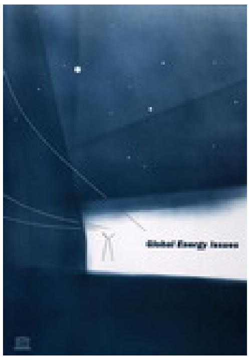

International Journal of Global Energy Issues

ISSN online: 1741-5128 - ISSN print: 0954-7118
https://www.inderscience.com/ijgei

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DOI: 10.1504/IJGEI.2023.10056904

Article History:

Received:	30 December 2021
Last revised:	21 February 2022
Accepted:	27 September 2022
Published online:	03 December 2023

Modelling of optimal transportation route selection based on artificial bee colony algorithm

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Abstract: Optimising enterprise management and reducing logistics costs have become the common focus of Chinese logistics companies. This study mainly discusses the modelling of optimal transportation route selection based on artificial bee colony algorithm. In this paper, the designed bee colony algorithm is used to solve the cross-dock vehicle scheduling part in the mathematical model, and the cross-dock gate allocation and vehicle parking sequence scheduling schemes are obtained. Then, the scheduling scheme is used as the known condition of the path optimisation part, and the vehicle transportation path is optimised by using the bee colony algorithm, and the total cost is minimised in the process of mutual iteration. The research results show that the proportion of leading bees is 70% when the best calculated average value is obtained, and 90% when the variance of the calculated results is the smallest.

Keywords: artificial bee colony algorithm; transportation mode; optimal path; selection modelling.

Reference to this paper should be made as follows: Liu, H., Zhang, P. and Wu, H. (2024) 'Modelling of optimal transportation route selection based on artificial bee colony algorithm', *Int. J. Global Energy Issues*, Vol. 46, Nos. 1/2, pp.90–111.

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1 Introduction

At present, the cost of logistics transportation is relatively high, and the timeliness requirements for the transportation of goods are also high. How to improve the efficiency of cargo distribution and reduce the cost of logistics transportation is an urgent problem to be dealt with at present. The purpose of this paper is to find a reasonable cost calculation model of the distribution path after studying the problems existing in the current cargo distribution process, and design and optimise the corresponding logistics vehicle distribution path. Under the influence of the rapid development of the global economy and the rapid progress of modern technology, the logistics sector as a new type of industry is also quietly expanding its development to internationalisation. Among them, a topic that has attracted international attention is always to reduce the total cost of logistics and distribution.

The establishment of a mathematical model for the optimisation of the enterprise's cargo distribution route has a wide range of research prospects and application values in the application of the distribution process in theory and practice. It can improve the efficiency and benefit of logistics distribution of enterprises, and provide good technical support for the development of enterprises under the new situation. It uses a fixed formula to calculate the value of savings between the stores that need to be delivered, and sorts the value of savings in descending order. It adds stores to the delivery route in turn, until all stores are arranged and finally an optimised delivery route is obtained.

The vehicle routing problem defines a type of combinatorial optimisation problem, which is used to optimise the travel route of vehicles that travel multiple times. Only by sorting the saving value to get the distribution route, it is easy to have the route crossing.

Moreover, the algorithm actually considers fewer influencing factors, and does not comprehensively consider the problem of vehicle loading. Whether it has time to constrain the delivery of vehicles and whether the delivery tasks are single, whether the delivery vehicles should be returned to the distribution centre or the weather emergencies and other practical issues. Gao et al. (2017) believed that inspired by the fact that division of labour and cooperation has played an extremely important role in the development of human history, he developed a new artificial bee colony algorithm based on information learning (ILABC for short). In ILABC, each generation divides the entire population into several sub-populations through clustering. It also dynamically adjusts the size of the subpopulation based on the last search experience, with a clear division of labour. In addition, these two search mechanisms are designed to facilitate the exchange of information in each sub-group and between different sub-groups as cooperation. Finally, the comparison results of many benchmark functions show that compared with the most advanced algorithms selected, the method he proposed is competitive and effective (Gao et al., 2017). Horng (2017) believed that the Stochastic Economic Batch Scheduling Problem (SELSP) considers the production of multiple standardised products in inventory on a single machine with limited capacity and set-up costs under random demand, random setup time and random production time. SELSP is an NP-hard inventory problem, and SELSP's current solutions can be classified as analytical or heuristic. However, in these two methods, the calculation time required to obtain the optimal solution is still not satisfactory. In his research, SELSP was first formulated as a Fixed Sequence Base Oil (FSBS) system with a limited batch strategy. Then, he proposed an algorithm that combines the Artificial Bee Colony (ABC) method and the Ordinal Optimisation (OO) theory, abbreviated as ABCOO. This allows reasonable calculation time to find a good enough base oil level for the FSBS system. The algorithm he proposed combines the advantages of multi-directional search in ABC and the advantages of target softening in OO. Finally, he used the ABCOO algorithm to solve a SELSP involving 12 products and three queuing models (Horng, 2017). Gu et al. (2017) believed that parameter estimation of fractional-order chaotic systems is an important issue in non-linear science, which has attracted more and more attention in recent years. He transformed parameter estimation into a multi-dimensional optimisation problem, and proposed a new solution based on the Artificial Bee Colony (ABC) algorithm to solve the optimisation problem. And he ordered a chaotic system to verify the effectiveness of the proposed method (Gu et al., 2017). Ding et al. (2017) proposed a new Artificial Bee Colony algorithm with Dynamic Population (ABC-DP), which cooperates with the idea of extending the life cycle evolution model to balance the trade-off between exploration and development. The ABC-DP he proposed is a model that is more in line with the reality of the bee colony, in which bees can dynamically reproduce and die during the entire foraging process, and the population size changes with the operation of the algorithm. Then, he uses ABC-DP to solve the Optimal Power Flow (OPF) problem in the power system, which treats cost, loss and emission effects as objective functions. He proposed a 30-bus IEEE test system to illustrate the application of the proposed algorithm. His simulation results are also compared with Non-dominated Sorting Genetic Algorithm II (NSGAII) and Multi-Objective ABC (MOABC) to illustrate the effectiveness and robustness of the proposed algorithm (Ding et al., 2017). Guo and Zhang (2017) believed that with increasing attention to waste collection and recycling, Reverse Logistics (RL) has become a hot topic in research and business. Since the Location and Routing Problem (LRP) in RL is a NP-complete heuristic algorithm, especially those based on swarm intelligence, it is very popular in his research. In his research, RL's vehicle Routing Problem (RP) and Location Allocation Problem (LAP) are both considered as a whole. First, he analysed the characteristics of LRP in RL; second, he established a mathematical model of the problem; then, he proposed a new discrete Artificial Bee Colony (ABC) algorithm with greedy adjustment. Experimental results show that the new algorithm can efficiently and effectively approximate the optimal solution (Guo and Zhang, 2017). Zhong et al. (2017) believed that human learning optimisation is a simple and effective meta-heuristic algorithm, in which three learning operators are developed. That is, random learning operators, individual learning operators and social learning operators can effectively search for optimal solutions by imitating human learning mechanisms. He used a set of Gaussian parameter values instead of a constant to diversify the learning ability of DHLO and enhance the robustness of the algorithm (Zhong et al., 2017). As an important part of logistics operation, logistics distribution plays a pivotal role in the entire logistics process. To some extent, the level of logistics distribution also determines the level of development of the logistics industry. However, there are many problems in the process of logistics distribution, such as unreasonable transportation routes and high-empty load rate. Logistics distribution is an important part of logistics cost, and the level of distribution cost determines the survival of logistics enterprises. Therefore, effectively improving the quality and efficiency of transportation and reducing the distribution cost of enterprises are important ways to promote the development of the logistics industry. The driving process of road transport vehicles can be divided into load trip and idling trip according to their carrying conditions, and the idling trip can include empty trip and no-load trip. The emptying trip mainly refers to the trip of the vehicle from the parking lot to the loading location, or from the last unloading location back to the parking lot. No-load trip refers to the trip of the vehicle from the unloading location to the next loading location during transportation operations. The ratio of the vehicle's load travel to the total travel is called the vehicle travel utilisation rate, which is one of the important factors that affect the vehicle utilisation efficiency. The idling journey of a vehicle is entirely a consumable production process. The less the idling journey of a vehicle, the higher the utilisation efficiency of the vehicle and the lower the transportation cost. Therefore, in the transportation and production process, scientific and reasonable organisation must be carried out to reduce the empty travel distance of vehicles and improve the efficiency of vehicle utilisation.

This article analyses and summarises the current research status of cross-docking vehicle routing, cross-docking vehicle scheduling and bee colony algorithm at home and abroad. As well as the description of the cross-docking vehicle scheduling problem, route optimisation problem and bee colony algorithm, on this basis, it is proposed to pass the cargo as the main object. Based on the connection between the inbound and outbound trucks, the inbound and outbound warehouse doors and customers, an integrated scheduling model for cross-docking vehicle scheduling and route optimisation is established. This turns the actual cross-docking problem into a mathematical problem of combinatorial optimisation. Then, according to the characteristics of the research problem, design the bee colony algorithm, genetic algorithm and improved bee colony algorithm to solve the model. The basic idea of applying ant colony algorithm to solving optimisation problems is: use the walking path of ants to represent the feasible solution of the problem to be optimised. All paths of the entire ant colony constitute the solution space of the problem to be optimised, and ants with shorter paths release more pheromone. As time progresses, the accumulated pheromone concentration on the shorter path gradually increases, and the number of ants choosing this path increases. In the end, the entire ant will be concentrated on the best path under the effect of positive feedback, at this time the corresponding is the optimal solution of the problem to be optimised.

2 Modelling research methods for the selection of optimal transportation routes

2.1 Modelling of urban road network

At present, urban roads are composed of various intricate trunk roads, auxiliary roads, branch roads and so on. Whether the vehicle is running smoothly in the traffic network reflects the operating efficiency of the entire urban traffic network. In route guidance planning, it is a common and effective method to use graph theory to model the entire traffic network.

1) *Abstract modelling of urban road network*: In specific problems, we can abstract the traffic road network into diagrams of different structures according to the needs of the problem. To solve the specific problem of urban logistics and distribution, we construct the urban traffic road network into an undirected weighted graph (Badem et al., 2017).

$$G = (V, R) \tag{1}$$

Among them, V is the set of road intersections, and R is the set of road sections between two intersections. In the figure, we often mark the length of the road section, the average time to pass the road section and other indicators, which are the cost value of the edge.

2) *Marking of the substitute value of road sections*: Planning the optimal path can be understood as the optimal cost of the planning path. The focus of choosing the weight is different, and the final result will be different. At present, there are three common path costs: path distance, travel time and comprehensive weight. In real life, the state of the traffic network changes rapidly, and only considering the path distance or travel time cannot effectively reflect the change of the traffic state. It also cannot cope with the sudden situation in traffic, and it is very likely to cause the failure of traffic route guidance in the end. The path weight that integrates these two types of information (or more path information) shows advantages, which is very beneficial to the construction of intelligent transportation systems. The path selection problem has been deeply studied and explored by scholars at home and abroad. This problem has also attracted much attention in the field of logistics, and has high-research significance. Nowadays, the algorithm to solve this problem can be roughly

divided into two aspects: precise algorithm and heuristic algorithm. The common accurate algorithms are: branch and bound method, cutting plane method and dynamic programming algorithm.

In this article, we will use path distance and average travel time to comprehensively label the cost value of a path, each accounting for 0.5. Among them, we use a dynamic update strategy for the average travel time, which stipulates that if the average travel speed of a vehicle on a route is lower than 15 km/h, we call this route in a congested state. At this time, we need to double the weight value of its travel time, that is, multiply by 2; if the average travel time of a vehicle on a route is 15 km/h to 30 km/h, we say that the route is in a normal state, and the travel time weight is processed normally; if the average travel time of a vehicle on a route is greater than 30 km/h (not exceeding the maximum speed of the route), we call the route unobstructed. At this time, we need to halve the weight of travel time, that is, divide by 2. The average speed of vehicles on the path comes from the traffic control centre.

The initialisation of the population is to give the initial solution of the population according to the coding rules. The algorithm must initialise the population at the beginning. According to the different forms of the initialisation method, it can be divided into *M* random method, fixed value setting method, two-step method, hybrid method and specific application method. Random number generator is the most commonly used method. The fixed value setting law is more inclined to produce uniformly distributed points in the search space.

Therefore, the optimisation of the algorithm initialisation can consider the optimisation of the maximum number of selections. In addition, the initial population of the standard artificial bee colony algorithm is randomly generated, and the initial population has a great influence on the convergence speed of the algorithm and the optimal solution. For the problem to be solved optimally, it is necessary to optimise the generation method of the initial population. A good initialisation method can improve the diversity of the algorithm's initial food sources, so that the initial solution of the algorithm can be evenly distributed in the search space. It can also improve the algorithm's global search ability and avoid converging to local extreme points. First, the path distance and average travel time must be dimensionlessly processed in order to standardise each attribute value. The search algorithm is actually a process of constructing a solution tree based on initial conditions and expansion rules and finding nodes that meet the target state. From the perspective of the final algorithm implementation, all search algorithms can be divided into two parts: control structure (the way of expanding nodes) and generating system (expanding nodes). And all algorithm optimisation and improvement are mainly done by modifying its control structure. The purpose of dimensionlessness is to eliminate the effect of dimension and order of magnitude on each attribute value. This step can be completed by number transformation, we use z-score standardised processing method here. This method standardises the data based on the mean and standard deviation of the original data. The calculation method for standardising the original data of each attribute to the new data using *z*-score is: new data=(original data-mean)/standard deviation (Jiang and Dong, 2017).

$$z\text{-score} = \left(s - \text{mean}\left(s\right)\right) / sd\left(s\right) \tag{2}$$

Specific steps are as follows:

- *Step 1*: It needs to ask for the arithmetic mean and standard deviation of each variable.

In the initial stage of artificial bee colony algorithm population, all solutions are generated by hired bees (He et al., 2017):

$$x_i^j = \min\left(x_i^m\right) + \mathrm{r}\left(\max\left(x\sum m\right) - \min\left(x^m\right)\right) \tag{3}$$

The hired bee searches for a new solution in the neighbourhood space corresponding to solution x_i^j recorded by it (Hajisalem and Babaie, 2018):

$$v_i^m = x_i^m + r\left(x_i^m - x_k^m\right) \tag{4}$$

The quality of the nectar contained in the food source corresponding to the artificial bee colony algorithm-generally the higher the requirement, the better, that is, the higher the corresponding fitness value, the better (Ma et al., 2017a).

$$FIT\left(x_i\right)_m = 1/\left(1 + f\left(x_i\right)\right) \tag{5}$$

$$FIT\left(x_i\right)_n = 1 + a\left(1 + f\left(x_i\right)\right) \tag{6}$$

Among them, $FIT\left(x_i\right)$ is the fitness function corresponding to the solution x, indicating the level of solution quality.

- *Step 2*: It is standardised processing (Ma et al., 2017b).

$$Y_{ij} = {\left(x_{ij} - x\right)}\Big/{s_i} \tag{7}$$

Among them: Y_{ij} is the standardised variable value, x_{ij} is the actual variable value.

- *Step 3*: It swaps the sign before the inverse indicator, and here it swaps the sign before the average travel time. The standardised variable value fluctuates around 0, and we add 100 to each standardised value to ensure that most of the values are positive.

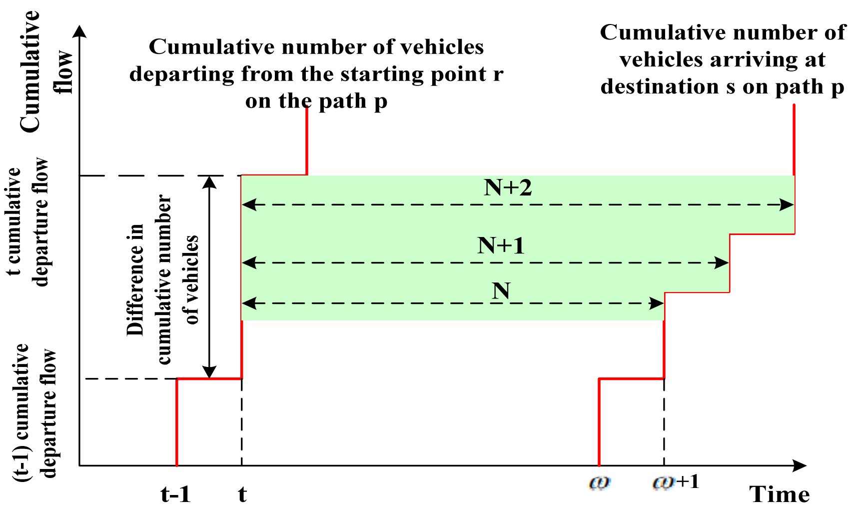
Finally, the cost value of the entire road section is marked. A simple weighting method is used here, and the path distance and the average travel time each account for 0.5. It can be seen that the smaller the cost of the path, the better the path. For all travellers who depart at time *t* and choose route $p \in p^r$, the average time is equal to (Shui and Szeto, 2017):

$$\eta = \frac{\int_{\lambda_1}^{\lambda_2}\left(\lambda_2 - \lambda_1\right)\mathrm{d}v}{\lambda_{t_1} - \lambda_{t_2}} \tag{8}$$

Among them, λ_2 represents the cumulative departure flow starting from the starting cell *r* and passing through the path *p* at time *t* (Berman et al., 2018).

In fact, in the case of time discretisation, the accumulated traffic volume leaving the cell *r* on the path *p* in the time interval *t* may not all reach the end point *s* at the same time. In this study, the average travel time is used to replace the actual travel time of the vehicle leaving the vehicle at the same time on the path. The cumulative flow curve used in this article is shown in Figure 1.

Figure 1 Cumulative flow curve



2.2 *Specific steps to improve the artificial bee colony algorithm*

The specific steps of artificial bee colony algorithm to solve Vehicle Routing Problem with Time Windows (VRPTW) are as follows:

1 The data is initialised, various parameters are set, and N random distribution routes are obtained, starting from the distribution centre, passing through all customers, and finally returning to the distribution centre to calculate the corresponding fitness (Adler and Page, 2019):

$$A_K = \{1, 2, \ldots, N\} - T \tag{9}$$

Among them, A_K represents the set of delivery routes that bee k can choose in the next step, and T represents the set of delivery routes that bee k has travelled by recording.

It updates the path residual information according to the current generation path information (Shen, 2017):

$$Q(N+1) = \delta Q(N) + \Delta Q(N) \tag{10}$$

in:

$$Q(N) = \sum\nolimits_{k=1}^{m} Q_{ij}^{k}(N) \tag{11}$$

In the formula, δ represents the volatilisation intensity of the pheromone left by the bees in the process of searching for honey, $\delta \in (0,1]$. $Q(N+1)$ represents the size of the pheromone remaining on the path of the *K*-th bee in the *N*+1-th generation iterative loop (Walton et al., 2017).

2 It leads the bee to search the neighbourhood of the initial nectar source and evaluate the fitness of the nectar source;

3 It leads the bee to bring back the nectar source information, follow the bee to choose the leading path according to the roulette strategy, follow the bee and the scout bee to choose the next nectar source, evaluate the adaptability of the new nectar source and make updates;

General formula of mutation operation (Lu et al., 2017):

$$v(t) = x(t) + F\left(x_b(t) - x_a(t)\right) \tag{12}$$

Among them, $v(t)$ is the individual obtained after differential mutation.

The improved local search formula:

$$x_i^m = x_i^t + F\left(x_i^t - x_K^t\right) + \phi(G' - x) \tag{13}$$

F is the differential variation factor.

In the artificial bee colony algorithm, there are three different models such as Bcs, Bqs and Bds to solve $\Delta Q(N)$.

$$\Delta Q_1(N) = \begin{cases} \delta / L_{ij}, & \text{The car passes through } N \text{ nodes through } ij \\ 0, & \text{Other} \end{cases} \tag{14}$$

It uses the Bqs model of local information:

$$\Delta Q_2(N) = \begin{cases} \delta / d_{ij}, & \text{The car passes through } N \text{ nodes through } ij \\ 0, & \text{Other} \end{cases} \tag{15}$$

It uses the Bds model of local information (Marie et al., 2017):

$$\Delta Q_3(N) = \begin{cases} \delta, & \text{The car passes through } N \text{ nodes through } ij \\ 0, & \text{Other} \end{cases} \tag{16}$$

In the formula, δ represents a constant of the total amount of pheromone left on the path, which can be taken at different iteration stages; d_{ij} represents the distance between customer points i and j (Lin et al., 2017).

4 Repeating steps 2 and 3;

5 The iteration reaches the maximum set number, the iteration is terminated and the result is output.

2.3 The validity check of the improved ABC algorithm

In order to verify the effectiveness of the improved ABC algorithm proposed in this paper, this paper first compares the ABC algorithms that adopt different selection strategies. It then selects the most suitable *P* parameter for different ratios of the leading bees to the colony. Finally, it verifies the effectiveness of the ABC algorithm using the food update strategy based on the taboo table. For the convenience of description, this article will abbreviate the ABC algorithm that adopts the fitness sorting strategy as ABC-R, and the ABC algorithm that adopts the elite retention strategy as ABC-E. The ABC algorithm that will adopt the tournament selection strategy will be referred to as ABC-T, and the new ABC algorithm that will lead the proportion of bees will be referred to as ABC-P. The ABC algorithm that adopts the food update strategy based on the taboo table is abbreviated as TLABC.

In the process of verifying the algorithm, the following four representative objective functions are used: Sphere function, Rosenbrock function, Rastrigin function and Griewank function. The mathematical model is as follows:

Sphere function (Pauliuk et al., 2017):

$$f(x) = \sum_{i=1}^{n} x^2 \tag{17}$$

The optimal solution of this function is (Antonisse et al., 2017):

$$\min f(x) = f(0,0,\ldots,0) = 0 \tag{18}$$

Rosenbrock function:

$$f_2(x) = \sum_{i=1}^{n-1} \left[\left(x_{n+1} - x_n \right)^2 + \left(x_{n-1} + x_n \right)^2 \right] \tag{19}$$

Rastrigin function (Zhou and Wang, 2017):

$$f_3(x) = \sum_{i=1}^{n} \left[x_i^2 - 10\cos(\lambda x) + 10 \right] \tag{20}$$

Rastrigin function (Zhou and Wang, 2017):

$$f_4(x) = \sum_{i=1}^{n} \frac{x^2}{4000} - \prod COS\left(\frac{x}{i} \right) + 1 \tag{21}$$

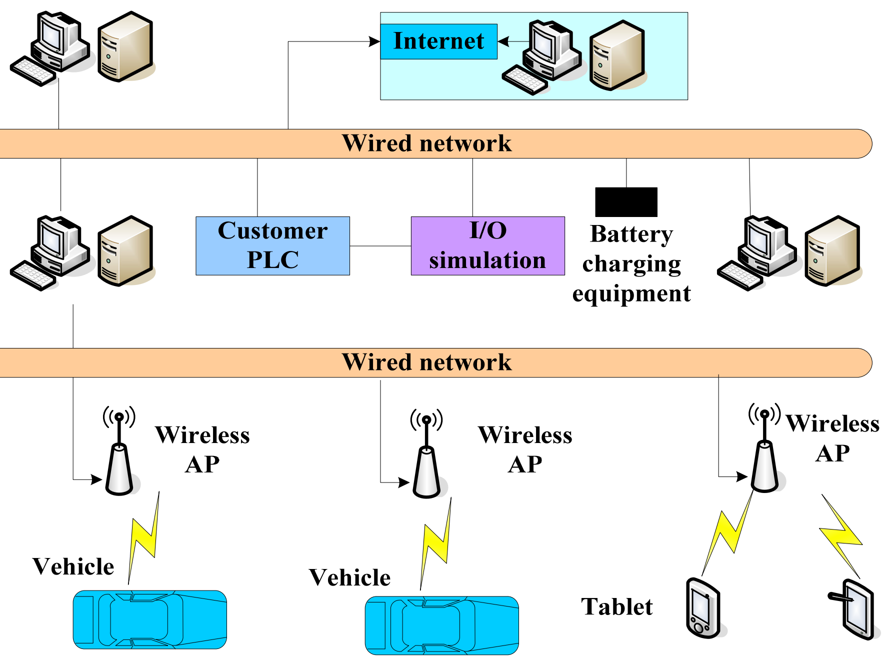
2.4 System architecture of vehicle dispatching platform

(1) *System working principle*: The structure of the vehicle scheduling platform designed in this paper is a three-tier architecture. Namely the client layer, application server layer and database layer, as shown in Figure 2. Each of these three layers can be deployed on different computers. The client is divided into the design side and the running side. The configuration end adopts the C/S structure, which allows users to quickly and flexibly configure the data model, process model, organisational structure and report templates to achieve the establishment of business systems. The

running end adopts the B/S structure, and the business designed by the configuration end can be displayed on the web to realise remote applications. For most users, such as on-site dispatchers, C/S architecture will be adopted. It directly operates the server through the client, which is easy to operate and has good interaction capabilities.

(2) *System deployment structure*: According to the situation of this system, the customer needs to set up a suitable vehicle dispatching platform network in its factory. The following equipment needs to be provided in the network: two servers, one as an application server, one as a database server and Oracle or SQL Server database software is installed in the database server. The official version of SQLServer not only has the powerful capabilities of the existing data platform, but also fully supports cloud technologies and platforms. It can also quickly build corresponding solutions to achieve data expansion and application migration between private and public clouds, helping thousands of enterprise users to quickly achieve a variety of data experiences through breakthroughs. The system deployment structure is shown in Figure 2.

Figure 2 The structure of the vehicle scheduling platform



2.5 Functional structure design

The application layer is composed of multiple application function modules, and the application function is a means to realise business value. Because different users have different requirements for application functions, many application functions need to be constructed or adjusted according to the specific needs of users during the system implementation stage. The AGV vehicle dispatching platform provides some prefabricated application function modules, mainly covering the following contents:

(1) *Task optimisation*: It uses the proposed method to solve the VRPTW problem to solve the problems in the system.

(2) *Task management*: It is responsible for the generation of tasks, as well as the addition, deletion and modification of tasks that have been generated.

(3) *Vehicle management*: It is responsible for the addition and deletion of AGV vehicles and the editing of vehicle IP addresses and other information.

(4) *Traffic management*: It coordinates the operation of multiple AGVs. When interference occurs, measures such as waiting to avoid traffic jams or collisions are prevented, and abnormal phenomena such as deadlocks between AGVs are avoided.

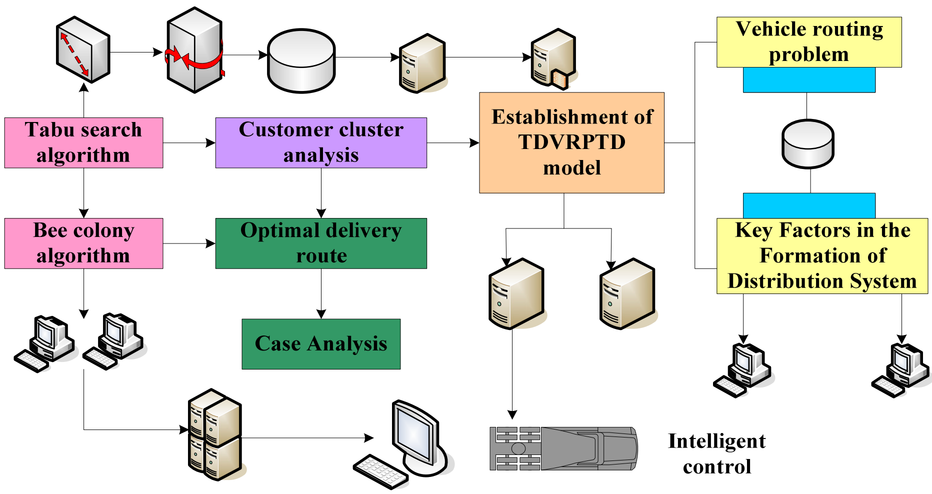
(5) *Path management*: It modifies, deletes and edits tasks obtained by the task optimisation module, and manages tasks manually entered by users.

(6) *Communication management*: It is responsible for the communication between the vehicle dispatch system and the AGV vehicle system, I/O equipment and web. It has two use cases for communication receiving and communication sending.

(7) *I/O management*: It is responsible for controlling the I/O equipment, so as to control the I/O equipment to coordinate the actions of the AGV when necessary. For example, when the AGV enters the elevator, it controls the opening and closing of the elevator door and the destination floor it goes to, and when the AGV is loading, it controls the work of the loading equipment and so on.

(8) *Real-time monitoring*: It monitors the status of the AGV and the operating status of the entire system in order to deal with abnormalities. The platform layer is a self-developed vehicle dispatch system. The vehicle scheduling system provides powerful sharing functions, construction tools and extensible interfaces for the construction of application functions, which is the basis for the stable and safe operation of the system. The data layer adopts the internationally popular Oracle or SQL Server relational database. It has powerful data storage and query capabilities, applied to massive data management and has good stability. It has been described academically as a problem of determining the route of a vehicle. Each route starts from the starting point, visits a subset of customers in a specific sequence and then returns to the warehouse. Each customer must be assigned to a route, and the delivery weight required by the customer cannot exceed the load capacity of the delivery vehicle. The centre of the vehicle routing problem is to choose a route with the least total cost of delivery.

Figure 3 Intelligent vehicle path planning



In order to better reflect the difference in solution quality and solution time between the improved bee colony algorithm and the basic bee colony algorithm, the solution quality G_1 and the solution time G_2 to measure the relationship between the two are defined, and the calculation is as follows:

$$G_1 = \left(ABC_1 - \lambda ABC_2\right) / \lambda ABC_1 \tag{22}$$

$$G_2 = \left(\lambda ABC_2 - ABC_1\right) / \lambda ABC_2 \tag{23}$$

where ABC_1 and ABC_2 represent the average total cost and average solution time of the basic bee colony algorithm, and λABC_1 and λABC_2 represent the average total cost and average solution time of the improved bee colony algorithm (Mohammadi et al., 2017).

Search behaviour of bee colony algorithm:

$$x_i^t = x_i^{t-1} + \lambda L(x)\left(x_i^t - g\right) \tag{24}$$

The calculation formula of $L(\mathrm{x})$ is:

$$x_i^{t+1} = x_i^t + \eta\left(x_j^t - x_k^t\right) \tag{25}$$

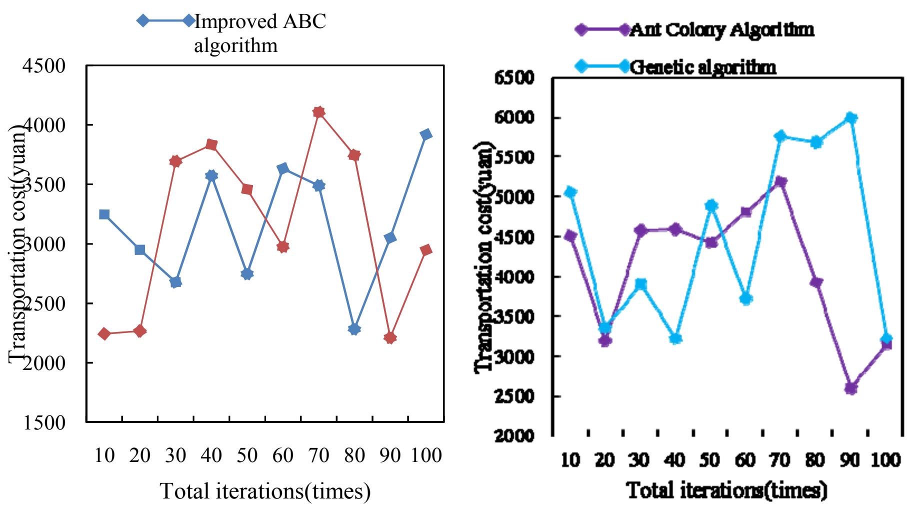
Among them, η is a random number that obeys a uniform distribution on (0,1) (Wang and Yi, 2017).

3 Modelling results of optimal path selection for transportation

The vehicle routing problem usually refers to a series of customer points. By properly organising and planning the driving route of the vehicle, the delivery vehicle can pass through various customer points in an orderly manner. It also allows these customers to achieve the lowest total transportation cost under certain constraints.

In order to verify the operational performance of the improved artificial bee colony algorithm, the problem is simulated with the unimproved artificial bee colony algorithm, ant colony algorithm and genetic algorithm. The comparison between the result and the improved ABC algorithm is shown in Figure 4. Compared with the comprehensive data obtained after solving the first and second customer groups, the improved ABC algorithm has the fastest calculation speed. Compared with the unmodified ABC algorithm, ant colony algorithm and genetic algorithm, the total delivery cost saves 236.8 yuan, 832.5 yuan and 1879.3 yuan, respectively, which proves that the improved ABC algorithm has superiority in solving this type of problem.

Figure 4 Comparison of different algorithms (see online version for colours)



In the experiment, set the population number SN to 100, the dimension D of the test function to 50, and the maximum number of iteration cycles to 1000. The local iteration limit is 100 times, and the algorithm solves the problem 30 times and takes the average value. Table 1 shows the results of using the ABC algorithm with different selection strategies to solve the calculation examples.

Table 1 ABC algorithm with different selection strategies to solve the results of each example

Function	*Evaluation*	*ABC*	*ABC-R*	*ABC-E*	*ABC-T*
Sphere	Mean	63.4010	27.08788	73.2401	50.7205
	Best	18.2306	9.198528	32.6 798	1.34504
Rosenbrock	Worst	1 12.708	48.37636	102.696	129.656
	Variance	22.4569	9.852501	16.9937	37.9774
Rastrigin	Mean	9.55187	4.268246	9.70300	3.19891
	Best	4.44506	1.002397	5.11039	4.92251
Griewank	Worst	12.8542	7.830433	12.5371	1.38679
	Variance	1.82797	7.830433	1.77150	2.67373

Table 2 shows the experimental results of various examples using different leading bee ratios. Table 2 shows the calculation results of four examples under different lead bee ratios *P*, (take 60%, 70%, 80% and 90%, respectively). It can be seen that for the Sphere problem, when the leading bee ratio is 70%, the best calculated average can be obtained. When the lead bee ratio is 90%, the variance of the calculation result is the smallest and when *P* is 40%, the best optimal calculation result can be obtained.

Table 2 Experimental results using different lead bee ratios for each calculation example

Function	*Evaluation*	*60%*	*70%*	*80%*	*90%*
Sphere	Mean	64.2842414	68.6828682	68.2684148	68.0802 684
	Best	42.4148168	28.600608	21.608114	28.2642141
Rosenbrock	Worst	11.480100	86.161168	86.6264641	81.866224
	Variance	26.6826842	26.202841	26.4841102	24.8666601
Rastrigin	Mean	1.42618820	8.6818242	8.46044288	8.26242106
	Best	8.28468822	4.2462486	6.2688111	4.41402268
Griewank	Worst	22.6048448	22.262068	20.4418260	22.2402418
	Variance	2.02824486	2.82268882	2.22060268	2.124416422

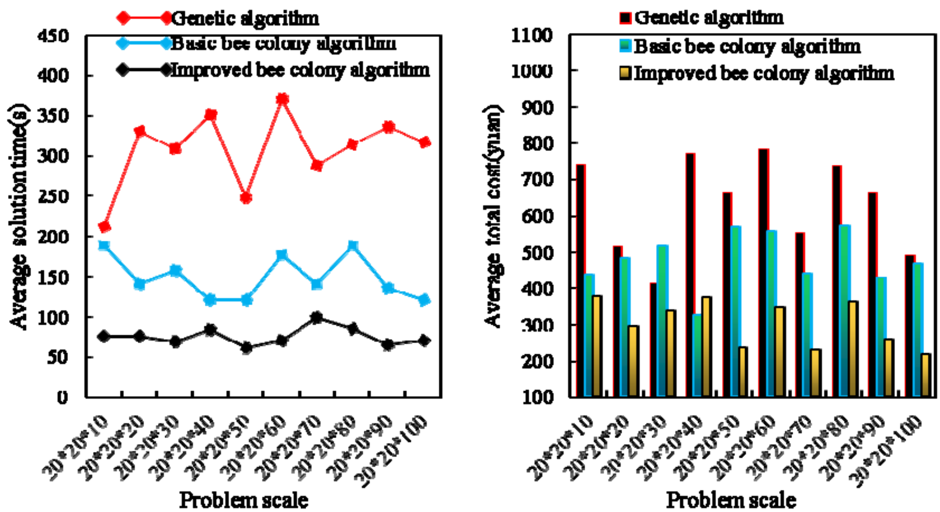
The experimental results of each calculation example using the ABC algorithm based on the taboo table food update strategy are shown in Table 3. It can be seen from Table 3 that compared with the ABC algorithm, TLABC can always obtain better average calculation results and variances for different examples. But for single-peak problems such as Sphere and Rosenbrock, the ABC-T algorithm has no obvious or no advantage over the ABC algorithm. For multi-peak problems such as Rastrigin and Griewank, the ABC-T algorithm has obvious advantages over the ABC algorithm in the calculation results. This is mainly because the TLABC algorithm always uses the forbidden list in the food update process to prevent the scout bees from repeatedly searching for abandoned food sources. The food update process in the ABC algorithm was originally a process to increase the diversity of the population and prevent the algorithm from falling into premature maturity. Therefore, after the TLABC algorithm is added to the forbidden list, it enhances the algorithm’s ability to avoid premature convergence and jump out of the local optimal solution. Therefore, TLABC is most suitable for solving multimodal problems, while the traditional ABC algorithm is more suitable for solving unimodal problems.

Table 3 Experimental results of each calculation example using the ABC algorithm based on the taboo table food update strategy

Function	*Evaluation*	*ABC*	*TLABC*
Sphere	Mean	63.4020644	63.3863588
	Best	28.2306680	32.583484
Rosenbrock	Worst	222.608282	80.0885232
	Variance	22.456868	26.2266230
Rastrigin	Mean	8.55286652	8.34882530
	Best	4.44506836	4.32320356
Griewank	Worst	22.8542262.	22.2465625
	Variance	2.82686638	2.62862 803

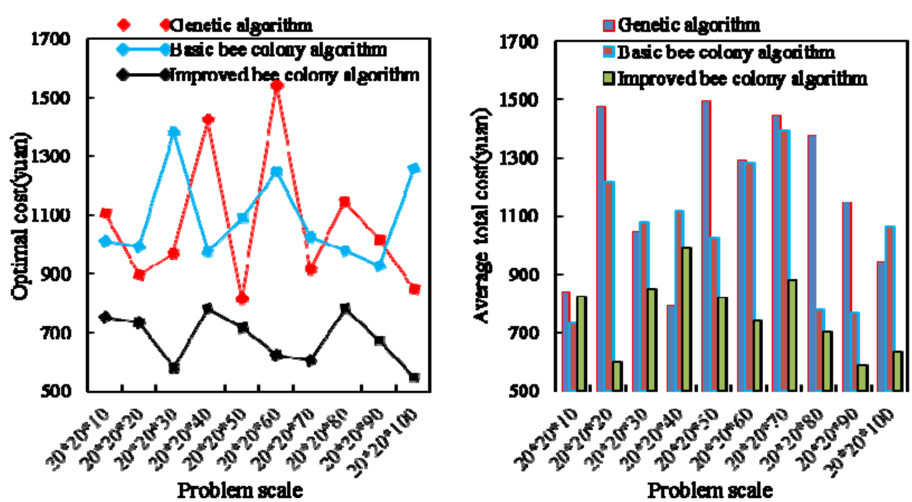
For small-scale problems, the improved bee colony algorithm is similar to the basic bee colony algorithm and genetic algorithm in terms of solving quality. All of them can find the optimal solution, and the improved bee colony algorithm is consistent with the basic bee colony algorithm in the solution time, which is better than the genetic algorithm. The result of small-scale problem solving is shown in Figure 5.

Figure 5 Small-scale problem solving results (see online version for colours)



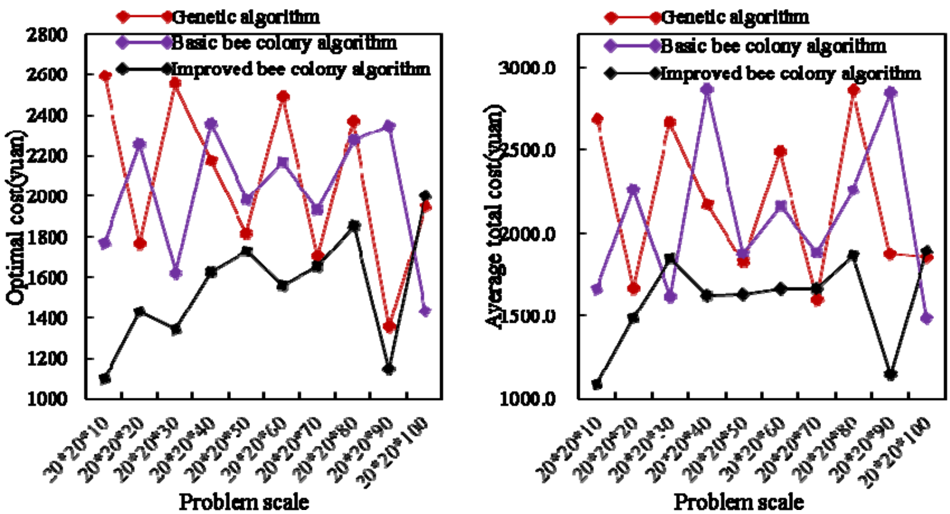
For medium-scale problems, the improved bee colony algorithm performs better than the other two algorithms. It is also better than the basic bee colony algorithm and genetic algorithm in terms of solving time. The result of solving the medium-scale problem is shown in Figure 6.

Figure 6 Results of solving medium-scale problems (see online version for colours)



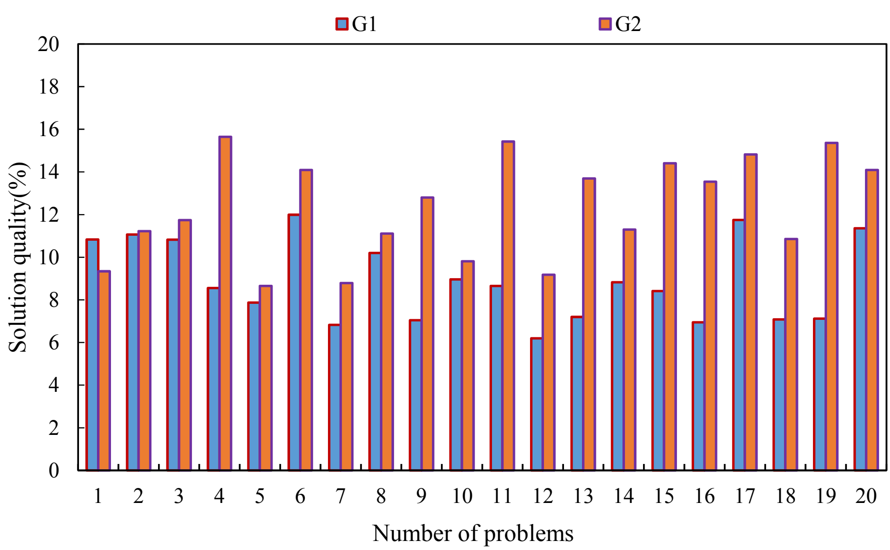
For large-scale problems, the performance of the improved bee colony algorithm is basically the same as that of medium-scale problems. The results of large-scale problem solving are shown in Figure 7.

Figure 7 Large-scale problem-solving results (see online version for colours)



Through the intuitive comparison of histograms, compared with the basic bee colony algorithm, the advantage of the improved bee colony algorithm in the solution quality is more obvious than the disadvantage in the solution time. The comparison of solution quality advantages is shown in Figure 8.

Figure 8 Comparison of solution quality advantages (see online version for colours)



It is assumed that the number of light trucks owned by the company is 20 kg, the truck's own weight is 2000 kg, and the rated load is 8000 kg. The truck is traveling on a straight road without traffic jams, and the average speed of the vehicle is 60 km/h. The fuel consumption per unit distance when the truck is empty is 0.08 L/(km), and when it is fully loaded, the fuel consumption per unit distance is 0.236 L/(km). The conversion rate of fuel to carbon dioxide is 2.65 kg/L, the vehicle start-up cost is 80 yuan/time and the unit distance transportation cost is 2 yuan/km. The specific parameters are shown in Table 4.

Table 4 Specific parameters

Meaning	*Value*
Number of trucks	20
Truck weight	2000 kg
Rated load	8000 kg
Vehicle speed	60 km/h
Fuel consumption per unit distance at no load	0.08 L/km
Fuel consumption per unit distance at full load	0.236 L/km
Conversion rate of fuel to carbon dioxide	2.65 kg/L
Start-up cost of the vehicle	80 yuan/time
Transport cost per unit distance	2 yuan/km

The parameters of the improved artificial bee colony algorithm mainly include: the size of the bee colony, the proportion of bees collected, the maximum number of searches for nectar sources, the maximum number of iterations and the length of the taboo table. The specific numerical settings are shown in Table 5.

Table 5 Specific value settings

Meaning	*Value*
Colony size	80
Percentage of bees collected	0.5
Maximum number of searches for nectar sources	50
The maximum number of iterations	500
The length of the taboo list	20

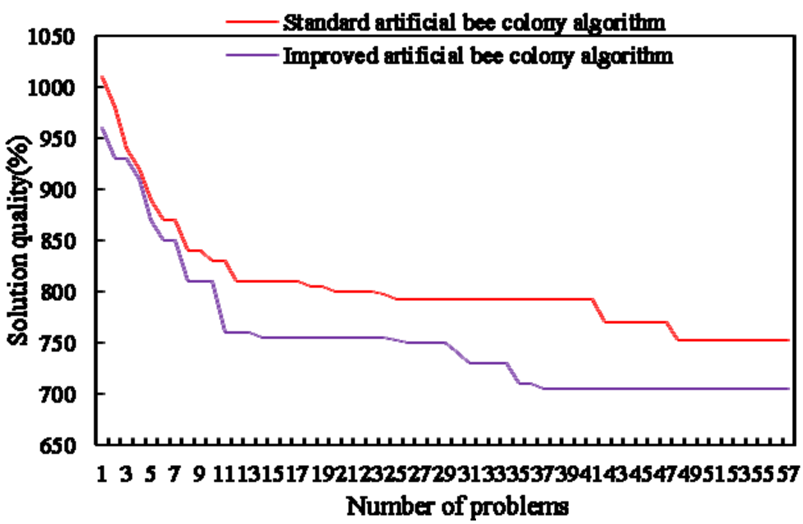
In order to verify the effectiveness of the improved algorithm, this paper uses both the standard artificial bee colony algorithm and the improved artificial bee colony algorithm to solve the vehicle scheduling model. Among them, the algorithm parameter settings are the same, and the running results of 20 times are collected, respectively, and the statistical analysis is shown in Table 6.

It can be seen from the standard deviation of the optimal solution obtained from the results of 20 runs that the improved artificial bee colony algorithm is more stable than the standard artificial bee colony algorithm after multiple runs. The convergence curve of transportation cost is shown in Figure 9.

Table 6 20 running results

	Optimal solution	*Standard ABC*	*Improve ABC*
Minimal transportation cost	Average value	794.21	774.24
	Standard deviation	822.473	797.148
Minimum carbon emissions	Optimal solution	13.24	17.952
	Average value	42.39	41.395
	Standard deviation	47.173	43.847
Maximum customer satisfaction	Optimal solution	3.137	1.748
	Average value	1.932	1.937
	Standard deviation	1.917	1.927

Figure 9 Convergence curve of transportation cost (see online version for colours)



4 Discussion

For the standard bee colony algorithm, the accuracy of the optimal solution is not high and it is easy to fall into the local optimum in the later stage of the algorithm evolution. It is mainly improved from two aspects, and the improved optimisation algorithm is used to solve the Vehicle Routing Problem (VRP) of logistics distribution. Therefore, this article mainly introduces the following two parts in detail: the progress of the bee colony algorithm in improvement and application; the research progress of the solution to the vehicle path planning problem. Through research, it is found that most of the existing swarm intelligence algorithms cannot find the optimal route in solving the vehicle routing problem of more than one delivery point. Moreover, the shortest path obtained is low in accuracy and slow in convergence, and these problems are urgently for us to study and solve. Dynamic VRP refers to the corresponding adjustment of the output route according to the time change. The information related to scheduling includes customer information, system information and vehicle information, which may change after the route is planned.

In the practical application of modern logistics and distribution, there are many different distribution points, various types of distribution items and extremely uneven weights, which make optimising vehicle path planning problems have many unimaginable difficulties. However, the urban road traffic route planning is complicated, and the road infrastructure construction difference between urban and rural construction and other issues. This makes there are many uncertain interference factors in the specific distribution process. Moreover, the widely distributed distribution points have different requirements for the delivery time of the items, which increases the difficulty in solving the actual logistics and distribution problems. Considering the above situation comprehensively, it can be concluded that reducing the cost of distribution, reducing the total distance and finding the optimal planning path in the logistics distribution to maximise the income is the problem that needs to be solved in the logistics distribution. The route of logistics distribution is realised based on the existing urban road system. With the acceleration of urban modernisation, the scale of cities has become larger and larger, and more and more vehicle congestion, traffic control and public facilities transformation that affect urban traffic are also increasing. This leads to large changes in urban distribution routes, and it is difficult to meet the requirements of distribution. Combined with the uncertainty of customer demand in VRP, the vehicle routing problem is dynamically studied, and the corresponding mathematical model and algorithm are established. This is an important link in the optimisation of logistics distribution path based on dynamic demand, and it is closer to the actual operation.

The business of logistics distribution includes two parts: short-distance distribution and long-distance trunk transportation. Long-distance transportation can be carried out through the fixed trunk lines of the enterprise. The urban logistics distribution studied in this paper mainly refers to the short-distance distribution business of logistics enterprises within the city, which mainly includes three types of distribution tasks: receiving, delivering and collecting and delivering. For logistics distribution business, the goal of logistics enterprises is to minimise the overall distribution cost and maximise customer satisfaction as much as possible. There are many constraints that need to be considered in the distribution scheduling, such as vehicle load constraints, single-vehicle single maximum travel distance constraints, vehicle type constraints, etc., making the problem have the characteristics of multi-objective and multi-constraint. In addition, the transportation resources of enterprises are limited, and resource utilisation must be considered in the distribution process. From the description of logistics distribution, the core of this problem is actually a vehicle path planning problem. The distribution vehicle starts from the starting point of the distribution, and sends the goods that meet the demand to all the corresponding demand points on the route. As for the solution of the vehicle path planning problem, it can be regarded as a problem of solving global optimisation. Therefore, the reasonable allocation of vehicles and the planning of vehicle delivery routes enable the final delivery of goods to various demand points in accordance with the specified needs. It can effectively improve the efficiency of logistics and distribution and can achieve one or more purposes such as reducing distribution costs and obtaining maximum profits, saving distribution time, and increasing the utilisation rate of distribution vehicles. Most of the current research is to establish a model for a certain problem's constraint conditions, and then use different solving algorithms to solve it.

And these studies are basically based on the pre-appointed environmental conditions. Without these environmental conditions, research is meaningless. Therefore, how to construct a high-quality and robust vehicle routing problem solution method in combination with the actual situation has important theoretical significance and practical value.

The traffic sequence planning problem is a problem that contains multiple constraints. In the process of solving, not only need to consider factors such as assembly direction and assembly tool changes, but also need to consider the feasibility of assembly sequence. In this article, for those parts with large volume or gravity, the probability of being selected during the initialisation process will be very large. In the initialisation process of the assembly sequence, this paper uses two important parameters, heuristic information and pheromone, on the basis of fully absorbing the advantages of ant colony algorithm. In the phases of hiring bees and following bees, a variety of crossover operations are used to improve the quality of the solution.

5 Conclusion

The basic problems of logistics distribution vehicle routing in urban environment can be divided into: time-varying distribution, multi-level distribution, multi-trip distribution and distribution using dynamic information. Aiming at the problem of enterprise cargo distribution, this article will choose an improved artificial bee colony algorithm to deal with. It constructs a logistics item distribution route optimisation model that comprehensively considers vehicle transportation costs, vehicle travel distance and road congestion. In this paper, choosing the artificial bee colony hybrid algorithm to optimise the distribution path of logistics vehicles is a powerful way to improve the efficiency of logistics operation and reduce the cost of logistics transportation.

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