

## Research Article

# Optimizing the Cargo Location Assignment of Retail E-Commerce Based on an Artificial Fish Swarm Algorithm

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An efficient storage strategy for retail e-commerce warehousing is important for minimizing the order retrieval time to improve the warehouse-output efficiency. In this paper, we consider a model and algorithm to solve the cargo location problem in a retail e-commerce warehouse. The problem is abstracted into storing cargo on three-dimensional shelves, and the mathematical model is built considering three objectives: efficiency, stability, and classification. An artificial swarm algorithm is designed to solve the proposed models. Computational experiments performed on a warehouse show that the proposed approach is effective at solving the cargo location assignment problem and is significant for the operation and organization of a retail e-commerce warehouse.

## 1. Introduction

Under the new retail model, customers have higher and higher requirements on the timeliness of online shopping distribution with the rapid popularization of online shopping. E-commerce warehouse managers are interested in finding the most economical way which minimizes the costs involved in terms of energy consumption, distance traveled, and time spent. As one of the important subsystems of the logistics system, the sorting system plays an important role in picking orders accurately and timely.

Electronic retail pursues a demand-driven organization with high product variety, small order sizes, and reliable short response times. An order lists the items and quantities requested by a customer from a distribution centre or a warehouse. The amount of daily orders reaches 20,000 to 30,000. Customer satisfaction is one of the key performance indicators of the retail e-commerce warehousing centre, and it mainly depends on the accuracy and timeliness of orders. It is reported that the picking order time accounts for about 50% of the order response time on average [1], which accounts for the largest proportion in the operation links such as warehousing, loading and unloading, and information processing. In addition, the travel time accounts for about

50% of the order picking time in the process of starting, searching, travel, sorting, and other picking, which is the most time-consuming work with the largest labor consumption. As a consequence, minimizing the order retrieval time plays a critical role in improving the warehouse-output efficiency for any logistics system. There are four methods to reduce travel times or distances by means of more efficient control mechanisms in warehouses [2]: (1) determining a product item order for picking routes, (2) zoning the warehouse, (3) assigning orders to batches, and (4) assigning products to the correct cargo location. Cargo location optimization refers to the reasonable type and quantity of items stored in the corresponding cargo location, which minimizes the costs involved in terms of distance traveled and/or time spend.

One of the most important concerns of warehouse managers is finding the most cost- and time-efficient way to pick orders placed by customers, which would allow the company to be seen to be a reliable company that satisfies its customers [3]. Cargo location assignment requires assigning a position for each cargo. An appropriate position for each cargo is important and influences the operational efficiency of warehouses [4]. Therefore, Cargo location assignment plays a critical role in improving customer satisfaction and

minimizing warehouse operational costs. Storage assignment is an important decision problem in warehouse operation management. It involves the placement of a set of items in a warehouse in such a way that some performance measure is optimal. The main purpose of using a storage location assignment system is to establish the parameters for ease of identification and location of items in warehouses.

## 2. Literature Review

The optimization problem of cargo location assignment has received a significant amount of attention. Many scholars studies on cargo location assignment primarily from the viewpoints of cargo turnover efficiency, shelf stability, and warehouse storage strategy to minimize the total order picking distance. Jiao et al. considered the working performance and security requirements of an automatic warehouse. A simple weighted genetic algorithm was used to solve the weighted and normalized multiobjective models [5]. Zhang et al. studied the metrological centres of cargo locations with many constraint rules in warehouses and proposed a simulated annealing algorithm to reassign cargo locations based on a prepartitioning strategy [6]. Li et al. proposed to separately use the traditional genetic algorithm and a virus coevolutionary genetic algorithm to solve the cargo location optimization problem [7]. Tang et al. put forward a storage strategy to optimize the cargo location using multilane shelves according to the material characteristics of a large amount of warehousing, multiple varieties, and large volume differences for typical shipping enterprises [8]. Xie et al. proposed a novel bilevel grouping optimization model for solving the storage location assignment problem with grouping constraint. Sophisticated fitness evaluation and search operators were designed for both upper and lower level optimization [9]. Yang et al. discussed the Container Stacking Position Determination Problem, specifically focusing on the storage space allocation problem in container terminals [10]. Xie et al. developed an efficient Restricted Neighbourhood Tabu Search algorithm to solve the storage location assignment problem with grouping constraints [11]. Flamand et al. investigated retail assortment planning along with store-wide shelf space allocation in a manner that maximizes the overall store profit [12].

Many authors have studied some optimization problems, including picking routes, location assignment, and picking order distance to minimize operational cost. Battini et al. presented the storage assignment and travel distance estimation joint method, a new approach useful to design and evaluate a manual picker-to-parts picking system, focusing on goods allocation and distances estimation [13]. Guo et al. suggest that using head-up displays like Google Glass to support parts picking for distribution results in fewer errors than current processes [14]. Adasme et al. proposed four compact polynomial formulations based on classical and set covering p-median formulations and proposed Kruskal-based heuristics and metaheuristics based on guided local search [15]. Zhou et al. calculated the sum of the expected picking distance in the main channel and the expected picking distance of the subchannel, and a

mathematical model for return-shape picking paths of the V-type layout was established [16]. Duan et al. constructed a Stackelberg model in which one retailer sells a national brand (NB) and its store brands (SB) and maximized the category profit by allocating shelf space and determining the prices for the SB and NB products [17]. Luan et al. presented a Location-Routing Problem model to assist decision makers in emergency logistics. The model attempted to consider the relationship between the location of warehouses and the delivery routes to maximize the rescue efficiency [18]. Tian et al. presented new energy-efficient models of its sustainable location with carbon constraints. An artificial fish swarm algorithm (AFSA) was proposed to solve the proposed models [19]. Bortolini et al. faced the so-called unit-load assignment problem for industrial warehouses located in seismic areas presenting an innovative integer linear programming model [20]. Tian et al. studied the optimal location of a transportation facility and automotive service enterprise issue and presented a novel stochastic multi-objective optimization to address it [21].

Some of these studies also considered the inbound and outbound warehouse times, the stability of shelves, and the classification of cargo, as we do in this paper. However, when establishing the target model, these studies did not consider the actual layout of shelves. Our work in this paper is distinct in that we consider the influence of parity on the driving distance of a forklift. In this study, to solve the assignment problem using a genetic algorithm and an AFSA, the ideal point method is proposed for transforming multiple objectives into a single objective. Computational experiments show that the optimization effect of the AFSA is superior to that of the classical genetic algorithm. To sum up, the paper makes the following main contributions:

- (1) The paper takes multirow fixed shelves as the research object. According to the actual layout of warehouse shelves, the influence of  $X$  parity on the in-out storage efficiency in  $x$ -axis direction is considered on the basis of the existing optimization research model of cargo location.
- (2) The paper uses the modified ideal point method to construct the evaluation function and apply the AFSA to the optimal cargo location of the retail e-commerce.

The remainder of the paper is organized as follows. Section 3 describes the problem. Section 4 describes the assumptions and constructs the mathematical model. The solving algorithm is proposed in Section 5. Section 6 reports the numerical experiments and analysis of results. Section 7 presents the conclusions and future work.

## 3. Problem Description

Generally, retail e-commerce warehouses are mainly composed of a temporary storage area and a shelf area. The warehouse plan is shown in Figure 1. The warehouse consists of multiple aisles, each of which is relatively independent with separate shelves, and the inbound and outbound (I/O) points are unique. The process of goods entering the

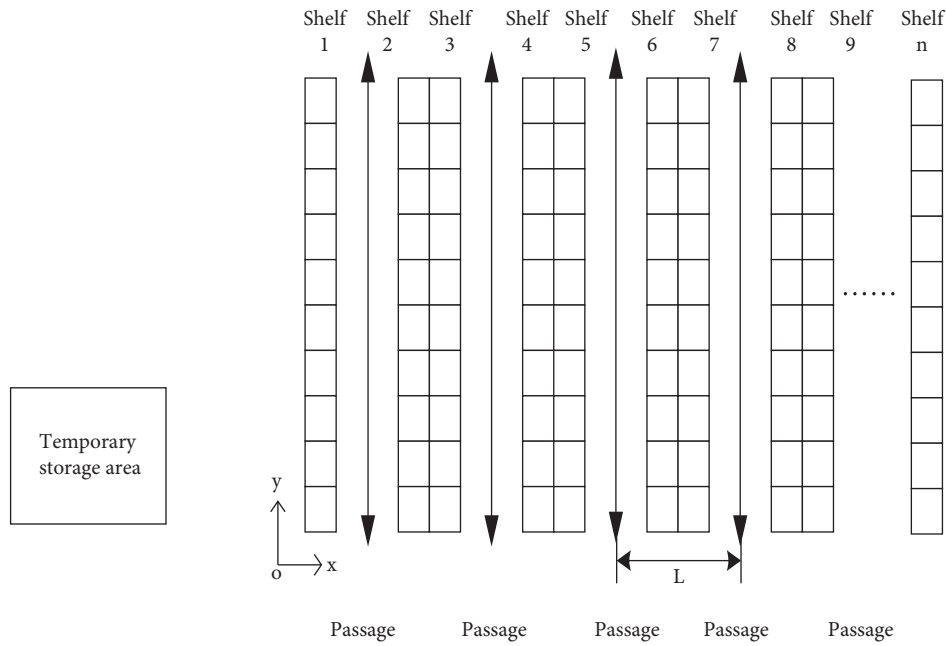


FIGURE 1: Warehouse plan.

warehouse includes carrying the goods to be stored from the storage area to the I/O points, followed by a forklift carrying the goods from the I/O points of the shelves to the cargo space. The shelf stereogram is shown in Figure 2.

At present, the storage strategy in the supermarket warehouse is random storage, which means that warehouse personnel use forklifts to randomly assign goods to the nearest idle shelves in the process of warehousing goods and putting them on shelves.

The warehousing of retail e-commerce enterprises is a special category of warehousing. Compared with traditional enterprise warehousing, retail e-commerce warehousing has the characteristics of using personnel as service objects and includes more kinds, shapes, and qualities of goods. At present, the following problems exist in the storage of goods and the allocation of cargo locations. First, due to the variety of goods in the supermarket warehouse and the random storage mode, goods are stored in a disorderly manner. It is easy for goods from different categories to be mislabelled and goods in adjacent positions to shift. Second, customers' demands for goods and their demand times are random, which require the supermarket warehouse to respond to orders quickly and efficiently. However, random storage makes the distribution of relevant goods scattered, and it takes more time to find similar goods when they are not in the warehouse, which leads to a low operational efficiency of the supermarket. Third, the appearances and weights of all kinds of goods that are stored in the supermarket warehouse are quite different. If the warehoused goods are randomly stored in idle positions, there may be low shelf stability and hidden safety risks.

In view of the abovementioned problems in the warehouse, this paper proposes the following optimization strategies for the assignment of storage space:

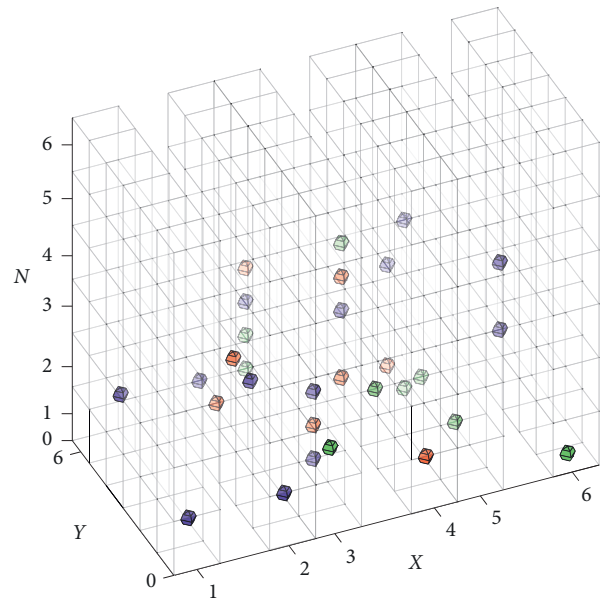


FIGURE 2: Shelf stereogram.

- (1) Three types of cargo location assignment strategies are used, including dedicated storage, randomized storage, and class-based storage [22]. A dedicated storage policy prescribes a particular location for the storage of each product, and no other item can be stored at that location, even if the space is empty. Random storage is used because of the necessity of optimizing the storage area, and materials are placed in existing idle positions. Randomized and dedicated storages are extreme cases of class-based storage policies; that is, randomized storage considers a

single class, and dedicated storage considers one class for each item. In addition, there is an increase in the costs of using space when the space is poorly used in dedicated storage, while when using random storage, much effort is placed on the order picking system. Class-based storage combines the features of the other two systems and can be a good alternative for making a warehouse more efficient in terms of the space that is used, the order picking operation, and the warehouse costs.

- (2) Higher frequency goods should be stored closer to the I/O points. The optimization goal of the warehouse is to reduce the total time of inbound and outbound goods over a certain period to the shortest time by optimizing the cargo location assignment. The most important performance measures in a warehouse are generally related to the time or effort required for cargo to enter and leave the warehouse, i.e., the storage and retrieval of items from the temporary storage area and their delivery to the point where they will be picked up by the appropriate forklift. After determining the storage of high-frequency outbound goods, the remaining cargo locations are arranged to store other goods. The total forklift travel time and the positions of higher frequency goods are strongly correlated, which has a strong impact on the warehouse operating efficiency. The closer a frequent item is to the I/O point, the lower is its total forklift travel time [23].
- (3) Generally, heavy cargo should be kept on the ground or at a lower position on the shelves to maximize shelf stability and improve security, and light cargo should be placed at higher positions on shelves, which can reduce the height of the whole shelving unit [4].
- (4) A previous study presented a detailed analysis of the calculation of the similarity coefficient and used the Rogers–Tanimoto similarity coefficient to measure the correlation between two goods [24]. Similar goods are more likely to occur in the same order; therefore, similar goods should be placed in a concentrated manner, which can significantly minimize the total order picking distance and time.

## 4. Assumptions and Modelling

**4.1. Assumptions.** The following reasonable assumptions are put forward to simplify the model:

- (1) A good only has one cargo location, and each cargo location can only store one product
- (2) The cargo box for each cargo inventory is a rectangular parallelepiped
- (3) Goods are stored on shelves in full boxes, and goods on one shelf are regarded as a whole
- (4) The volume of each good during each inbound and outbound delivery is less than the maximum storage capacity of the cargo location

- (5) The specifications of each cargo location are the same
- (6) The inbound and outbound points for cargo delivery are on the front row and 0th floor and column of the shelf
- (7) The horizontal speed and the vertical speed of the forklift and the all-electric transporters are uniform
- (8) The lift/landing times of the inbound and outbound equipment of the warehouse are negligible
- (9) All items are assigned to the system

**4.2. Definitions of Symbols.** The variables in the model are defined as follows:

$h, d,$  and  $w$ : the height of the cargo location, the depth of the cargo location, and the width of the cargo location, respectively

$W_i$ : the weight of one cargo location for the stock of cargo  $i$  ( $i = 1, 2, \dots, n$ )

$P_i$ : the number of inbound batches of cargo  $i$  during a certain period of time in a record

$x$ : the  $x$ th row of the shelf ( $x = 1, 2, \dots, a$ )

$y$ : the  $y$ th column of the shelf ( $y = 1, 2, \dots, b$ )

$z$ : the  $z$ th layer of the shelf ( $z = 1, 2, \dots, c$ )

$a, b,$  and  $c$ : the total number of shelves row, the total number of shelves column, and the total number of shelves layer, respectively

$V_x$ : average speed of an all-electric transporter

$V_y$ : average horizontal speed of a forklift

$V_z$ : average vertical speed of a forklift

$D_o$ : the distance between the temporary storage area and the inbound and outbound points of a shelf

$(r_i, s_i, t_i)$ : the central position coordinates of the goods in class  $i$

$t_{xyz}$ : the inbound time of goods at coordinates  $(x, y, z)$  ( $x_i, y_i, z_i$ ) and the position coordinates of the goods in class  $i$

## 4.3. Modelling

**4.3.1. Efficiency Model.** In this paper, the first objective is to improve the inbound and outbound efficiencies of the warehouse by minimizing the total forklift travel time. This objective can be optimized by placing higher frequency goods nearer to the entrance of the warehouse. The total forklift travel distance needs to be analysed and calculated, including the distance from the temporary storage area to the assigned location, which is described as follows. When the distance traveled by the forklift to place all goods into storage is calculated, the first row and the second row have the same distance in the  $x$ -axis direction, the third row and fourth row have the same distance in the  $x$ -axis direction, and so on. Therefore, the driving distance of the forklift is as follows:

$$f_1(x, y, z) = \min \sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c P_i \cdot t_{xyz},$$

$$t_{xyz} = (y - 0.5) \cdot \frac{w}{V_y} + \frac{(z - 1) \cdot h}{V_z} + \frac{D_x}{V_x} + \frac{D_o}{V_x},$$

$$D_x = \begin{cases} x \cdot \frac{L}{2}, & x \text{ is an odd number,} \\ (x - 1) \cdot \frac{L}{2}, & x \text{ is an even number,} \end{cases} \quad (1)$$

where  $L$  is the distance between the centre lines of the adjacent shelf passages.

**4.3.2. Stability Model.** Cargo locations are assigned to minimize the centre of gravity, which is the basic goal of warehouse operations. Only under the premise of ensuring shelf stability is the realization of the other optimization objectives meaningful. To meet the requirement for shelf stability, this paper focuses on the vertical direction. We only consider the  $z$ -axis direction in the centre of the shelf. The sum of the coordinates of all goods in the  $z$  direction can be used to determine whether the shelf is sufficiently stable. This evaluation function is calculated as

$$f_2(x, y, z) = \min \frac{\sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c W_i \cdot z \cdot h}{\sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c W_i}. \quad (2)$$

**4.3.3. Classification Model.** When cargo locations are allocated, the relevance of the goods needs to be considered, and strongly similar cargoes should be assigned to the same shelf area. Therefore, an objective function is built as follows. At first, we should calculate the distance between each good and the central coordinates of similar goods. Then, we need to calculate the distance between each good and the central coordinates of similar goods and compute the sum of these distances. This distance is calculated as

$$f_3(x, y, z) = \min \sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c \sqrt{(x_i - r_i)^2 + (y_i - s_i)^2 + (z_i - t_i)^2}. \quad (3)$$

In summary, the multiobjective mathematical model of cargo location optimization is as follows:

$$\begin{cases} f_1(x, y, z) = \min \sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c P_i \cdot t_{xyz}, \\ t_{xyz} = (y - 0.5) \cdot \frac{w}{V_y} + \frac{(z - 1) \cdot h}{V_z} + \frac{D_x}{V_x} + \frac{D_o}{V_x}, \\ f_2(x, y, z) = \min \frac{\sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c M_i \cdot z \cdot h}{\sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c M_i}, \\ f_3(x, y, z) = \min \sum_{x=1}^a \sum_{y=1}^b \sum_{z=1}^c \sqrt{(x_i - r_i)^2 + (y_i - s_i)^2 + (z_i - t_i)^2}, \end{cases} \quad (4)$$

where  $x = 1, 2, \dots, a$ ,  $y = 1, 2, \dots, b$ , and  $z = 1, 2, \dots, c$ , when  $x$  is an odd number  $D_x = x \cdot (L/2)$ , otherwise, when  $D_x = (x - 1) \cdot (L/2)$ .

**4.3.4. Transformation of the Target Function.** In practical applications, we show that minimizing the total forklift travel distance, maximizing shelf stability and minimizing the distance between similar cargoes are conflicting criteria. Therefore, taking into account these three objectives, a balance should be set to adjust the cargo location assignment. To evaluate these three criteria simultaneously, this paper proposes using the ideal point method to construct an evaluation function. This method allows for different objectives to be evaluated and assigns different weights to them in the final calculation. First, the algorithms are used to find the optimal solution (i.e., the ideal point) of each target. Then, the distance between the actual point and the ideal point of each objective function is calculated. Finally, the difference between the actual point and the ideal point of each objective function is weighted accordingly. The objective functions can be transformed as follows:

$$F_i(x, y, z) = \left[ \frac{f_i(x, y, z) - f_i^*(x, y, z)}{f_i^*(x, y, z)} \right], \quad (5)$$

$$f(x, y, z) = \min \left\{ \sum_{i=1}^3 \alpha_i \cdot \left[ \frac{f_i(x, y, z) - f_i^*(x, y, z)}{f_i^*(x, y, z)} \right]^2 \right\}^{1/2}, \quad (6)$$

where  $x = 1, 2, \dots, a$ ,  $y = 1, 2, \dots, b$ , and  $z = 1, 2, \dots, c$ , when  $x$  is an odd number  $D_x = x \cdot (L/2)$ , otherwise, when  $D_x = (x - 1) \cdot (L/2)$ .

## 5. Algorithms

Artificial fish swarm algorithm (AFSA) [19], which was presented by Li in 2002, is a new swarm intelligence optimization method by simulating fish swarm behavior. It is an effective method to solve optimization problems, e.g., facility location allocation [19], traveling salesman problem [25], and sorting activities [26]. Besides, reference [25] concludes that AFSA has strong global search ability and fast convergence rate and obtains a better solution. Specific performance in the following aspects: (1) it possesses fast convergence speed and is able to be used to solve the practical problems. (2) As for the accessions that do not need so high precision, it can be used to get an acceptable result quickly. (3) No need of question's strict mechanism pattern and no need of the accurate description to questions, this will extend the application range. Thus, we propose to adopt AFSA to solve the problem of cargo location assignment.

**5.1. Principle of the AFSA.** Assuming an  $N$ dimensional space, the fish population is  $X_i = (x_{i1}, x_{i2}, \dots, x_{in})$ . Every artificial fish's present state can be expressed as  $X_i(x_{i1}, x_{i2}, \dots, x_{in})$ , where  $i = 1, 2, \dots, N$  and  $(x_{i1}, x_{i2}, \dots, x_{in})$  represent the optimized states of the artificial fish. The food concentration in the present location of

the artificial fish can be expressed as  $Y = f(x)$ . The variable visual refers to the range of vision of the artificial fish, and step represents the maximum step length of the artificial fish.  $|X_j - X_i|$  is the distance between artificial fish  $X_i$  and  $X_j$ ,  $\delta$  is the crowding factor, and try\_number is the maximum number of trials of artificial fish in which fish prey every time.

**5.1.1. Preying Behaviour.** There is an assumption that the present state of artificial fish is  $X_i$ . Then, the artificial fish randomly selects a state  $X_j$  within its visual range, which means that  $|X_j - X_i| \leq \text{visual}$ . If  $f(x_i) < f(x_j)$ , then the artificial fish selects  $X_j$  as the current state. If not, the artificial fish selects a new state again and compares it to the current state. After attempting try\_number repeatedly, if the state cannot satisfy the advancement condition, then artificial fish  $X_i$  performs a random behaviour. This process is expressed as a mathematical formula as follows:

$$X_{\text{nest}} = X_i + \text{rand} * \text{step} * \frac{X_j - X_i}{\|X_j - X_i\|} \quad (7)$$

**5.1.2. Swarming Behaviour.** The current position of an artificial fish is  $X_i$ , and the distance between the artificial fish and another artificial fish at any position in its visual field is  $|X_j - X_i|$ . The variable nf is the number of partners within the visual range of the artificial fish, and  $X_c$  is the centre position of a swarm of strong fish. If  $(Y_c/n_f) > \delta Y_i$ , the food concentration at  $X_c$  is high and less crowded, and then, the fish swims toward the centre. If not, artificial fish  $X_i$  conducts preying. The introduction of a crowding factor can largely avoid the artificial fish being trapped in the local minima due to the high density of fish at a certain location. The following behavior is a mathematic description:

$$X_{\text{nest}} = X_i + \text{rand} * \text{step} * \frac{X_c - X_i}{\|X_c - X_i\|} \quad (8)$$

**5.1.3. Following Behaviour.** Following behaviour is similar to swarming behaviour. Using  $X_i$  as the current state of an artificial fish, the fish will search for the optimum companion  $X_{\text{max}}$  within its perceptual area. If  $(Y_{\text{max}}/n_f) > \delta Y_i$ , there is much food and the artificial fish are not crowded; otherwise, the artificial fish have to prey. The step moving follows the following rule:

$$X_{\text{nest}} = X_i + \text{rand} * \text{step} * \frac{X_{\text{max}} - X_i}{\|X_{\text{max}} - X_i\|} \quad (9)$$

**5.2. Chromosome Coding Design.** When an AFSA is used to solve the cargo location assignment problem, its coding can be expressed via two methods: an expression based on the cargo location and an expression based on the goods. The chromosome coding based on the cargo location coding method is as follows.

Each artificial fish refers to a way of allocating goods to be stored. A number of nonrepeating values (i.e., the number of stored goods) are randomly selected from a number of values (i.e., the number of cargo locations) as artificial fish. The position of each component of the artificial fish represents the number of goods, and the value of each component of the artificial fish represents the number of locations. The one-dimensional vector is then converted into a three-dimensional vector of  $x$ ,  $y$ , and  $z$ .

Assuming there are 5 goods to be put into storage, the possible chromosomes are, for example,  $\{5 \ 4 \ 2 \ 1 \ 3\}$ . The artificial fish indicates that good no. 1 is stored in the fifth location. Good no. 2 is stored in the fourth location, good no. 3 is stored in the second location, and so on. In addition, the artificial fish also indicate that good no. 1 is stored in the (1, 1, 5) section, good no. 2 is stored in the (1, 1, 4) section, and so on.

**5.3. Procedure of the AFSA.** The procedure of the AFSA is as shown in Figure 3.

Step1: initializing the AFSA parameters  $N$ , step, visual, try\_number, max gen, and  $\delta$ .

Step 2: setting bulletin board to record the current status of each artificial fish and select the optimal value record.

Step 3: updating the state of every artificial fish. The states of artificial fish are dynamically updated as follows. Supposing that the current state of an artificial fish is  $X_i$ . First, the artificial fish tries to follow. If that fails, the artificial fish swarms. If swarming fails, the artificial fish preys. Finally, if preying fails, the artificial fish enacts a random behaviour, and  $\text{max gen} = \text{max gen} - 1$ .

Step4: evaluating the fitness value of each artificial fish using formula (6). The steps are repeated until the termination condition is met.

## 6. Numerical Experiments

**6.1. Data Preparation.** In this chapter, first, we should obtain data about product characteristics, which include the type (i.e., how many different goods there are), the goods weight and frequency, and the goods number and the original coordinates for each good in the warehouse. Moreover, the warehouse characteristics are required, which include its dimensions (i.e., length and width), layout, forklift speed, and distance (i.e., the distance between the temporary storage area and the inbound and outbound points and the distance between the centre lines of the adjacent shelf passage). Finally, the parameters of the AFSA are set.

To make the simulation experiment more convenient, three categories of goods (A, B, and C) are used, including 30 goods (nos. 1–30), which are selected from the supermarket for the MATLAB simulation experiment. Class A contains the 13 cargo numbers of 2, 4, 7, 9, 10, 12, 14, 21, 22, 23, 24, 28, and 29, and the central coordinates of its position are (1, 3, 3). Class B contains the 9 cargo numbers of 3, 6, 8, 11, 18, 19,

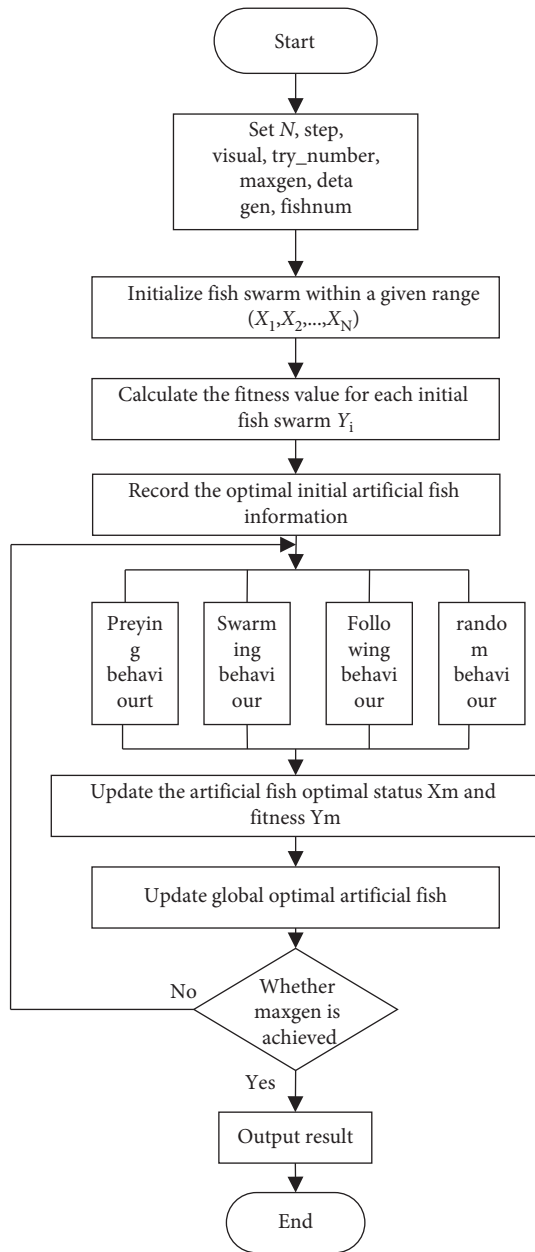


FIGURE 3: Flow chart of artificial fish swarm algorithm.

20, 25, and 27, and the central coordinates of its position are (3, 3, 4). Class C contains the 8 cargo numbers of 1, 5, 13, 15, 16, 17, 26, and 30, and the central coordinates of its cargo position are (6, 4, 3). The related cargo data for the certain T-mall supermarket in August 2019 are shown in Table 1.

In addition, to facilitate the calculation, each position's height ( $h$ ) is 1.6 m, the width ( $w$ ) is 1 m, and the depth ( $d$ ) is 1.2 m. The number of rows ( $a$ ), columns ( $b$ ), and layers ( $c$ ) on the shelves is 6. The speed of the electric truck ( $V_x$ ), the horizontal speed of the forklift ( $V_y$ ), and the vertical speed of the forklift ( $V_z$ ) are all 1.4 m/s. The distance between the temporary storage area and the inbound and outbound points of the shelf ( $D_O$ ) is 7 m, and the distance between the centre line of the adjacent shelf passage ( $L$ ) is 3.7 m.

The parameters of the AFSA are set as follows. The population size, max gen, try\_number, visual,  $\delta$ , and  $(\alpha_1, \alpha_2, \alpha_3)$  are set to 60, 140, 100, 100, 0.8, and (0.35, 0.35, 0.3), respectively.

6.2. Contrast Experiment. MATLAB, 2015version, launched by MathWorks Inc., is used, and the test is conducted on a Windows 32-bit operating system. In this section, we evaluate the proposed AFSA approach and compare it with the classical genetic algorithm (GA) and particle swarm optimization (PSO) from previous work [4, 27]. According to the evaluation function based on the ideal point method, the paper makes the following arrangement. First, the single target is simulated by three algorithms to find the optimal value of the single target. Then, the optimal value of a single objective is substituted into the evaluation function, and three single objectives are integrated into multiple objectives. Besides, the multiobjective simulation experiment is carried out by three algorithms, and the optimization results of the three algorithms are compared. Finally, a scale simulation experiment is conducted to verify the universality of the model and the proposed AFSA algorithm.

6.2.1. Simulation and Comparison Experiment for the Inbound Efficiency. To evaluate the first objective, we conducted 20 times simulations using the GA, PSO, and AFSA. After the three algorithms are each iterated 200 times, the optimized result diagrams that are obtained are shown in Figures 4 and 5. The optimized results obtained based on the three algorithms reveal the following:

- (1) The results of the PSO, GA, and AFSA show that the program can converge after a limited number of iterations and obtain optimized results.
- (2) In terms of the number of iterations, AFSA uses little iteration than the other algorithms. The PSO and GA converge in 167 and 178 iterations, respectively, while the AFSA only needs 109 iterations to converge.
- (3) Figure 4 illustrates that the optimized result of AFSA is superior to that of the PSO and GA in terms of the forklift operating time. The functional values using the PSO and GA are reduced from the initial value 983.2857 to 787.3571 and 672.5714, which reduce 19.9259% and 31.5996%, respectively. When using the AFSA, the functional value decreases to 617.6429, which is 37.1858% lower than the initial value.
- (4) Comparing the optimized position in Figure 5 from the AFSA with the position in Figure 1 before optimization, it can be seen that most goods allocated to positions are near the I/O points.

The results indicate that the three algorithms can improve the warehouse-input efficiency to some extent, but some goods are placed on higher levels and similar goods are scattered.

TABLE 1: Goods data.

Number	Frequency of good $P_i$	Weight $W_i$ (kg)	Original coordinates of the cargo position
1	2	2.80	(5, 6, 1)
2	8	8.60	(3, 2, 4)
3	1	4.91	(3, 6, 3)
4	1	3.52	(2, 3, 4)
5	2	2.81	(3, 6, 5)
6	1	3.16	(4, 6, 5)
7	2	4.25	(6, 5, 2)
8	2	5.13	(5, 2, 2)
9	3	1.30	(1, 5, 3)
10	1	2.16	(4, 6, 3)
11	2	2.50	(6, 1, 1)
12	1	5	(2, 6, 2)
13	4	2.48	(4, 1, 2)
14	2	8.65	(2, 1, 2)
15	1	1.62	(3, 2, 3)
16	3	1.45	(4, 6, 1)
17	6	2.45	(2, 5, 2)
18	2	2.31	(3, 6, 2)
19	2	1.98	(5, 4, 2)
20	1	2.23	(4, 4, 2)
21	2	5.06	(3, 2, 2)
22	1	2.96	(5, 6, 4)
23	2	2.48	(6, 5, 4)
24	2	1.12	(5, 5, 6)
25	4	6.54	(3, 1, 3)
26	3	3.79	(4, 6, 4)
27	3	5.04	(5, 5, 1)
28	3	4.70	(1, 1, 2)
29	2	12.57	(3, 6, 4)
30	5	3.10	(2, 4, 4)

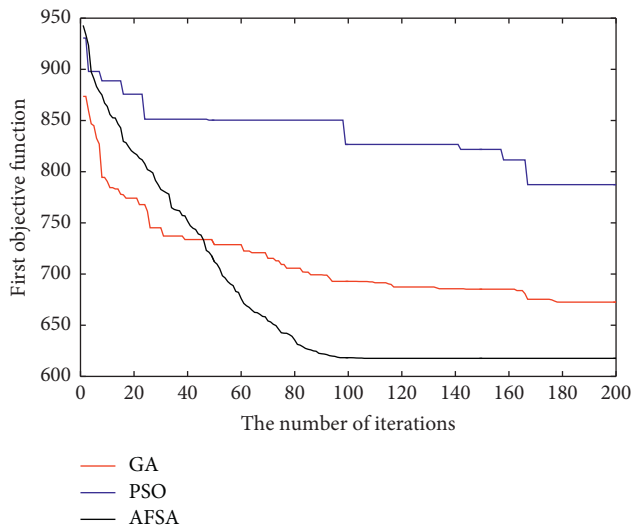


FIGURE 4: Comparison diagram of the stereograms from iterations of the algorithms.

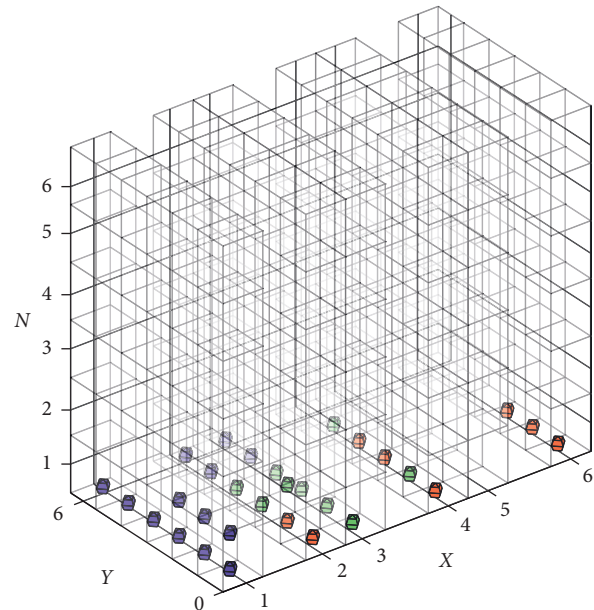


FIGURE 5: Optimized cargo position.

6.2.2. *Simulation and Comparison Experiment for Shelf Stability.* To assess the second goal, the PSO, GA, and AFSA are used to perform 20 simulation experiments. After the three algorithms are iterated 200 times, the optimized result

diagrams that are obtained are shown in Figures 6 and 7. The optimized results obtained based on the three algorithms reveal the following:



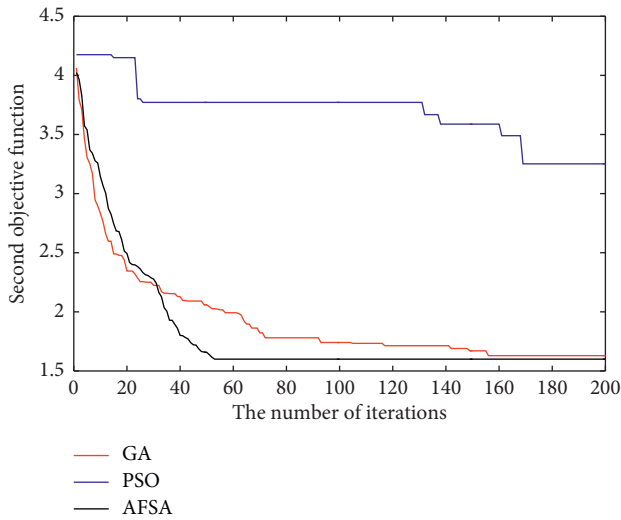


FIGURE 6: Comparison diagram of the stereograms from iterations of the algorithms.

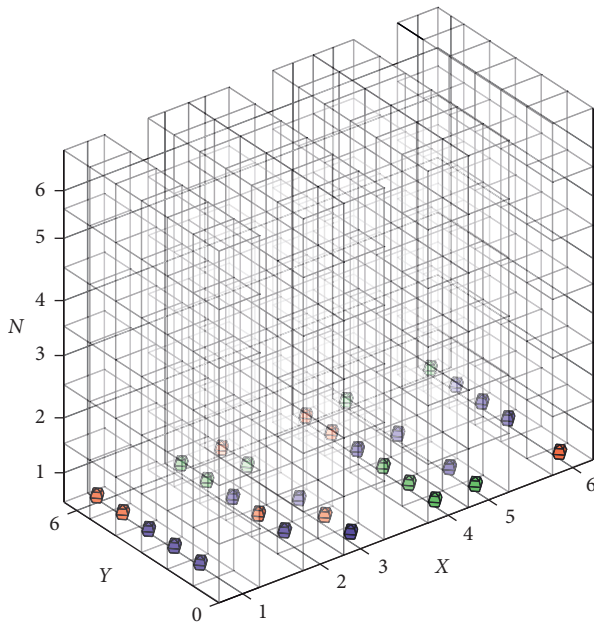


FIGURE 7: Optimized cargo position.

- (1) The results of the PSO, GA, and AFSA show that the program can converge after a limited number of iterations and obtain optimized results.
- (2) In terms of the number of iterations, the AFSA uses little iteration than the PSO and GA. The PSO and GA converge in 162 and 156 iterations, respectively, while the AFSA only needs 55 iterations to converge.
- (3) Figure 6 illustrates that the optimized result of the AFSA is superior to that of the PSO and GA in terms of the forklift operating time. The functional values using the PSO and GA are reduced from the initial value 4.5874 to 3.2517 and 1.6296, which reduce 29.1167% and 64.4766%, respectively. When using

the AFSA, the functional value decreases to 1.6, which is 65.1219% lower than the initial value.

- (4) Comparing the optimized position in Figure 7 from the AFSA with the position in Figure 1 before optimization, it can be seen that most goods are placed on the bottom shelves.

The results indicate that the two algorithms can improve shelf stability to some extent, but some goods are allocated to cargo spaces far from the I/O points and similar goods are scattered.

6.2.3. *Simulation and Comparison Experiment for Cargo Classification.* To assess the third goal, the PSO, GA, and AFSA are used to perform 20 times simulation experiments. After the three algorithms are each iterated 200 times, the optimized result diagrams that are obtained are shown in Figures 8 and 9. The optimized results obtained based on the three algorithms reveal the following:

- (1) The results of the PSO, GA, and AFSA show that the program can converge after a limited number of iterations and obtain optimized results.
- (2) In terms of the number of iterations, the AFSA uses little iteration than the PSO and GA. The PSO and GA converge in 187 and 194 iterations, respectively, while the AFSA only needs 100 iterations to converge.
- (3) Figure 8 illustrates that the optimized result of the AFSA is superior to that of the PSO and GA in terms of the forklift operating time. The functional values using the PSO and GA are reduced from the initial value 104.622 to 55.3044 and 37.6389, which reduce 47.1388% and 64.0239%, respectively. When using the AFSA, the functional value decreases to 31.5563, which is 69.8378% lower than the initial value.
- (4) Comparing the optimized position in Figure 9 from the AFSA with the position in Figure 1 before optimization, it can be seen that similar goods are assigned near the central cargo spaces, which greatly increased the concentration of related goods.

The results indicate that the three algorithms can improve the concentration of similar goods to some extent, but some goods are allocated to cargo spaces far away from the I/O points and some goods are placed at higher levels.

6.2.4. *Simulation and Comparison Experiment for Multiobjectives.* Goods are mixed, the inbound and outbound times are optimized, and shelf stability and cargo classification are performed to maximize the warehouse operating efficiency and minimize the warehouse operating costs.

When only considering a single objective, the PSO, GA, and AFSA are used to solve the problem of cargo location optimization. The multiple operation results of the PSO, GA, and AFSA show that the program can converge after a limited number of iterations and obtain optimized results.

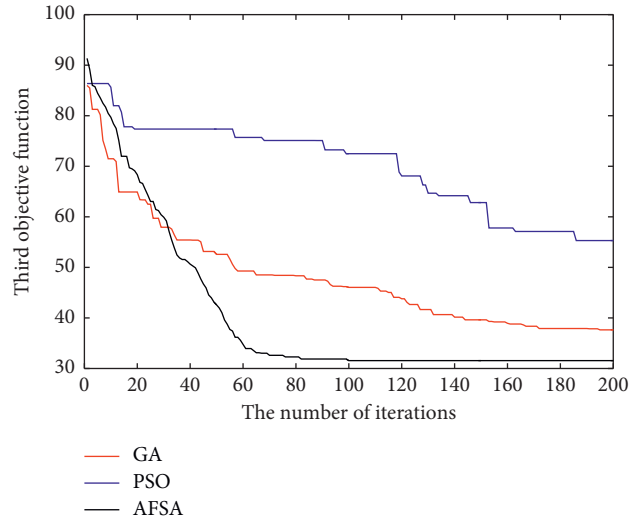


FIGURE 8: Comparison diagram of the stereograms from iterations of the algorithms.

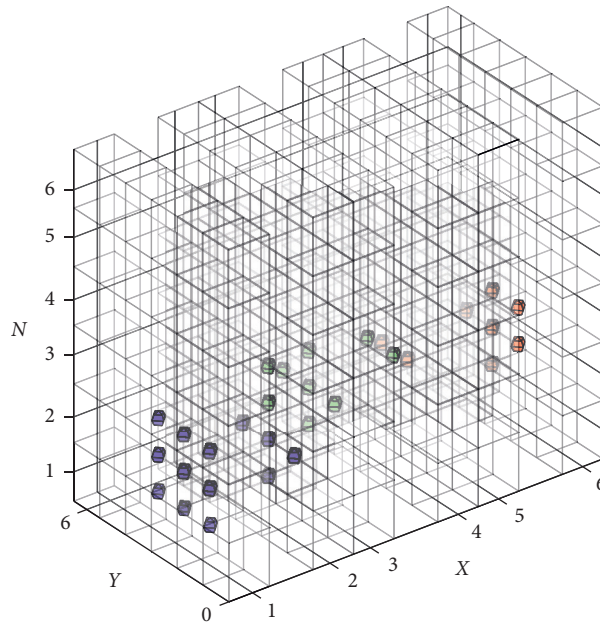


FIGURE 9: Optimized cargo position stereogram.

Comparing the results of the PSO, Ga, and AFSA, we find that the AFSA obtains better results. Therefore, the results of the AFSA are chosen as the ideal point. Therefore,  $f_1^*(x, y, z)$  is 617.6429,  $f_2^*(x, y, z)$  is 1.6, and  $f_3^*(x, y, z)$  is 31.5563. These three ideal points are input into formula (6)

to convert the multiobjective function into a single objective function as the evaluation function of the algorithm. The transformed evaluation function eliminates the influence of different dimensions through the ideal point method.

$$f(x, y, z) = \min \sqrt{0.35 \left[ \frac{f_1(x, y, z) - 617.6429}{617.6429} \right]^2 + 0.35 \left[ \frac{f_2(x, y, z) - 1.6}{1.6} \right]^2 + 0.3 \left[ \frac{f_3(x, y, z) - 31.5563}{31.5563} \right]^2}. \quad (10)$$

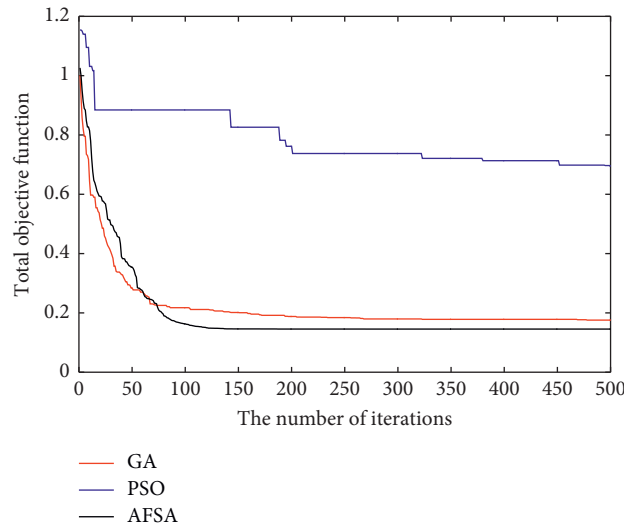


FIGURE 10: Comparison diagram of the stereograms from iterations of the algorithms.

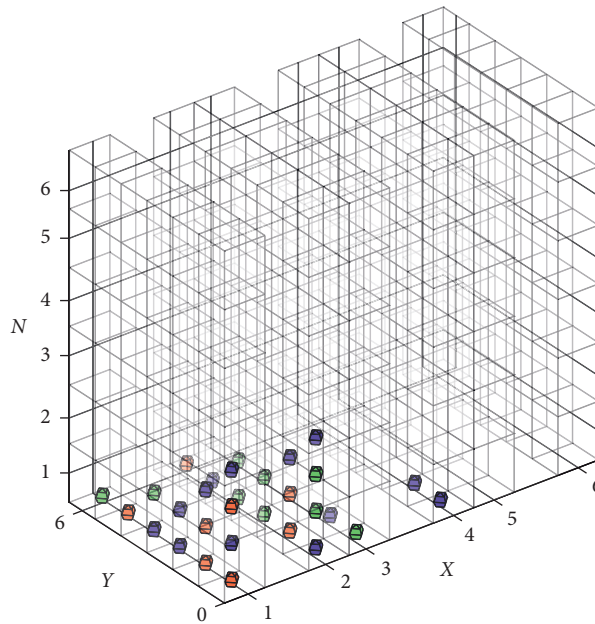


FIGURE 11: Optimized cargo position.

We use the abovementioned three algorithms to optimize the comprehensive objective, and formula (10) is used as the fitness function for the three algorithms. The three algorithms are used to conduct 20 simulations and generate a comparison diagram of the iterations. After 500 iterations, the optimized result diagrams that are obtained are shown in Figures 10 and 11. The optimized results obtained based on the three algorithms reveal the following:

- (1) The results of the PSO, GA, and AFSA show that the program can converge after a limited number of iterations and obtain optimized results.
- (2) Figure 10 illustrates that the optimized result of the AFSA is superior to that of the PSO and GA in terms of the comprehensive objective. The functional

values using the PSO and GA are reduced from the initial value 1.1683 to 0.6945 and 0.17568, which reduce 40.5499% and 84.962%, respectively. When using the AFSA, the functional value decreases to 0.1455, which is 87.5484% lower than the initial value.

- (3) Comparing the optimized position in Figure 11 from the AFSA with the positions in Figures 3–8, it can be seen that similar goods are assigned nearer to its central cargo space and most goods are placed on the bottom shelves.

When comparing the results of the PSO, GA, and AFSA based on the data presented in Table 2, it shows that AFSA is better than the PSO and GA with regard to single objective

TABLE 2: Optimized result.

Objective function	Before optimization	PSO optimization	Optimization percentage (%)	GA optimization	Optimization percentage (%)	AFSA optimization	Optimization percentage (%)
First objective	983.2857	787.3571	19.9259	672.5714	31.5996	617.6429	37.1858
Second objective	4.5874	3.2517	29.1167	1.6296	64.4766	1.6	65.1219
Third objective	104.622	55.3044	47.1388	37.6389	64.0239	31.5563	69.8378
Total objective	1.1683	0.6945	40.5499	0.17568	84.9620	0.1455	87.5484

TABLE 3: Optimized cargo position coordinate.

Good number	Position coordinates
1	(4, 1, 1)
2	(1, 1, 1)
3	(2, 3, 4)
4	(1, 3, 3)
5	(4, 2, 1)
6	(3, 3, 4)
7	(1, 3, 2)
8	(2, 1, 3)
9	(1, 2, 1)
10	(1, 2, 4)
11	(2, 2, 3)
12	(1, 4, 2)
13	(2, 1, 2)
14	(1, 2, 2)
15	(6, 4, 3)
16	(2, 3, 1)
17	(2, 1, 1)
18	(2, 3, 3)
19	(2, 1, 4)
20	(2, 2, 4)
21	(2, 3, 2)
22	(1, 4, 3)
23	(1, 1, 3)
24	(1, 2, 3)
25	(1, 1, 2)
26	(2, 4, 1)
27	(2, 2, 2)
28	(1, 3, 1)
29	(1, 4, 1)
30	(2, 2, 1)

optimization and multiobjective optimization. The PSO and GA are superior to the former one in terms of the convergence speed. However, the AFSA has strong global research ability and can obtain a better solution. The abovementioned results indicate that combining the model with the AFSA can significantly shorten the inbound and outbound working times for the warehouse, maximize the shelf stability, and increase the concentration of related goods. The final cargo position coordinates after comprehensively considering the optimization of the three objectives based on the AFSA are shown in Table 3.

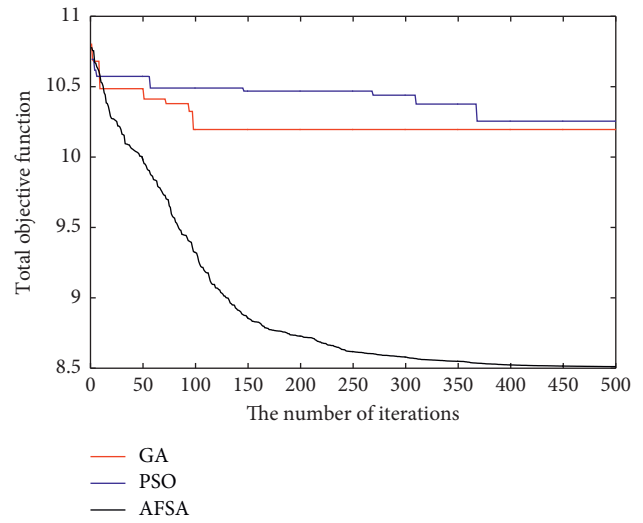


FIGURE 12: Iterative comparison graph of the algorithm.

6.3. *Scale Experiment.* To demonstrate the effectiveness of the proposed AFSA to the cargo location optimization problem, we conducted 20 simulations experiments on 150 goods apart from 30 goods by the PSO, GA, and AFSA along with acquiring a comparison diagram of the iterations.

The algorithms iteration diagram in Figure 12 shows that the three algorithms can converge stably within 500 iterations. Additionally, it demonstrates AFSA has higher convergence speed than the PSO and GA.

The optimized results of the PSO, GA, and AFSA in Table 4 indicate that AFSA has better optimization effect than the PSO and GA. The total optimized values using the PSO and GA are reduced from the initial value 10.778 to 10.2551 and 10.1958, which reduce 4.8514% and 5.402%, respectively. When using the AFSA, the functional value decreases to 8.5114, which is 21.0295% lower than the initial value.

The abovementioned results of scale experiment indicate the universality of the proposed model and the AFSA to solve the cargo location assignment. It can significantly shorten the inbound and outbound working times for the warehouse, maximize the shelf stability, and increase the concentration of related goods.

TABLE 4: Optimized result.

Objective function	Before optimization	PSO optimization	Optimization percentage (%)	GA optimization	Optimization percentage (%)	AFSA optimization	Optimization percentage (%)
First objective	11765.6429	11299.0714	3.9655	11128.1429	5.4183	9604.1429	18.3713
Second objective	5.4213	4.8922	9.7597	4.5511	16.0515	3.2388	40.2579
Third objective	517.78	437.7003	15.4660	433.0441	16.3652	296.9073	42.6576
Total objective	10.778	10.2551	4.8514	10.1958	5.4020	8.5114	21.0295

## 7. Conclusion

The paper takes multirow fixed shelves as the research object and considers the influence of parity on the in-out efficiency of the  $x$ -axis. This paper constructs a multiobjective mathematical model in which the objectives are efficiency, stability, and classification; and then, the multiobjective model is converted into a single objective model. Finally, this paper uses the PSO, GA, and AFSA to separately solve the problem. The Optimized results show that AFSA is significantly more efficient than PSO and GA, and the model presented in the paper can achieve better retail enterprise warehouse slotting optimization using the AFSA, thus greatly reducing the operating costs. In the future, the algorithm will be further improved to improve the solution efficiency, and more target objectives will be considered.

## Data Availability

The “original cargo location information” data used to support the findings of this study are included within the article, and the simulation experiment code is included within the supplementary materials.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

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## Supplementary Materials

The simulation experiment code are included within the supplementary materials. (*Supplementary Materials*)

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