Intelligent Optimization of Logistics Paths Based on Improved Elite Artificial Bee Colony Algorithm

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With the rapid development of e-commerce and logistics industry, logistics path optimization has gradually become a key bottleneck restricting enterprises from improving service quality and reducing operating cost. Therefore, the study introduces an elite swarm strategy, which uses elite individuals to guide the honey search in the hiring bee stage, and proposes an intelligent optimization model for logistics paths based on an improved artificial swarm algorithm. The study is calculated using Windows 10, Intel Core i7 CPU, NVIDIA GeForce GPU, 64GB memory, and Matlab simulation software. The experimental results show that in the single-mode test function, the Avg and Std of the elite swarm algorithm are on average six orders of magnitude lower than the other three algorithms. In the multi-mode test function, the Avg and Std of the elite swarm algorithm are on average seven orders of magnitude better than the other three algorithms, which is far superior. The area enclosed by the model precision-recall curve and the coordinate axis is 0.96, and the F1 value is 97.7%. In the simulation test, the model plans the delivery path for 20 customer points with a total path length of 5221.43km, a total delivery cost of 83908.38 yuan, a vehicle loading rate of 97.4%, and a solution time of 2.8s. The research results indicate that the logistics path intelligent optimization method has good comprehensive performance. It can effectively reduce logistics transportation costs, which has important guiding significance and application value for actual logistics operations. This model not only provides an efficient path optimization tool for logistics enterprises, but also offers new ideas and methods for logistics path optimization research.

Povzetek: Uvedena je izboljšana inteligentna optimizacija poti z elitnim algoritmom umetne čebelje kolonije (EABC) za logistiko, kar zmanjša stroške transporta in izboljša učinkovitost.

1 Introduction

Recently, with the rapid development of global economic integration, the logistics industry is experiencing significant growth due to the expansion of e-commerce [1]. Logistics path optimization, as a key issue in logistics management, directly affects the operational efficiency and cost control of enterprises. How to quickly find the optimal transportation path in the complex and ever-changing logistics environment has become an urgent problem to solve [2]. The development of the logistics industry has undergone a transformation from traditional manual management to modern and intelligent management [3]. Early logistics path optimization relied heavily on experience and manual calculations. With the development of computer technology and algorithms, optimization methods based on mathematical models and computational intelligence have gradually been introduced [4]. Influenced by artificial intelligence and big data technology, the application of intelligent optimization algorithms in logistics path optimization has become increasingly widespread [5]. Among them, the Artificial Bee Colony (ABC) algorithm has been extensively applied in function optimization, neural network training, and pattern recognition due to its simplicity, robustness, and adaptability. In existing research on logistics path optimization, ABC, as a swarm intelligence optimization algorithm, gradually approaches the optimal solution through information sharing and cooperation among bees. Farahbakhsh H et al. proposed an improved ABC algorithm that combined an acceptance rejection method to limit the random search space, improve algorithm speed, and reduce iteration times. The movement step size of bees was used to determine parameters, guiding the algorithm to reach the global optimum. The superiority of the algorithm was verified in engineering problems related to virtual power plant planning and multiple benchmark function tests [6]. Huo F et al. built an optimized ABC algorithm on the basis of chaos theory Tent mapping for threshold selection in image segmentation. This algorithm constructed a complementary encoding scheme. The complementary properties were utilized to adjust local optimal solutions. The experiment demonstrated that the algorithm had strong ability to obtain the optimal solution and convergence performance [7]. Zhang L et al. built an optimized ABC based on reverse learning to address the low convergence accuracy and slow convergence speed. This algorithm introduced the bystander bee stage to accelerate convergence speed and incorporated Cauchy reverse learning in the reconnaissance stage. The superiority was verified through experiments on 13 standard tests [8]. Yilmaz Acar et al. built a binary ABC for multi-objective resource allocation problems. This algorithm combined advanced local search and binary format of transfer functions. Through experimental verification, the proposed algorithm could effectively solve resource allocation problems in large-scale problems and achieve high accuracy with fewer evaluation iterations [9].

Vehicle Routing Problem (VRP) is a crucial problem in logistics and transportation, aimed at improving transportation efficiency, reducing cost, and decreasing energy consumption by optimizing vehicle routes. Bao S et al. proposed two-phase and three-phase methods based on the Ising machine. Complex problems were divided into sub-problems and mapped to a quadratic unconstrained binary optimization model to adapt to the structure of the Ising machine. The effectiveness of this method was validated through performance comparison on datasets of standard traveling salesman problem and capacity limited VRP [10]. Sun W et al. proposed a joint routing scheduling optimization strategy on the basis of optimized grey wolf optimization. This strategy combined historical experience learning, and cross TS operators. Simulation experiments displayed that this strategy could quickly solve large-scale vehicle network scheduling problems, generate scheduling results with excellent latency performance, and effectively reduce interference between streams, further reducing end-to-end latency [11]. Lin Y et al. proposed a multi automatic guided vehicle route planning method on the ground of deep reinforcement learning. This method utilized near end strategy optimization and long short-term memory to improve adaptability in handling temporary changes and sudden failures in tasks, which considered time step information. The designed method outperformed traditional methods in terms of convergence speed, demonstrating its potential for application in dynamic environments [12]. Chen Y et al. proposed an efficient multi-layer search algorithm that considered both customer service order and vehicle charging schedule simultaneously. This algorithm quickly obtained high-quality solutions through iterative threshold search and heuristic decoupling enumeration method. Numerous computational results indicated that this algorithm outperformed the most advanced methods in solution quality and computation time [13].

Table 1: Summary of relevant information of relevant studies.

Author	Research theme	Improved method	Main indicators	Shortcoming
Farahbakhsh et al. [6]	Power plant path planning	Limiting the random search space	Traffic efficiency	Poor performance in complex environments
Huo et al. [7]	ABC algorithm optimization	Complementary coding	Convergence performance	The algorithm has a long running time
Zhang et al. [8]	ABC algorithm reverse learning optimization	Introduction of the bystander view phase	Convergence accuracy and speed	It takes a lot of data to train
Yilmaz Acar et al. [9]	Multi-target resource allocation	Combined with the transfer function binary format	Convergence performance	The parameter requirements are relatively high
Bao et al. [10]	Vehicle routing problem	Two-stage approach based on the Ising machine	Transportation cost	The vehicle loading rate is relatively low
Sun et al. [11]	Joint routing and scheduling optimization	Cross TS operator	End-to-end delay	Poor flexibility
Lin et al. [12]	Multi-automatic guide vehicle path planning	Proximal strategy optimization and long-and short-term memory	Convergence speed and robustness	The model complexity is relatively high
Chen et al. [13]	High-level multi-efficiency search	Heuristic decoupling enumeration method	Computational efficiency	The calculation accuracy is insufficient
Current study	Logistics path optimization	Elite swarm strategy	Loading rate and distribution efficiency	/

In summary, although numerous scholars have conducted extensive research on ABC algorithm and path optimization, most algorithms still exhibit problems like slow convergence speed, susceptibility to local optima, and low computational efficiency while improving path optimization capabilities. Therefore, an innovative ABC algorithm based on elite bees (EABC) is proposed to reduce the probability getting stuck in local optima and improve computational efficiency by enhancing its global and local search capabilities. It is expected to optimize logistics routes to reduce transportation cost and time, and achieve efficient operation of logistics enterprises in complex and changing practical environments.

Based on the above relevant studies, Table 1 is summarized, in which the research theme, main index methods and shortcomings of relevant studies are summarized.

2 Methods and materials

2.1 Construction of multi-factor logistics vehicle path optimization model

VRP is one of the classic combinatorial optimization problems in combinatorial optimization and operations research, mainly involving how to design the optimal path for a group of vehicles under limited vehicle resources to meet the needs of dispersed customers while minimizing the total cost. This usually includes vehicle running time, fuel consumption, distance, etc. [14]. Firstly, the schematic diagram of logistics vehicle path planning problem is shown in Figure 1.

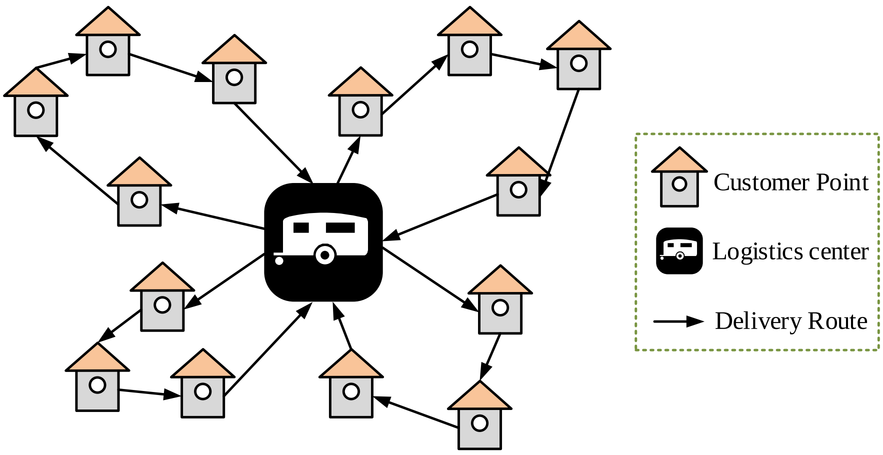


Figure 1: Flow vehicle path planning problem diagram.

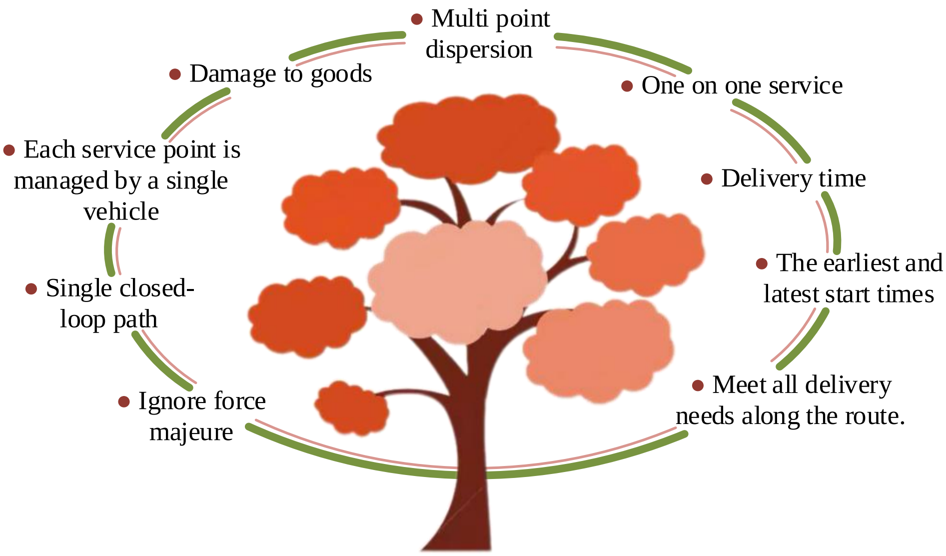


Figure 2: Optimized logistics vehicle routing model.

In Figure 1, the distribution center is located in the center, and customer points are distributed around. Arrows indicate possible delivery routes, connecting distribution centers and customer points, or connecting different customer points. The delivery vehicle departs from the distribution center, follows the planned route for delivery, and goes back to the center. The goal of delivery path planning is to find the optimal route that minimizes the total distance or optimizes delivery efficiency under other constraints [15]. In the operation process of logistics services, efficiency and cost-effectiveness are the core considerations, and timeliness directly affects customer satisfaction. Delivery cost is also the key factor in customer decision-making. Therefore, the study constructs an optimized logistics vehicle path planning model, which will reduce transportation cost and shorten delivery cycles through innovative strategies, thereby improving customer satisfaction. The main architecture and assumptions are shown in Figure 2.

In Figure 2, the basic hypothesis system is constructed for the model to enhance its applicability and logicality. Firstly, the impact of external non dominant factors such as force majeure on the transportation process is ignored. The second is to focus on optimizing a single closed-loop path. Thirdly, there may be freight loss. Fourthly, the vehicle type is consistent and there is no overloading situation, and each service point is only managed by a single vehicle. Fifthly, a flexible delivery strategy with multi-point dispersion is adopted. The sixth is to implement the principle of one-on-one service. Seventhly, the delivery time is considered. The eighth is to set the earliest and latest start time for the service. Ninth, each truck needs to choose the optimal path among numerous potential paths when performing tasks, and meet the delivery needs of all demand points on that path. The core goal is to reduce the total delivery cost and improve customer satisfaction. In the total distribution costs, it is divided into three major categories: fixed cost, transportation cost, and fuel consumption cost. In addition, considering that the cost of freight loss is directly related to the customer satisfaction, it is included in the customer satisfaction. Firstly, the fixed cost expression is shown in Equation (1).

$$F_C = \sum_{k=1}^{m} F_k Z_k \tag{1}$$

In Equation (1), F_C represents the fixed total cost. m signifies the number of vehicles. F_k signifies the fixed cost of delivering once. Z_k is the parameter, and a value of 1 indicates the execution of this delivery. Otherwise, it is not executed. Secondly, the expression for transportation cost is shown in Equation (2).

$$T_C = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} D_C D_{ijk} X_{ijk} \tag{2}$$

In Equation (2), T_C represents the total transportation cost. D_C signifies the transportation cost per unit distance. D_{ij} represents the distance metric between adjacent customers i and j on the path. X_{ijk} is the decision variable that identifies whether the identification vehicle chooses the path directly from i to node j . Finally, the fuel consumption cost is shown in Equation (3).

$$E_C = \sum_{k=1}^{m}\sum_{i=1}^{n}\sum_{j=1}^{n} X_{ijk} E_c T_{ij}^k + \sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=1}^{n} Y_{ijk} E_{c'} T_{rj}^k \tag{3}$$

In Equation (3), E_c and $E_{c'}$ respectively represent the fuel consumption per unit time during driving and the fuel consumption when the vehicle is parked at the customer point but the engine is not turned off. T_{ij}^k signifies the time from i to j . T_{rj}^k signifies the loading and unloading time of the vehicle at node j . Y_{ijk} indicates whether the vehicle is parked at customer points i and j . In addition, in customer satisfaction analysis, the cost of freight loss is linked with the time window penalty cost to comprehensively consider the overall satisfaction of customers with delivery services. Firstly, the freight loss during the driving process and loading and unloading process is shown in Equation (4).

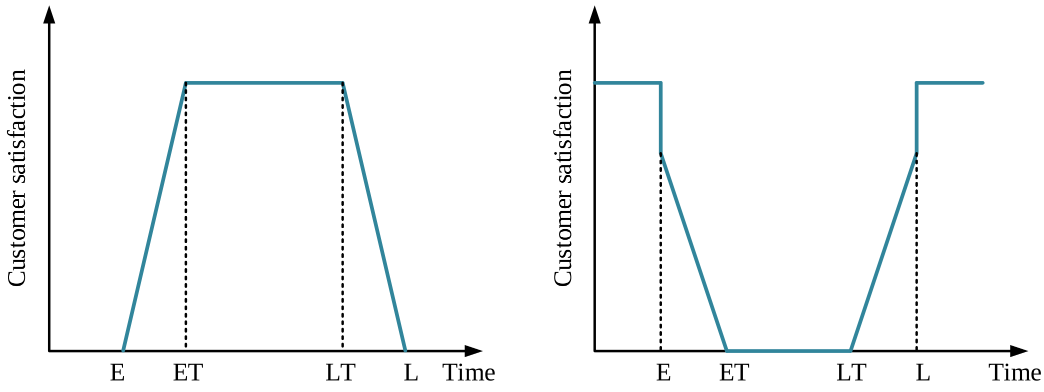
$$L_C = (v_1 - v_2)\sum_{k=1}^{m}\sum_{i=0}^{n}\sum_{j=1}^{n} Y_j^k Q_j^k (2 - e^{-\omega_1 T_{ij}^k} - e^{-\omega_2 T_{rl}^k}) \tag{4}$$

In Equation (4), Y_j^k represents whether to load or unload at j . Q_j^k represents the remaining quantity of goods after the vehicle arrives at customer point i . ω_1 and ω_2 respectively represent the unit time freight loss coefficients during vehicle operation and unloading. v_1 and v_2 respectively represent the unit price and insured unit price of the product. Secondly, in the construction of time window penalty cost, the relationship between vehicle arrival time, time window penalty cost, and customer satisfaction will be quantified. In large-scale distribution, the vehicle's load gradually decreases as the distribution distance grows, and fuel consumption decreases. Delivering within the time window agreed upon with the customer results in the highest customer satisfaction and no time penalty cost. Whereas delivering both before and after the time window affects customer satisfaction, which triggers a penalty cost, the closer the time window the higher the customer satisfaction and the lower the penalty cost. The customer satisfaction and penalty cost curves at different arrival times are shown in Figure 3.

Figure 3 (a) shows the relationship between customer satisfaction and vehicle arrival time. Figure 3 (b) shows the relationship between penalty cost curve and vehicle arrival time. In Figure 3 (a), $[E, ET]$ and $[LT, L]$ respectively represent the earliest arrival time range and latest arrival limit that the customer can accept. $[ET, LT]$ represents the expected arrival time range of the customer, which is the core time period agreed upon by both parties. In Figure 3 (b), customer satisfaction reaches its peak at point $[ET, LT]$, while the cost of violation penalties is the lowest. As the arrival time of the vehicle gradually approaches ET within $[E, ET]$, although satisfaction remains at a high level, the cost of violation penalties tends to decrease. On the contrary, within the $[LT, L]$ interval, as the arrival time of vehicles is delayed, customer satisfaction gradually decreases and the cost of violation penalties increases. The two extreme ranges of $[-\infty, E)$ and $(L, +\infty]$ are far from the customer acceptance range, so they are set to trigger infinite penalty cost. The customer satisfaction is zero. Therefore, based on the above calculations, taking into account cost, freight loss, customer satisfaction, and time cost, the minimum transportation cost is the ultimate goal of the model, as shown in Equation (5).

$$MINA_C = w_1 F_C + w_2 T_C + w_3 E_C + w_4 L_C + w_5 P_C \tag{5}$$

In Equation (5), F_C, T_C, E_C, L_C, and P_C respectively represent fixed cost, transportation cost, fuel consumption cost, cargo freight loss, and penalty cost incurred due to exceeding the time window. w_1, w_2, w_3, w_4 and w_5 represent the weight coefficients of the above five factors, respectively.



(a) Relationship between customer satisfaction and vehicle arrival time

(b) Relationship between penalty curve and vehicle arrival time

Figure 3: Relationship between customer satisfaction, penalty cost and arrival time.

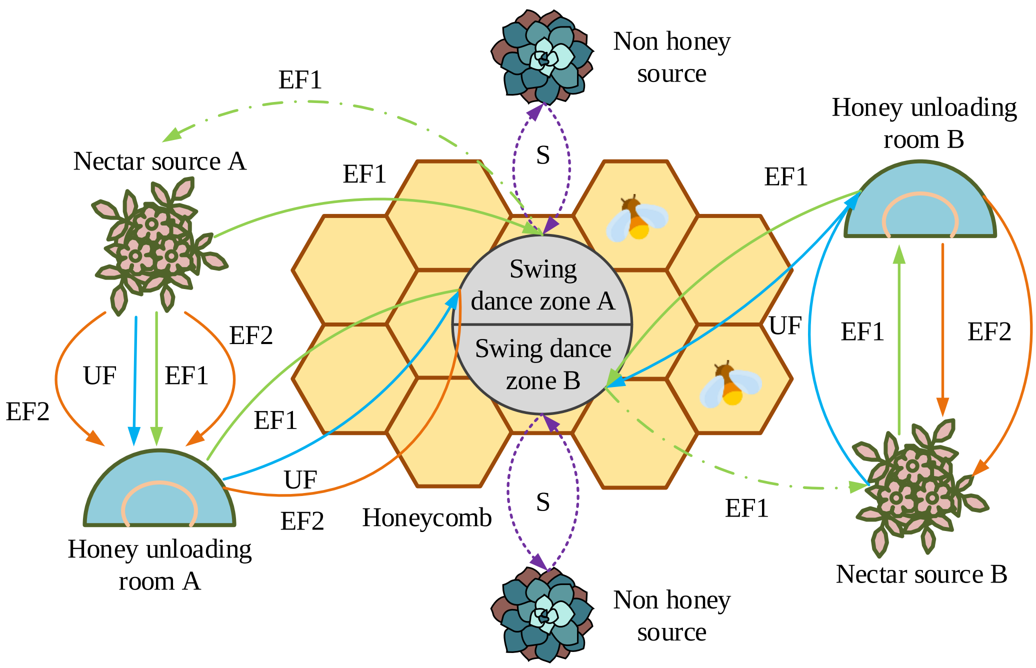


Figure 4: Bee collecting honey process.

2.2 Design of path planning model based on improved ABC

After constructing the objective function and constraint conditions of the multi-factor logistics path planning model, further optimization solutions for logistics paths will be designed. The ABC is to simulate the swarm intelligence behavior of bees in searching for nectar. The optimal solution is searched by simulating the foraging and information exchange process of bees. The optimization problem is solved by the cooperation of three bees: worker bees, observation bees, and reconnaissance bees [16]. The honey harvesting process is shown in Figure 4.

As shown in Figure 4, after completing the honey collection task of honey source B, the worker bees will go to the honey unloading area B to unload the obtained nectar. At this moment, worker bees face three choices. Firstly, if it is assessed that the resources of honey source B have been depleted, the worker bees will transform into reconnaissance bees and immediately explore new honey source locations, namely the route UF to S. Secondly, worker bees go directly to the swing dance area and perform a specific "swing dance" to convey information about honey source B to surrounding observation bees, aiming to attract them to the honey source, namely, the route EF1. Thirdly, the worker bees return to honey source B to continue their honey harvesting operation, i.e. route EF2. Under the ABC algorithm framework, each nectar source point in the solution space is mapped to a potential optimized solution, and the abundance of nectar contained within it is used as an indicator of fitness, reflecting the quality of the corresponding solution. Furthermore, the implementation process of ABC is shown in Figure 5.

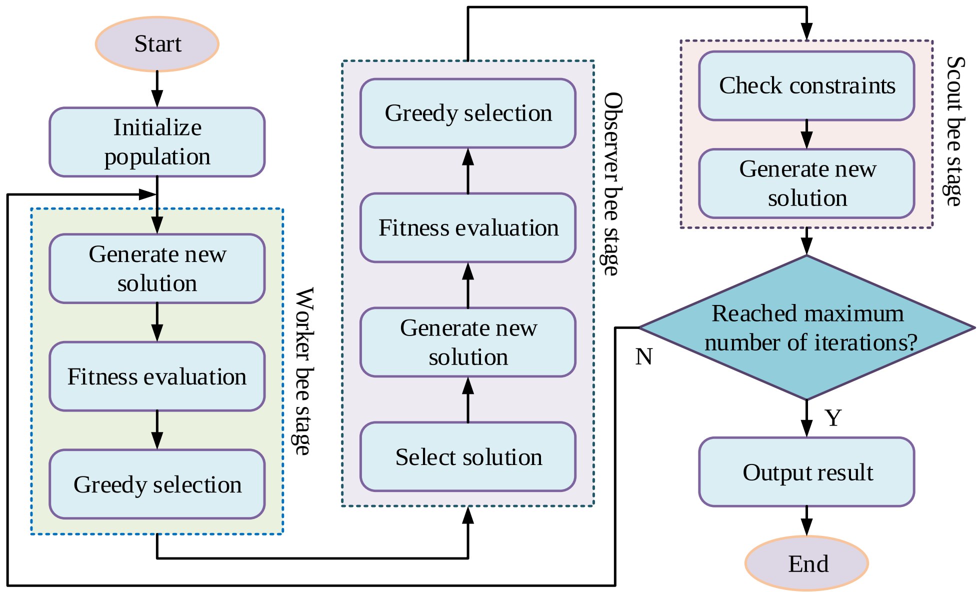


Figure 5: ABC algorithm implementation flow chart.

As shown in Figure 5, the first is to generate an initial population and evaluate the fitness values of each initial solution. Secondly, in the worker bee stage, there are three steps: searching for new solutions, evaluating new solutions, and selecting new solutions. If the fitness value outperforms the current solution, the current solution will be updated to the new solution. Otherwise, it will remain unchanged. During the bee observation phase, the probability of each solution being selected is calculated and a local search is carried out on the solution to generate a new solution and calculate its fitness. If the fitness value outperforms the current solution, it will be updated. Otherwise, it will remain unchanged. In the reconnaissance bee stage, if a solution does not improve after multiple updates, it is considered to be in a stagnant state, and the reconnaissance bee will randomly produce a new solution to replace the stagnant solution. In each iteration, the currently found global optimal solution is updated and recorded. If the maximum iteration is satisfied at this point, the iteration is stopped and the result is output. The initial solution is shown in Equation (6) [17].

$$x_{ij} = lb + rand * (ub - lb) \tag{6}$$

In Equation (6), x_{ij} represents the solution of the current worker bee. i is the honey source. j is the dimension. $rand$ represents a random number. ub and lb respectively represent the upper and lower limits of the honey source search range. Subsequently, during the worker bee stage, the calculation for searching for new honey sources is shown in Equation (7) [18].

$$v_{ij} = x_{ij} + \phi * (x_{ij} - x_{kj}) \tag{7}$$

In Equation (7), x_{kj} represents a randomly selected neighbor solution of x_{ij}. φ is a random number. After evaluating the adaptability of the new honey source, according to the principle of greedy selection, the newly discovered one is compared with the current honey source. If the adaptability of the new outperforms the existing honey source, it is updated and replaced. The probability calculation of hiring bees being selected is shown in Equation (8).

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{8}$$

In Equation (8), SN signifies the honey sources.

P_i represents the probability of hiring bees being selected. fit_i represents the fitness where the hired bees are located. However, in traditional ABC algorithms, there are drawbacks such as slow convergence speed and insufficient local search ability. At the same time, in response to the constraints of logistics vehicle path planning, the elite individual search and parameter set strategies are introduced to enhance the search efficiency. In the process of selecting elite bees, it is necessary to ensure that there is a moderate gap between them to avoid redundancy. Secondly, the fitness of elite bees needs to be closely aligned with the currently calculated optimal solution, in order to effectively expand the range of high-quality candidates. Firstly, the number of elite bee individuals is shown in Equation (9).

$$rn = \frac{pr}{100} \times N \tag{9}$$

In Equation (9), rn signifies the elite bee. pr signifies the ratio of elite individuals to all individuals in the population. N represents the total number of individuals in the population. The separation distance between elite bees depends on the specific setting of the radius parameter, which has a direct impact on the size of the elite bee population. If the set radius value is too large, it will lead to a reduction in the number of members in the elite bee set, which may miss many potential local optimal solutions. Therefore, the radius parameter calculation for the distance between elite bees is shown in Equation (10).

$$raduis = (x_j^u - x_j^l) * r \tag{10}$$

In Equation (10), x_j^u signifies the upper limit of the search space, and x_j^l signifies its lower limit. $r \in [0,1]$ is a proportional parameter. The population size of the elite bees is selected through adaptive parameters, and in the early stage of the algorithm operation, the number of elite bees is high, focusing on a wide range of search and determining the approximate range of the nectar source. As the number of iterations increases, the number of elite bees is scaled down, focusing on improving the search accuracy of the optimal solution. This can help to conduct a fast search in the early stage, and reduce the consumption of resources and improve the search accuracy in the later stage. The next step is the hiring bee stage. As the research has established an elite bee colony, two random elite bees are used for search to accelerate the convergence speed, as displayed in Equation (11).

$$x'_{i,j} = s_{r,j} + rand(-a,a)(x_{i,j} - x_{r,j}) \tag{11}$$

In Equation (11), $s_{r,j}$ and $x_{r,j}$ respectively represent the coordinates of the elite bees randomly selected from the elite bee list in the j-th dimension, and the corresponding value of variable a in that dimension. $rand(-a,a)$ is a random parameter. A specific probability selection mechanism is introduced in elite bees, where individuals are assigned probability values to dominate the selection process. The probability calculation is shown in Equation (12).

$$P_i = \frac{1}{1+f(S_i)} \Bigg/ \sum_i^{S_{size}} \frac{1}{1+f(S_n)} \tag{12}$$

In Equation (12), S_{size} represents the size of the elite bee population. $f(S_i)$ and $f(S_n)$ represent the fitness of the first and n-th elite bees, respectively. Subsequently, each scout bee follows the probability selection criterion to select a specific solution from the elite bee list for exploration, and generates a series of new candidate solutions around each selected elite bee individual. The expression is shown in Equation (13).

$$s'_{i,j} = s_{r,j} + rand(-a,a)(x_{r_1,j} - x_{r_2,j}) \tag{13}$$

In Equation (13), $x_{r_1,j}$ and $x_{r_2,j}$ represent the corresponding values of two different solutions. $s'_{i,j}$ represents the generated new value. Therefore, based on the above calculations, the EABC process is shown in Figure 6.

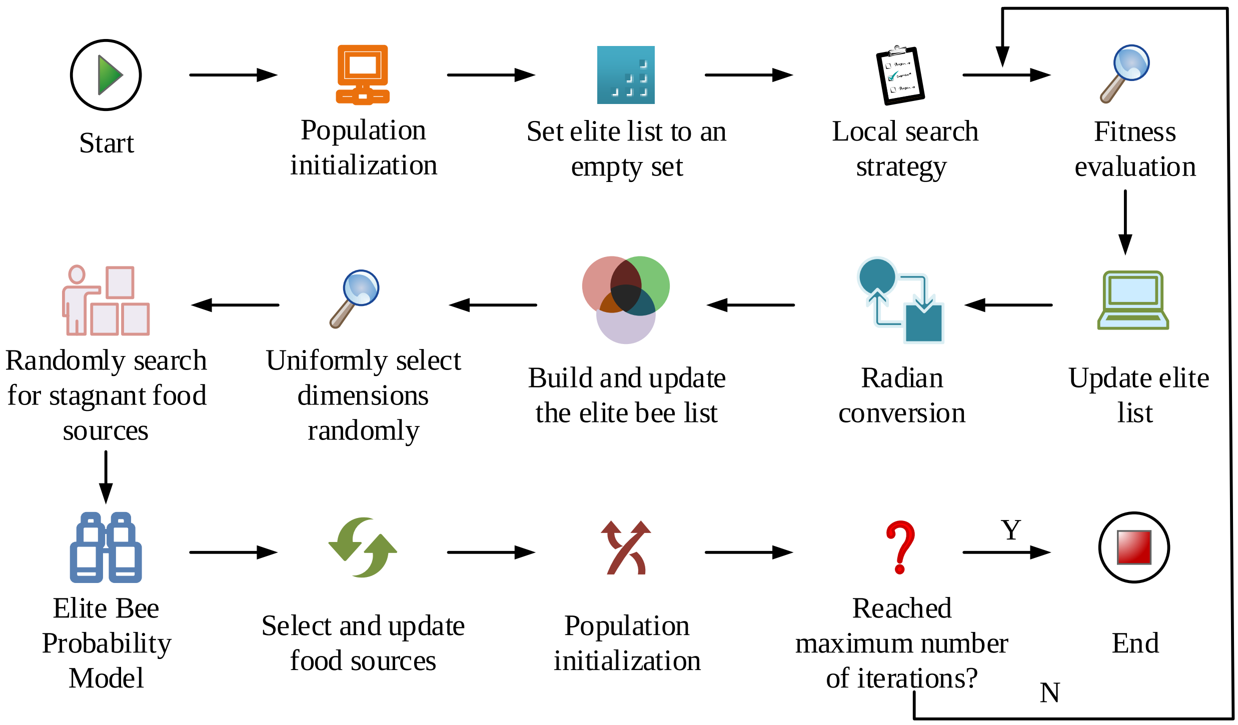


Figure 6: The process of EABC.

EABC first randomly generates an initial population and sets an elite bee list S. A local search strategy is applied to optimize the initial population, and then enter the loop iteration stage. Based on fitness values, the population is sorted. Then the elite bee list is constructed and updated. In the hiring bee step, the dimension is randomly selected for search, and new fitness values are calculated to update the elite bee list. The reconnaissance bee step randomly searches for stagnant food sources to prevent falling into local optima. Subsequently, the elite bee probability model is used to select reference scholars and apply search equations. The food sources are selected and updated in the bee observation step, and useless elite bees are deleted. When the maximum iteration is satisfied, the iteration is terminated and the optimal solution is output.

3 Results

To exhibit the performance of the designed model based on the EABC model, a series of tests were conducted on EABC first. In the second section, simulation tests were conducted on the logistics vehicle path planning model based on EABC to verify the practical application effect of the model.

3.1 Performance testing of improved EABC algorithm

The study used Windows 10 as the operating system, Intel Core i7 CPU, NVIDIA GeForce GPU, 64GB of memory, and Matlab. Firstly, the EABC algorithm was tested on several benchmark functions to assess the effectiveness of the improved ABC. ABC, Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) were used as comparative algorithms. In the experiment, the maximum iteration was 1000, the number of bee colonies was 30, and the dimension was 20. In both unimodal and multimodal function tests, each set of tests was repeated 10 times and averaged. In the results of both test functions, there was a significant difference (P<0.05).

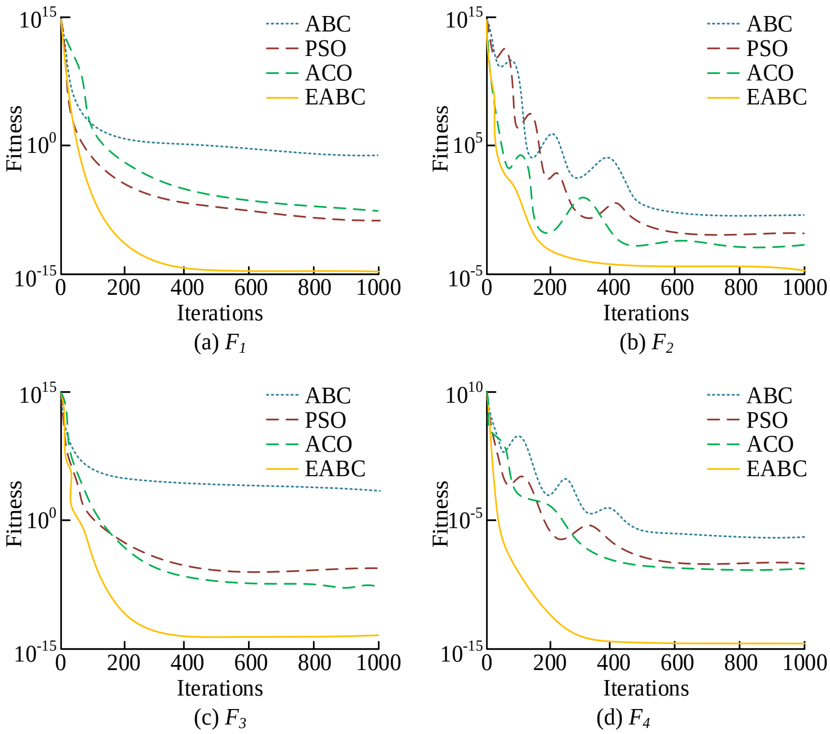


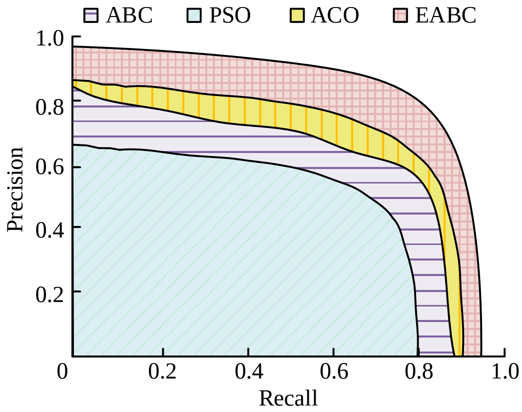
Figure 7: Convergence curves of each algorithm.

Table 2: Mean and standard deviation results.

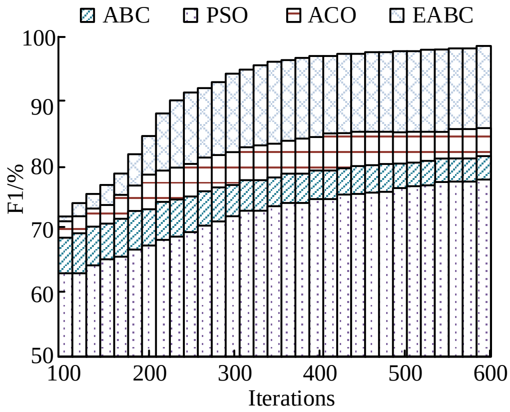
Function			**Index**	**ABC**	**PSO**	**ACO**	**EABC**
Unimodal function	Sphere	F_1	Avg	8.17e-12	7.75e-14	2.75e-15	2.75e-20
			Std	2.78e-12	3.61e-14	4.85e-15	6.51e-20
	Rosenbrock	F_2	Avg	8.22e-14	7.34e-17	2.84e-18	2.64e-21
			Std	2.52e-14	3.23e-18	6.54e-18	6.41e-21
Multimodal function	Rastrigin	F_3	Avg	6.55e-11	6.41e-10	2.57e-13	2.45e-16
			Std	2.93e-11	2.95e-10	4.28e-13	5.49e-16
	Griewank	F_4	Avg	8.79e-12	6.84e-12	5.74e-15	3.61e-19
			Std	7.55e-12	5.22e-12	3.87e-15	9.45e-19

Table 2 shows the optimized mean and standard deviation of ABC, PSO, ACO, and EABC algorithms running 100 times on the uni-modal functions Sphere and Rosenbrock, as well as on the multimodal functions Rastrigin and Griebank. The EABC algorithm achieved optimal optimization mean and standard deviation on both unimodal and multimodal benchmark functions. Compared with the traditional ABC algorithm, it had made progress. To further quantify the impact of the introduced elite bee colony strategy on convergence speed, the convergence curves of the four models on different benchmark test functions are shown in Figure 7.

Figures 7 (a), 7 (b), 7 (c), and 7 (d) show the convergence curves of four algorithms tested on F_1, F_2, F_3, and F_4, respectively. In Figure 7 (a) and Figure 7 (b), the EABC had the optimal convergence speed and fitness values on the two uni-modal benchmark test functions F_1 and F_2, reaching convergence after 425 and 381 iterations, respectively. On the benchmark functions F_3 and F_4 in Figure 7 (c) and Figure 7 (d), the EABC algorithm achieved convergence at the 409th and 361st iterations, respectively, confirming the feasibility of introducing elite bee colonies to improve convergence speed. Finally, the study introduced the VRPTW dataset, which was used to address the time window constraints added in vehicle path optimization problems. It was commonly used to test the performance of various vehicle path optimization algorithms. The Precision Recall (PR) curves and F1 values of each algorithm on the dataset are shown in Figure 8.

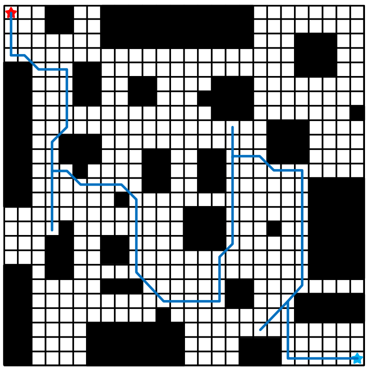


(a) PR curves test

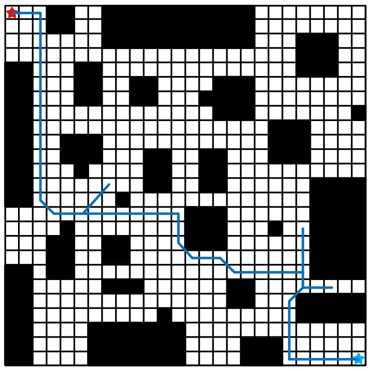


(b) F1 value test

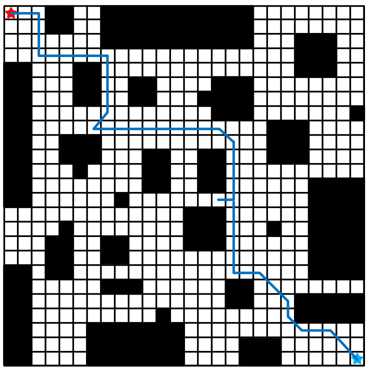
Figure 8: PR curve and F1 value results.



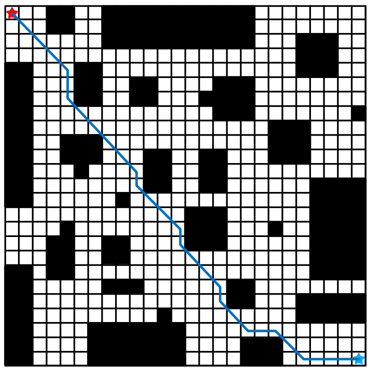
(a) ABC



(b) PSO



(c) ACO



(d) EABC

Figure 9: Paths of various algorithms in simple environment.

Figures 8 (a) and 8 (b) display the PR curves and F1 value test results of four algorithms on the dataset, respectively. In Figure 8 (a), the area enclosed by the PR curve and coordinate axis of ABC, PSO, ACO, and EABC algorithms was 0.84, 0.68, 0.87, and 0.96, respectively. In Figure 8 (b), as the number of iterations increased, the F1 values of each algorithm showed a gradual upward trend in the early stages and tended to stabilize in the later stages. When the number of iterations was 600, the F1 values of each algorithm were 82.4%, 78.2%, 86.5%, and 97.7%, respectively. The EABC had good comprehensive performance.

3.2 Simulation testing of logistics path planning based on EABC

On the basis of verifying the performance of EABC algorithm, the research further tested the practical application effect of logistics vehicle path planning based on EABC. Firstly, the path search simulation experiments of ABC, PSO, ACO, and EABC algorithms in a simple planar environment are displayed in Figure 9.

Figures 9 (a), 9 (b), 9 (c), and 9 (d) display the path search results of ABC, PSO, ACO, and EABC algorithms in a simple two-dimensional environment, respectively. In Figure 9 (a), the ABC algorithm generated 27 inflection points and showed 3 local optima. Because in the honey source update stage of the ABC algorithm, the variation in location between the current honey source and other randomly selected honey sources can easily lead to getting stuck in local optima, resulting in the inability to exit the current search area. In Figure 9 (b), the PSO algorithm generated 18 turning nodes and fell into local optima 3 times. In Figure 9 (c), the ACO algorithm generated 16 turning nodes, which were trapped in local optima twice. In Figure 9 (d), EABC only had 11 inflection points and not trapped into a local optimal solution. From this, the improved EABC had good convergence accuracy and speed, which could achieve excellent optimization efficiency in path optimization simulation testing. Subsequently, Matlab was used to simulate and model the logistics distribution points, namely customer locations, including 1 distribution center and 20 customer points to be delivered, with a total of 6 vehicles. All four models underwent 10 simulation experiments, and the optimal delivery path obtained is shown in Figure 10.

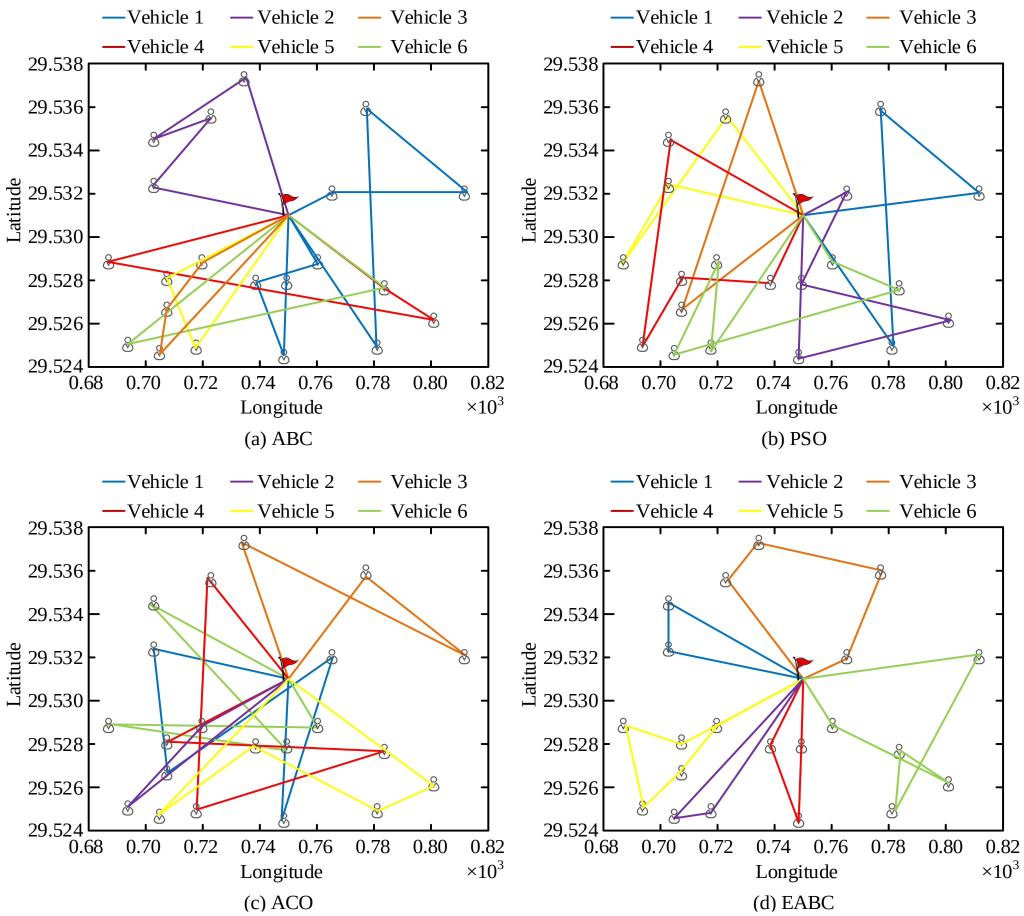


Figure 10: Optimal path planning diagrams for different algorithms.

Figures 10 (a), 10 (b), 10 (c), and 10 (d) display the optimal path planning diagrams obtained from 10 simulation experiments for the ABC, PSO, ACO, and EABC models, respectively. The red flag represents the logistics distribution center, and the user icon represents the delivery point. There were many invalid turns and repeated paths in Figures 10 (a), 10 (b), and 10 (c). The EABC had the least number of invalid turns and short repeated paths, resulting in the best path planning results. To further quantify the results, the various costs of each model in the above path planning are displayed in Table 3.

Table 3: Multi indicator test results.

Model	**Index**						
	Total route length/km	**Average load rate/%**	**Fuel cost/¥**	**Freight loss cost/¥**	**Time delay cost/¥**	**Total delivery cost/¥**	**Calculation time/s**
ABC	5512.93	84.5	2483.30	22051.72	1339.64	88146.24	20.2
ACO	5381.56	85.3	2424.13	22423.17	1318.48	90141.13	18.9
PSO	5624.35	92.8	2533.49	20908.36	1282.35	85377.63	22.4
EABC	5221.43	97.4	2341.45	20719.96	1268.81	83908.38	2.8

Table 4: Compares the time complexity of the three algorithms.

Sample size	Model type	Average processing time (ms)	Standard deviation (ms)	Time complexity $O(n^2)$ evaluation
1000	EABC	21.4	2.0	Lower
	ABC	20.8	2.6	Lower
	ACO	31.5	3.4	Normal
2000	EABC	78.5	5.2	Lower
	ABC	75.6	7.8	Lower
	ACO	107.4	10.2	Normal
3000	EABC	177.8	8.3	Lower
	ABC	176.2	9.1	Lower
	ACO	357.6	12.5	Higher

Table 5: Sensitivity of different algorithms for analysis.

Number of distribution points	Arithmetic	Load factor/%	Total cost/¥	Route planning time/s
20	EABC	97.4	83908.38	2.8
	ABC	84.5	88146.24	20.2
	ACO	85.3	90141.13	18.9
40	EABC	95.3	146503.21	3.1
	ABC	80.2	185724.18	35.3
	ACO	81.5	209516.54	22.5
60	EABC	94.6	197892.15	5.2
	ABC	79.2	253815.96	60.3
	ACO	80.1	286575.56	51.6

Table 3 displays the path length, loading rate, fuel consumption cost, freight loss cost, time window penalty cost, delivery cost, and solution time of each optimal path. As shown in the table, compared with traditional ABC and other comparative models, the logistics vehicle path planning based on EABC had significant advantages in path length, loading rate, and various costs. The vehicle loading rates for the optimal paths of ABC, PSO, ACO, and EABC models were 84.5%, 85.3%, 92.8%, and 97.4%, respectively. In terms of running time, the solution time for the four models was 20.2s, 18.9s, 22.4s, and 2.8s, respectively. In order to analyze the computational complexity of the EABC algorithm and the comparison algorithm, the time required by the two algorithms to process the same amount of data under the same hardware conditions was measured experimentally. The results of the time complexity comparison of the three algorithms are shown in Table 4.

In Table 4, when the sample size was 1000, 2000 and 3000, the average processing time of the EABC algorithm was 21.4ms, 78.5ms and 177.8ms respectively, which was only slightly higher than that of the benchmark algorithm ABC, and much lower than that of the ACO algorithm. The standard deviation of EABC algorithm was the minimum value, and the processing time of the algorithm was the most stable. The results showed that the EABC algorithm had lower computational complexity and higher computational efficiency, and with the increase of the number of samples, the growth rate of time complexity $O(n^2)$ was much lower than that of the ACO algorithm. For the complexity and variability of the logistics and distribution environment, the study analyzed the sensitivity of different algorithms, and a comparison of the results is shown in Table 5.

In Table 5, as the number of distribution points increased, the vehicle load factor of each algorithm was gradually decreasing, and the total distribution cost and route planning time were gradually increasing. However, the load factor of the EABC algorithm decreased more slowly than the ABC and ACO algorithms, and the load factor of the three algorithms decreased by 2.8%, 5.3%, and 5.2%, respectively, when the number of distribution points was 60. The total cost of the three algorithms increased by ¥113,983.77, ¥165,669.72, and ¥196,434.43, and the path planning time improved by 2.4s, 40.1s, and

32.7s, respectively.

4 Discussion

Aiming at the existing logistics distribution path optimization methods, the problems of long distribution path, high distribution cost and insufficient vehicle loading rate, the study proposed an elite bee colony algorithm to optimize the logistics distribution path. The experimental results showed that the EABC algorithm reached convergence at 400 iterations in both single-mode and multi-mode benchmark test functions, and the convergence speeds were better than other algorithms, and the optimal fitness values obtained were around 10-15.In the test functions, the ABC, PSO and ACO algorithms reached convergence at 500, 600 and 800 iterations, respectively.The EABC algorithm achieved the convergence at 500, 600 and 800 iterations, respectively.The EABC algorithm, through the hiring bees stage in the The EABC algorithm had fewer inflection points as it used two different searches to obtain different solutions, and the higher value of adaptation was used as a candidate solution to reduce the generation of local optimal solutions. The population size of the elite bees was selected through adaptive parameters, and in the early stages of the algorithm's operation, the number of elite bees was higher, focusing on extensive search and determining the approximate range of nectar sources. As the number of iterations increased, the number of elite bees decreased and the focus was on improving the search accuracy of the optimal solution. This helped to perform fast search at early stages and reduce resource consumption and improve search accuracy at later stages. The proposed EABC algorithm was not only used for path optimization in logistics and distribution, but also in the field of takeaway delivery with similar attributes, urban services such as street cleaning and garbage collection, and in traffic management and emergency rescue, etc., which could improve the efficiency and reduce the cost of work.The EABC algorithm could still fall into local optimal solutions when the performance of the test set was poor, and subsequently, it could be added to the algorithm with a forbidden search strategy could be added to the algorithm to store the local extremes in the taboo table to further avoid local optimal solutions.

5 Conclusion

Traditional logistics path optimization methods typically only consider fixed transportation needs and paths, without taking into account other potential transportation cost. The study introduced the elite bee colony mechanism to enhance the global and local search capabilities of ABC. A logistics vehicle path optimization model was constructed based on EABC. The performance test results showed that EABC achieved the optimal optimized mean and standard deviation on both uni-modal and multi-modal benchmark functions. On the convergence curve, EABC had lower fitness than other algorithms, with the best convergence speed and accuracy. The area enclosed by its PR curve and coordinate axis was 0.96, and the F1 value at 600 iterations was 97.7%. In a simple two-dimensional environment experiment, the inflection point generated by the EABC optimal path was only 11, and the number of times it fell into a local optimal solution was 0. In the optimal path test of 20 customer points, the total path length of EABC was 5221.43km, the total delivery cost was 83908.38 yuan, the vehicle loading rate was 97.4%, and the solution time was 2.8s. From this, he logistics path intelligent optimization model based on EABC has shown significant advantages in improving logistics efficiency and reducing transportation cost, which has broad application prospects. EABC algorithms are not only applied to logistics and distribution, but also in the field of takeaway delivery with similar attributes, and can be applied to urban services, such as street cleaning and garbage collection, etc., as well as in traffic management to reduce congestion and improve the efficiency of road use. In the future, more influencing factors still need to be considered. Further in-depth research is necessary in large-scale practical applications and algorithm optimization to achieve more efficient and practical logistics path optimization solutions.

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