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Research Article

The Intelligent Selection Method of Distribution Sites Driven by the Intelligent Optimization Algorithm

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For the internal enterprise, the intelligent selection of logistics distribution sites can optimize the distribution route, which is conducive to reducing the total distribution cost and improving the enterprise revenue. This paper takes urban logistics distribution point selection optimization as the research content and compares and analyses the applicability of different intelligent algorithms to logistics data. The AFSA is selected as the optimization algorithm, and knowledge learning is introduced to optimize the algorithm. The optimized AFSA model is applied to the mathematical model of distribution point selection. An intelligent algorithm-driven logistics distribution point selection model is established, and the optimized AFSA is used to solve the problem. Based on the actual case of CSC Logistics Company, the route of the distribution point in a region of CSC Logistics Company is optimized and the model is validated and solved. The results show that GWO and AFSA search capabilities are significantly better than of other intelligent algorithms, but there is some instability in the GWO algorithm. The AFSA is most suitable for solving logistics-related problems. The optimized AFSA considering knowledge learning has high efficiency and good optimization results. CSC Company uses this intelligent algorithm to select distribution sites intelligently, which shortens the total logistics path and improves the distribution efficiency. The total mileage of the initial route is 115 km. After intelligent algorithm optimization, the total mileage of the distribution changes to 83 km, which reduces by 32 km and 28% compared with the original route. The whole distribution process saved about 1.5 hours, which fully optimized the efficiency of distribution.

1. Introduction

As the third profit source of enterprises, logistics plays an important role in the development of enterprises [1]. In June 2014, the State Council of China issued the medium- and long-term plan for the development of the logistics industry, which emphasized the importance of the logistics industry and its impact on people's livelihood. The logistics industry shows its strong vitality under the strong promotion of national policies. According to the data analysis of the official website of the National Bureau of Statistics, with the development of e-commerce, online sales have shown an "explosive" growth trend [2]. In the first half of 2018, the national online retail volume was about 4081 billion, an increase of more than 30% year-on-year. Among the 4081 billion retail sales in the whole network, the retail sales of physical goods was 3127.7 billion, an increase of more than 30%, accounting for about 17.4% of the total retail sales of consumer goods in the whole society [3]. Driven by expanding domestic demand and increasing consumer demand, the e-commerce logistics express market is also developing at a high speed. The popularity of e-commerce platforms such as Taobao, JD.com, and Pinduoduo has not only changed people's purchasing methods but also made the express logistics industry rise rapidly [4]. In 2010–2020 alone, nearly 3000 express logistics enterprises were added in China. According to the statistics of the State Post Office, in the past five years, the National Express service has developed rapidly. The scale of the business increased from 5.7 billion pieces of express delivery in 2010 to 10.3 billion pieces of express delivery in 2021. The growth rate of the express delivery business from 2013 to 2018 was about 40% per year, as shown in Figure 1. According to the statistical analysis of the State Post Office, in 2018, China's express business

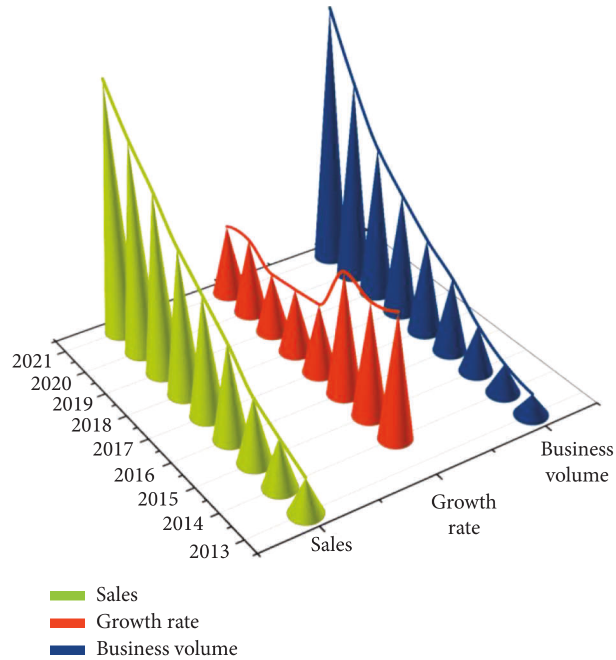

Figure 1: The express delivery business data.

volume exceeded 50 billion pieces for the first time [5]. China's express business volume continued to rank first in the world, accounting for nearly 50% of the global express business volume. The business volume has increased 19 times in the past 10 years, and it has ranked first in the world for 8 consecutive years, making China the first in the express industry among countries. At the same time, the logistics industry in other countries is also developing rapidly. For example, famous third-party logistics service giants have established integrated logistics service networks in various parts of India to provide seamless transfer services for outsourcing operators, importers, exporters and global trade operators in the Indian market. It can be seen that the logistics industry has a broad market prospect, which has a great impact on the development of enterprises and countries [6].

However, with the rapid development of the logistics express industry, many enterprises are also facing many problems [7]. The efficient and intelligent material distribution system and the scheme is a strong support for the development of the e-commerce industry. Modern logistics technology integrates Internet of things technology, path optimization, and decision-making control to improve the level of modern logistics [8]. Therefore, efficient material distribution optimization has become the breakthrough point of modern logistics transportation system reform. Logistics distribution mainly completes the delivery of goods from the distribution center to the customer's distribution point. At present, researchers usually regard the logistics distribution scheme as a mathematical model to solve the traveling salesman problem. However, the logistics distribution is affected by the commodity value, the types of commodities required by each distribution point, and the volume of distribution vehicles occupied by the commodities, so the distribution traveler model is more complex. Among them, the problem of "difficult selection of logistics distribution sites" is particularly prominent [9]. Logistics distribution refers to the logistics activities within a certain area, according to the customer's goods demand, through several logistics nodes, and through the operational processes such as loading and unloading, sorting, packaging, splitting, and assembly, finally, the designated goods are delivered to the customer at the designated place in a reasonable way [10]. Logistics distribution is a kind of operation mode in the modern circulation industry which integrates commodity flow, information flow, and transportation flow. The time of logistics distribution is highly variable, resulting in frequent "secondary delivery," which reduces the efficiency of distribution. However, if more distribution vehicles are added, it will not only increase the cost of logistics transportation but also increase the burden of urban traffic, making the traffic situation more crowded and complex. Therefore, the logistics industry is also constantly optimizing its own distribution mode to achieve cost and quality control while ensuring distribution efficiency [11].

After entering the 1990s, with the rapid development of electronic, communication, computer, and other technologies, researchers began to use computers as auxiliary tools to study the logistics scheduling problem from the perspective of artificial intelligence [12]. The intelligent optimization algorithm is a kind of meta-heuristic random search algorithm derived from biology. Because its search process is stochastic, can easily jump out of local search, and has the adaptive ability to the environment, some specific types of optimization algorithms have been initially applied in logistics distribution problems and have achieved initial results [13], for instance, genetic algorithm, simulated annealing algorithm, particle swarm optimization, hybrid optimization algorithm, immune optimization algorithm, ant colony optimization algorithm, and artificial fish swarm optimization algorithm. These intelligent optimization algorithms find the optimal solution in the search space through continuous iteration and overcome the dependence of quasi-Newton algorithm on the initial value of calculation to a certain extent. At the same time, they also solved the problem that the conventional algorithm is difficult to find the global optimum and ensured the convergence of the algorithm [14]. Most importantly, with the continuous improvement of the logistics information management system, various business data, traffic data, and express information can be collected in real time from the database platform of logistics enterprises [15]. These data record the timeliness, transportation mode, and distribution requirements of different types of express delivery and are comprehensive and detailed descriptions of the entire logistics distribution process. Through the statistical machine learning algorithm represented by the artificial neural network, the model is directly established based on a large amount of data. By fitting the distribution relationship of variables and targets, the impact mechanism of logistics transportation efficiency can be analyzed from multiple angles and all directions, avoiding the simplification of a large number of factors in the conventional modeling [16].

Therefore, the intelligent optimization algorithm used to solve complex optimization problems can often get better results and has potential application value for logistics distribution problems [17]. Based on this, the concept of intelligent distribution point selection came into being. This method is a modern comprehensive logistics distribution mode that can be perceived, analyzed, processed, and adjusted in time in the selection of logistics distribution sites [18].

The purpose of this paper is to study the application of intelligent optimization algorithms in the selection of logistics distribution sites. On the one hand, the applicability of different intelligent optimization algorithms in the optimization of logistics distribution is studied and analyzed, and an optimized algorithm suitable for large numbers of logistics is proposed, in order to further improve the efficiency and accuracy of the algorithm and provide an efficient, stable, and good performance solution to the path optimization problem. On the other hand, based on the proposed algorithm, a mathematical model driven by intelligent optimization algorithm is established, which provides data support for the decision-making scheme to improve the efficiency of logistics distribution. Therefore, this paper comprehensively uses logistics data and the intelligent optimization algorithm technology to explore a new development mode of express logistics and proposes an intelligent selection method of logistics distribution sites driven by the intelligent optimization algorithm.

2. Selection and Optimization of the Intelligent Optimization Algorithm

2.1. Comparison of Intelligent Algorithms. Although the traditional optimization algorithm has the advantages of fast calculation speed, less parameters, fast speed, simple model, and good robustness, it is easy to converge prematurely, the accuracy of seeking parameters is not high, and later evolution is easy to fall into local solution. The intelligent optimization algorithm has strong global search performance, can accurately find feasible solutions, has a wide range of parameter settings, and does not require high initial values of parameters.

In order to compare and analyze the advantages and disadvantages of different intelligent optimization algorithms, this paper compares quantum particle swarm optimization (QPSO), moth flame optimization (MFO), sine cosine optimization (SCA), simulated annealing (SA), grey wolf optimization (GWO), and the performance of the artificial fish swarm algorithm (AFSA) [19].

In this paper, three types of common business functions are selected from several logistics data for simulation experiments to evaluate the performance of the algorithm. Here, A is the cost test function, B is the traffic test function, and C is the distance calculation test function. In order to reduce statistical errors and produce convincing results, 30 independent experiments were performed for each algorithm. The operating system of the experimental environment is Windows 10, and the processor is Intel®Xeon®Gold 6154 CPU@3.00 GHz with 32 GB of memory. The integrated development environment is matlabr2017b, the population is set to 50, and the maximum number of iterations is 1000. The population was set to 50, and the maximum number of iterations was 1000.

For each test function, the performance of the algorithm is evaluated by comparing the convergence curves of the execution time to find the optimal value.

The solution results of six intelligent optimization algorithms on each test function are summarized in Table 1. The parameter AE in the table represents the average error between all the solved optimal values and the actual optimal values, ESTD represents the standard deviation of the error, mine represents the minimum error, and MaxE represents the maximum error.

For the logistics cost test function, GWO and AFSA show excellent solution accuracy. The average value of the solution is very close to the global optimal value. The standard deviation in 30 experiments is small, and the effect is the best. The QPSO effect is good, the average value and standard deviation are also within the acceptable range, the SCA and GWA effects are general, the average value of the solution obtained by SA is far from the real global optimal solution, and the optimal value obtained by multiple experiments is far less than other algorithms, with the worst effect.

For the traffic test function, GWO, AFSA, and MFO all find the global optimal value. The QPSO effect is general, and the SCA and SA effects are the worst. The test results are basically consistent with the results of the cost test function. It should be noted that there is a great difference between the average value of the solution obtained by GWO in the distance calculation test function and the real global optimal solution, and the test result is significantly different from that of AFSA.

On the whole, GWO and AFSA have better search ability than other algorithms, and AFSA has better effect than GWO. The results of QPSO and MFO are in the middle level, and the results of SCA and SA are poor.

To verify the stability and convergence of the six algorithms, we compare the convergence of each algorithm based on different functions, as shown in Figure 2. The GWO algorithm and the AFSA have premature convergence in the test function, but the accuracy of solution is better than of other algorithms. The two algorithms converge when the number of iterations is less than 400, and the solution accuracy is much better than other algorithms, which shows that the two algorithms can maintain a good balance between global search and local development. The accuracy of other algorithms improves with the increase of iteration times.

According to the horizontal analysis in Figure 2, the AFSA requires the least number of iterations when the same solution accuracy is reached. Although the GWO algorithm can also obtain the optimal value when performing global search, the convergence speed is slow. Although the search population is converging toward the solution center, many iterations are wasted on random target finding. Once the population diversity is reduced, there is no corresponding strategy to help jump out of the local optimal solution. Even

Table 1: The solution results of intelligent optimization algorithms.

Types	Statistical values	QPSO	MFO	SCA	SA	GWO	AFSA
A	AE	1.1	2.3	4.5	7.2	1.2	0.1
	EStd	3.4	5.3	2.9	3.1	0.8	0.2
	MinE	9.1	3.1	3.4	3.7	0	0
	MaxE	12.4	18.3	76.1	100.2	4.5	1.2
B	AE	2.2	3.3	2.5	8.2	3.4	0.9
	EStd	4.4	6.3	3.9	6.1	1.1	0.9
	MinE	6.7	0	12.4	13.1	0	0
	MaxE	9.4	4.3	66.1	88.2	5.5	0.3
C	AE	3.3	4.3	3.5	5.2	7.3	0.1
	EStd	7.4	7.3	3.9	5.8	3.2	0.2
	MinE	7.7	8.8	11.4	10.1	5.4	0
	MaxE	29.4	54.3	106.1	108.2	33.5	0.8

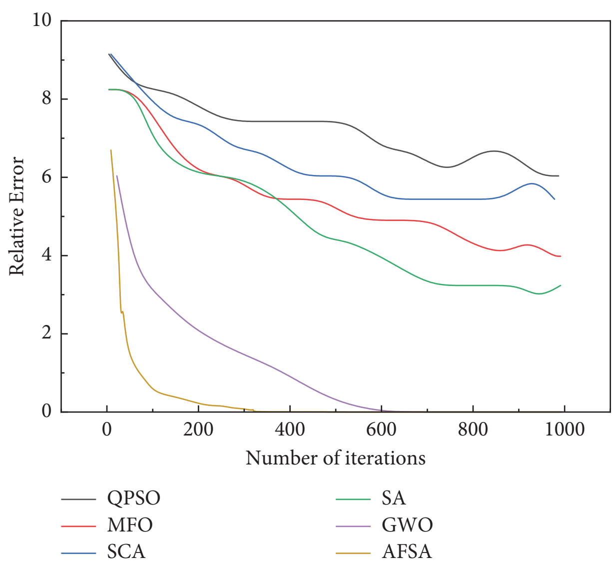

Figure 2: The convergence of each algorithm based on different functions.

if the maximum number of iterations is increased, the effect is not optimized, which indicates that the GWO algorithm has certain instability. Among all the algorithms, the SA algorithm has the worst convergence effect. In the process of solving, it falls into the local optimum many times earlier, resulting in huge errors and poor stability. Although the principle of the QPSO algorithm is simple, its global search ability is strong but its search accuracy is not enough, and the search range is concentrated in several regions. In conclusion, the artificial fish swarm algorithm is selected as the analysis algorithm to establish the model.

2.2. Artificial Fish Swarm Algorithm and Optimization. The artificial fish swarm algorithm is a swarm intelligence optimization algorithm that simulates the behavior of fish swarm [20]. The algorithm simulates four behaviors of fish, namely, random behavior, foraging behavior, swarm behavior, and tail chasing behavior. Each individual position in the fish school is to be solved. By comparing the food concentration in the field of vision of the four behavior modes, the objective function value is placed in the bulletin board to achieve the optimal solution of the problem. The calculation flow is shown in Figure 3.

The artificial fish swarm algorithm only refers to the information of the historical optimal position of the population in the process of optimization and lacks the interaction of information and knowledge between individuals and groups. Therefore, the algorithm can be optimized from the perspective of knowledge learning, making full use of the group knowledge information, and using the similarity clustering function to divide the fish population into different regions, so that the fish population can carry out targeted regional knowledge learning and dimension knowledge learning. The process of individual knowledge learning can also be regarded as a decision-making process. Decision-making is a high-level cognitive process, which usually refers to the decision-makers using scientific methods to mine the hidden useful knowledge of the given knowledge and integrate it to form an implementation plan in order to achieve a certain goal. The group is the collection of cognitive resources of each decision-making individual. The purpose of individual interaction is to make useful knowledge by the individual or the group, so as to fully and effectively transfer, share, and utilize the knowledge.

The basic equation of informatics is as follows:

$$Q[s + \Delta s] = Q[s] + \Delta s. \tag{1}$$

This formula shows that with the increase of learning time, the knowledge potential energy $Q[S]$ possessed by decision-makers also increases and the increased knowledge level Δs is related to their original knowledge and external knowledge. For individual fish, the knowledge potential energy can be expressed by the fitness value of its position.

Let t_{jx} be the position of individual j at time t; then, its corresponding knowledge level is F_{tjx}. That is, when an individual's fitness value is better, its knowledge potential energy is also larger; otherwise, the knowledge potential energy is smaller. The knowledge learning rate is given by the following formula:

$$\xi_i^t = \frac{e^{\mathrm{Score}_i^t}}{e^{\mathrm{Score}_1^t} + e^{\mathrm{Score}_2^t} + \cdots + e^{\mathrm{Score}_m^t}},$$
$$\mathrm{Score}_j^t = \begin{cases} 1, \; if\,(f_{\mathrm{worst}} = f_{\mathrm{best}}), \\ \dfrac{f_{\mathrm{worst}}^t - f_j^t}{f_{\mathrm{worst}}^t - f_{\mathrm{best}}^t}, \text{ others}, \end{cases} \tag{2}$$

where f_{j}^t is the fitness value of individual J, f_{best}^t and $f_{\mathrm{worst}}^{\mathrm{t}}$ are the best and worst fitness values of the population at time t, and m is the number of fish stocks. It can be seen that the better the fitness value of an individual fish, the greater its knowledge potential energy score; on the contrary, the worse the fitness value of an individual fish, the smaller its knowledge potential energy score.

The positions determined by historical knowledge are as follows:

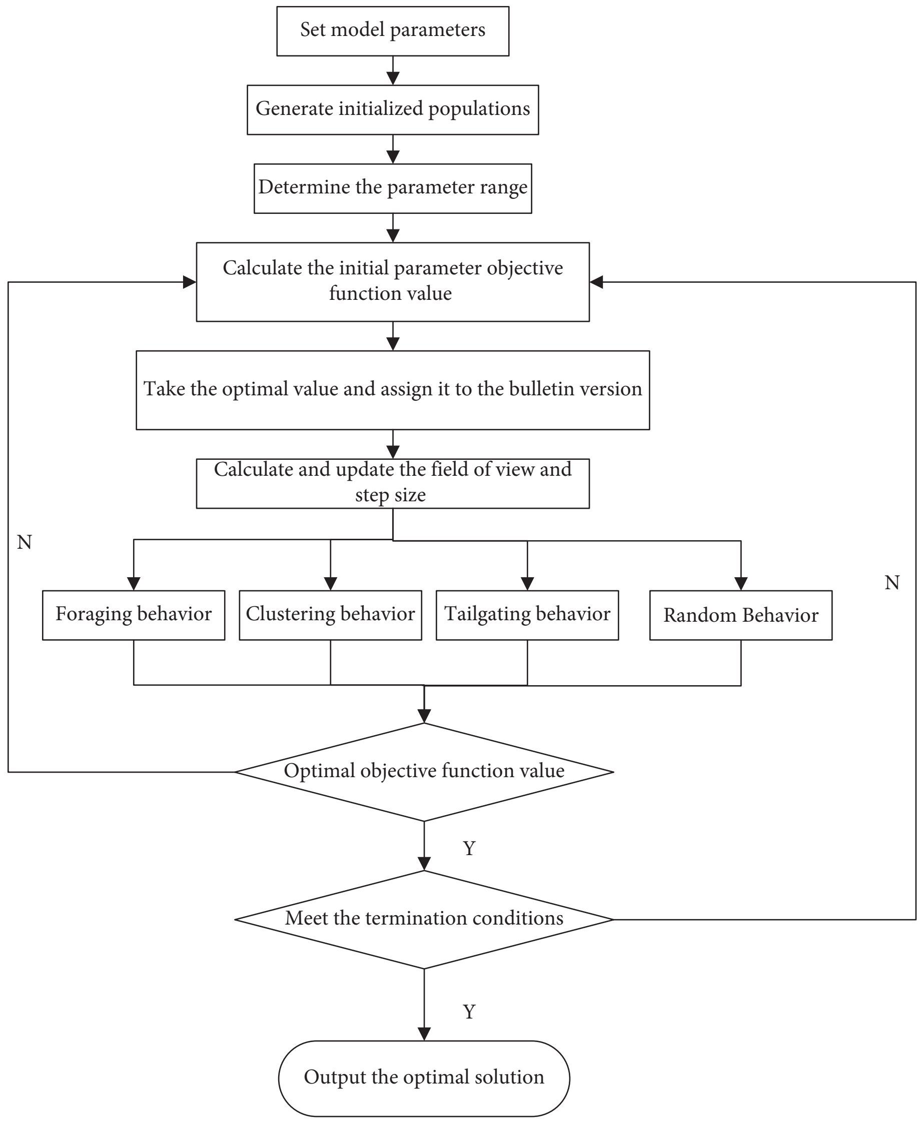

Figure 3: The calculation flow of AFSA.

$$p_i^t = \sum_{j=1}^{T} \xi_i^{t-j} x_i^{t-j}, \tag{3}$$

where t is the historical algebra and t_{ji} and x_{ij}^t are the learning rate and position of individual i at time t_j, respectively.

Compared with the standard artificial fish swarm algorithm, the evolution equation of the artificial fish swarm algorithm based on individual historical knowledge learning is as follows:

$$v_i^{t+1} = v_i^t + \left(x_{\mathrm{i}}^t - x^*\right) \cdot f_i \cdot \mathrm{rand1} + \left(x_{\mathrm{i}}^t - p_i^t\right) \cdot f_i \cdot \mathrm{rand2}. \tag{4}$$

2.3. Test Simulation. Two data sets A and B are selected for performance evaluation using benchmark test examples. Data set A consists of 12×6 to 9×9, composed of 11 groups of logistics data, with 1 instance in each group. Data set B consists of 20×5 to 75×20, with 3 instances in each group, and we repeated calculation for 30 times.

The algorithm is implemented by visual studio. In order to better evaluate the experimental results, the average percentage deviation (ARPD) is used as the performance parameter of the algorithm. The formula is defined as follows:

$$\mathrm{ARPD} = \frac{1}{N} \sum_{i=1}^{N} \frac{C_i(H) - C_i^*}{C_i^*} \times 100\%, \tag{5}$$

where n represents the number of times the instance runs, $C_i(H)$ is the $C_{\max}$ value obtained by the algorithm h to solve the instance I, and C_i^* is the best solution found so far. The smaller the ARPD, the higher the optimization efficiency of the algorithm. In the calculation process, the maximum number of iterations is 30; the population size is the product of the number of machines; the step factor is 0.1; the index parameter is 1.5; the discovery probability is 0.25.

In order to further verify the effectiveness of the optimized AFSA in solving the optimal value, the optimized AFSA is compared with OPSO, MFO, and SCA algorithms on data set A, and also with SA, GWO, and standard AFSAs on data set B. Figures 4 and 5, respectively, show the ARPD change curves of each algorithm on data sets A and B.

The solution efficiency of the optimized AFSA is 0.00 on the A data set, which is better than that of OPSO, MFO, and SCA. It shows that the algorithm can effectively solve small-scale data sets and has better optimization effect. At the same time, the discoverable AFSA is superior to other comparative algorithms in 17 of the 21 B data set cases. Compared with the average ARPD, QCS algorithm is the best, with the average ARPD of only 0.22, followed by the standard AFSA, which is 0.54, and the worst is SA, which is 0.88. Compared with other algorithms, the optimized AFSA improves by more than 20%. This shows that the optimized AFSA has some advantages over other algorithms.

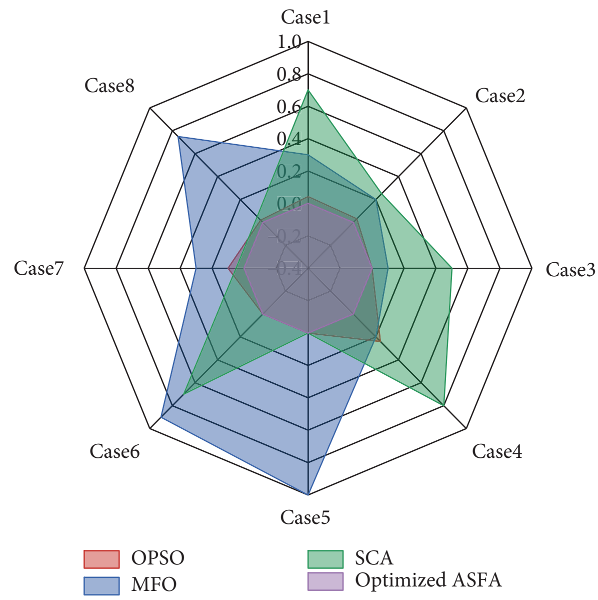

Figure 4: The ARPD based on data set A.

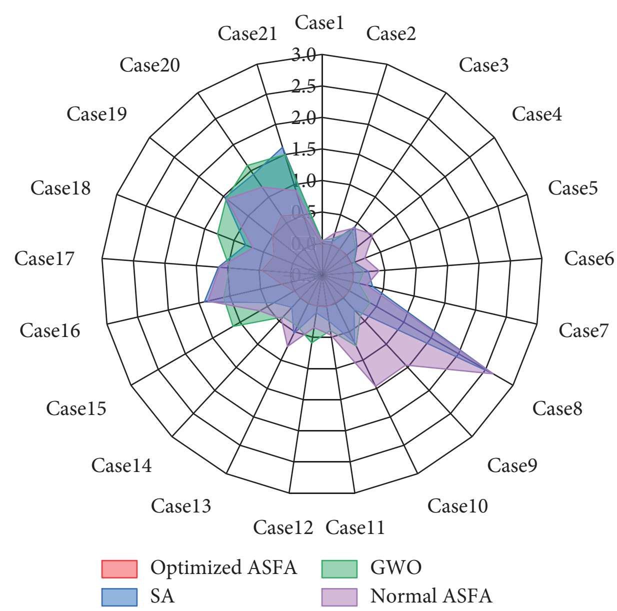

Figure 5: The ARPD based on data set B.

3. Design and Establishment of the Mathematical Model for Intelligent Selection of Logistics Distribution Sites

3.1. Model Establishment. Reasonable selection of distribution sites can provide convenience for couriers and customers, effectively improve distribution efficiency and reduce distribution costs, and have good social and economic benefits. The reasonable selection of logistics distribution sites can not only improve the quality of logistics service but also reduce the cost of logistics distribution [21]. The optimal selection model of logistics distribution sites needs to consider many factors such as environment, economy, customers, and geographical location [22]. In order to simplify the solution process, the following assumptions are made in the mathematical model:

(1) Multiple candidate distribution centers are responsible for delivering goods to customers (demand points), regardless of loading and unloading time

(2) In a fixed period of time given by a service period, each vehicle can carry out multijourney transportation of goods

(3) For each route, the vehicle departs from a candidate distribution center and returns to the candidate distribution center

(4) The capacity constraints of the candidate distribution centers are not considered

(5) The transportation cost per unit time of each distribution vehicle is a fixed value

(6) In each cycle (day), each demand point should be served by one vehicle only once

The operation process of the mathematical model for intelligent selection of distribution sites established in this paper is as follows:

(1) Determine the location and quantity of demand points.

(2) Determine the reasonable coverage of distribution sites.

(3) Select appropriate methods to determine the location of distribution sites.

(4) According to the actual geographical environment of the demand point, eliminate the nodes that are not convenient for the construction of the distribution point, and determine the final distribution point location according to the principle of the shortest "pick-up distance."

The decision goal is how to determine the best location of the distribution point from the potential geographical location and optimize the vehicle route from the warehouse to the customer. On the premise of meeting the vehicle carrying capacity and the capacity of the distribution center, we reduce the operation and distribution cost of the entire logistics distribution system, so as to minimize the total cost of the entire logistics network and achieve the purpose of system optimization [23]. Based on this, a mathematical model is developed, which mainly studies the vehicle routing problem with multi-journey operation strategy and distribution center location based on dynamic demand. In this model, the customer location node and customer demand are uncertain factors. Other parameters and variables are defined as follows:

N: total number of demand points (customers)

i, j: subscript of demand point, $i, j = 1,2,3, \ldots, N$

W: candidate distribution centers

u, v: candidate distribution center

SC: construction cost of a single distribution center

R: the total number of vehicle k trips

q: the delivery quantity to the demand point *J* in one cycle

Q: the maximum loading capacity of the vehicle

VC: the vehicle start-up cost of each cycle

TC: vehicle transportation cost per unit time

t_{ij}: travel time from demand point *I* to demand point *J*

t_{ui}: travel time from the candidate distribution center u to the demand point *I*

T: maximum service time of a single delivery vehicle

M: an arbitrary large positive number

Decision variables are defined as follows:

x_{ijk}^r: if the vehicle k provides delivery service from the demand point i to the demand point j during the journey r, then $x_{ijk}^r = 1$; otherwise, $x_{ijk}^r = 0$

v_{kui}^r: if the vehicle k starts from the distribution center u and arrives at the demand point i, then $v_{kui}^r = 1$; otherwise, $v_{kui}^r = 0$

u_{kvj}^r: if vehicle k returns to v in distribution from demand point j, then $u_{kvj}^r = 1$; otherwise $u_{kvj}^r = 0$

Yu: if the candidate distribution center u is selected, $Yu = 1$; otherwise, $Yu = 0$

The model uses the following objective functions and constraints with the objective of minimizing the following values [24]:

$$Z = \mathrm{SC}\sum_{N=1}^{W} Y_N + VC\sum_{k=1}^{K}\sum_{N=1}^{W}\sum_{i=1}^{N}\sum_{r=1}^{1} V_{kui}^r + \mathrm{TC}\sum_{k=1}^{K}\sum_{r=1}^{R_i}\left(\sum_{N=1}^{W}\sum_{i=1}^{N} t_{Ni}\cdot V_{kui}^r + \sum_{i=1}^{N}\sum_{j=1}^{N} t_{ij}\cdot X_{ijk}^r + \sum_{V=1}^{W}\sum_{j=1}^{N} U_{kij}^r\right). \tag{6}$$

The restrictions are as follows:

$$\sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{r=1}^{R_i} X_{ijk}^r = 1, j = 1, 2, \cdots, N, i \neq j, \tag{7}$$

$$\sum_{u=1}^{W}\sum_{i=1}^{N} V_{kui}^r = \sum_{u=1}^{W}\sum_{i=1}^{N} V_{kvj}^r r = 1, 2, \cdots, R_k, k = 1, 2, \cdots, K, \tag{8}$$

wherein equation (6) is the objective function, which represents the minimization of the total logistics system cost, specifically including the distribution center construction cost, vehicle start-up cost, and transportation cost. Equation (7) guarantees that only one vehicle serves each demand point. For any starting vehicle in any journey, the number of trips in and out of the distribution center should be the same, as shown in equation (8).

At the same time, the following constraints are set for the distribution process:

(1) Each distribution point can only be distributed by one distribution center

(2) The cargo volume of each distribution route shall not exceed the carrying capacity of the vehicle

(3) All vehicles meet the demand of the distribution point

(4) Ensure that the delivery vehicle is unique to the delivery point

3.2. Selection of Distribution Sites. In essence, the problem of selecting distribution sites is to transform the multi-distribution point problem into a single distribution point problem, which can be handled by the whole method. The whole method is to solve the problem from the perspective of the whole. At this time, the distribution centers and distribution points are regarded as a unified whole. Compared with the decomposition method, the whole method has strong global optimization ability. Figure 6 is a schematic diagram of the solution of the whole method [25]. The specific solution process of the whole method is as follows:

(1) First, a general distribution center shall be set in the system and directly connected with each actual distribution point. No distribution point is allowed between the virtual and real distribution centers. At this time, each actual distribution center is regarded as a special distribution point.

(2) It is assumed that all distribution vehicles in the distribution system start from the general

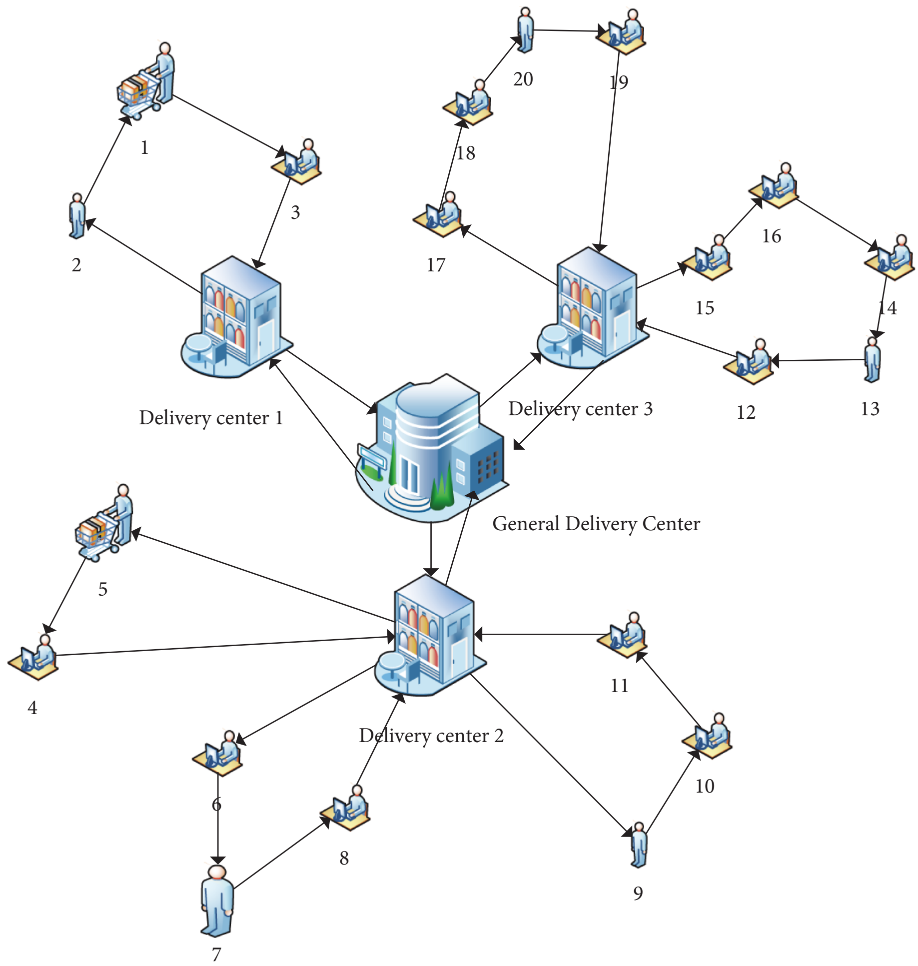

Figure 6: The schematic diagram of the solution of the whole method.

distribution center and must pass through the actual distribution center before driving to the distribution point for service. When the distribution vehicle completes the distribution task, it must first return to the original actual distribution center and then return to the general distribution center. If the distribution vehicle can continue to execute the task according to the model constraints after completing the distribution task and returning to the distribution center, the general distribution center can send the vehicle back to the distribution center in the previous distribution cycle to start a new round of distribution tasks.

(3) It should be pointed out that the general distribution center is only an ideal point, and the distance between the general distribution center and the actual distribution centers is zero. Therefore, there will be no travel distance, travel time, and no operating cost. It can be assumed as the only parking place of distribution vehicles in the distribution network, but each distribution vehicle is still parked in the actual distribution center.

When using the whole method to solve the multi-distribution center logistics vehicle routing problem, each distribution point to be served in this distribution network does not belong to a certain actual distribution center but it assigns each distribution point to be served to the corresponding actual distribution center according to the actual situation based on the entire distribution network. The introduction of the general distribution center makes it possible to directly model the entire distribution network, solves the problem that the time of the logistics vehicle routing problem cannot be directly connected, and effectively improves the global optimization ability of the logistics distribution network. Therefore, the overall method is adopted to analyze and solve the selection of logistics distribution sites. Based on this idea, the optimized AFSA intelligent algorithm in the previous section is introduced to optimize the selection of multiple distribution sites.

4. Application and Case Analysis

4.1. Current Situation Investigation. The time of this questionnaire survey is September 2021. A total of 1000 questionnaires were distributed to the operation area of CSC Logistics Company, of which 886 were recovered and 810 were valid. We carry out strict quality control on the data. The standards are as follows: (1) anonymous investigation; (2) random survey; (3) the baseline of dissatisfaction is dissatisfied + very dissatisfied more than 15%; (4) the baseline of satisfaction is very satisfied + more than 70% satisfied and less than 15% dissatisfied. The statistical results of the satisfaction rate questionnaire are shown in Figure 7. In the satisfaction survey of distribution efficiency, we mainly designed the timeliness of distribution and the management of distribution.

From the satisfaction survey on the distribution efficiency in this area, it can be seen that the proportion of users who are satisfied with the distribution speed is 32%, the proportion of users who choose to be very dissatisfied is 21%, and the proportion of users who choose to be dissatisfied is 22%. In terms of the proportion of satisfaction, the proportion of this area is not high. Users are generally satisfied with the distance from the distribution point and think it is convenient. In terms of timeliness of distribution, the proportion of very dissatisfied with the selection reached 31%, followed by the dissatisfied proportion of 28%, with very low satisfaction. To sum up, the distribution situation in this area needs to be optimized.

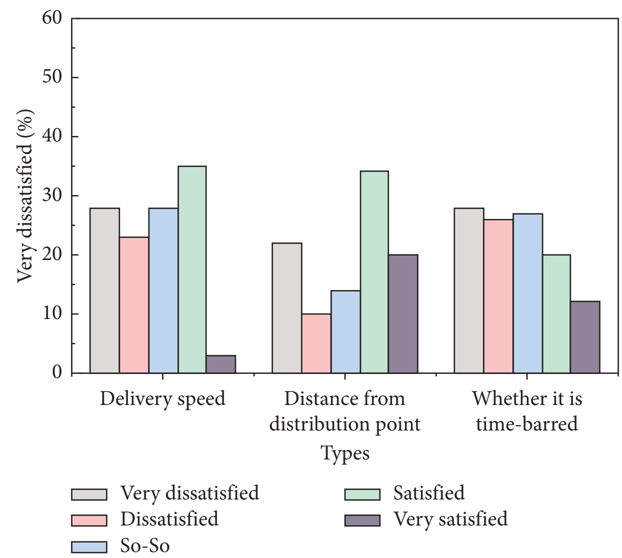

Figure 7: The satisfaction survey on the distribution efficiency.

4.2. Selection of Model Parameters. By studying the case of CSC Company's logistics distribution, combining the data of distribution center and distribution point in the case and the problem of CSC Company's distribution route optimization, the parameter selection is carried out. The logistics distribution project in the case is that a single distribution center provides distribution to multiple mutually dispersed distribution sites and needs to provide distribution within the time constraints of each distribution point. After the distribution service is completed, the logistics vehicles return to the distribution center. Therefore, the mathematical model established in this paper is applied to distribution planning, and the model parameters are collected and checked according to the actual data in the case. The optimization process is based on the optimized AFSA intelligent algorithm to solve the model, reducing the total cost of distribution and improving the distribution efficiency and logistics service level.

4.3. Distribution Site Data Preparation. The distance between each distribution point and the quantity of goods required by each distribution point are shown in Table 2 and Figure 8. The objective of the solution is to minimize the transportation cost on the premise of ensuring the distribution efficiency.

Table 2: The quantity of goods required by each distribution point.

Distribution site	X coordinate	Y coordinate	Business volume
1	4.6	3.6	220
2	2.2	0.8	520
3	1.6	4.8	760
4	0.8	2.4	520
5	2.2	2	310
6	3.8	1.6	370
7	1.4	4.6	160
8	4.2	1.2	490
9	4.8	1.4	340
10	4.2	3.4	430
11	2	2	310
12	2.4	0.4	220
13	0.6	4	340
14	3.4	3.4	610
15	1.8	1.8	190
16	4.4	0.8	130
17	1.2	4.4	190
18	4	2.2	160
19	4.8	5	310
20	3	3.6	520

4.4. Optimization of Route Cost and Distribution Efficiency. The optimized route is shown in Figure 9, and the specific cost indicators are shown in Table 3.

Comparing the results before and after optimization, the following can be seen:

(1) The total process is shortened, and the distribution efficiency is optimized. The total mileage of the initial distribution route is 115 km. After the optimization of the intelligent algorithm, the total mileage of the distribution route becomes 83 km, reducing 32 km and 28% compared with the original route. Under other conditions unchanged, the distribution vehicle travels at an average speed of 60 km/h, which saves about 1.5 hours in the whole distribution process and fully improves the distribution efficiency.

(2) The load rate is increased. After intelligent algorithm optimization, the distribution route only needs 4 vehicles to complete the distribution, reducing the use of distribution vehicles, reducing the company's fixed cost and improving the vehicle load rate. The average load of the distribution route optimized by the intelligent algorithm is 89.8%, and the optimized load rate is higher, which is more conducive to the development of the enterprise.

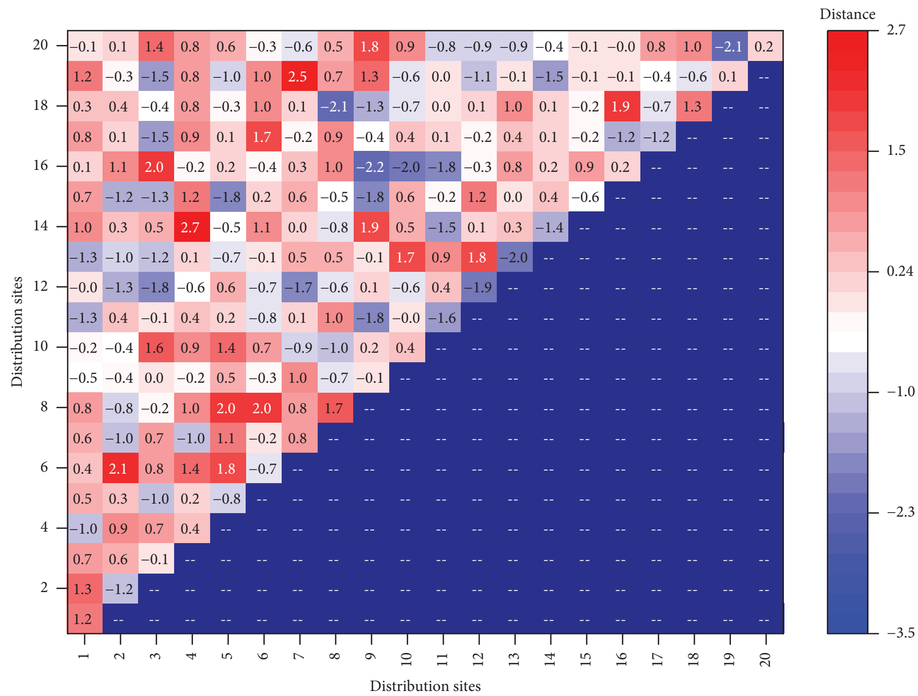

Figure 8: The distance between each distribution point.

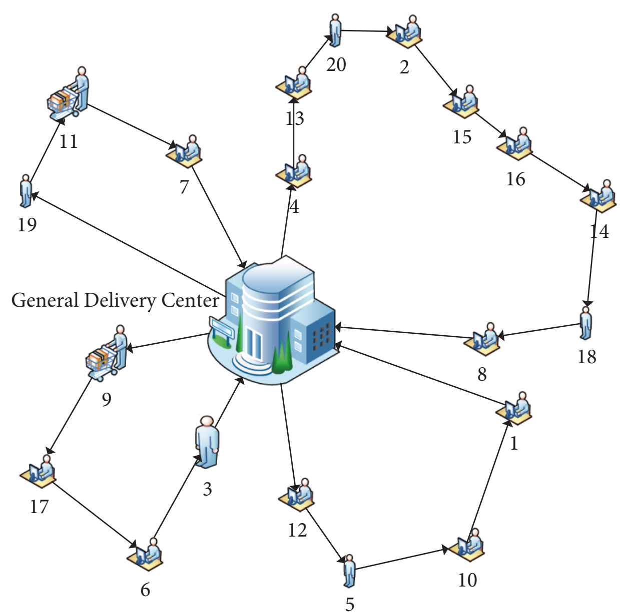

Figure 9: The optimized route.

Table 3: The specific cost indicators.

Number	Route	Total business volume	Load rating (%)	Mileage (km)
1	0–9–17–6–3–0	1630	92	15
2	0–12–5–10–1–0	1180	91	18
3	0–19–11–7–0	780	91	16
4	0–4–13–20–2–15–16–14–18–8–0	3480	85	34

(3) The total cost is reduced. After the intelligent algorithm optimization, the cost of the distribution route is lower than the original route. After optimization, the number of vehicles used becomes less and the fixed cost changes from 1967 yuan to 1599 yuan, a decrease of 15.8%. After optimization,

the total mileage becomes shorter, and the cost of goods damage in transit is greatly reduced. The cost of goods damage is changed from 801 yuan to 702 yuan, a decrease of 12.1%. At the same time, the total mileage of distribution after optimization is shorter, and the driver has enough time to deliver goods, which greatly improves customer satisfaction. The total cost is changed from 5099 yuan of the original route to 4038 yuan, a decrease of 17.2%.

(4) There is feasibility of intelligent algorithm. The optimized AFSA is superior to the original path in every index of the optimized distribution path, and the speed of finding the optimal solution is obviously faster than the genetic algorithm. This shows the feasibility of the optimized AFSA and the validity of the model established in this paper.

4.5. Suggestions. The construction of logistics is very important for fresh food and agricultural products enterprises. For the outside of the enterprise, it can guarantee the quality of products and quickly improve the enterprise image. For the internal part of the enterprise, the optimization of the distribution route is conducive to reducing the total distribution cost of the enterprise and improving the income of the enterprise. Based on the above research, the following suggestions are put forward for the future development of the company:

(1) Build the logistics distribution management system and optimize the route. In terms of the current development, CSC Company can consider establishing its own logistics distribution management system, which can not only simplify the logistics distribution information, strengthen the relationship between various logistics departments in the distribution center, and better cope with the changing market and suppliers. Moreover, by establishing the logistics distribution system, the rapid and accurate optimization of the distribution route can be realized. Select the appropriate distribution route, reduce the distribution cost, and improve the income of the enterprise.

(2) Control the number of distribution vehicles and improve the loading rate. The company can consider making improvements in other aspects while reducing costs by optimizing the distribution route. Regulate the number of outgoing vehicles of transport vehicles, and select the appropriate number of vehicles for distribution according to the demand of distribution sites. The distribution vehicle is different from the general vehicle, and the fixed cost caused by the vehicle loss and manpower and the transportation cost caused by the fuel consumption in the distribution process are much higher. To reduce the total distribution cost of the company, the method of increasing the vehicle weight rate of transportation can also be adopted. That is, when the transport vehicle is used correctly without speeding, overloading, fatigue driving, and other strict compliance with laws and regulations, the number of vehicles will be reduced and the load capacity will be increased. Considering the company's interests, the specific requirements of customers and the distribution sequence, the company can consider renting transport vehicles to reduce capital investment.

(3) "End joint distribution" can be implemented. Combined with the joint distribution from the secondary distribution center to the terminal distribution point, it will form a complete joint distribution from secondary distribution to the completion of distribution. If it can be implemented, it will be a further application of joint distribution. Joint distribution can be studied together with logistics express collection, and the two-way integration of express terminal collection and delivery can be implemented, so as to further improve logistics efficiency and reduce logistics costs.

(4) The number of distribution sites in the community can be further determined based on the optimal service radius of the end distribution sites and the time satisfaction of customers. At this point, we can start with the relationship between the service capacity and the service radius of logistics nodes, then find the cost of logistics nodes with different radii, introduce time satisfaction as a cost loss item, and finally find the partial derivative of the radius for the total cost to obtain the optimal radius.

(5) As for the model of distribution point selection, since the logistics data is in the hands of the express company and can only be obtained by investigation, the data volume is limited, which has a certain impact on the training of the model and the accuracy of the model. If the accuracy of the model is to be further improved, a large number of community data are required to train the model.

5. Conclusion

This paper focuses on the selection and optimization of urban logistics distribution sites and analyses the applicability of different intelligent algorithms to logistics data. The AFSA is selected as the optimization algorithm, and the optimization of the algorithm is realized by introducing knowledge learning. The optimized AFSA model is applied to the mathematical model of distribution point selection. An intelligent algorithm-driven logistics distribution point selection model is established and solved by using the optimized AFSA. Combined with the actual case of CSC Logistics Company, the route of logistics distribution point in a certain area is optimized and the model is verified and solved. The conclusions of this paper are as follows:

(1) On the whole, GWO and AFSA have better optimization ability than other intelligent algorithms and AFSA has better effect than GWO. Although the GWO algorithm can also get the optimal value when

performing global search, its convergence speed is slow and there is certain instability. Therefore, the AFSA is most suitable for solving logistics-related problems.

(2) Knowledge learning is introduced into the AFSA for improvement. The solution efficiency of the optimized AFSA is 0.00 on the A data set, which is better than OPSO, MFO, and SCA. It shows that the algorithm can effectively solve small-scale data sets and has better optimization effect. Compared with other algorithms, the optimized AFSA improves by more than 20%. This shows that the optimized AFSA has some advantages over other algorithms.

(3) After CSC Logistics Company uses this intelligent algorithm to select logistics distribution sites, the total process of logistics route becomes shorter and the distribution efficiency is optimized. The total mileage of the initial distribution route is 115 km. After the optimization of the intelligent algorithm, the total mileage of the distribution route becomes 83 km, reducing 32 km and 28% compared with the original route. About 1.5 hours were saved in the whole distribution process, which fully optimized the distribution efficiency.

(4) The construction of logistics is very important for fresh and agricultural products enterprises. The optimization of distribution route is conducive to reducing the total distribution cost of enterprises and improving the income of enterprises. For the future development of CSC Company, it is suggested to build a logistics distribution management system, optimize the route, control the number of distribution vehicles, and improve the loading rate.

Data Availability

The labeled data set used to support the findings of this work is available from the corresponding author upon request.

Conflicts of Interest

The author declares that there are no conflicts of interest.

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