9                   | 10                          | 1.3                         | (3,1,4)                         |
| 10                  | 8                           | 2.16                        | (2,4,1)                         |
| 11                  | 1                           | 2.5                         | (2,4,2)                         |
| 12                  | 4                           | 5                           | (1,3,5)                         |
| 13                  | 8                           | 2.48                        | (5,6,1)                         |
| 14                  | 3                           | 8.65                        | (1,2,2)                         |
| 15                  | 9                           | 1.62                        | (3,4,4)                         |
| 16                  | 9                           | 3.45                        | (6,6,2)                         |
| 17                  | 9                           | 2.45                        | (1,1,5)                         |
| 18                  | 5                           | 2.31                        | (4,1,6)                         |
| 19                  | 1                           | 1.98                        | (3,1,6)                         |
| 20                  | 4                           | 2.23                        | (2,3,1)                         |
| 21                  | 6                           | 5.06                        | (5,2,2)                         |
| 22                  | 9                           | 2.96                        | (4,1,1)                         |
| 23                  | 8                           | 4.48                        | (4,3,2)                         |
| 24                  | 2                           | 1.12                        | (3,3,3)                         |
| 25                  | 6                           | 6.54                        | (3,5,2)                         |
| 26                  | 6                           | 3.79                        | (1,6,5)                         |
| 27                  | 5                           | 5.04                        | (4,3,6)                         |
| 28                  | 3                           | 4.7                         | (5,5,4)                         |
| 29                  | 4                           | 12.57                       | (5,3,5)                         |
| 30                  | 2                           | 3.1                         | (1,6,6)                         |
| 31                  | 5                           | 6.97                        | (5,6,5)                         |
| 32                  | 3                           | 2.5                         | (4,6,3)                         |
| 33                  | 2                           | 10.41                       | (1,2,6)                         |
| 34                  | 4                           | 8.12                        | (6,1,3)                         |
| 35                  | 6                           | 6.28                        | (2,4,4)                         |
| 36                  | 4                           | 6.31                        | (4,3,3)                         |
| 37                  | 9                           | 8.85                        | (4,4,2)                         |
| 38                  | 4                           | 4.27                        | (4,5,4)                         |
| 39                  | 5                           | 4.62                        | (5,5,4)                         |
| 40                  | 4                           | 8.19                        | (4,6,3)                         |
| 41                  | 2                           | 3.51                        | (6,6,5)                         |
| 42                  | 11                          | 4.74                        | (1,2,4)                         |
| 43                  | 4                           | 5.77                        | (6,6,1)                         |
| 44                  | 3                           | 8.13                        | (1,3,2)                         |
| 45                  | 5                           | 7.83                        | (4,4,6)                         |
| 46                  | 1                           | 4.38                        | (3,5,5)                         |
| 47                  | 4                           | 8.92                        | (6,1,2)                         |
| 48                  | 2                           | 3.51                        | (1,2,5)                         |
| 49                  | 5                           | 9.16                        | (5,6,5)                         |
| 50                  | 1                           | 10.53                       | (5,4,2)                         |
mainly employed in the continuous problems. In the manuscript, the problem called the cargo position optimization is a discrete type of problem. Besides, employing the parameter max gen is not necessary since it is related to the convergence of the algorithm. Figures 2–5 present the impacts of the four parameters on the total objective optimized value and the convergence speed of the algorithm.

The Fish Swarm size \( N \) is adjusted to attain the most appropriate value. Then, the other parameters are equated to those values that are \( \text{trynumber} = 110, \ \text{visual} = 120, \ \text{delta} = 0.8, \) and max gen = 500. When \( N \) increases, how the total target value and iteration speed are altered can be observed. Figure 2 shows that the total target value and the iteration speed have a downward trend when the Fish Swarm size \( N \) increases. When the scale of Artificial Fish Swarm \( N \) is assigned to 90, both the total target value and the convergence rate can reach a better state.

The maximum heuristic times denoted by \( \text{trynumber} \) are adjusted to attain the most appropriate value. Then, the other parameters are assigned to \( N = 90, \ \text{visual} = 120, \ \text{delta} = 0.8, \) and max gen = 500, respectively. Figure 3 shows that \( \text{trynumber} = 110 \) is the most reasonable when the curve of total target value and convergence rate is a concern.

Similarly, Figures 4 and 5 show that setting \( \text{visual} = 120 \) and \( \text{delta} = 0.8 \) in the AFSA can lead to having a better solution.

5.3. The Contrast Experiment. In this subsection, the simulation experiment first obtains a new allocation way for the optimization targets of energy consumption and the overall shelf stability. Afterward, the present optimization targets extend the general targets by adding the association rules mining, which obtains another allocation way. The performances of these two approaches of the cargo location-allocation are primarily compared based on the travel distance of test orders. Lastly, a statistical test was employed to verify the outcomes of the analysis and the validity of the model and the method in this manuscript.

The fitness function of AFSA is constructed by the distance between the optimal value and the actual point. The optimal values of the Target 1 and Target 2 are calculated by using AFSA and the results are 80527 and 1.1095, respectively.

Comparing two methods provides some useful insights. Firstly, optimal results are attained not utilizing the association rules in the experiment after adjusting the parameters. On the other hand, the parameters of the experiment employing association rules are consistent with those of the first experiment. Secondly, the average value of 20 runs of the experiment was selected as the final optimization value of the two methods.

5.3.1. Experiment without Taking into Account the Association Rules. When just taking into account both Target 1 and Target 2 in the above model, the results of the experimentation are obtained by AFSA shown in both Figures 6(a) and 6(b). When compared with Figure 1, seen in Figure 6(a) and Figure 6(b), the I/O point greatly reducing the energy consumption of the items in and out of the storage. Meanwhile, they are placed in the location at the bottom of the shelf meaning that the overall stability of the shelf is significantly improved. Additionally, according to the iteration curve of AFSA presented in Figure 6(b), the algorithm can converge stably within 500 iterations.

The final results show that the value of Target 1 is optimized from the initial value 202258.5205 to an optimized value 91807.0375, which decreased by 54.6091%. The value of Target 2 is optimized from 4.7211 to 1.5894, which decreased by 66.3341%. The new method of cargo location-allocation is obtained shown in Table 2. The 50 items are stored in the corresponding cargo locations in the new allocation way. The result of the experiments suggests that the distance of the test order is 840 by the allocation way of the optimized cargo location and the distance of the test order is 900 by the
allocation way of the initial cargo location decreased by 6.667%.

5.3.2. Experiments Taking into Account the Association Rules. Based on the above experiments, the optimization targets extend the above targets by adding frequent items stored nearby in this experiment. When taking into account both Target 1 and Target 2 and the frequent items stored nearby in Target 3, the results of the experiments also are obtained by AFSA shown in Figures 7(a) and 7(b), respectively. When compared with Figure 1, seen in Figure 7(a) are most of the items allocated in the cargo locations near to the I/O point greatly reducing the energy consumption of items in and out of the storage. Meanwhile, they are placed in the location at the bottom of the shelf meaning that the overall stability of the shelf is significantly improved. Additionally, according to the iteration curve of AFSA in Figure 7(b), the algorithm can converge stably within 500 iterations.

The final results show that the value of Target 1 is optimized from the initial value 202258.5205 to optimized value 90787.6995 decreased by 55.1130%. The value of Target 2 is optimized from 4.7211 to 1.5870 decreased by 66.3855%. The new way of the cargo location-allocation is obtained as shown in Table 2. The 50 items are stored in the corresponding cargo locations in the new allocation way. The results of the experiments suggest that the distance of the test order is 615 by the allocation way of the optimized cargo location and the distance of the test order is 900 by the allocation way of initial cargo location decreased by 31.6667%.

5.3.3. The Comparisons of the Two Experiments. $O(n^2)$ is the complexity of comparing the algorithms of the experiments. The time complexity in the programming language
Figure 6: (a) The optimized cargo position stereogram. (b) Algorithm comparison iteration diagram.

Table 2: Data of items.

| The number of items | Without considering association rules | Considering association rules |
|---------------------|---------------------------------------|-------------------------------|
| 1                   | (4,6,1)                               | (3,6,1)                       |
| 2                   | (2,3,1)                               | (2,4,1)                       |
| 3                   | (1,3,2)                               | (2,3,2)                       |
| 4                   | (4,4,1)                               | (3,4,1)                       |
| 5                   | (1,3,3)                               | (2,2,3)                       |
| 6                   | (2,2,3)                               | (2,3,3)                       |
| 7                   | (3,5,1)                               | (4,5,1)                       |
| 8                   | (1,4,2)                               | (2,4,2)                       |
| 9                   | (2,1,2)                               | (2,1,2)                       |
| 10                  | (2,1,3)                               | (2,2,2)                       |
| 11                  | (4,1,2)                               | (3,1,2)                       |
| 12                  | (2,6,2)                               | (2,6,2)                       |
| 13                  | (1,2,2)                               | (1,1,3)                       |
| 14                  | (4,3,1)                               | (3,3,1)                       |
| 15                  | (1,1,3)                               | (1,2,2)                       |
| 16                  | (1,1,1)                               | (1,2,1)                       |
| 17                  | (1,1,2)                               | (1,1,2)                       |
| 18                  | (1,2,3)                               | (1,2,3)                       |
| 19                  | (2,6,3)                               | (4,1,2)                       |
| 20                  | (2,3,3)                               | (1,4,3)                       |
| 21                  | (2,2,2)                               | (2,5,1)                       |
| 22                  | (2,2,1)                               | (2,1,1)                       |
| 23                  | (1,3,1)                               | (1,3,1)                       |
| 24                  | (2,1,4)                               | (1,1,4)                       |
| 25                  | (2,4,1)                               | (1,4,1)                       |
| 26                  | (2,3,2)                               | (2,1,3)                       |
| 27                  | (2,4,2)                               | (1,4,2)                       |
| 28                  | (4,2,1)                               | (4,2,1)                       |
| 29                  | (1,6,1)                               | (3,1,1)                       |
| 30                  | (2,5,3)                               | (1,5,3)                       |
| 31                  | (1,5,1)                               | (1,3,2)                       |
| 32                  | (2,4,3)                               | (2,4,3)                       |
is represented by $m \times n$, which is composed of $n = 90$ being the number of Artificial Fish Swarm and $m = 500$ being the maximum number of iterations used by the algorithm. Hence, $m = 5n$ was used. The FP-Tree Algorithm was employed to extract association rules, which would increase the time complexity $O(p)$ in this research. On the other hand, $p = 60$ was used as the number of sample orders. Thus, the time complexity of the method suggested in this manuscript becomes $O(n^2) + O(n)$. Since $p$ and $n$ belong to the same order of magnitude, the method proposed herein has witnessed a small increment in time complexity based on the comparison algorithm. Besides, the running time of the comparing experiment was 186.2675s. On the other hand, the experiment adopting the FP-Tree Algorithm and AFSA was 657.3835s, whose difference was 471.116s that was higher than the former. As a result, when compared with the AFSA, the proposed method can attain an approximate optimal effect regarding the distance of order picking within a certain computation time. Hence, it adds less time complexity. Therefore, the optimized effects of energy consumption and shelf stability are close to the outcome of the AFSA.

The outputs of the simulation experiments compared are shown in Table 3. We report that the experiment taking into

| The number of items | Without considering association rules | Considering association rules |
|---------------------|--------------------------------------|------------------------------|
| 33                  | (3,4,1)                              | (4,4,1)                      |
| 34                  | (3,1,1)                              | (4,1,1)                      |
| 35                  | (1,4,1)                              | (2,3,1)                      |
| 36                  | (1,6,2)                              | (2,5,2)                      |
| 37                  | (1,2,1)                              | (2,2,1)                      |
| 38                  | (1,4,3)                              | (1,3,3)                      |
| 39                  | (2,5,2)                              | (1,5,2)                      |
| 40                  | (3,2,1)                              | (3,2,1)                      |
| 41                  | (1,6,3)                              | (2,5,3)                      |
| 42                  | (2,1,1)                              | (1,1,1)                      |
| 43                  | (1,5,2)                              | (1,6,2)                      |
| 44                  | (3,3,1)                              | (4,3,1)                      |
| 45                  | (2,6,1)                              | (1,6,1)                      |
| 46                  | (3,6,1)                              | (4,6,1)                      |
| 47                  | (4,1,1)                              | (2,6,1)                      |
| 48                  | (1,5,3)                              | (2,6,3)                      |
| 49                  | (2,5,1)                              | (1,5,1)                      |
| 50                  | (4,5,1)                              | (3,5,1)                      |
account the association rules can achieve less travel distance for the test order than not taking into account the association rules where energy consumption does not increase and shelf stability does not decrease. The value of Target 1 in the simulation experiment not taking into account the association rules is optimized by 54.6091% when compared with the initial value, while the value of Target 1 in the simulation experiment taking into account the association rules is optimized by 55.1130% when compared with the initial value. On the other hand, the value of Target 2 in the simulation experiment not taking into account the association rules is optimized by 66.3341% when compared with the initial value, while the value of Target 2 in the simulation experiment taking into account the association rules is optimized by 66.3855%. Therefore, the optimization outcomes of both goal 1 and goal 2 in the two experiments are the same. The travel distance of the test order obtained by the first simulation experiment is optimized by 6.6667% when compared with the initial value. The travel distance of the test order obtained by the second simulation experiment is optimized by 31.6667%, which is improved by 25% when compared with the former. The results of simulation experiments taking into account the association rules are better than the results of simulation experiments not taking into account the association rules for the picking distance of the test order when the energy consumption of the items in and out of the storage and the shelf stability reach the same optimization value, which can be explained as follows.

5.4. Verification of the Conclusions

5.4.1. The Experiments for the Different Number of the Items

The usability of the proposed association rules mining is demonstrated for the optimization of the cargo location. Hence, we conduct experiments employing 30, 70, 90, 130, and 170 items apart from 50 items, respectively. Tables 4–7 report the results of our proposed experiment taking into account the association rules and not taking into account the association rules, respectively. The values of both Target 1 and Target 2 and initial and optimal values of the test order distance are obtained for the different number of the items as shown in Table 4.

The optimized values of the single target corresponding to the different number of the items can be attained with the experiment either utilizing the association rules and or not utilizing the ones shown in Table 5 according to the steps of the simulation experiment above.

Then, several simulation experiments were conducted to assess the performance of the FP-Tree. The target values presented in both Tables 4 and 5 were employed to compute the optimized percentages of Target 1, Target 2, and test order picking distance in the simulation experiment utilizing or not utilizing the association rules, respectively, denoted in Table 6.

Finally, the optimized percentages of Target 1 and Target 2 and test order distance in the simulation experiment not utilizing the association rules in Table 6 are chosen as the benchmarks. The outcomes denote that the benchmarks are subtracted from the optimized percentages of Target 1 and Target 2 and test order distance in the simulation experiment utilizing the association rules denoted in Table 7.

Finally, the comparison results are presented in curves. The results of the experiments by taking into account the association rules lead to a considerable improvement compared to not taking into account the association rules. According to the comparison curves of Target 1 shown in Figure 8, when compared with the curves of the initial and the optimal values, the curves of the optimized values of simulation experiment not taking into account the association rules and taking into account the association rules coincide. According to the comparison curves of Target 2 in Figure 9, when compared with the curves of the initial and the optimal values of Target 2, the curves of the optimized values of the simulation experiment not taking into account the association rules and taking into account the association rules coincide. Additionally, Figure 10 shows the picking distance comparison curves of the test orders over the different numbers of the items. It represents that both picking distances of text orders in the simulation experiment not taking into account the association rules and taking into account the association rules are lower than the initial picking distance. However, the optimization degree of the picking distance in the experiment taking into account the association rules is better than the optimization range of the picking distance in the experiment not taking into account the association rules. Generally, when compared with the simulation experiment not taking into account the association rules, the total distance can be decreased significantly by the experiment employing the association rules not taking into account increasing the energy consumption and decreasing the shelf stability.

5.4.2. Running Statistical Test

To judge whether the conclusion provided above is reliable or not, the statistical test, called the paired sample mean test, is conducted to
determine whether there is a significant difference between the optimization effects of the association rules and experiments not utilizing association rules. The optimization effects of experiments deal with the energy consumption, the shelf stability, and the distance of the order picking. Hence, the objective is to decide whether the optimization effects of energy consumption, the shelf stability, and the distance of the order picking behave the same as the ones whose optimized effect is in the experiments not utilizing association rules. The optimized percentage of each target employs 30, 50, 70, 90, 130, and 170 products, respectively, and conditions of the two experiments are presented in Table 6.

(1) The optimized outcomes of the energy consumption are tested after two experiments are conducted.

The null hypothesis and alternative hypothesis are represented as follows:

### Table 3: Data of the items.

| Target functions | Initial value | Not taking into account the association rules | Not taking into account the association rules (%) | Taking into account the association rules | Taking into account the association rules (%) |
|------------------|---------------|-----------------------------------------------|-----------------------------------------------|-------------------------------------------|-----------------------------------------------|
| Target 1         | 202258.5205   | 91807.0375                                    | 54.6091                                       | 90787.6995                                | 55.1130                                       |
| Target 2         | 4.7211        | 1.5894                                        | 66.3341                                       | 1.587                                     | 66.3855                                       |
| Picking distance | 900           | 840                                           | 6.6667                                        | 615                                       | 31.6667                                       |

### Table 4: The initial and the optimal values of each single target.

| Number of items | Target 1 Initial value | Target 2 Initial value | Picking distance | Target 1 Single target optimal value | Target 2 Single target optimal value |
|-----------------|------------------------|------------------------|------------------|--------------------------------------|--------------------------------------|
| 30              | 110542.2357            | 3.7606                 | 885              | 39872                                | 0.8                                 |
| 50              | 202258.5205            | 4.7211                 | 900              | 80527                                | 1.1095                              |
| 70              | 273865.2278            | 5.0688                 | 1330             | 125190                               | 1.2611                              |
| 90              | 434942.3138            | 5.1419                 | 2130             | 243120                               | 1.5762                              |
| 130             | 571449.73             | 4.7087                 | 2520             | 307960                               | 2.1645                              |
| 170             | 744384.8193            | 4.724                  | 3028             | 446680                               | 2.7609                              |

### Table 5: The optimization values for each single target.

| Number of items | Target 1 Without taking into account the association rules | Target 2 Without taking into account the association rules | Picking distance Without taking into account the association rules | Target 1 Taking into account the association rules | Target 2 Taking into account the association rules | Picking distance Taking into account the association rules |
|-----------------|----------------------------------------------------------|----------------------------------------------------------|------------------------------------------------|-----------------------------------------------|-----------------------------------------------|----------------------------------------------------------|
| 30              | 51229.2478                                               | 0.83231                                                  | 399                                          | 51398.2718                                   | 0.83231                                     | 312                                                       |
| 50              | 91807.0375                                               | 1.5894                                                   | 840                                          | 90787.6995                                   | 1.587                                       | 615                                                       |
| 70              | 143181.8787                                              | 1.5527                                                   | 910                                          | 143736.6967                                  | 1.6078                                      | 647                                                       |
| 90              | 277383.6008                                              | 1.9022                                                   | 1890                                         | 284470.6593                                  | 1.8598                                      | 1410                                                      |
| 130             | 343235.2265                                              | 2.1906                                                   | 2347                                         | 365492.8285                                  | 2.2367                                      | 1851                                                      |
| 170             | 471758.8858                                              | 2.917                                                    | 2806                                         | 480056.4822                                  | 3.0596                                      | 2648                                                      |

### Table 6: The optimization percentage for each target.

| Number of items | Target 1 (%) Without taking into account the association rules | Target 2 (%) Without taking into account the association rules | Picking distance (%) Without taking into account the association rules | Target 1 (%) Taking into account the association rules | Target 2 (%) Taking into account the association rules | Picking distance (%) Taking into account the association rules |
|-----------------|----------------------------------------------------------------|-------------------------------------------------------------|------------------------------------------------|-----------------------------------------------|-----------------------------------------------|-------------------------------------------------------------|
| 30              | 53.66                                                          | 77.87                                                       | 54.92                                         | 53.50                                         | 77.87                                         | 64.75                                                       |
| 50              | 54.61                                                          | 66.33                                                       | 6.67                                          | 55.11                                         | 66.39                                         | 31.67                                                       |
| 70              | 47.72                                                          | 69.37                                                       | 31.58                                         | 47.52                                         | 68.28                                         | 51.35                                                       |
| 90              | 36.23                                                          | 63.01                                                       | 11.27                                         | 34.60                                         | 63.83                                         | 33.80                                                       |
| 130             | 39.94                                                          | 53.48                                                       | 6.87                                          | 36.04                                         | 52.50                                         | 26.55                                                       |
| 170             | 36.62                                                          | 38.25                                                       | 7.33                                          | 35.51                                         | 35.23                                         | 12.55                                                       |

### Table 7: The difference between the two optimized values.

| Number of items | Target 1 (%) Without taking into account the association rules | Target 2 (%) Without taking into account the association rules | Picking distance (%) Without taking into account the association rules | Target 1 (%) Taking into account the association rules | Target 2 (%) Taking into account the association rules | Picking distance (%) Taking into account the association rules |
|-----------------|----------------------------------------------------------------|-------------------------------------------------------------|------------------------------------------------|-----------------------------------------------|-----------------------------------------------|-------------------------------------------------------------|
| 30              | -0.16                                                          | 0.00                                                        | 9.83                                          | -0.16                                         | 0.00                                          | 9.83                                                        |
| 50              | 0.50                                                           | 0.06                                                        | 25.00                                         | 0.50                                          | 0.06                                          | 25.00                                                       |
| 70              | -0.20                                                          | -1.09                                                       | 19.77                                         | -0.20                                         | -1.09                                         | 19.77                                                       |
| 90              | -1.64                                                          | 0.82                                                        | 22.53                                         | -1.64                                         | 0.82                                          | 22.53                                                       |
| 130             | -3.90                                                          | -0.98                                                       | 19.68                                         | -3.90                                         | -0.98                                         | 19.68                                                       |
| 170             | -1.11                                                          | -3.02                                                       | 5.22                                          | -1.11                                         | -3.02                                         | 5.22                                                        |
\( \bar{d} = 0, \quad H_0: \bar{d} = 0, \quad H_1: \bar{d} \neq 0. \)  

(7) 

\( S_d \) represents the standard deviation of the difference variable employing the data presented in Table 7, which is defined and computed by

\[
S_d = \sqrt{\frac{\sum d^2 - (\sum d)^2}{n - 1}} = 1.5738. 
\]

(8) 

The \( T \) statistic is defined and computed by

\[
T = \frac{\bar{d}}{S_d/\sqrt{n}} = -1.6887. 
\]

(9) 

The following result is attained by looking up the \( t \) table at the significance level of \( \alpha = 0.05 \) with \( n - 1 \) degree of freedom:

\[
t_{\alpha/2} (n - 1) = t_{0.025} (5) = 2.5706
\]

(10) 

The comparison \( |T| < t_{\alpha/2} \) showing the acceptance of the null hypothesis implies that there is no significant difference in the optimization effect of energy consumption between the experiments utilizing the association rules and not utilizing the association rules, respectively.

(2) The optimized results of shelf stability after running a statistical test using the data in Table 7 are denoted by

\[
S_d = \sqrt{\frac{\sum d^2 - (\sum d)^2}{n - 1}} = 1.341,
\]

\[
T = \frac{\bar{d}}{S_d/\sqrt{n}} = -1.2816,
\]

\[
t_{\alpha/2} (n - 1) = t_{0.025} (5) = 2.5706.
\]

(11) 

The comparison \( |T| < t_{\alpha/2} \) showing the acceptance of the null hypothesis implies that there is no significant difference in the optimization effect of shelf stability between the experiments utilizing the association rules and not utilizing the association rules, respectively.

(3) Similarly, the optimized results of shelf stability after running statistical test employing the data in Table 7 are denoted by

\[
S_d = \sqrt{\frac{\sum d^2 - (\sum d)^2}{n - 1}} = 7.741,
\]

\[
T = \frac{\bar{d}}{S_d/\sqrt{n}} = 5.3808,
\]

\[
t_{\alpha/2} (n - 1) = t_{0.025} (5) = 2.5706.
\]

(12) 

The comparison \( |T| > t_{\alpha/2} \) showing the rejection of the null hypothesis implies that there is a significant difference in the optimization effect of the distance of order picking between the experiments utilizing the association rules and not utilizing the association rules, respectively.
It can be said that the optimization results of the distance of order picking are better in the experiments utilizing association rule. The optimization outcomes of the energy consumption and shelf stability are the same as the former when compared with the experiments not utilizing association rules.

6. Conclusion

In this manuscript, an approach based on the proposed FP-Tree Algorithm and AFSA can obtain a much better allocation way of cargo location to significantly reduce the picking order distance. The FP-Tree Algorithm, called a data mining technique, is employed to determine the relation rules implying demand structure extracted directly from the customer data. Besides, the frequent list of items generated by the FP-Tree Algorithm not only corresponds to some requirements of minimum support but also provides the local stability of the shelf. The results suggest that taking into account the association rules significantly decreases the total travel distance without increasing energy consumption and decreasing the shelf stability. The efficacy of the proposed method is confirmed by the experiment employing different quantities of items extracted from an e-commerce warehouse. Therefore, employing the FP-Tree Algorithm and AFSA looks more effective in finding the solution to the issue of cargo location-allocation than does the AFSA. The proposed method is a novel approach to deal with this kind of problem. Furthermore, it can be easily applied to retail e-commerce and has a larger potential value for the applications of the logistics industry.

The proposed method has some limitations: only the binomial frequent list of items is attained to conduct the research when extracting association rules. The problem of cargo location-allocation could become more complicated if the larger frequent list of items stored nearby is also considered. Therefore, the suggested method is more suitable for small retail enterprises having less number of product categories. Besides, test orders are drawn from a known dataset. However, unpredictability is a widely encountered situation when dealing with actual orders, which has a great effect on the distance of order picking. It would be more practical to combine the optimization of order position with the actual strategy of order picking. Future work will focus on dealing with these issues.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

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