A DYNAMIC PATH OPTIMIZATION MODEL OF IOT DELIVERY VEHICLES FOR E-COMMERCE LOGISTICS DISTRIBUTION

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Abstract. Logistics and distribution is a vital link to guarantee the stable supply of the e-commerce market and the healthy development of the industry. With the constant growth of the e-commerce, the efficiency and service quality of logistics and distribution have been paid more and more attention to. Therefore, the study firstly Considering distribution fixed cost, transportation penalty cost and carbon emission cost, the vehicle routing optimization model is transformed into the lowest transportation cost model, then uses an improved traditional artificial fish swarm algorithm to find the optimum way for this model, and finally verifies its performance and applicability through experiments. The performance test results show that the algorithm finds the optimal solution 3589 and 3590 in 63 and 78 iterations in the Oxford Robot Car dataset and Apollo Scape dataset, respectively; the average running time of the algorithm is 11.864s and 11.967s in the 10 operation time tests; in the operation function test, the algorithm. The algorithm was able to overcome the local optimal solution problem. The applicability simulation shows that this algorithm stabilizes after 53 iterations, the minimum cost of the optimal solution of the model is $41,224, and the total distance of distribution is 9035 km. The research algorithm is fast in finding the optimal value, which is close to it, indicating that the algorithm is highly efficient and reliable, and can greatly optimize the path of e-commerce logistics delivery vehicles, and give a theoretical foundation for the optimization of logistics delivery paths in other industries.

Key words: Artificial Fish Swarm Algorithm; Logistics and Distribution; Path Optimization; E-Commerce

1. Introduction. Optimizing the dynamic path of e-commerce logistics and distribution vehicles can lift the distribution efficiency, reduce distribution costs and improve customer satisfaction [1]. Traditional e-commerce logistics methods have found it difficult to meet the needs of the modern market as the e-commerce continues to develop. Reasonable optimization of the logistics path can improve its efficiency and will deduct distribution spending. Therefore, e-commerce logistics and distribution route optimization is becoming essential [2]. Most of the traditional e-commerce logistics delivery methods are based on mathematical models or heuristic algorithms, but these methods suffer from high computational complexity, long solution time and cannot guarantee to find the globally optimum solution. Therefore, there is a need to find an efficient and reliable optimisation method to solve the E-commerce Logistics Distribution Vehicle (ECLDV) path planning problem. The IoT and the rise of modern heuristic algorithms have brought new opportunities for e-commerce logistics delivery. The opportunities are often accompanied by challenges, as current IoT technology standards are not yet harmonised and there are many security and technical issues [3, 4]. Modern heuristic algorithms also have their advantages and disadvantages. The Artificial Fish Swarm Algorithm (AFSA), which is suitable for dealing with vehicle path optimisation models, suffers from a tendency to fall into local optimum solutions, many parameter adjustments and slow convergence [5]. Therefore, the study proposes a dynamic path model for vehicle distribution based on IoT technology and improved AFSA to perfect the model of e-commerce logistics vehicles, in anticipation of solving the path optimization problem of ECLDVs. The research content is segmented into four sections: Part 1 mainly explains the research results of many experts on the vehicle path optimization problem and AFSA; the second part primarily explains the establishment and optimization strategy of the vehicle distribution path model based on IOT technology and improved AFSA; the third part mainly explains the algorithm's performance test and the simulation application test results of the model; the fourth part mainly explains the test analysis of the results.

1.1. Overview. With the progress of today's e-commerce industry, internet logistics and distribution has become one of the main businesses of e-commerce platforms. To address it, many professionals have

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studied the optimization of distribution routes in a general sense. For addressing this issue, numerous scholars have conducted survey on distribution path optimisation in a general sense, and Bai R et al. proposed a hybrid approach combining ML and analytical methods to address the shortcomings of VRP applications. The approach uses ML tools in combination with analytical techniques to solve VRP. results show that the approach enhances VRP modelling and improves the performance of their algorithm [6]. Abdirad M et al. propose a two-stage hybrid algorithm to reduce transport costs in DVRP applications. The algorithm first constructs the initial route and then corrects it with an improved algorithm, which could effectively decrease transportation costs while satisfying customer needs [7]. Peng et al. propose a multiple-change transportation model with time windows to deduct the expenditure of urban-suburban logistics distribution and improve user satisfaction. The model establishes a minimum cost objective function under the constraints of time window and multiple trips, and is solved using a hybrid algorithm of packaging and genetics. This method can effectively optimise the entire distribution system [8]. Dhanare proposes a hybrid algorithm to overcome the shortest route problem and data transmission delays in connected vehicle technology. The algorithm combines ant-colony and firefly algorithms to discuss the best route, which is proven to be effective in selecting the best route and reducing travel time [9]. Bouziyane et al. propose a multi-objective local search method for the vehicle route disruption in pharmaceutical distribution with soft time windows. The method uses a hybrid algorithm-based neighbourhood search in vehicle route optimisation. The method is effective in meeting the dynamic needs of customers [10]. The AFSA is an important part of modern heuristic algorithms, mainly used in engineering optimization, economic management, machine learning and other fields. It can realize parameter search optimization according to the real-time changes of the model. Liu et al. artificially designed a reasonable urban large-scale traffic network, proposed a multi-objective optimization model for the urban traffic network problem, and then used the AFSA combining crossover operator and variational operator to solve the optimization problem. It can find the optimal solution of the model [11]. Yin et al. propose an improved AFSA to solve the problem of detecting the accuracy of energy consumption parameters of green energy efficient buildings. First is to use a hierarchical clustering method to build a classification model, and then the AFSA was used to construct an optimization function. This greatly lift the detection accuracy [12]. Sheik Abdullah proposes to use data classification techniques to effectively deploy the algorithm and set the algorithm parameters to modify the behaviour of the fish swarm. The accuracy of the algorithm improved by about 90% in different data sets [13]. Yuan et al. studied the delivery vehicle paths of several stations in order to optimise the courier business in Beijing and raised an adaptive simulated annealing and AFSA to solve the CVRP problem. The algorithm uses an adaptive vision strategy to adjust the visual range, while the search process uses "deterministic" probabilities to accept the worst solution through the Metropolis criterion. This is extremely efficient and accurate [14]. Bai et al. propose an AFSA built on a WSN to adapt the algorithm to the complexity and variability of the environment. The algorithm uses viscous fluids and artificial fish as algorithm nodes, while relevant events are directly linked to 'food'. This algorithm can effectively handle crosstalk data and improve the immunity of the algorithm to interference [15]. In summary, many experts and scholars have designed a large number of improved algorithms for optimising logistics distribution paths. The traditional AFSA, as an effective search strategy, is often applied to logistics distribution path optimisation. However, due to the limitations of this algorithm cannot optimise the dynamic path of logistics vehicle distribution more efficiently and accurately. Therefore, the research proposes the study of dynamic path of ECLDVs based on IoT and improved AFSA.

2. IoT and AFSA based vehicle path model construction and optimization strategy. This section focuses on the construction and optimisation of a dynamic path model for logistics vehicles based on IoT technology and improved AFSA. The IoT technology can quickly transfer real-time information between merchants, customers and delivery vehicles to improve the efficiency of delivery vehicles. And for the problem of the algorithm, the study adds improvements by parameter analysis setting and introducing $y = e^{-x}$ to transform the path optimisation model into the lowest cost mathematical problem model before using the improved algorithm to find the optimal solution.

2.1. Mathematical model construction for distribution vehicle paths based on. As an emerging technology, the Internet of Things (IoT) can achieve interconnection between devices and between people and things, thus improving the efficiency of e-commerce logistics distribution [17]. Generally speaking, the
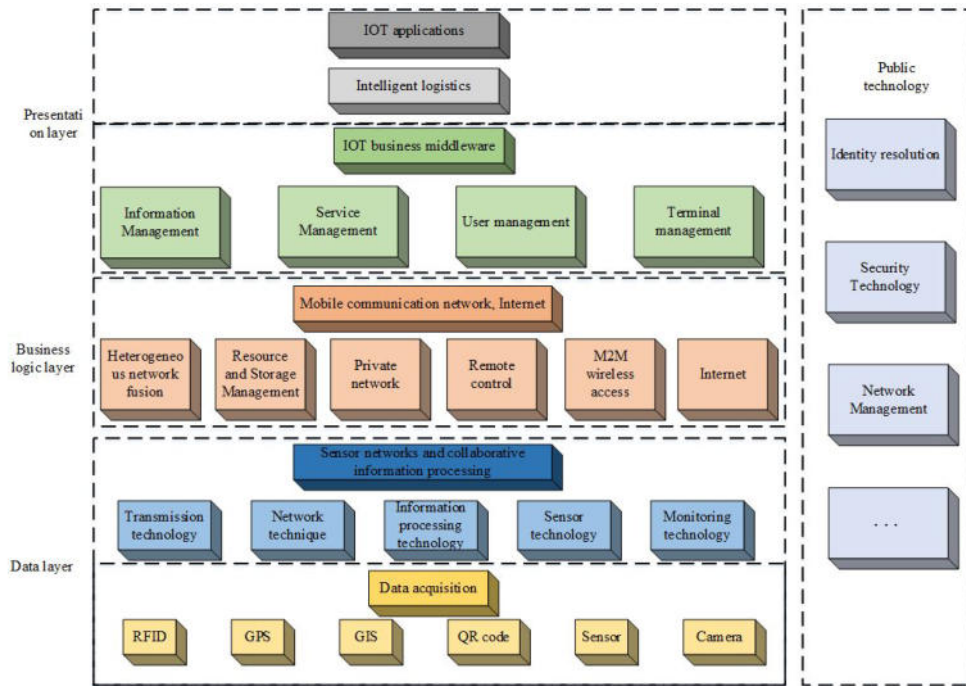
Fig. 2.1: Architecture of IoT System

e-commerce distribution IoT adopts a three-layer architecture model, the specific structure is Figure 2.1. In Figure 2.2, the first layer of this IoT is the sensing layer, which mainly completes data collection, item identification and logistics monitoring through relevant technologies; layer2 is the network layer, which mainly applies 5G communication technology to transmit the data information collected and collated from e-commerce logistics to the layer3; while layer3 is the application layer, which will make decision analysis and judgement of logistics transportation based on data information, its own reality and user needs [16] . Based on this IoT technology, a distribution flow chart for e-commerce logistics can be designed, as shown in Figure 2.2.

As Figure 2.2, the distribution process of e-commerce logistics based on IoT technology is roughly as follows: the network platform collects and organises the user's demands and transmits it to the path optimisation model; the model calculates the distribution plan and transmits it to the vehicle terminal of the distribution vehicle; at the same time, the vehicle terminal also transmits the product and vehicle information back to the network platform in time [17] . However, traditional logistics vehicle delivery ways exist problems, e.g. low efficiency, high costs and uncertain delivery times, all of which can be translated into a mathematical problem model. The essence of the vehicle path optimization problem is the optimal solution to the mathematical problem model of delivery costs and transport routes. To facilitate the analysis of this mathematical problem model, set $L = \{l_1, l_2, l_3 \ldots l_n\}$ on behalf of the logistics distribution centre and customer distribution points; $K = \{k_1, k_2, k_3 \ldots k_n\}$ on behalf of the transport vehicles involved in distribution; $A = \{(i,j)|i, j \in L, i \neq j\}$ on behalf of each distribution point between the arc set. The first is the fixed cost of vehicle distribution, which is calculated in Equation 2.1.

$$C_1 = (a + b + c) \sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} v_{ijk} x_{ijk} t_{ijk} \tag{2.1}$$

The fixed cost of distribution in Equation 2.1; a is the depreciation cost; b is the maintenance cost; c is the cost of fuel used per unit of time; v_{ijk} , x_{ijk} and t_{ijk} are the speed, decision variables and time of
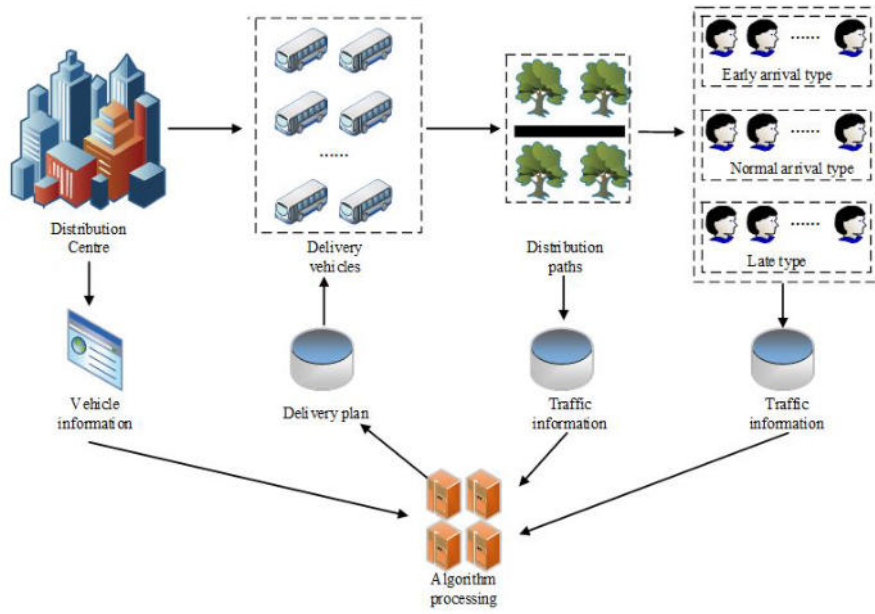
Fig. 2.2: Schematic diagram of e-commerce logistics distribution path

the distribution vehicle k between the distribution points i and j , respectively. The decision variables are calculated in Equation 2.2.

$$x_{ijk} = \begin{cases} 1\ Delivery\ Truck\ k\ drives\ from\ i\ to\ j \\ 0\ \ \text{If not} \end{cases} \tag{2.2}$$

The second is the cost of penalties, as there are overtime compensation costs in e-commerce logistics during delivery. The overtime compensation cost is the cost incurred by the customer when the delivery vehicle fails to reach the delivery point on time, causing losses to the customer, and the customer therefore penalises the company. If the delivery time is within $[e_i, l_i]$, the penalty cost is 0; if the delivery point is reached early, the penalty cost coefficient is $u_w^1(w = 1, 2)$; if the delivery point is reached overtime, the penalty cost coefficient is $u_w^2(w = 1, 2)$. The time window penalty cost function can be constructed from this in Equation 2.3.

$$C_{ki}^3 = \begin{cases} u_w^1(w = 1, 2)\ 0 \le T_i \le e_i \\ 0\ e_i \le T_i \le l_i \\ u_w^2(w = 1, 2)l_i < T_i < \infty \end{cases} \tag{2.3}$$

In Equation 2.3 T_i is the delivery vehicle arrival time. The total cost of penalties can be obtained from Equation 2.3 in Equation 2.4.

$$C_2 = \sum_{k=1}^{K} \sum_{i=1}^{n} C_{ki}^3 T_i \tag{2.4}$$

Finally, there is the cost of carbon emissions. Some studies have shown that the fuel consumption of distribution vehicles is related to both vehicle weight and vehicle speed. According to the constructed IoT system, the carbon emission can be calculated by accurately recording the real-time data, e.g. the distance and time of the delivery vehicle's journey in Equation 2.5.

$$P_{ijk}^1 = (\alpha_0 + \alpha_1 v_{ijk} + \alpha_2 v_{ijk}^3 + \frac{\alpha_3}{v_{ijk}^2})d_{ijk} \tag{2.5}$$

In Equation 2.5, $\alpha_0, \alpha_1, \alpha_2, \alpha_3$ are carbon emission factors; is carbon emissions. The carbon emissions due to the change in vehicle weight are calculated in Equation 2.6.

$$P_{ijk}^1 = \beta d_{ijk} q_{ijk} \tag{2.6}$$

In Equation 2.6, d_{ij} is the distance between i and j ; P_{ijk} is the carbon emission caused by the change of load; q_{ijk} is the load of the distribution vehicle from the distribution point i to j ; β is the carbon emission factor at load. The cost of carbon emissions during the entire distribution process is obtained from Equation 2.5 and Equation 2.6, see Equation 2.7.

$$C_3 = C_e \omega (\alpha_0 + \alpha_1 v_{ijk} + \alpha_2 v_{ijk}^3 + \frac{\alpha_3}{v_{ijk}^2}) \beta \ d_{ijk} \ q_{ijk} \tag{2.7}$$

In equation (7), ω is the carbon emission coefficient. C_e is Carbon price per unit. The total cost objective function is constructed grounded on Equation 2.1, 2.4 and 2.7, which is listed in Equation 2.8.

$$\begin{cases} C_{min} = C - 1 + C_2 + C_3 \\ C_1 = (a + b + c) \sum_{k=1}^{K} \sum_{i=1}^{n} \sum_{j=1}^{n} v_{ijk} x_{ijk} t_{ijk} \\ C_2 = \sum_{k=1}^{K} \sum_{i=1}^{n} C_{ki}^3 T_i \\ C_3 = C_e \omega (\alpha_0 + \alpha_1 v_{ijk} + \alpha_2 v_{ijk}^3 + \frac{\alpha_3}{v_{ijk}^2}) \beta \ d_{ijk} \ q_{ijk} \end{cases} \tag{2.8}$$

The constraints of Equation 2.8 are shown in below.

$$x_{ijk} = 0 \text{ or } 1 \qquad\qquad \forall k, i, j (i \neq j) \tag{2.9}$$

$$q_k \leq Q \qquad\qquad k \in K \tag{2.10}$$

$$\sum_{j=0}^{n} \sum_{k=1}^{K} x_{ijk} = 1 \qquad\qquad i \in \{1, 2, 3, \ldots n\} \tag{2.11}$$

$$\sum_{i=0}^{n} \sum_{k=1}^{K} x_{ijk} = 1 \qquad\qquad j \in \{1, 2, 3, \ldots n\} \tag{2.12}$$

$$\sum_{i=0}^{n} q_i \cdot \sum_{j=0}^{n} x_{ijk} \leq Q \qquad\qquad k \in K \tag{2.13}$$

$$q_{ijk} = q_{(j-1)ik} \qquad\qquad k \in K \forall i.j (i \neq j) \tag{2.14}$$

$$\sum_{j=1}^{n} = \sum_{j=1}^{n} \leq 1 \qquad\qquad k \in K, i \in \{1, 2, 3, \ldots n\} \tag{2.15}$$

$$T_{jk} = T_{ik} + t_{ijk} x_{ijk} \qquad\qquad \forall i, j, (i \neq j) \tag{2.16}$$

In above equations. Equation 2.9 represents the distribution vehicle k from the i to the j distribution point obeying the piecewise variables between 0 and 1 ; Equation 2.10 constrains the load of the distribution vehicle to be greater than the demand at the distribution point; Equation 2.11 and Equation 2.12 constrains the distribution vehicle to serve all customers once; Equation 2.13 constrains the total load of all vehicles to be greater than the total demand at the distribution point; Equation 2.14 constrains the continuity of the delivery of the distribution vehicle; Equation 2.15 constrains the departure and return of the distribution vehicle from the logistics distribution centre; Equation 2.16 constrains the continuity of the delivery.

2.2. Vehicle path optimization strategy based on AFSA algorithm. The study has transformed the delivery vehicle path optimisation problem into a minimum delivery cost function model solving problem, for which modern heuristics are usually used. The modern heuristic algorithm has its own advantages and disadvantages. Considering that the vehicle load, fuel consumption and user demand are changing in real time during the distribution process, the study has decided to use the improved AFSA to solve the problem. The

traditional AFSA consists of four behaviours: foraging, swarming, tail-chasing and randomisation [18]. The foraging behaviour, in which the artificial fish finds the water with the most food through its own mutual perception with the environment, is the basis of the whole algorithm and is calculated in Equation 2.17.

$$\begin{cases} X_j = X_i + Rand() \bullet Visual \\ if(Y_j < Y_i)X_{i/next} = X_i + Rand() \bullet Step \bullet \frac{X_j - X_i}{\|X_j - X_i\|} \\ else \quad X_{i/next} = X_i + Rand() \bullet Step \end{cases} \tag{2.17}$$

In above equation, X_i is the state of the fish at the moment and Y_i is its fitness value; X_j is the state of the other artificial fish and Y_j is its fitness value; $Step$ is the step size; $Rand()$ is a random function between 0 and 1. In equation 2.17, if , $Y_i < Y_j$, then X_i moves one step towards X_j ; if $Y_i > Y_j$, then X_j is reselected; if the condition cannot be satisfied after many attempts, then it moves one step at random. Agglomeration behaviour is where artificial fish spontaneously swim to the middle of a school in order to gather towards a place where there is more food, and in order to avoid congestion, this behaviour enhances the global and stable convergence of the algorithm, which is calculated in equation (2.11).

$$\begin{cases} if \ (Y_c < Y_i)\&\frac{n_f}{n} \ \delta \\ X_{i/next} = X_i + Rand() \bullet Step \bullet \frac{X_j - X_i}{\|X_j - X_i\|} \\ else \ \text{conduct prey} \end{cases} \tag{2.18}$$

In Equation 2.18, X_c is the centre of the school; n_f is the number of other artificial fish perceived; n is the number of artificial fish in the field of view; δ is the congestion factor. In Equation 2.18, if $\frac{n_f}{n} < \delta$ and $Y_c < Y_i$, the artificial fish move towards the central location; if $\frac{n_f}{n} > \delta$ and $Y_c > Y_i$, they search for other waters and perform the foraging behavior. Tail-chasing behaviour is the behaviour of the artificial fish to follow other fish to find food quickly, this behaviour enhances the rate of convergence of the algorithm and is calculated in Equation 2.19.

$$\begin{cases} if \ (Y_{min} < Y_i)\&\frac{n_f}{n} \ \delta \\ X_{i/next} = X_i + Rand() \bullet Step \bullet \frac{X_j - X_i}{\|X_j - X_i\|} \\ else \ \text{conduct prey} \end{cases} \tag{2.19}$$

In Equation 2.19 if $\frac{n_f}{n} < \delta$ and $Y_{min} < Y_i$, the artificial fish X_i move 1step towards X_{min} ; if $Y_{min} > Y_i$ and $Y_{min} > Y_i$; then search for other waters and perform the foraging behaviour. Random behaviour is where the fish swim aimlessly and this behaviour rises the search capability. The basic steps of a traditional AFSA are shown in Figure 2.3.

Although the traditional AFSA to find the optimal solution has the benefit of simple operation and fast convergence, there are also numerous disadvantages: the algorithm converges slowly at a later stage; the optimal solution is a range is not precise; parameter settings can affect the performance [19, 20]. To address these problems,On the basis of the traditional artificial fish swarm algorithm, an improved logistics distribution method of artificial fish swarm algorithm is proposed by adopting improved strategies such as fish swarm visual field adaptation, moving step length adaptation and parameter setting, which can accelerate the algorithm convergence speed and improve the accuracy and efficiency of the algorithm.the study first uses the control variable method to find the optimal value of the algorithm parameters, so as to improve the accuracy and efficiency to find the optimal solution. In addition, the $y = e^{-x}$ function is introduced to combine the algorithm's field of view and step size to ensure that the algorithm converges quickly and then obtains the optimal solution, and increases the local search and prevents oscillation when the field of view and step size are small in the later stage. The algorithm parameters of the search for optimality include parameters such as fish population size and number of attempts, which are discussed and analysed in Figure 2.4.

Figure 2.4 shows that the larger the number of fish in the algorithm, the more powerful the search capability of the optimal solution, but the corresponding amount of operations will also increase. Therefore, it is crucial to select the suitable number of fish according to the actual situation, under the precondition of ensuring the algorithm's optimal accuracy and computing speed. As shown in Figure 4, when the amount of attempts is
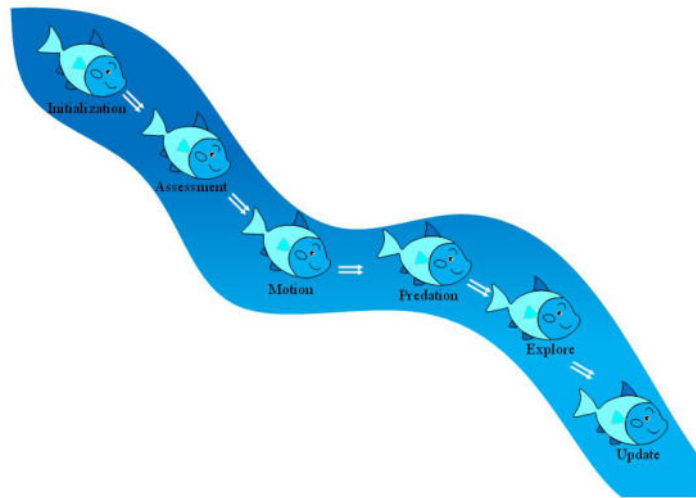
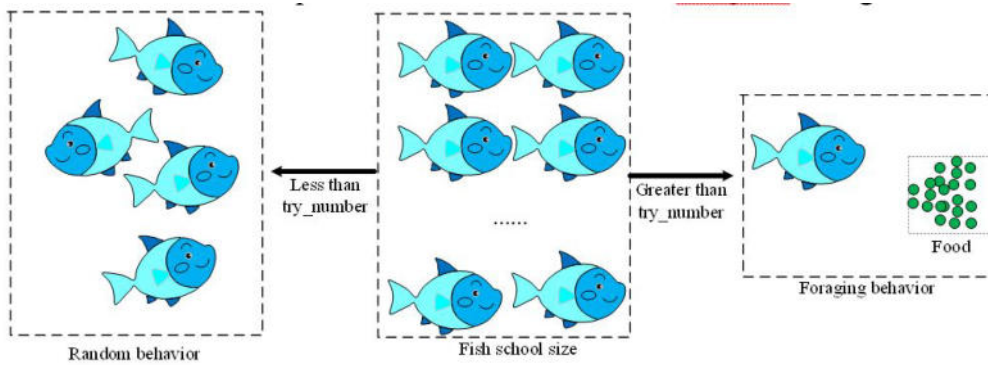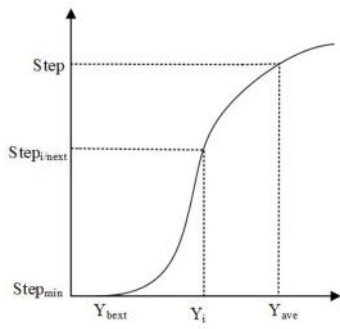Fig. 2.3: Flow chart of artificial fish school algorithm

Fig. 2.4: Analysis of fish school size and number of attempts

small, the fish perform foraging behaviour; when the number of attempts is larger, there is no suitable target and the fish perform random behaviour. With a small attempt numbers, it is easier to avoid getting trapped in a local optimal solution, improving search efficiency and accuracy. The improvement method of introducing the function combined with the parameters of the algorithm is mainly for the adaptive step and field of view in the algorithm, where the adaptive step improvement method is shown in Equation 2.20.

$$\begin{cases} y = e^{-x} \\ Y_{best} < Y_i < Y_{ave} \\ x = \frac{Y_i - Y_{best}}{Y_{ave} - Y_{best}} \\ if Y_i > Y_{ave}, Step_{i/next} = Step \\ else Y_{best} < Y_i < Y_{ave} \ Step_{i/next} = e^{-x} \bullet Step \end{cases} \tag{2.20}$$

In Equation 2.20, Y_{ave} and Y_{Best} are the average and optimal fitness value. The adaptive visual field

(a) Adaptive Step Size Asjustment Curve
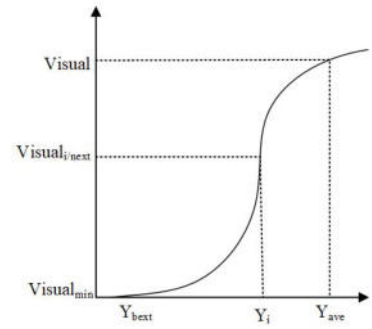
(b) Adaptive Field of View Adjustment Curve

Fig. 2.5: Adaptive step size and field of view adjustment curve
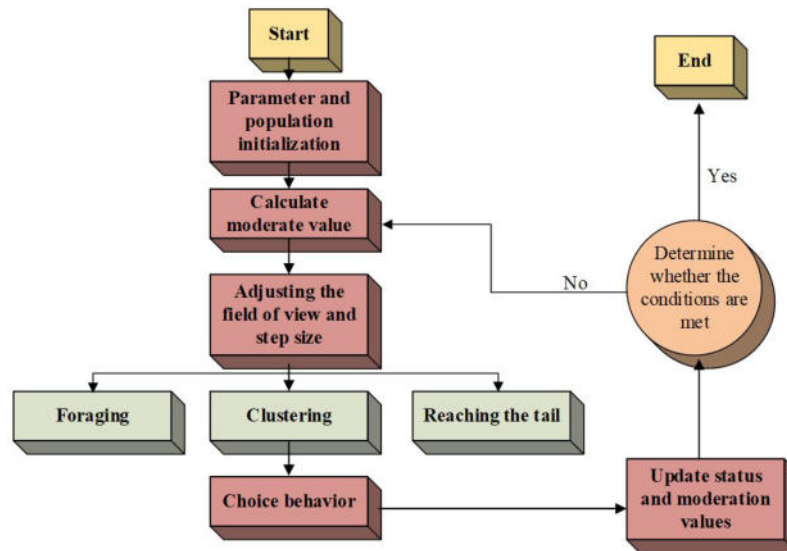

Fig. 2.6: Basic flowchart for improving artificial fish schools

improvement method is shown in Equation 2.21.

$$\begin{cases} y = e^{-x} \\ Y_{best} < Y_i < Y_{ave} \\ x = \frac{Y_i - Y_{best}}{Y_{ave} - Y_{best}} \\ if Y_i > Y_{ave}, visual_{i/next} = visual \\ else\ Y_{best} < Y_i < Y_{ave}\ visual_{i/next} = e^{-x} \bullet visual \end{cases} \tag{2.21}$$

The adaptive adjustment curves for both are shown in Figure 2.5.

The flow chart of the improved algorithm can be obtained according to the traditional AFSA and the improved algorithm scheme, see Figure 2.6.

The general flow of the improved AFSA in Figure 2.6, is as follows: first, set the parameter values according

Table 3.1: Selection of computer hardware and algorithm parameters for performance simulation experiments

| Equipment	Model
CPU	Intel Core i7-4590
Internal storage	32GB
Hard Drive	256GB SSD
Graphics card	RTX 4090
Operating system	Windows 10
Computer language	MATLAB
Artificial fish scale	100
Max iteration numbers	200
Try number	7
Step	1
Visual	4

to the improved optimal parameters; then, solve the fitness value and record the whole optimal value according to the problem characteristics; then adjust the spotting and step-size of the artificial fish according to its fitness value and position state; select their behaviour according to the fitness value; finally update their current position state and compare it with the previous fitness value and end if the requirement is satisfied, if not then revert to solving the fitness function for the solution.

3. Performance and application analysis of a vehicle path optimization model based on IoT and improved AFSA. This section focuses on the performance and application analysis of the vehicle path optimisation model based on IoT and improved AFSA. After setting up the experimental parameters and the simulation environment, the computing time, the optimal solution finding ability and the computing power of the research algorithm, the AFSA, the ant colony algorithm (ACA) and the artificial neural network (ANN) were tested. And the data of actual logistics distribution were selected as parameters for simulation and testing of the optimization model.

3.1. Performance analysis of improved AFSA. To verify the accuracy and effectiveness of the improved AFSA, simulation experiments need to be performed. The computer hardware used for the experiments is displayed in Table 3.1.

For the mathematical model of delivery vehicle path optimisation, ensuring the stability and efficiency is a prerequisite for optimising the vehicle path problem. Because the path mathematical model involves real-time paths such as weather, road conditions, roads and oncoming vehicles, the study selected the Oxford Robot Car dataset and ApolloScape dataset as the test set to test the various performances of the research algorithm. To ensure the authenticity and reliability of the tests, the traditional AFSA, ACA and ANN with the same experimental conditions were selected as controls. The study first two different data sets, the four algorithms of the search for the optimal solution to test, the results are Figure 3.1.

As shown in Figure 3.1a, the relationship between the best solution and the iterations for the four algorithms in the Oxford Robot Car dataset is shown in Fig. 3.1(b). The other three algorithms are AFSA with 105 iterations to find the optimal solution 3540, ACA with 124 iterations to find that 3577, and ANN with 93 iterations to find 3560. Figure 3.1b displays the connection of the optimal solution and the iterations of the algorithms in the ApolloScape algorithm in the dataset as a function of the number of iterations to find the bast way. It is still the research algorithm that has the widest range of optimality seeking. The frequency of fluctuations in this dataset is higher than in Figure 3.1a, with 78 iterations of the research algorithm yielding an optimal solution of 3590. 110 iterations of AFSA yielded an optimal solution of 3543, 74 iterations of ACA yielded an optimal solution of 3552, and 82 iterations of ANN yielded an optimal solution of 3573. These results indicate that the research algorithm has a wider range of solutions to find, with a relatively small number of iterations and a relatively large ones. The algorithm's efficiency was then tested in both datasets by evaluating the algorithm according to the time it took to find the optimal solution. 100 tests were carried out, of which
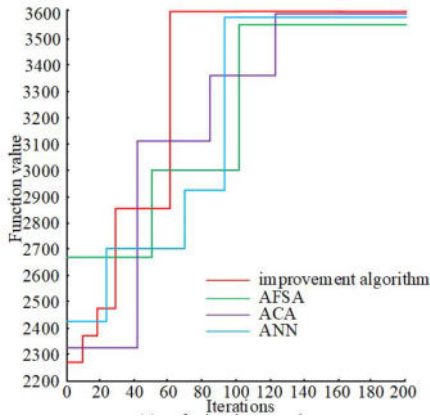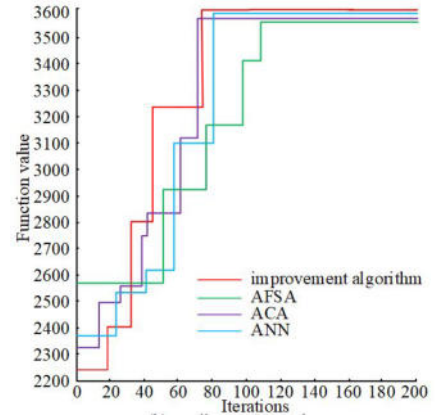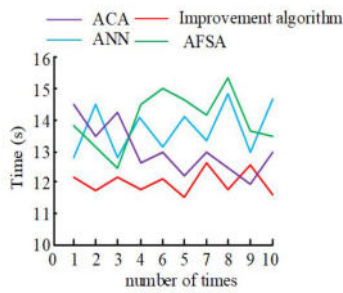
(a) Oxford Robot Car Dataset   (b) AppolloScape Car Dataset
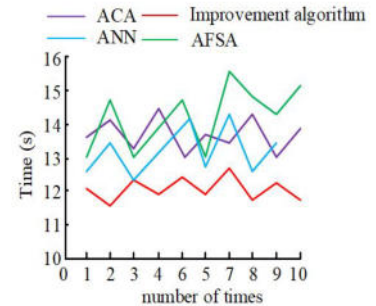
Fig. 3.1: Optimization solution test results of four algorithms

(a) Oxford Robot Car Dataset   (b) AppolloScape Car Dataset

Fig. 3.2: Optimization solution test results of four algorithms

10 were selected and the results are shown in Figure 3.2.

As shown, Figure 3.2a shows the results of the computing time tests for the four algorithms for finding the optimal solution in the Oxford Robot Car dataset. Based on the fluctuation of the line, the research algorithm has less fluctuation than the other three algorithms and is generally smoother. The mean run time of the three is 13.764s, 13.957s and 13.293s respectively. Figure 3.2b shows the average run-time of the four in the ApolloScape dataset for the operation time test results of the four algorithms for searching the optimal solution. Similar to Figure 2.5a, the fold fluctuations of the study algorithms are relatively smooth. The longest operation time is 12.768 s, the lowest is 11.498 s, and the average is 11.967 s. The average operation times of the three algorithms, AFSA, ACA and ANN, are 14.832 s, 13.589 s and 13.253 s. These results indicate that the research algorithms are highly stable and efficient. Finally, the Oxford Robot Car dataset was used as the main dataset to test the computing functions of the research algorithm and the traditional AFSA, and the results are shown in Figure 3.3.

As shown in Fig. 3.3 the five coordinate point solutions to obtain the optimum are (0,0), (10.1,10.1), (-10.1,10.1), (10.1,-10.1) and (-10.1,-10.1). It can be seen that the traditional AFSA has a local optimal solution
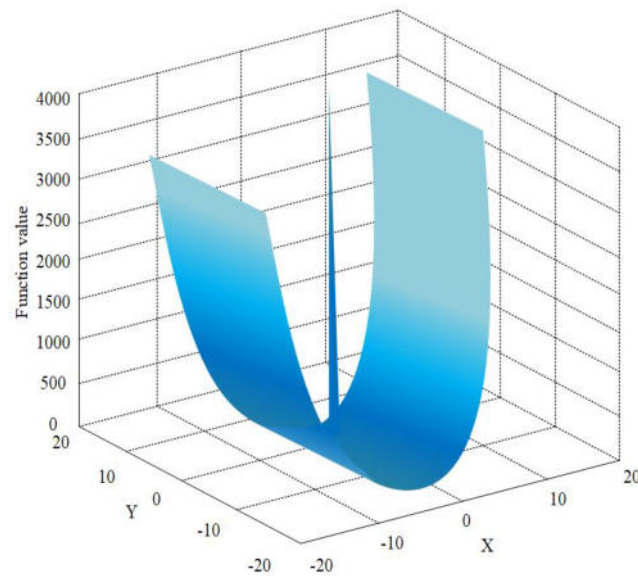
Fig. 3.3: Research Algorithm and Traditional AFSA Operational Function Test Results

in the operation, while the improved research algorithm searches for the optimal solution more accurately.

3.2. Analysis of the application of an improved AFSA-based vehicle path optimization model.
The best standard for this study was determined by minimizing the cost of the objective optimization function. And certain constraints have been set in the method section, which limits the feasibility of the algorithm. Make the algorithm achieve optimal results under constraint conditions.For verifying the practical application effect of the vehicle optimisation mode, the study selects the actual data of an e-commerce logistics distribution station as parameters, and then uses four algorithms, namely the research algorithm, AFSA, ACA and ANN, to find the optimal solution for this e-commerce logistics distribution model. As the final solutions of these algorithms are infinitely close to the optimal solutions, they are highly stochastic in nature. Therefore, the study is run 50 times consecutively with the four methods, and the best solution among them is taken as the optimal solution of the model. The details are exhibited in Figure 3.4.

As Figure 3.4, all four algorithms solve for the optimal value decreases as the iterations increases. The research algorithm stabilised(The stability of the algorithm refers to the characteristic that the output result of the algorithm no longer changes significantly after a certain number of iterations. The significance of stability is that it provides a kind of predictability, that is, the research can predict with relative certainty the results that the algorithm will produce in subsequent iterations.) at 53 iterations and the optimal solution for the model's comprehensive cost was $41,224; the ANN algorithm stabilised at 71 iterations and the optimal solution for the model's comprehensive cost was $48,651; the ACA algorithm stabilised at 62 iterations and the optimal solution for the model's comprehensive cost was $49,623; the AFSA algorithm stabilised at 88 iterations and the optimal solution for the model's comprehensive cost was $56,874 The AFSA algorithm stabilised at 88 iterations and the optimal solution was $56,874.The expected best value set is 37625 yuan. The comparisons of these four show that the research algorithm has the lowest number of iterations to find the optimal solution and the smallest integrated cost optimal value. The closest expected best value to the setting. The distribution roadmap was then plotted based on the resulting integrated cost optimal solution and compared with the pre-optimisation roadmap, the results of which are shown in Figure 3.5.

The red part in Fig. 3.5 refers to the distribution centres; the numbered dots represent the distribution points. From the optimized distribution route, the number of vehicles in each distribution centre has changed. one more vehicle in S1 distribution centre and one less vehicle in S3. From the distribution route, S1 distribution
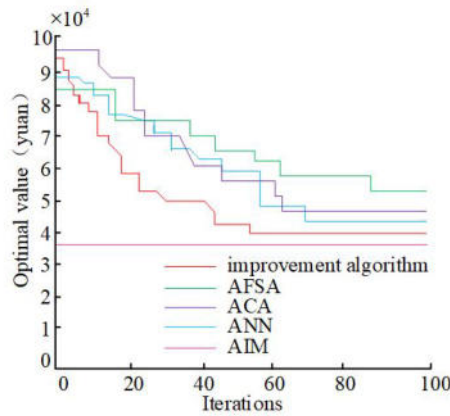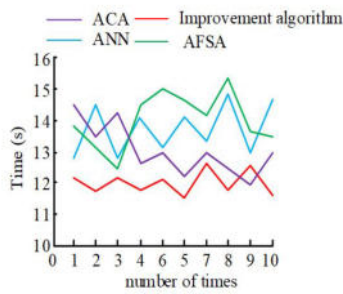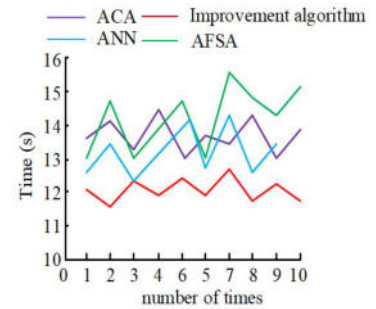
Fig. 3.4: The relationship between the minimum comprehensive cost of different algorithms and the number of iterations

(a) Before Optimization

(b) After Optimization

Fig. 3.5: Delivery route map

centre changed from S1-5-1-S1 to S1-5-S1, S1-1-S1; S2 distribution centre changed from S2-3-2-S2 to S2-3-S2, S2-2-20-10-S2; S3 distribution centre changed from S3-14-S3 to S3-14-17, S3-6-15 to After optimising the layout of the distribution network, changing the route and the number of distribution vehicles, the lowest cost distribution path for e-commerce logistics is obtained. The comparison of the results before and after the optimisation of the ECLDV paths is shown in the Table 3.2.

As can be seen from Table 3.2, all data has been improved after optimisation. The total distance of distribution before optimisation was 12,351 km and the total cost was \$62,453; the total distance of distribution after optimisation was 9,035 km and the total cost was \$41,224. The total distribution distance after optimisation was 3316 km less than that before optimisation, and the total cost was 17,229 yuan less. In summary, the method used in the study not only saves costs, but also improves transport efficiency and realises the optimisation of e-commerce logistics distribution paths.

4. Conclusion. The booming e-commerce market requires a more efficient and faster logistics and distribution operation system. The research first establishes a dynamic path model for logistics and distribution vehicles based on IoT technology, then transforms the optimisation of this path model into a mathematical problem model with the lowest cost optimal solution, then improves the AFSA by setting parameters and

Table 3.2: Comparison of results before and after optimization of delivery paths

/	Total distance (km)	Total cost (yuan)
Before optimization	12351	58453
After optimization	9035	41224
Optimization quantity	3316	17229

introducing new functions, and finally uses the improved algorithm to seek out the optimal solution. The algorithm proposed in study finds the optimal solution 3589 in 63 iterations with an average running time of 11.864 s. The other three algorithms, AFSA, ACA and ANN, find the optimal solution in 105, 124 and 93 iterations respectively. The other three algorithms, AFSA, ACA, and ANN, iterated 110, 74, and 82 times respectively to find the optimal solution. The other three algorithms, AFSA, ACA and ANN, iterated 110, 74 and 82 times respectively to find the optimal solutions 3543, 3552 and 3573, with an average running time of 14.832s, 13.589s and 13.253s respectively. and the research algorithm was able to overcome the shortcomings of the local optimal solution in the algorithm's operational function test. In the simulation application test using actual data of an e-commerce logistics as parameters, the research algorithm tends to be stable in 53 iterations, and the lowest cost of the optimal solution of the model is RMB 41,224, and the total distance of distribution is 9035 km. The cost saving over the traditional model is RMB 17,229 and the transport distance saving is 3316 km. It shows that the vehicle distribution path model grounded on IoT and improved AFSA proposed by the research has high accuracy and precision, and can greatly optimize the dynamic path model of ECLDV. However, the research model does not take into account the costs arising from other factors such as environmental pollution and personnel mobility, Environmental pollution caused by vehicle exhaust emissions may affect air quality, health and safety, vehicle dispersal and restriction, energy consumption, strategy adjustment and other aspects, and have an impact on transportation costs. On the other hand, personnel mobility may lead to delayed delivery times, re planning of delivery routes, and so on. and there are many complex IoT technologies, Further optimization of the research model is needed to address this series of issues

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