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IoT-driven logistics economy Smart warehousing and automated delivery system Energy efficiency improvement

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Abstract The rapid development of Internet of Things (IoT) technology has prompted the transformation and upgrading of the logistics industry, and the intelligent warehousing and automatic distribution system has become a key link in the development of modern logistics economy. This study builds an intelligent warehousing and automatic distribution system based on the Internet of Things technology, adopts MVC design pattern and Spring, MyBatis framework to develop a warehouse management platform, and establishes a multi-objective optimization model and an improved ant colony algorithm for the logistics and distribution problems. The system realizes instant sensing and identification of goods through RFID, sensor network and other technologies, and completes the functions of goods inbound, outbound, query and statistics, etc. Meanwhile, it uses hardware such as intelligent shuttle and AGV to improve the efficiency of goods processing. For distribution path optimization, this paper improves the ACO algorithm in terms of initial pheromone, transfer rule and update strategy, and introduces chaotic perturbation mechanism to enhance the search capability. The experimental results show that the improved algorithm improves the convergence speed by 44.44% and reduces the distribution distance by 2.46% compared with the traditional ACO algorithm when there are 25 customer points; when the number of customer points is increased to 55, it reduces the distribution distance by 6.75% and 6.63% compared with the genetic algorithm and the traditional ACO algorithm, respectively. The system efficiency optimization simulation verifies the practicality of the model in the distribution of fresh agricultural products, which can minimize the total cost and reduce the carbon emissions under the conditions of meeting the customer time window and load limitations, and provides intelligent solutions based on the Internet of Things (IoT) technology for the logistics enterprises, which is of great significance for the sustainable development of the logistics economy.

Index Terms internet of things technology, intelligent warehousing, automatic distribution, logistics economy, multi-objective optimization, improved ant colony algorithm

I. Introduction

The state has taken the logistics industry as a means to adjust the industrial and economic structure, transform the mode of economic development and enhance the vitality of the national economy and other objectives, and the modern logistics industry has gradually transformed into a national strategic basic industry [1], [2]. Vigorously developing the logistics industry is an important aspect of economic development in the new era. However, the logistics industry has some limitations in the transportation and warehousing. The low efficiency of manual work under the traditional warehousing mode can no longer adapt to the development needs of modern logistics in terms of high efficiency and low cost, and it is difficult to deal with large-scale, cross-regional flow of goods, exposing many problems, such as backlog of inventory, distribution delays, and non-transparent information, which seriously restricts the overall efficiency of logistics [3]-[5]. The rapid development and application of intelligent warehousing and logistics technology represented by the Internet of Things, big data, artificial intelligence, robotics, etc., realizes the automation, intelligence and digitization of warehousing and logistics, and provides a new opportunity for the development of logistics economy [6], [7].

Intelligent warehousing and automatic distribution system as an important technical means to improve logistics efficiency, its impact on logistics efficiency has been systematically verified through a number of cases and data, proving that it has a significant effect in reducing manual errors, improving the speed and accuracy of goods processing, real-time monitoring of inventory, optimizing the production and distribution process, and reducing the operating costs [8]-[11]. Using IoT technology to deploy sensors, RFID tags, etc. on objects such as goods, warehousing equipment, transportation tools, etc., to realize real-time perception and data collection of objects, and real-time transmission of information such as location, status, and environmental conditions of the goods to the management system to realize automated distribution according to the information of the order, so that the managers can accurately grasp the entire logistics dynamics [12]-[15]. For example, the quantity of inventory in the warehouse can be monitored in real time through sensors. With the help of GPS positioning equipment, real-time tracking of the location and status of transportation vehicles is realized. However, the current problems of sensor standardization and system data privacy and security have not been solved, limiting the development of the logistics industry.

Today's global economic integration process has accelerated, the logistics industry as an important part of the modern economic system, plays a vital role in the development of the national economy. Along with the rapid rise of e-commerce, the demand for logistics and distribution has shown explosive growth, and the traditional logistics model has been difficult to meet the demand for fast, efficient and accurate distribution. The logistics industry is facing many challenges such as high distribution costs, low efficiency and low customer satisfaction. Especially in warehousing, the traditional manual management method has low degree of informationization, cargo tracking difficulties, inaccurate inventory management and other problems; in distribution, the path planning is unreasonable, resulting in a high rate of vehicle idling, increased transportation costs, carbon emissions and other prominent issues. The rapid development of Internet of Things (IoT) technology provides new ideas and new methods to solve these problems. Through radio frequency identification (RFID), sensor networks, global positioning systems and other technical means, the Internet of Things realizes comprehensive sensing, reliable transmission and intelligent processing of items, and provides technical support for the intelligence and automation of logistics warehousing and distribution systems. In recent years, scholars at home and abroad have conducted extensive research on the application of IoT technology in the field of logistics. In terms of distribution path optimization, many scholars have used various intelligent algorithms for research, such as genetic algorithm, ant colony algorithm, particle swarm algorithm and so on. However, most of the existing research focuses on the optimization of a single technology or a single link, and lacks the systematic research on the whole process of logistics, especially the lack of in-depth discussion on the integration and application of IoT technology and intelligent algorithms.

This study organically combines IoT technology with intelligent warehousing and automatic distribution system, and builds an intelligent logistics system based on IoT by starting from two key aspects: system architecture design and distribution path optimization. Firstly, the layered design idea is adopted to construct the architecture of intelligent warehouse management system from three levels of perception layer, network layer and application layer, and the MVC design mode is applied to develop the system software. Secondly, for the optimization problem of logistics and distribution path, a multi-objective optimization model is established, considering the two objectives of total cost minimization and carbon emission minimization, and an improved ant colony algorithm is proposed to solve the model. Based on the traditional ACO algorithm, it is improved in four aspects, namely, initial pheromone distribution, transfer rule, global pheromone update and chaotic perturbation mechanism, in order to improve the convergence speed and solving accuracy of the algorithm. Finally, the system efficiency optimization simulation is carried out through the case of fresh produce distribution to verify the effectiveness and practicality of the proposed method.

II. Efficiency optimization of smart warehousing and automated distribution systems

II. A. System design

II. A. 1) Overall design

This warehouse management platform is based on the item sensing and identification technology provided by IoT technology to realize instant access to the quantity and spatial location information of various items in the warehouse. In the perception layer, the typical technologies utilized include sensor networks, global positioning systems, RFID technology and so on. The network layer provides all-weather full-coverage network communication function for intelligent warehouse management, so as to realize the absolute consistency between online and offline. The application layer realizes the interconnection of the various hardware and software subsystems of the system, which is mainly based on machine-to-machine communication (M2M) technology and management strategy. The intelligent warehouse management system based on the Internet of Things realizes the structured design of the system, using the idea of layered design, so that the data and information can be exchanged between the various layers. From the perception layer, network layer, application layer as the system entry point and through the call interface to realize the business logic, the resulting system software structure is shown in Figure 1.

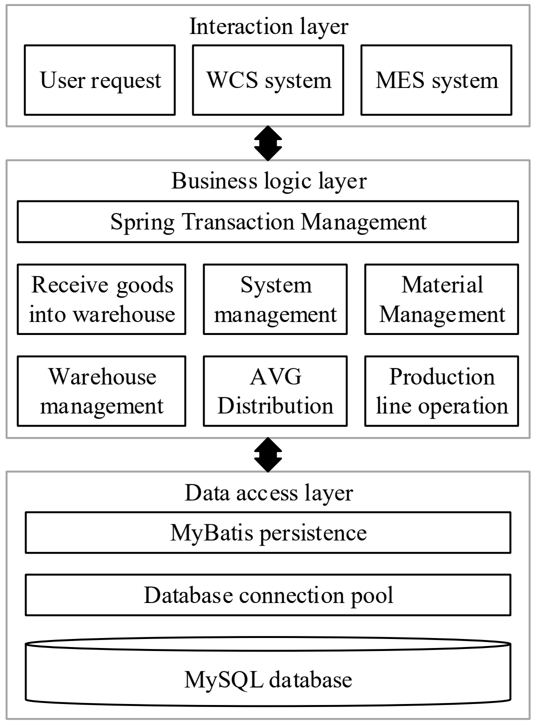

Figure 1: System software structure diagram

The functional framework of this system adopts the classic MVC design pattern, which divides the whole system into interaction layer, business logic layer and data access layer, and at the same time uses Spring, My Batis and other frameworks to assist in the development, so that the development is more concise and efficient, and the logic is clear.

In addition, through the electronic data interchange (EDI) [16], to realize the exchange of business system data between enterprises. Help enterprises to integrate the supply chain, reduce inventory, and realize lean production. Make the business documents between enterprises automatically and safely exchanged without manual participation, reduce errors, realize high-speed and safe supply chain data exchange, increase the efficiency of both sides of the trade, and establish trade trust. In terms of warehousing management, the accuracy and efficiency of warehousing is improved by optimizing relevant algorithms. In terms of hardware, four-way shuttle, cross-belt sorting system, AGV (robot-guided vehicle), and intelligent shuttle control system are adopted to improve the efficiency of cargo transportation, storage, and sorting.

II. A. 2) System functional components

The system functions are mainly divided into cargo operation, cargo inventory and information query. Among them, the modules corresponding to the system functional structure are as follows.

(1) Cargo Inventory Module. This module is mainly responsible for the collection of information on goods in storage and the inventory of the quantity of goods. It only needs to read the tag through RFID reader to get the corresponding information of the goods and upload its information to the center server through the Internet, meanwhile updating the information of goods inventory and counting the quantity of increased inventory.

(2) Goods out of storage module. This module is mainly responsible for the collection of goods out of the warehouse information and the inventory of the quantity of goods.

(3) In-stock quantity information query module. The module is mainly queried through the central server, which stores the cargo information.

(4) Outbound quantity information query module. The module is mainly through the central server to query, the central server stores the cargo information.

(5) Cargo information query module. This module is mainly queried through the central server, which stores the cargo information.

(6) Inventory quantity information query module. This module is mainly used to query through the central server, which stores the cargo information.

(7) Cargo position information query module. The module is mainly through the central server to query the cargo space information, dynamic allocation of cargo space, maximize the use of storage space, to avoid the problem of uneven distribution of goods in warehousing.

(8) Cargo statistics module. This module is mainly operated through the handheld personal digital assistant scanning code, by reading the label on the signage, cargo statistics, and finally return the data to the central server.

(9) Statistical report module. This module is mainly through the goods outgoing and incoming information to carry out statistical reports, synchronized by the central server of the relevant goods information, can realize the system statistics of goods, generate the corresponding reports.

II. B. Optimization model for logistics and distribution

II. B. 1) Problem description and assumptions

It is known that there are a certain number of customer points in a certain area, and the demand for goods at each customer point is given as well as the coordinates of the location of the customer point. The distribution center warehouse provides the required goods to the customer points, and the vehicles distribute the goods to the customer points. Each vehicle starts from the distribution center, arrives at the corresponding customer point and completes the distribution task, and finally returns to the distribution center, under certain constraints, to achieve the purpose of the minimum total transportation cost, the least amount of time consumed, and the highest level of customer satisfaction. Therefore, three assumptions are set up as follows:

Assumption 1: There is only one distribution center warehouse point, i.e. all vehicles can only depart from the distribution center warehouse.

Assumption 2: All distribution vehicles have the same capacity and the vehicles travel at a constant speed.

Assumption 3: The location coordinates of all customer points have been obtained before scheduling the distribution vehicles.

II. B. 2) Multi-objective modeling

Throughout the model, 0 is used to denote the distribution center warehouse. $N=\{1,2,\cdots,n\}$ denotes the set of nodes of customers. i and j denote the serial number of the distribution center warehouse or customer points, respectively. s denotes the serial number of the distribution vehicles: l denotes the total number of vehicles. q denotes the load capacity of each distribution vehicle. a_0 denotes the fixed cost of the vehicle. a_i denotes the transportation cost of the vehicle from i to j. p is the carbon emission generated by the distribution vehicle during transportation. d_{ij} denotes the distance from i to j. m_i denotes the amount of freight transportation at customer point i. h denotes the number of road segments passed by the delivery vehicle. c_{i0} denotes the total amount of products between customer point i and the distribution center warehouse. x_{ij} denotes the 0-1 variable of whether the distribution vehicle travels from customer point i to j, i.e., $x_{ij}=1$ when the distribution vehicle arrives at customer point j from customer i, otherwise $x_{ij}=0$. The x_{ijs} denotes the 0-1 variable of whether or not the delivery vehicle s arrives at the customer point j from the customer point i, i.e., $x_{ijs}=1$ when the delivery vehicle s is traveling from i to j, otherwise $x_{ijs}=0$. The y_{is} denotes the 0-1 variable of whether the task at customer point i is accomplished by the delivery vehicle s, i.e., $y_{is}=1$ when the task at customer point i is accomplished by the delivery vehicle s, otherwise $y_{is}=0$. And let the total cost be Z_1 and the total carbon emission level be Z_2.

From the description and analysis of the problem, it can be seen that the total cost of logistics vehicle distribution should be considered first, which includes vehicle transportation cost and vehicle fixed cost. When the total cost is the smallest and need to consider the lowest carbon emissions in the transportation process, so that the dual objective function can be obtained:

$$\min Z_1=\sum_{i=0}^{n}\sum_{j=0}^{n}\sum_{s=1}^{l}a_{ij}x_{ijs}+a_o\cdot s \tag{1}$$

$$\min Z_2=p\cdot\sum_{(i,j)\in\{0\}\cup N}d_{ij}\cdot x_{ij} \tag{2}$$

However, the routes in the vehicle transportation process are not enough to be portrayed by the objective function alone; the optimal routes for distribution need to be controlled by several constraints. The distribution process requires that each customer point can only receive the service of -delivery vehicles, and all transportation tasks are completed by l vehicles -together, i.e.:

$$\sum_{s=1}^{l} y_{is} = \begin{cases} 1, i = 1, 2, \cdots, n \\ l, i = 0 \end{cases} \tag{3}$$

Each vehicle delivering goods cannot exceed its rated weight, i.e. $\sum_{i=0}^{n} m_i y_{is} \le q, s = 1, 2, \cdots, l$. There are and only -vehicles arriving at and departing from a -customer point, i.e.:

$$\sum_{i=0}^{n} x_{ijs} = y_{js}, j = 1, 2, \cdots, n; s = 1, 2, \cdots, l \tag{4}$$

$$\sum_{j=0}^{n} x_{ijs} = y_{is}, i = 1, 2, \cdots, n; s = 1, 2, \cdots, l \tag{5}$$

It is necessary to ensure that the distribution vehicle starts and stops at the distribution center warehouse, i.e. $\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij} \le h, h = n + 1$.

Therefore, based on the above analysis, the multi-objective optimization model [17] of logistics and distribution path is obtained as follows:

$$\min Z_1 = \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{i=1}^{l} a_{ij} x_{ij_k} + a_o \cdot s \tag{6}$$

$$\min Z_2 = p \cdot \sum_{(i,j) \in [0] \cup N} d_{ij} \cdot x_{ij} \tag{7}$$

$$s.t. \sum_{s=1}^{l} y_{is} = \begin{cases} 1, i = 1, 2, \cdots, n \\ l, i = 0 \end{cases} \tag{8}$$

$$\sum_{i=0}^{n} m_i y_{is} \le q \tag{9}$$

$$\sum_{i=0}^{n} x_{ijs} = y_{js} \tag{10}$$

$$\sum_{j=0}^{n} x_{ijs} = y_{is} \tag{11}$$

$$\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij} \le h \tag{12}$$

$$h = n + 1 \tag{13}$$

$$c_{i0} = 0, \forall i \in N \tag{14}$$

$$x_{ij} \in \{0, 1\} \tag{15}$$

$$x_{ijs} \in \{0, 1\} \tag{16}$$

$$y_{is} \in \{0,1\} \tag{17}$$

The above formula requires rationalization of logistics and distribution vehicle paths so that the total cost is minimized. Ensure that carbon emissions are minimized, i.e., reduce the level of pollution generated by the vehicles. Ensure that each customer point in the distribution process can only receive the services of - one distribution vehicle, and all the transportation tasks are completed by l vehicles - together. Vehicle load constraints ensure that a single vehicle cannot deliver more than its rated load. It is guaranteed that one and only one vehicle arrives and departs from a customer point. Ensure that distribution vehicles start and stop at the distribution center warehouse. Ensure that the vehicle returns to the distribution center warehouse, and that it returns empty.

II. C.Model solving based on improved ant colony algorithm

Ant colony algorithm [18] is - a new type of heuristic algorithm, which is widely used in various fields, in solving the vehicle path problem, although it can plan the path from the starting point to the target point and has strong robustness, but there are shortcomings such as easy to fall into the local optimum, stop convergence prematurely, long search time, low efficiency, etc. Here, respectively, we improve the algorithm in terms of the initial pheromone, the transfer rule and the The initial pheromone, transfer rule and pheromone updating method are improved here, which speeds up the algorithm's search for optimization in the initial stage and improves the search efficiency of the algorithm.

II. C. 1) Initial pheromones

At the initial moment, the total amount of pheromone and the distance between each demand point and the distribution center are used as the pheromone distribution matrix, therefore, the influence of each demand point is different from each other, which increases the probability of the better path to be selected and speeds up the algorithm's search for the optimal speed in the initial stage. The improved mathematical expression for the initial pheromone is:

$$\tau_{ij}(0) = \frac{Q}{d_{1i} + d_{1j}} \tag{18}$$

where, Q-The total amount of pheromone released by the ants per - search. d_{1i} - the actual distance between demand point i and the distribution center.

II. C. 2) Transfer rules

The basic ant colony algorithm only considers the distance between customer i and customer j in the transfer rule, which is easy to fall into local optimization. Considering the time window width of customer i and customer j and carbon emission, the improved expression is as follows:

$$j = \begin{cases} \arg\max\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[1/width_j\right]^{\gamma}\left[1/z_{ij}\right]^{\omega}, q < q_0 \\ p_{ij}^k, q \geq_0 \end{cases} \tag{19}$$

The probabilistic model p_{ij}^k is shown in equation (20).

$$p_{ij}^k = \begin{cases} \dfrac{\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[1/width_j\right]^{\gamma}\left[1/z_{ij}\right]^{\omega}}{\sum\limits_{s=allowed_i}\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}\left[1/width_j\right]^{\gamma}\left[1/z_{ij}\right]^{\omega}} j \in allowed_k \\ 0, j \in allowed_k \end{cases} \tag{20}$$

where, q-an assumed fixed threshold to control the state transfer rule parameters. q_0-a random number on the interval [0, 1], when $q < q_0$, a deterministic search model is used, and when $q \geq_0$ a modified probabilistic model is used. α - pheromone concentration importance factor. β, ω and γ -heuristic function importance factors. $\eta_{ij} = 1/d_{ij}$ -heuristic function. $Width_{ij} = l(i) - e(i)$ - the width of the customer's time window, the tighter the time window, the more urgent the customer's need, prioritize the service to such customers. Z_{ij} - the carbon emissions generated by the distribution vehicles from demand point i to demand point j on the path, the smaller the value, the higher the concentration of pheromone accumulated from point i to point j, the higher the likelihood of the ants to choose that path.

II. C. 3) Global pheromone update strategy

The process of convergence to the optimal solution of the ant colony algorithm is a reflection of the increasing pheromone concentration, and the pheromone updating strategy is of great significance for the successful search of the ant colony algorithm. The traditional ant colony algorithm only utilizes the overall information of the ants passing through the path (the total length of the passing path) to calculate the released pheromone concentration, and does not distinguish between the current optimal path and the worse path, so that its pheromone distribution can not be changed quickly, which leads to the algorithm's poor convergence speed and solution quality. The improved pheromone update mathematical expression is:

$$\tau_{ij}(t+1) = (1-p)\tau_{ij}(t) + \Delta\tau_{ij} + \Delta\tau_{ij} \tag{21}$$

where the expressions for $\Delta\tau_{ij}, \Delta\tau_{ij}^{kk}$ and $\Delta\tau_{ij}^{*}$ are shown in Equation (22).

$$\begin{cases} \Delta\tau_{ij} = \sum_{kk=1}^{sizepop} \Delta\tau_{ij}^{kk} \\ \Delta\tau_{ij}^{kk} = \begin{cases} \dfrac{Q}{l_{kk}}, & l_{kk} \le l_{ave} \text{ And side } (i, j) \text{ is the currently selected path} \\ 0, & l_{kk} > l_{ave} \end{cases} \\ \Delta\tau_{ij}^{*} = \begin{cases} \dfrac{Q}{l_{best}}, & \text{Edge } (i, j) \text{ belongs to the current optimal path} \\ 0, & \text{Edge } (i, j) \text{ does not belong to the current optimal path} \end{cases} \end{cases} \tag{22}$$

where, $\Delta\tau_i(t)$ - pheromone concentration on the path between demand point i and demand point j at the t th iteration. p - Volatilization factor of pheromone on the path after each - iteration. $\Delta\tau_{ij}$ -Total amount of pheromone change between point i and point j for each - iteration. $\Delta\tau_i^k$ - The value of the contribution of the kk th ant to the pheromone alteration of point i vs. point j in that iteration. $\Delta\tau_{ij}^{*}$ -extra reward for the optimal path obtained so far, allowing the pheromone on that path to be further-strengthened. l_{kk} -The total length of the path chosen by the kk th ant. $l_{b\alpha t}$ -The total length of the currently obtained optimal path. $sizepop$ -Total number of ants.

II. C. 4) Chaotic Disturbance Mechanisms

Ant colony algorithm is applied to the vehicle path problem, if the ant colony (vehicle) search to get the same feasible solution, the algorithm may fall into the local optimum at this time, then the introduction of chaotic perturbation mechanism, first of all, the pheromone is chaotically initialized to give new heuristic information to search for paths, the specific improvement method is as follows: first of all, according to the chaos iteration equations to generate a group of chaotic variables The chaotic variables are generated by Logistic mapping (a classical chaotic mapping) in the following way:

$$F_{ij}(t+1) = \mu F_{ij}(t) * [1 - F_{ij}(t)] \tag{23}$$

However, chaotic initialization can make the algorithm fall into local optimal solution while speeding up the convergence speed, so in order to add chaotic perturbation in the pheromone updating after the ants have finished the -round of searching, the traversal and randomness of searching can be increased. The expression of pheromone update after the introduction of chaotic perturbation is:

$$\tau_{ij}(t+1) = (1-p)\tau_{ij}(t) + \Delta\tau_{ij} + \Delta\tau_{ij}^{*} + \xi F_{ij}(t) \tag{24}$$

where, ξ -adjustable coefficient, a constant. $F_{ij}(t)$ - Chaotic variable. μ -control variable.

The specific process of model solving is as follows:

(1) Initialize the parameters, set the maximum number of iterations $Maxiter$, generate the initial pheromone between each client point, initialize Nc (number of iterations) = 0, and determine the function value of each parameter.

(2) Create a taboo table, so that all ants (distribution vehicles) from the distribution center, under the premise of satisfying the constraints, select the next demand point, and add this demand point to the taboo table.

(3) If the distribution vehicle does not satisfy the demand of the next customer point, the distribution vehicle returns to the distribution center, updates the contraindication table, and repeats the process until all customer points are all added to the contraindication table, which is updated to satisfy the time window and load constraints.

(4) Local optimization of distribution paths within each path is performed using 2-opt.

(5) After all ants complete the cycle, the pheromone is updated, the feasible solution obtained in the current iteration is calculated and compared with the feasible solution obtained in the previous generation, and the optimal solution is recorded, and if the feasible solution derived from the algorithm 5 times remains unchanged, a chaotic perturbation mechanism is introduced and the pheromone is updated.

(6) When $Nc = Nc + 1$ and $Nc < Maxiter$ then execute steps (2)~steps (5), otherwise the algorithm iteration ends and outputs the optimal solution.

III. Intelligent warehousing and automatic distribution system efficiency optimization simulation

III. A. Description of the algorithm

In this paper, a fresh produce distribution case in Province A is used as a research example to study the fresh produce logistics and distribution optimization problem for a single distribution center and 15 stores, with detailed information on the location of the distribution center, the location of each store, the customer time window, the customer demand, and the service time, as shown in Table 1. The X coordinate of the distribution center is 13271.607km and Y coordinate is 2896.716km. Their optimal and acceptable time windows are 5:30-18:00 and 5:00-18:30, respectively.

Table 1: Delivery data for fresh agricultural products

Number	X coordinates (km)	Y coordinates (km)	Quantity (t)	Best time window	Acceptable time window	Service time (min)
0	13271.607	2896.716	0	5:30-18:00	5:00-18:30	0
1	13270.704	2898.857	1.0	7:00-9:00	6:30-10:20	23
2	13270.468	2900.730	1.5	7:20-9:00	7:00-9:30	22
3	13269.096	2899.421	1.0	7:30-9:00	7:00-10:00	16
4	13268.752	2898.413	1.0	7:00-8:30	6:40-9:30	15
5	13271.668	2901.603	2.1	7:00-9:00	6:30-9:40	15
6	13269.149	2901.435	2.2	7:30-9:30	7:00-10:30	15
7	13267.974	2900.328	1.8	7:30-9:00	7:00-10:00	20
8	13270.206	2902.489	1.2	6:00-8:00	5:30-8:30	10
9	13267.915	2898.209	1.5	6:30-8:20	6:00-9:00	20
10	13266.668	2900.785	1.3	6:40-8:30	6:10-10:00	20
11	13267.416	2902.802	1.1	7:30-9:00	7:00-10:00	25
12	13269.22	2903.535	0.5	6:50-8:30	6:20-9:30	15
13	13265.984	2902.387	1.5	5:30-17:00	5:00-17:30	10
14	13272.994	2901.037	0.5	6:00-8:00	5:30-9:00	20
15	13272.982	2902.442	2.5	7:30-9:00	7:00-9:30	26

According to the coordinates of the distribution center and the location of each store, its location distribution scatter plot is shown in Figure 2.

III. B. Operational environment

In this paper, Lenovo G470 is used as the experimental computer, the operating system is Windows 7 Flagship 64-bit SP1, discrete graphics card, Intel Core i5 2450M CPU with 2.6GHz frequency and 8GB memory, MATLAB R2014a is used as the simulation platform, and the improved ant colony algorithm is designed to solve this paper's arithmetic example.

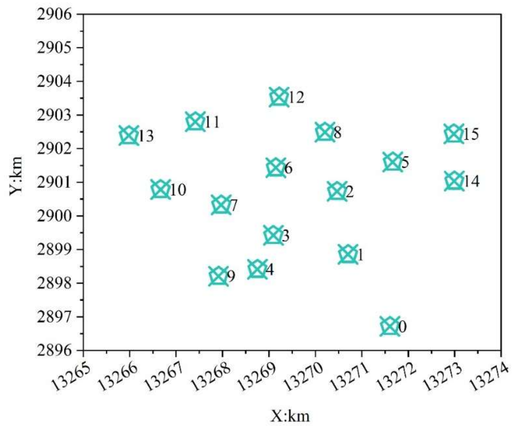

Figure 2: Distribution center and the location of each shop is distributed

III. C. Example solution and analysis

III. C. 1) Algorithm Stability Verification

In order to determine the optimal number of iterations for the algorithms in this paper and to verify the stability of the algorithms, different numbers of iterations are set to solve for the minimum cost of the three algorithms in the case of different customer satisfaction. Since the maximum value of customer satisfaction is 100%, select a few of the representative satisfaction, such as customer satisfaction of 100%, 85%, 70%, respectively, to solve the total cost at this time. The optimal number of iterations when the algorithm converges, the stability of the algorithm, and the effectiveness of the solution are determined by comparing the solution results. In the case of customer satisfaction of 100%, 85%, 75%, the solution results of the three algorithms with different number of iterations are shown in Table 2-Table 4, respectively. By representing the results in the table in images, the relationship between the number of iterations and the solution results is shown in Figure 3-Figure 5.

By solving the minimum cost under different customer satisfaction conditions by GA, ACO and improved ACO algorithms, it can be found that:

(1) In terms of convergence speed, GA gradually converges when iterations are carried out up to 600 times.ACO and improved ACO converge the algorithms to the minimum value when iterations are carried out up to 500 generations. It shows that the improved ACO and ACO converge at a comparable speed, which is faster than GA, and can converge in fewer iterations to obtain the optimal value.

(2) In terms of solution accuracy, under the same number of iterations, the improved ACO solution results are better than both GA and ACO, and the final solution results are also minimized.

Therefore, in order to improve the solving efficiency and solving accuracy, this paper sets the maximum number of iterations Max_iter=500.

Table 2: Customer satisfaction is optimal solution for 100% time algorithm

Iteration number	GA	ACO	Improved ACO
100	1315.94	1279.68	1246.52
200	1307.72	1264.78	1234.53
300	1286.89	1258.87	1225.16
400	1283.58	1252.06	1220.54
500	1280.42	1246.06	1216.25
600	1275.62	1243.73	1216.35

Table 3: Customer satisfaction is optimal solution for 85% time algorithm

Iteration number	GA	ACO	Improved ACO
100	1136.50	1082.02	1077.46
200	1127.27	1076.10	1066.78
300	1122.43	1064.84	1058.17
400	1118.52	1059.91	1053.60
500	1114.51	1054.08	1052.76
600	1107.62	1053.66	1052.84

Table 4: Customer satisfaction is optimal solution for 70% time algorithm

Iteration number	GA	ACO	Improved ACO
100	1119.57	1076.08	1068.59
200	1112.15	1074.63	1053.72
300	1102.05	1062.19	1050.70
400	1098.45	1058.59	1045.62
500	1095.98	1052.50	1039.72
600	1087.55	1052.35	1035.25

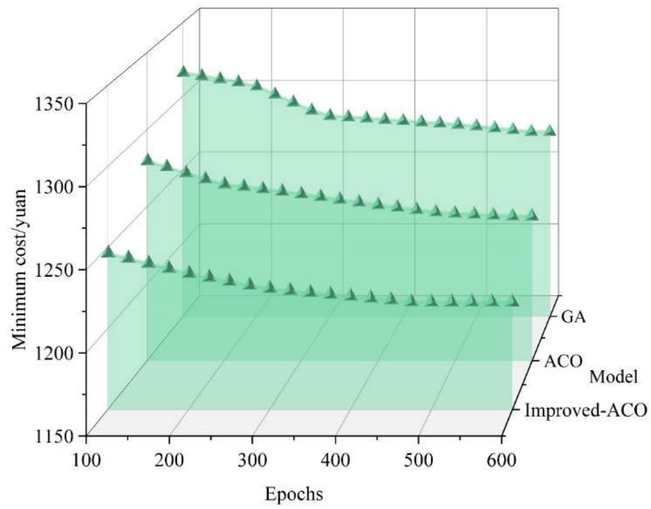

Figure 3: Satisfaction is 100% of the solution results and the number of iterations

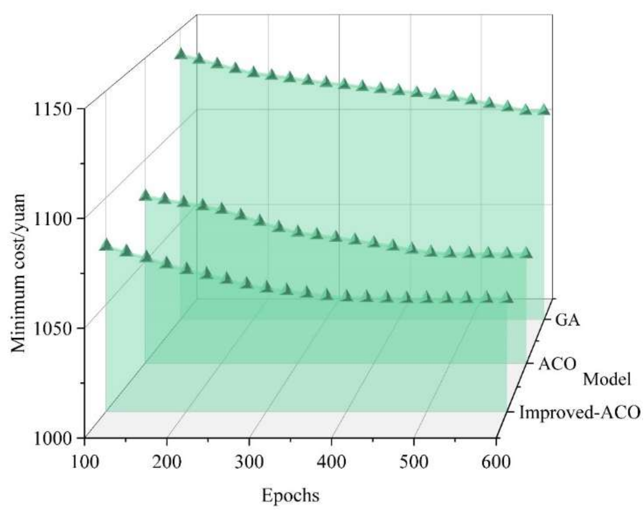

Figure 4: Satisfaction is 85% of the solution results and the number of iterations

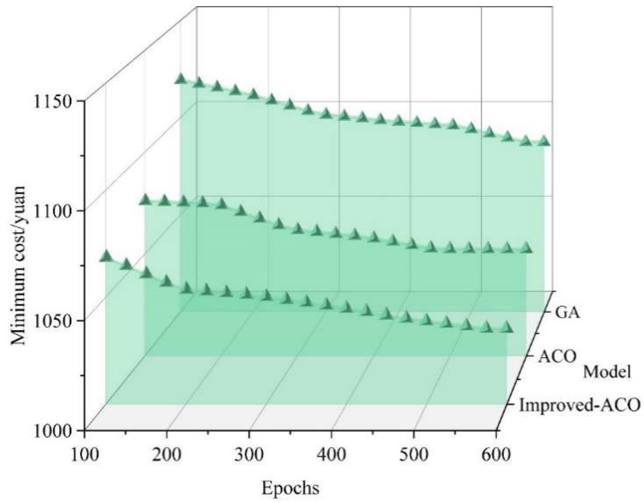

Figure 5: Satisfaction is 70% of the solution results and the number of iterations

III. C. 2) Validation of the effectiveness of the improved ACO algorithm

Problem description: distribution according to a logistics distribution center, a vehicle, multiple customer points case. Take the distribution distance as the objective function, set the same population size, number of iterations for the improved ant colony algorithm and the genetic algorithm respectively, and finally, run the results for 5 times to verify the horizontal comparison between the improved ant colony algorithm and the genetic algorithm. Using the ant colony algorithm, the improved ant colony algorithm set the same parameters, population size, the number of iterations, and finally, the results obtained were run five times, the improved ant colony algorithm and the traditional ant colony algorithm were verified in a longitudinal comparison. The parameters of traditional ant colony algorithm and improved ant colony algorithm are set as follows:

Population size: 120

Iteration number: 100.

Pheromone factor constant factor: 2.

Pheromone importance factor: 2.

Heuristic function importance factor: 6.

The experimental results of this experiment are shown in Table 5. According to the experimental results, it can be seen that the genetic algorithm and the improved ant colony algorithm are tested in the same experimental environment, and when the number of customer points is 15, the two algorithms find the same average distance. When the number of customer points increased to 25, the improved ACO algorithm reduced the average distance by 5.05% compared to the genetic algorithm. When the number of client points is 35, 45 and 55, the improved ACO algorithm reduces the average distance by 5.08%, 5.70% and 6.75%, respectively, compared with the genetic algorithm.

Table 5: Improved ant colony algorithm is compared with the genetic algorithm

Customer points	Solving algorithm	Distribution average distance (km)
15	GA	262
	Improved ACO	262
25	GA	376
	Improved ACO	357
35	GA	433
	Improved ACO	411
45	GA	509
	Improved ACO	480
55	GA	755
	Improved ACO	704

Table 6 shows the longitudinal comparison between the improved ACO algorithm and the traditional ACO algorithm, when the number of customer points is relatively small, the difference in the average distance of the path is small. When the number of terminal customer points is 15, the improved ACO algorithm obtains the same average distance of the path compared to the traditional ACO algorithm, and when the number of terminal customer points is more, the advantage of the improved ACO algorithm compared to the traditional ACO algorithm is shown. When the number of customer points is 55, the improved ACO algorithm reduces the average distance of the distribution path by 6.63% compared to the traditional ACO algorithm.

Table 6: Improved ant colony algorithm is compared with the genetic algorithm

Customer points	Solving algorithm	Distribution average distance (km)
15	ACO	262
	Improved ACO	262
25	ACO	366
	Improved ACO	357
35	ACO	424
	Improved ACO	411
45	ACO	522
	Improved ACO	480
55	ACO	754
	Improved ACO	704

Select the number of customer points for 25 to analyze, Figure 6 for the traditional ant colony algorithm to solve the shortest distance schematic, where, number 0 for the logistics and distribution center, number 1 to number 25 for the customer points. The green line segment is the vehicle trajectory. Figure 7 shows the convergence status of distribution distance under different iteration numbers. As can be seen from the figure, the distribution distance reaches the shortest around generation 45, and the value of the shortest distribution distance does not change during the subsequent iterations. The average distance has been fluctuating during the iteration process, indicating that new individuals continue to join in during the iteration process.

Fig. 8 shows the schematic diagram of the improved ACO algorithm for solving the shortest distance distribution path, and Fig. 9 shows the convergence status of the distribution distance under different iteration numbers. By comparing with the traditional ACO algorithm, it can be seen that the distribution distance of the traditional ACO algorithm is 366km, and the distribution path of the improved ACO algorithm is 357km, and the shortest distribution distance of the improved ACO algorithm is reduced by 2.46% compared with that of the traditional ACO algorithm, and the distribution distance of the improved ACO algorithm starts to reach the shortest distance at generation 25, and the average distance fluctuates within a certain range after the distribution distance reaches the shortest distance. After that, the average distance also fluctuates within a certain range.

In summary, by analyzing the simulation results of traditional ant colony algorithm and improved ant colony algorithm for solving the distribution distance respectively, it can be seen that compared with the traditional ant colony algorithm, the improved ant colony algorithm has improved the convergence speed of the algorithm by 44.44%, and the distribution distance of the vehicle has been reduced by 2.46%, which verifies the effectiveness of the improved ant colony algorithm.

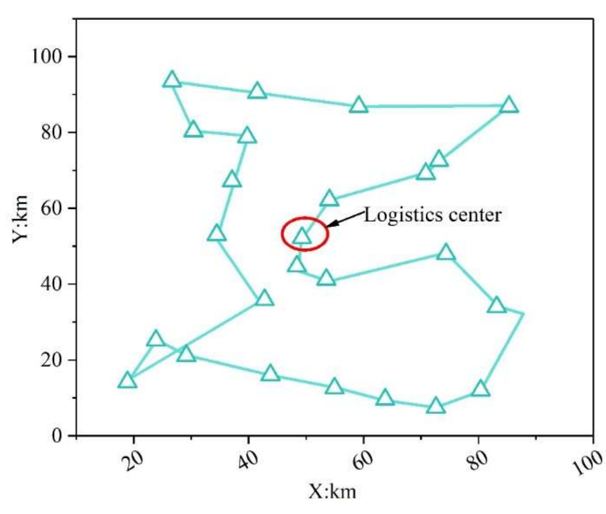

Figure 6: Traditional ant colony algorithm shortest path diagram

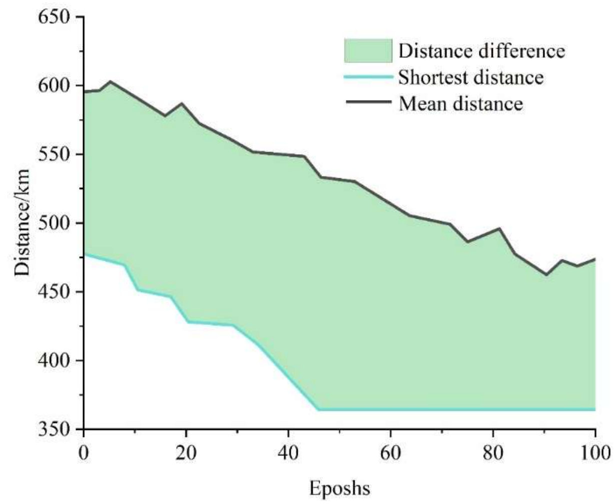

Figure 7: The traditional ant colony algorithm converges

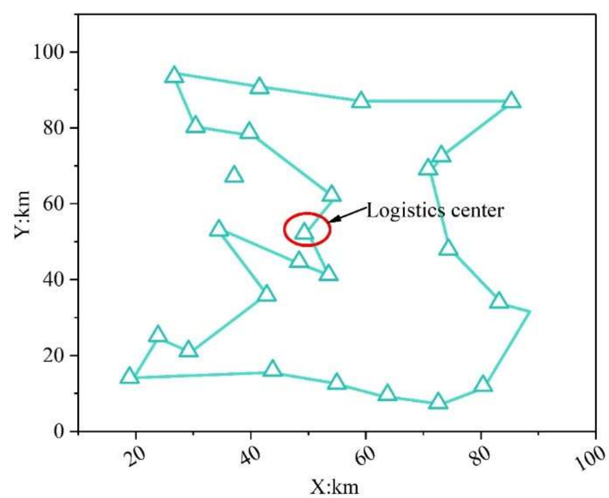

Figure 8: Improved ant colony algorithm shortest path diagram

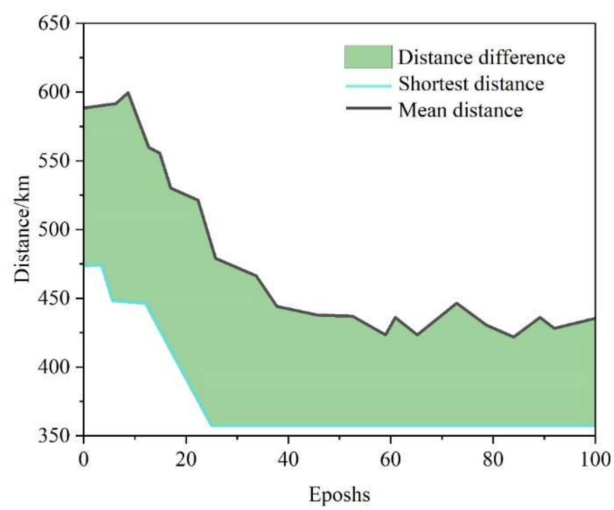

Figure 9: Improved ant colony algorithm converges

IV. Conclusion

The application of Internet of Things (IoT) technology in the field of logistics brings new opportunities for intelligent warehousing and automatic distribution system. By analyzing the overall design and functional composition of the system, a warehouse management platform based on MVC design pattern is established, which realizes the core functions such as cargo operation, inventory and information query. The multi-objective optimization model considers the two objectives of minimizing the total cost and minimizing the carbon emission level, and is solved by the improved ant colony algorithm. Aiming at the shortcomings of the traditional ACO algorithm which is easy to fall into local optimization, it is improved in three aspects, namely, initial pheromone, transfer rule and pheromone updating, and the chaotic perturbation mechanism is introduced to enhance the algorithm's searching ability. Simulation results show that when the number of customer points is 25, the improved ACO algorithm increases the convergence speed by 44.44% and reduces the delivery distance by 2.46% compared with the traditional ACO algorithm; when the number of customer points is increased to 55, the delivery paths obtained by the genetic algorithm and the traditional ACO algorithm are reduced by 6.75% and 6.63%, respectively. This shows that the improved ACO algorithm has faster convergence speed and higher solution accuracy, which is especially suitable for solving large-scale logistics and distribution path optimization problems. The combination of Internet of Things technology and intelligent algorithms not only improves the efficiency of logistics warehousing and distribution system, but also reduces carbon emissions while reducing logistics costs, which provides a strong support for the sustainable development of logistics economy.

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