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Research Article

An Enhanced Ant Colony Algorithm-Based Low-Carbon Distribution Control Method for Logistics Leveraging Internet of Things (IoT)

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This paper presents a low-carbon vehicle routing optimization model to reduce energy consumption and carbon emissions in logistics and distribution. The model is solved using a hybrid algorithm of simulated annealing and ant colony optimization. It enhances the information pheromone concentration update process and directionality by introducing a carbon emission factor and a multifactor operator. Additionally, an adaptive elite individual reproduction strategy is employed to improve algorithm efficiency. In this case study focusing on cold chain logistics distribution, both the model and algorithm under consideration were evaluated. The findings affirm the effectiveness of the model in reducing carbon emissions and demonstrate the efficiency and robustness of the algorithm. Through this analysis, the paper sheds light on environmentally sustainable practices in logistics distribution.

1. Introduction

In a world increasingly affected by global warming, the imperative to reduce carbon emissions has taken center stage. This concern is particularly pronounced in China, a major energy-consuming nation, which has committed to achieving carbon neutrality by 2060 [1, 2]. In response to China's broader goals of ecological civilization and emissions reduction, industries such as transportation and logistics are actively seeking green and low-carbon solutions. Notably, the logistics and transportation sector ranks as the second-largest contributor to fuel energy loss, accounting for over 30% of total societal losses. This has prompted efforts to integrate green logistics practices throughout the entire logistics chain to curb carbon emissions.

Under the guidance of China's macropolicy of ecological civilization development and the call for energy saving and emission reduction, the transportation and logistics industries are constantly seeking to develop green and low-carbon ways [3]. According to statistics, the logistics and transportation industry is the second largest fuel energy loss industry after the manufacturing industry, and the fuel energy loss accounts for more than 30% of the total social loss. In 2013, the Ministry of Transport issued a document. It proposed integrating ecological civilization into the logistics dispatch chain. This integration aimed to achieve the low-carbon goal of green logistics [4]. The road cargo transportation, as the main logistics mode in China, has high carbon emission cost and energy loss, although the shipment volume can be small. The supply chain is the most important source of carbon emissions in the logistics and transportation industry and is the main link in the operation process of the logistics system [5, 6]. Therefore, the realization and development of green low-carbon logistics, especially the optimization of logistics dispatch links will have an important impact on our ecosystem.

One significant facet of this transformation is the adoption of Internet of Things (IoT) technology. IoT, which integrates technologies like RFID, GPS, and artificial intelligence, offers real-time vehicle monitoring and intelligent control over factors such as refrigerated freight temperatures. This not only enhances distribution efficiency but also ensures complete traceability of carbon footprints, thereby contributing to the overarching goals of carbon reduction [7].

Domestic scholars have done a lot of research on the application of IoT in logistics in recent years. Literature [8] was based on radio frequency identification (RFID) technology to supervise the whole process of fresh agricultural products from the origin to the consumer. This guarantees food-enhanced consumer security. Literature [9] studied the risk control assessment of the agricultural products supply chain in the IoT environment, identified the supply chain risks at three levels, and came up with some specific methods and opinions. Literature [10] introduced WSN technology along with RFID-based technology. The purpose was to enable real-time transmission of environmental information for fresh agricultural products. This information would be monitored 24/7 by the information management system to ensure the quality of the produce. Literature [11] focused on the inclusion of the IoT and some modern information technology to make the quality of fresh agricultural products was effectively guaranteed. This solves the problem of no recourse for safety and quality problems in the traditional logistics of agricultural products. von Stietencron et al. [12] proposed a software framework for streaming analytics in edge cloud computing environments. The proposed framework leverages emerging technologies such as the IoT, edge computing [13, 14] techniques, and optimized decision making to sustainably meet customer needs by optimizing service costs. Lim et al. [15] used a text mining approach to explore customer satisfaction in cold chain logistics. The study mined and embedded contextual knowledge in deep networks through deep learning [16] and IoT techniques thereby effectively analyzing the factors affecting customer satisfaction in cold chain logistics.

Foreign scholars mostly focus on the application of IoT technology to the information traceability of fresh agricultural products. For example, literature [17] proposed the application of IoT RFID technology to supply chain management at a very early stage and made a detailed analysis of its role in supply chain management. Literature [18] used a sensor specialized in monitoring phytotoxic flavins together with RFID radio frequency devices. This allows monitoring whether toxic substances have contaminated fresh produce and ensures product quality. Literature [19] proposed a new information service system that solves the problem of difficult management of IoT data and traceability of agricultural products. Literature [20] used the new IoT technology to provide near-continuous monitoring of agricultural products from planting to harvesting. It can effectively store and retrieve information about the agricultural products, thus achieving real-time monitoring and ultimately promoting the improvement of the agricultural products supply chain.

To this end, how to reduce costs, improve efficiency, and be low-carbon while ensuring product safety has become one of the pressing issues in the logistics industry. In this context, this paper takes carbon emission minimization as the main goal and introduces IoT technology in modeling to efficiently manage the whole distribution process in order to expect to provide a reference direction for a new model of green and low-carbon logistics and distribution.

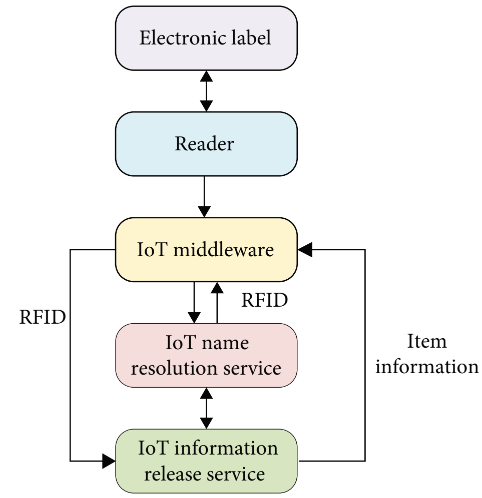

Figure 1: IoT structure diagram.

The purpose and significance of this paper is to create a low-carbon vehicle routing model using IoT. It reduces energy consumption and carbon emissions in logistics. The model combines simulated annealing (SA) and ant colony optimization, preventing local optimization issues. Innovations include integrating a carbon emission factor into pheromone updates, using adaptive strategies, and multifactor operators. Through experiments, the study proves the model's effectiveness, offering a blueprint for green logistics with lower carbon emissions, aligning with global environmental goals.

2. State of the Art

2.1. Internet of Things. In 1991, Professor Kevin Ash-ton of MIT proposed the concept of Electronic Product Code (EPC) as the prototype of IoT, and since then IoT has entered our vision [21]. The IoT connects the Internet to any object through various information-sensing devices and uses an agreed network protocol for information exchange and communication. The simple IoT structure is shown in Figure 1.

2.2. Low-Carbon Logistics. Low carbon refers to a philosophy of life that aims to reduce carbon emissions and create a safe and healthy living environment. Low-carbon economy is the core of green development, energy saving, and emission reduction, weighing the mission of environmental protection while gaining economic benefits to make economic development sustainable. Low-carbon logistics is derived from the concept of low-carbon economy, which is a product of adhering to the purpose of the concept of sustainable development. To achieve low-carbon logistics, advanced modern information technology such as the IoT is essential. The addition of the IoT enhances management efficiency, enabling informed decisions. Furthermore, transitioning to electric vehicles reduces energy consumption and carbon emissions, thereby achieving low-carbon logistics.

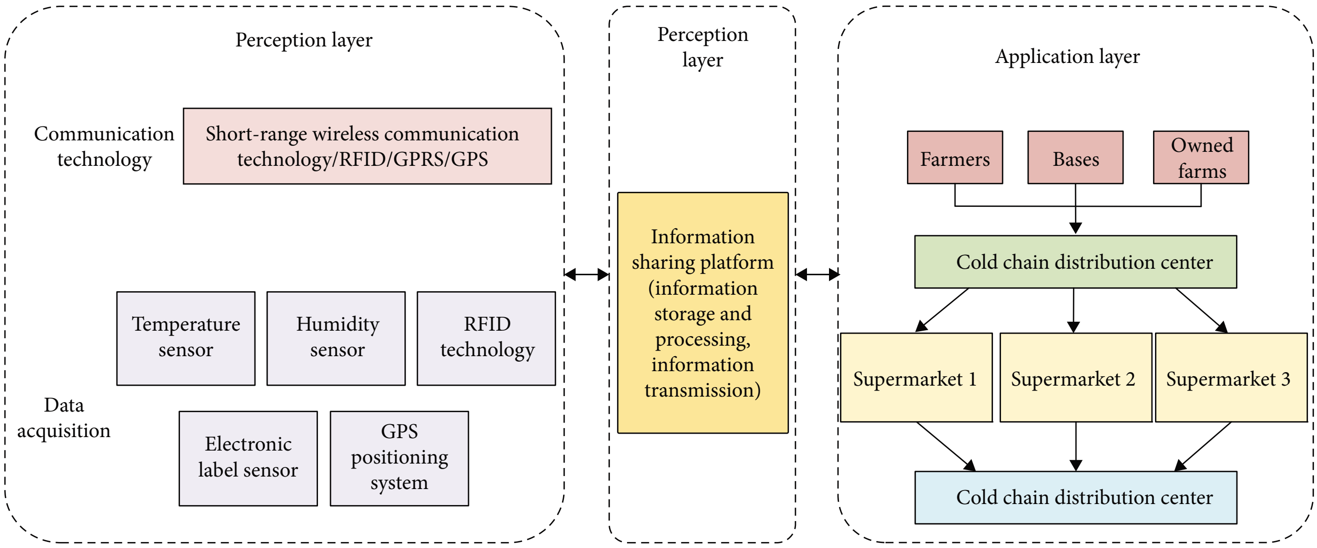

Figure 2: Low-carbon distribution model of cold chain logistics under the IoT environment.

Low-carbon logistics has the following characteristics: (1) the systemic nature of low-carbon logistics. According to a renowned Chinese scholar, a system is an organic entity comprised of specific functions resulting from the interaction and interdependence of various components. Logistics is actually an organic whole composed of transportation, storage, loading and unloading, packaging, circulation processing, distribution, information processing, and other links. Therefore, only when every part of the logistics system is decarbonized can low-carbon logistics be truly realized. (2) The two-way nature of low-carbon logistics. Low-carbon logistics is mobile, and the existence of the chain form leads to the characteristics of two-way low-carbon logistics. Positive and negative logistics exist simultaneously, forming a closed loop of the supply chain. In order to realize the low carbon logistics of the whole system, we should not only focus on the low carbon research of the forward logistics but also pay attention to the green development of the reverse logistics. (3) Horizontal and vertical integration of low-carbon logistics. The horizontal integration of low-carbon logistics refers to the cooperation between enterprises on a certain activity, through the integration and mutual use of resources between enterprises, to avoid waste and achieve low carbon. (4) The multiobjective nature of low-carbon logistics. Low-carbon logistics should be scientific and reasonable, multiobjective, and an organic whole coordinated with economic development. This approach ensures both the enterprise's interests and the green development of consumers' rights and the natural environment while guided by the principles of constructing an ecological civilization.

2.3. Low-Carbon Distribution Mode of Cold Chain Logistics under the IoT Environment. The addition of the IoT has creatively activated the modern agricultural products service distribution system. It makes the whole process of distribution fully intelligent and information-based operation, thus accelerating the transformation of fresh agricultural products market to intensive type and improving resource utilization and information level. This paper takes cold chain logistics distribution as an example and proposes a low-carbon distribution mode of cold chain logistics under the IoT environment. The purpose is to actively develop modern agricultural products circulation mode and promote the transformation and upgrading of traditional agricultural industry chain by intelligent agriculture. Large supermarkets are encouraged to collaborate directly with farmers in fresh agricultural product production regions. These products are transported using professional cold chain storage and logistics platforms, establishing an efficient cold chain logistics network to minimize inventory and reduce spoilage rates. According to the basic system of IoT, the low-carbon distribution model proposed in this paper is shown in Figure 2.

The cold chain logistics distribution mode under IOT environment makes the whole distribution process more "intelligent." It not only provides users with more accurate information and precise decisions but also the intelligent information management platform can improve logistics efficiency. At the same time of efficient and intelligent management, the information is open and transparent, and the products are traceable, which also enhances the satisfaction of consumers.

3. Methodology

3.1. Model Construction. Vehicle carbon emissions are mainly generated by the fuel consumed during the vehicle driving process. There are two types of methods for estimating vehicle fuel consumption: the MEET method and the CMEM method. Most of the CMEM methods use fuel consumption as the target to build a model to estimate carbon emissions. However, the CMEM methods are vulnerable to the influence of incomplete combustion of fuel. The MEET method has a wide range of applications. In this paper, MEET method is used. The calculation formula is shown below:

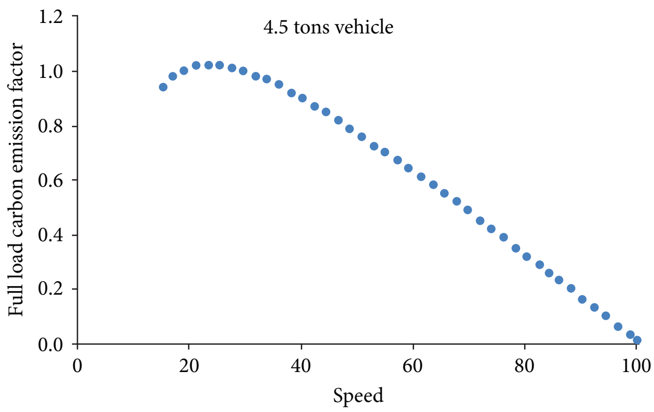

FIGURE 3: Carbon emission factor versus speed for fully loaded freight vehicles.

$$\theta_p(q) = g_0 + g_1 q + g_2 q^2 + g_3 q^3 + \frac{g_4}{q} + \frac{g_5}{q^2} + \frac{g_6}{q^3}. \tag{1}$$

The values of $g_0, g_1, \cdots, g_6$ are 110, 0, 0, 0.000375, 8702, 0, 0, respectively. For the purpose of intracity distribution, a 4.5-ton freight vehicle is used in this paper.

The carbon emission of freight vehicles is directly proportional to the cargo capacity. The carbon emission $\theta_l(q)$ of a fully loaded vehicle at different speeds for different types of vehicles is calculated as follows:

$$\theta_l(q) = \theta_p(q) \cdot \left(h_1 + h_2 q + h_3 q^2 + h_4 q^3 + \frac{h_5}{q} \right). \tag{2}$$

According to the load capacity of freight vehicles, the values of $h_0, h_1, \cdots, h_5$ are different, and the values of 4.5-ton vehicles are 1.27, −0.00235, 0, 0, and −1.33, respectively. The following shows the variation of carbon emission factors for a 4.5-ton vehicle at different speeds with full load and no load (see Figure 3).

It can be seen that, under the full load of 4.5 tons freight vehicle, after the speed q is higher than 23 km/hr, the faster the speed, the lower the carbon emission factor and the less the unit carbon emission.

In summary, the dynamic real-time carbon emission θ of the freight vehicle can be expressed as follows:

$$\theta(q, a_w) = \left(\theta_l(q) - \theta_p(q)\right) \cdot \frac{a_w}{A} + \theta_p(q), \tag{3}$$

where m stands for a freight vehicle and a_w stands for real-time cargo capacity.

The service time includes the loading and unloading time of the freight vehicle and the handover time with the customer. The freight vehicle does not produce carbon emissions during the service time. The vehicle loading is done at the distribution origin, so its loading time ns_w is not included in the vehicle travel distribution model. Only the unloading time ns_y^1 and the handover time ns_y^2 need to be considered for the service time ns_y of customer y. The unloading time is related to the demand v_y of customer y and the unloading quantity v_n (tons/hr) per unit time, i.e., $ns_y^1 = v_y / v_n$. If $ns_y^1 = 0$, it means that no goods are unloaded. $ns_j = ns_j^2 = 0$, it means that the service time is 0 when no customer node is reached. The service time of customer y can be expressed by the following equation:

$$ns_y = ns_y^1 + ns_y^2 = \frac{v_y}{v_n} + ns_y^2. \tag{4}$$

In the low-carbon distribution model of cold chain logistics, three optimization objectives are selected: The total carbon emissions generated by all vehicles in 1 day of distribution process is minimized, the total vehicle mileage D is minimized, and the total vehicle travel time T is minimized, C is the main optimization objective, the vehicle carbon emissions and D are closely related, and D is also the main optimization objective of VRP. In addition, T is also very important because there is a delivery time window constraint, and T is closely related to vehicle driver and vehicle daily management cost. In this paper, C, D, and T are selected as the three optimization objectives of the model. T, D, and C optimization objective functions are as follows:

$$\min \sum_{z=1}^{Z} \sum_{x=1}^{T} \sum_{y=1}^{T} \sum_{w=1}^{W} \sum_{r=1}^{R} \left(\sum_{u=0}^{U} \frac{d_{xj}^{ru}}{q_{xj}^{ru}} + ns_y \right) \cdot I_{xy}^{wr} \cdot J_{xy}^{wz}, \tag{5}$$

$$\min \sum_{z=1}^{Z} \sum_{x=1}^{T} \sum_{y=2}^{T} \sum_{w=1}^{W} \sum_{r=1}^{R} d_{xy}^{r} \cdot I_{xy}^{wr} \cdot J_{xy}^{wz}, \tag{6}$$

$$\min \sum_{z=1}^{Z} \sum_{x=1}^{T} \sum_{y=1}^{T} \sum_{w=1}^{W} \sum_{r=1}^{R} \sum_{u=1}^{U} d_{xy}^{ru} \cdot \theta\left(q_{xy}^{ru}, a_{xy}^{w}\right) \cdot I_{xy}^{wr} \cdot J_{xy}^{wz}. \tag{7}$$

Equation (5) indicates that the sum of total time T for completing all distribution tasks is minimized, including travel time, loading and unloading, and handover procedure time. Equation (6) indicates that the total distance traveled D is minimized. Equation (7) indicates that the total carbon emission C of all vehicles is minimized. Where $\theta\left(q_{xy}^{ru}, a_{xy}^{w}\right)$ is the carbon emission per unit mile traveled by vehicle w from node x to y, with speed q after the uth time change and real-time cargo capacity a.

3.2. Objective Function Constraint Subject To

$$\sum_{y=1}^{T} v_y \sum_{x=1}^{T} I_{xy}^{w} \leqslant A, (x, y) \in \{1, 2, \cdots, T\}, r \in R. \tag{8}$$

$$\overline{\tau_y} \leqslant n_y \leqslant \tau_y, y \in \{2, 3, \cdots, T\}. \tag{9}$$

$$\sum_{x=1}^{T} I_{xe}^{w} - \sum_{y=1}^{T} I_{ey}^{w} = 0, e \in \{2, 3, \cdots, T\}, w \in W. \tag{10}$$

$$\sum_{x=2}^{T} I_{1x}^{w} = \sum_{y=2}^{T} I_{y1}^{w} = 1, (x, y) \in \{2, 3, \cdots, T\}, w \in W. \tag{11}$$

$$I_{xy}^{tr} = [0, 1], (x, y) \in \{1, 2, \cdots, T\}, r \in R. \tag{12}$$

$$I_{xy}^{w} = [0, 1], (x, y) \in \{1, 2, \cdots, T\}. \tag{13}$$

$$J_{xy}^{wz} = [0, 1], (x, y) \in \{1, 2, \cdots, T\}, z \in Z. \tag{14}$$

Equation (8) represents the maximum vehicle load limit. Equation (9) represents the customer time window constraint. Equation (10) indicates that the vehicle needs to leave after completing the delivery task of any customer. Equation (13) represents the decision variables for selecting customer nodes. Equation (14) represents the decision variable of rescheduling in case of insufficient path optimization.

3.3. Algorithm Design. VRP is a traveler problem, which has been verified as NP-complete (nondeterministic polynomial complete) problem, i.e., difficult to solve by mathematical analysis. The ant colony optimization (ACO) and SA algorithms are more effective in solving VRP optimization. ACO needs to reconstruct the whole population every time, so it is less efficient and easy to fall into stagnation. SA accepts the updated solution with some probability, which is easy to jump out of local optimum and stagnation, the control is simple and coding is easy to implement. However, its computation time is longer, the effect of finding the optimum is average, and the optimization efficiency is not high. Therefore, in this paper, we propose a hybrid ant colony algorithm (SA-ACO) by combining the advantages of the above two algorithms. The algorithm achieves fast convergence by controlling the annealing temperature in SA and uses the Metropolis criterion of SA to prevent falling into local optimum and premature stagnation. Metropolis is a stochastic optimization method that is commonly used in the simulation of complex systems in statistical physics and related fields. It is often used to sample from probability distributions that are difficult to sample directly. A major advantage of the Metropolis algorithm is that it avoids local optimization, which allows it to explore a wider range of probability distributions and find the global optimum. It also has a faster convergence rate than other methods. The Metropolis algorithm works by proposing a new state or configuration of the system and then accepting or rejecting the offer based on the probability of the new state. The Metropolis algorithm avoids local optimization by allowing the system to occasionally accept proposals with a lower probability than the current state. This is because the acceptance probability is determined by the ratio of probabilities, not just the difference in probabilities. Thus, the algorithm can explore a wider range of probability distributions and find the global optimum. In addition to avoiding local optimization, the Metropolis algorithm has a faster convergence rate compared to other methods because it is a Markov chain Monte Carlo (MCMC) method. MCMC methods aim to generate a sequence of samples from a probability distribution and converge to the true distribution over time. The Metropolis algorithm is an MCMC method that in some cases, it has been shown to converge faster than other MCMC methods. Overall, the Metropolis algorithm is a powerful stochastic optimization method that is widely used in statistical physics and related fields. Its ability to avoid local optimization and its relatively fast convergence make it a valuable tool for modeling complex systems and sampling from difficult probability distributions.

The multiparameter pheromone concentration calculation in ACO is used to update the population and increase the memory of the population. A carbon emission factor is also designed to enhance the directionality of population optimization. The flow of the hybrid ant colony algorithm is shown in Figure 4.

The criterion for jumping out of the inner loop is to reach a set constant value of a certain number of cycles C_{r1}. The criterion for jumping out of the outer loop is to set a constant value of a certain number of cycles C_{r2} within which the fitness of the optimal solution no longer changes. In this paper, the algorithm follows the Metropolis sampling criterion to accept whether the individual $s_x(n)$ is updated to $s_x'(n)$ to avoid prematureness or stagnation. The probability function Ω is accepted as follows:

$$\Omega = \exp\left(-\frac{f\left(s_x'(n)\right) - f\left(s_x(n)\right)}{\Gamma}\right), \tag{15}$$

where Γ is the annealing and temperature control parameter, and its iterative calculation is shown in Equation (16). L is the number of iterations of the algorithm.

$$\Gamma_{g+1} = \Gamma_g \cdot \frac{L}{L + 0.1}. \tag{16}$$

In this paper, the algorithm is encoded in a real number way, and each feasible solution is a matrix with two rows. The first row of the matrix is the information on the order of delivery customer nodes, and the number "0" indicates the delivery origin. The vehicle starts from the origin and returns to the origin after completing the delivery task. The second row of the feasible solution matrix is the path selection information, and the path between some nodes contains multiple sequential sections (see Figure 5).

In Figure 5, the first line of code [0, 4, 3, 11, 0] indicates that a delivery vehicle starts from the origin "0," reaches the customer nodes 4, 3, and 11 for delivery service in order, and finally returns to the origin. The second line of path selection information, i.e., the vehicle selects the second path between nodes 0 and 4, the first path between nodes 4 and 3, the third path between nodes 3 and 11, and the second path from customer node 11 to the origin. The other delivery vehicles travel in the same order, until all the customer delivery services are completed.

In this paper, the adaptation degree of the individual population is related to the optimization objective. The model contains three optimization objectives, namely, carbon emission C, total travel path D, and total travel time T. The three optimization objectives have different units and are of different orders of magnitude. Therefore, it is necessary to adjust the order of magnitude of the optimization

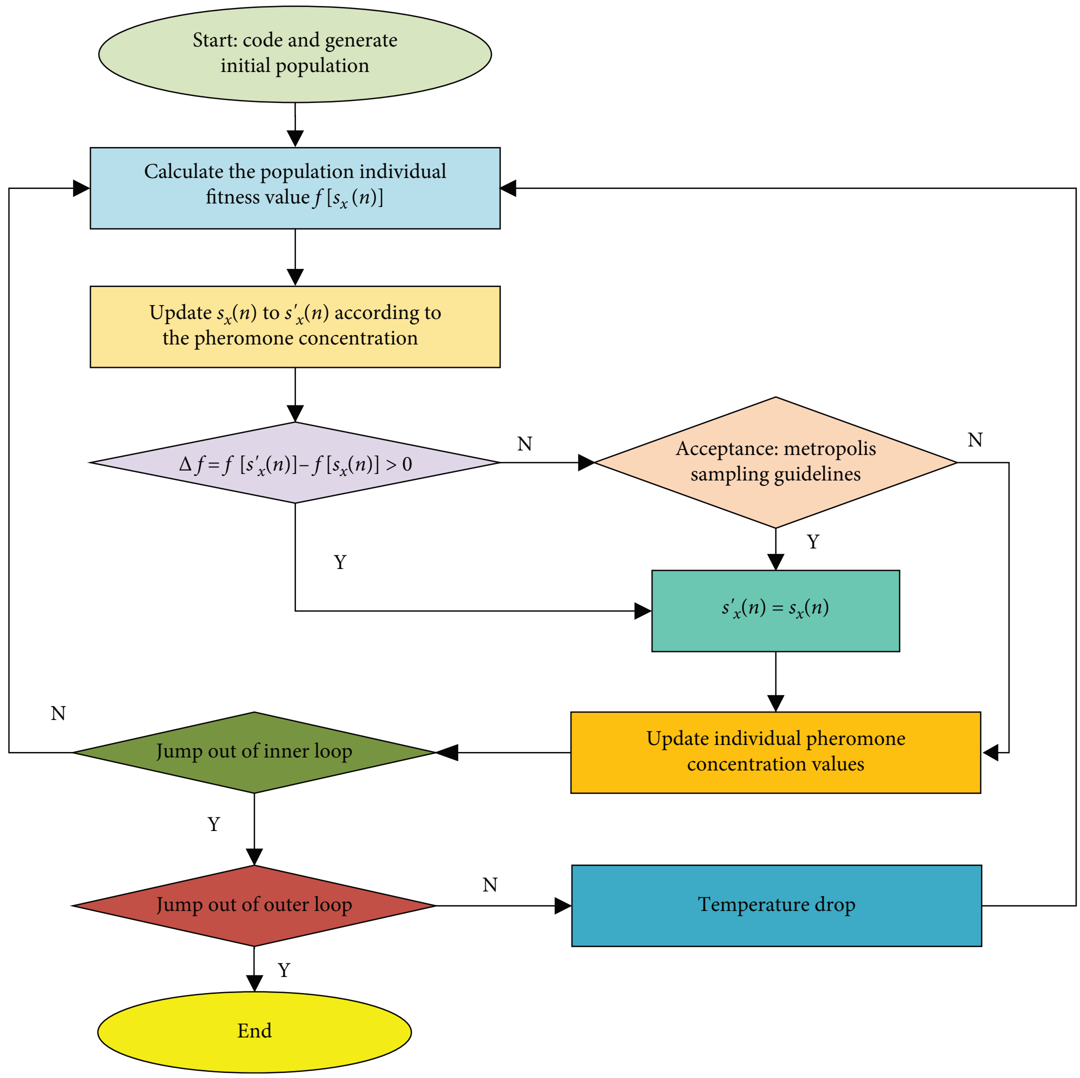

Figure 4: Hybrid algorithm flow.

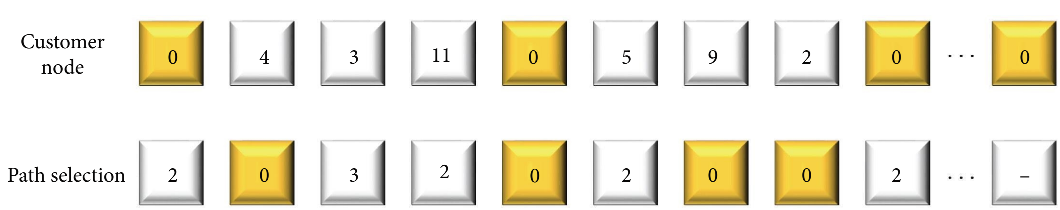

Figure 5: Coding.

objectives to fit their weight coefficients in the process of individual fitness calculation. In this paper, an adaptive fitness function $f(s)$ is used to eliminate the difference in order of magnitude of multiple objectives. The $f(s)$ is expressed as follows:

$$f(s) = \lambda_1 \frac{C_{\max}(s) - C(s)}{C_{\max}(s)} + \lambda_2 \frac{D_{\max}(s) - D(s)}{D_{\max}(s)} + \lambda_3 \frac{N_{\max}(s) - N(s)}{N_{\max}(s)}, \tag{17}$$

where λ_1, λ_2, and λ_3 represent the weighting coefficients of the three individuals, respectively, which need to be decided according to the degree of concern of the enterprise.

This paper proposes an adaptive elite individual reproduction strategy to renew individuals. It guarantees that the entire solution space can be searched. By dynamically retaining the good genes of elite individuals, the algorithm can improve its evolutionary efficiency. The population individuals of this algorithm are updated locally at two points, as shown in Figure 6.

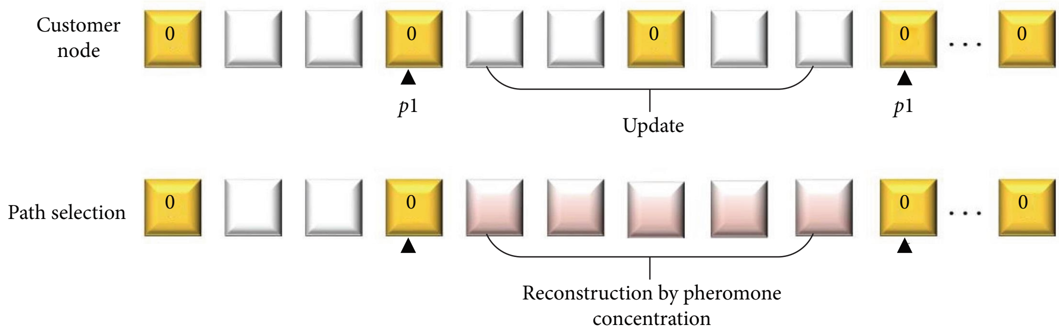

Figure 6: Update operator.

In the customer distribution node information code, the origin of each vehicle departure is set as code 0. All P vehicle distribution origins "0" are found, and the two distribution origins p_1 and p_2 are randomly selected, and the codes in the middle of the two distribution origins are reconstructed according to the pheromone concentration in ACO. Then, the information codes of the other parts beyond the two random points were directly copied to form the new population of individuals. The length p_{12} between these two points is calculated as follows:

$$p_{12} = \mathrm{int}\left[\frac{f_{\max}(s) - f(s)}{f_{\max}(s)} \cdot P\right] + 1. \quad (18)$$

The int[ ] in Equation (18) is rounded downward. $f_{\max}(s)$ is the maximum fitness value in the population of this generation. And if $p_{12} > P - p_1$, then p_2 is the last distribution origin of the individual, i.e., all the parts after p_1 are updated.

The adaptive elite individual reproduction strategy can quickly search the entire solution space. By constructing the individual localization according to the pheromone concentration, it can make the update directional while retaining the good information of other parts.

In this paper, we designed a multifactor calculation method including carbon emission factor to construct the pheromone visibility and pheromone increment update of ACO. This pheromone concentration is present in the path h between any two customer nodes (x, y) and in the road section r included in b. The probability that vehicle w starts from node x and selects the next node y is u_{xy}^{wb}. The calculation formula is given below:

$$u_{xy}^{wb} = \begin{cases} \dfrac{\left[\tau_{xy}^{tb}(n)\right]^{\alpha} \cdot \left[\eta_{xy}^{tb}(n)\right]^{\beta}}{\sum\limits_{y' \in \text{allowed}_{y'}} \left[\tau_{xy'}^{wb}(n)\right]^{\alpha}\left[\eta_{xy'}^{wb}(n)\right]^{\beta}}, & y \in \text{allowed}_{y'} \\ 0, & \text{other} \end{cases}, \quad (19)$$

where $\text{allowed}_{y'}$ denotes the set of customer nodes that have not been delivered yet.

(1) The update method for multifactor visibility of carbon emission factors. $\eta_{xy}^{wb}(n)$ is the visibility of ACO. Unlike the general calculation method that only considers distance, this paper uses a multifactor visibility calculation that includes carbon emission factor and service time factor. Its calculation method can be expressed as follows:

$$r_{xy}^{wb}(n) = \omega_1 \frac{1}{c_{xy}^{wb}} + \omega_2 \frac{1}{d_{xy}^{wb}} + \omega_3 \left(\sum_{u=0}^{U} \frac{d_{xy}^{ru}}{q_{xy}^{ru}} + ns_y\right)^{-1}, \quad (20)$$

where c_{xy}^{wb} is the carbon emission factor, which denotes the carbon emission generated by vehicle w choosing path b between customer nodes x, y. d_{xy}^{wb} is the distance factor, $\sum_{u=0}^{U} \frac{d_{xy}^{ru}}{v_{xy}^{ru}} + ns_y$ is the service time factor. ω_1, ω_2, and ω_3 are the weighting factors.

(2) Calculation of multifactor pheromone increments of carbon emissions. In Equation (19), $\tau_{xy}^{wb}(t)$ represents the pheromone concentration of the path b between customer nodes x, y selected by vehicle w. It is calculated as follows:

$$\tau_{xy}^{wb}(n) = (1 - \sigma)\tau_{xy}^{wb} + \sum_{m=1}^{M} \Delta\tau_{\mathrm{xy}}^{\mathrm{wbm}}, \quad (21)$$

where $0 < \sigma \leq 1$ is the pheromone evaporation rate. m is the number of ants. $m \in \{1, 2, \ldots, M\}$, $\Delta\tau_{xy}^{wbm}$ is the pheromone increment. In this paper, the carbon emission factor C_m, the total path length factor D_m, and the total travel time factor T_m are added to the calculation of the pheromone increment constructed in this paper. The calculation equation is expressed as follows:

$$\Delta\tau_{xy}^{tbm} = \begin{cases} \varepsilon_1(C_m)^{-1} + \varepsilon_2(D_m)^{-1} + \varepsilon_3(N_m)^{-1}, & m \text{ goes through } y \\ 0, & \text{other} \end{cases}, \tag{22}$$

where C_m, D_m, and T_m are the total carbon emissions, distance traveled, and total travel time in a feasible solution generated by the path taken by ant m, respectively. ε_1, ε_2, and ε_3 are the weighting coefficients.

The parameter settings used in the algorithm have a direct impact on its efficiency and effectiveness. In order to improve the convergence speed of the algorithm, this paper adopts the uniform design test method to determine the parameters. The population size is taken as 500, the initial annealing temperature $\Gamma_0 = 1{,}500$, the cooling factor 0.99, the number of inner cycles $C_{r1} = 1{,}000$, and the termination condition of the algorithm (jumping out of the outer cycle) is $C_{r2} = 1{,}000$ iterations, and the optimal solution fitness of the algorithm does not change anymore. The values of α and β in the path selection probability function of the algorithm are taken as 1, and the evaporation rate of pheromone $\sigma = 0.58$. The coefficients λ_1, λ_2, and λ_3 of the weight of the optimization objectives are taken as 1, i.e., equal importance is given to the three optimization objectives.

4. Results Analysis and Discussion

In this paper, IoT technology connects smart devices, sensors, and controllers to the network, i.e., by installing IoT devices on the delivery vehicles, the information of the delivery vehicles (location, speed, temperature, vehicle weight, etc.) is monitored and reported to the cloud server in real time to facilitate real-time scheduling and management. The basic information and scheduling strategies of the delivery vehicles used in the algorithm of this paper are dependent on the application of IoT technology.

4.1. Case Description. In this chapter, we introduce a model for optimizing low-carbon distribution pathways within cold chain logistics, specifically tailored for an IoT environment. We also present an algorithm to solve this model. To provide a practical illustration, we select the frozen food factory of SW Company located in P city as the backdrop for our case study. Utilizing this setting, we design a simulation example that adheres to the conditions stipulated by our model. The company currently has a group of professional teams, and its products and services are fully covered in P city and radiated to many counties and cities around P city, with a deep customer base. In recent years, as the demand for fresh produce from supermarkets has increased, the number of companies providing fresh produce delivery to supermarkets like SW has also increased year by year, and the competition pressure has increased. Seeking to reduce costs, improve operations, and increase competitiveness, SW has begun to focus on the expenses formed by the logistics chain. Therefore, this paper selects the data of 20 supermarkets that need to be delivered in P city on the same morning as the object of optimization for rational route planning. It is expected that a scientific method will be used to reduce the logistics cost and increase the competitiveness of the company. In this paper, the supermarkets within 10 km of P city are taken as the distribution objects of fresh agricultural products; the intersection of West Central Road and South Central Street is taken as the coordinate origin; the distance of the supermarkets from the coordinate origin indicates the corresponding positions (X, Y). The specific simulation data are shown in Table 1.

Since the carbon emissions of heterogeneous freight vehicles (freight vehicles of different models and different capacities) of less than 5 tons do not differ much. Therefore, SW company uses the same model of freight vehicle with the maximum load capacity of 4.5 tons for the simulation calculation of distribution and transportation. The fixed cost of using this type of refrigerated freight vehicle is 200 RMB per freight vehicle. Considering the distribution in the city road, the average speed is 50 km/hr, and the cost per kilometer is 3 yuan/km.

Due to the weight restriction on city roads, the paper stipulates that the maximum amount of refrigerated carriage is 9 tons at a time. The cost of the vehicle arriving at the supermarket in advance is 10 yuan/min, and the cost of delayed arrival is 60 yuan/min. The unit value of agricultural products is 6,000 yuan/ton. The unit refrigeration cost is 1.5 yuan/kcal and the heat load factor is 4944.69 kcal/hr. The fuel consumption per kilometer is 0.377 L/km when the refrigerated carriage is at the maximum cargo capacity and 0.165 L/km per kilometer when empty. 0.0066 g/(kg km) of CO_2 is generated from 1 km of refrigeration when the refrigerated carriage is loaded with 1 kg. The distance distribution between the distribution center and the supermarkets is shown in Table 1.

4.2. Analysis of Simulation Results. In the simulation experiment, a computer with CPU 3.3 GHz, 16G of RAM, and 64-bit Windows 11 operating system was used. In this paper, MATLAB R2017a is used as the simulation platform to test and analyze the algorithm. The population size is taken as 500, the initial annealing temperature $\Gamma_0 = 1{,}500$, the cooling factor 0.99, the number of inner cycles $C_{r1} = 1{,}000$, and the termination condition of the algorithm (jumping out of the outer cycle) is $C_{r2} = 1{,}000$ iterations, and the optimal solution fitness of the algorithm does not change anymore. The values of α and β in the path selection probability function of the algorithm are taken as 1, and the evaporation rate of pheromone $\sigma = 0.58$. The coefficients λ_1, λ_2, and λ_3 of the weight of the optimization objectives are taken as 1, i.e., equal importance is given to the three optimization objectives. The initialization parameters of the algorithm in this paper are the same. The distribution center and the location of each supermarket are drawn according to the supermarket demand information in Table 1.

According to the supermarket demand information data in Table 1, the distribution center and the location of each supermarket are drawn, as shown in Figure 7. Zero represents

Table 1: Supermarket demand information.

Number	Location (km)	Demand (ton)	Service time (min)
Distribution origin "0"	(6.9530, 7.6339)	0	0
Supermarket 1	(8.0139, 4.0506)	1.5	20
Supermarket 2	(5.5130, 3.6810)	0.5	10
Supermarket 3	(6.6681, 4.6419)	2	25
Supermarket 4	(6.9171, 6.3211)	1.5	20
Supermarket 5	(6.0134, 5.4363)	1.5	20
Supermarket 6	(2.9396, 1.2160)	1	15
Supermarket 7	(8.0371, 5.4265)	2	25
Supermarket 8	(4.1195, 2.4294)	1.5	20
Supermarket 9	(4.1418, 4.4869)	2	25
Supermarket 10	(5.7041, 1.8888)	1.5	20
Supermarket 11	(2.9996, 3.2988)	1.5	22
Supermarket 12	(1.7042, 3.7640)	1	15
Supermarket 13	(2.4039, 6.8323)	1	15
Supermarket 14	(4.2771, 6.5825)	0.5	10
Supermarket 15	(7.0333, 4.1502)	0.5	10
Supermarket 16	(6.2205, 1.1196)	1	15
Supermarket 17	(3.8067, 1.3939)	1.5	20
Supermarket 18	(0.9981, 5.3535)	0.5	10
Supermarket 19	(5.2214, 5.4478)	1	15
Supermarket 20	(4.7994, 1.6351)	2.5	30

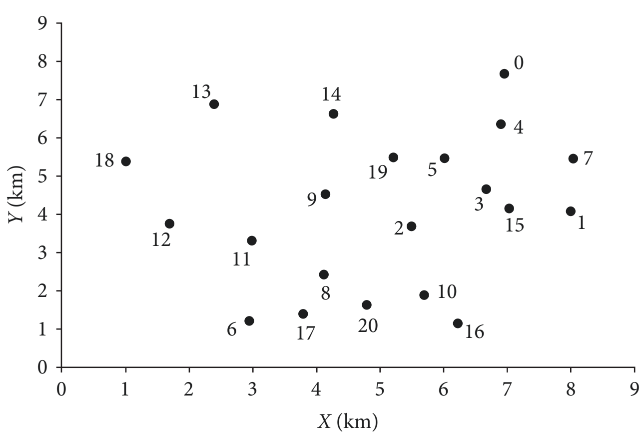

Figure 7: Distribution center and supermarket scatter.

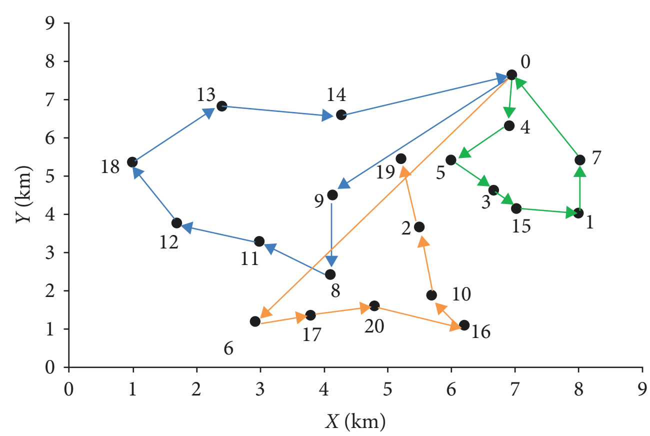

Figure 8: Optimal path diagram.

the distribution center, and 1–20 represent the location of each supermarket.

According to MATLAB run and decode to get the optimal path, the optimal path of this example is shown below (see Figure 8).

To sum up, the optimal solution of this paper is that three vehicles start from the distribution center, and the first one is 0-9-8-11-12-18-13-14-0 in sequence. The second vehicle is 0-6-17-20-16-10-2-19-0 in sequence. The third vehicle is 0-4-5-3-15-1-7-0 in sequence. The total delivery cost under this strategy is 9,776.53 yuan, and the carbon emission is 63.93 kg.

In this paper, the algorithm is solved using a hybrid ant colony genetic algorithm. The initialized population size is set to pop = 100, in which 50 individuals come from the ACO algorithm and the remaining individuals are randomly generated. Different values of carbon tax are taken and analyzed to study the effect on carbon emission, total cost, customer satisfaction, and vehicle delivery routes (see Figure 9).

Figure 9 reveals a close alignment between total cost fluctuations and carbon emissions. Carbon emissions primarily arise from fuel consumption and refrigeration equipment. The largest cost components are refrigeration and vehicle usage. Hence, carbon emissions reflect total costs. Customer satisfaction consistently exceeds 90%, confirming study expectations.

4.3. Robustness Analysis. The algorithm in this paper and three algorithms in literatures [22–24] and [25] have been run 50 times, respectively, and the average time t, error ξ, and

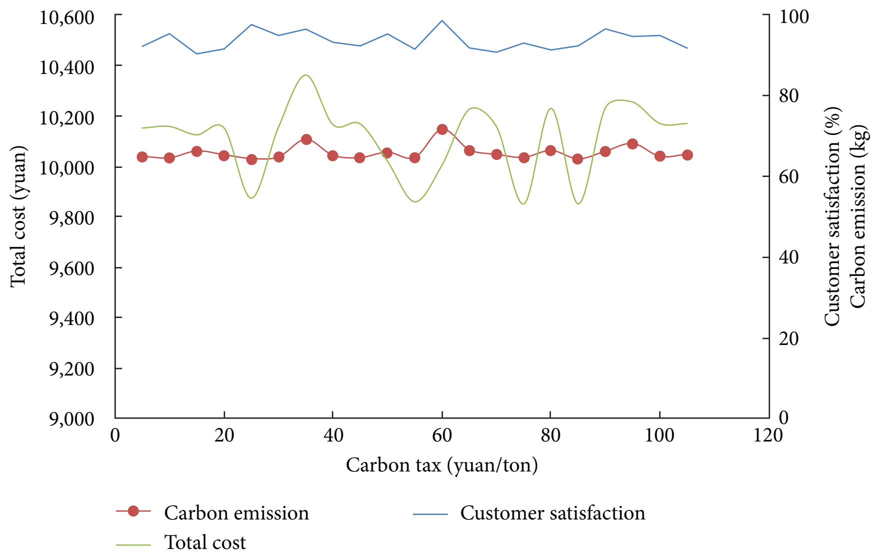

Figure 9: Total cost, CO_2 emissions, and customer satisfaction under different carbon taxes.

Table 2: Robustness analysis of the four algorithms.

Algorithm	Best	Ave	ξ (%)	r (%)	t (s)
Literature [22]	384.52	385.57	2.79	2.00	12.15
Literature [23]	378.82	389.79	2.48	5.00	9.57
Literature [24]	375.38	378.16	2.65	10.00	6.79
Literature [25]	372.29	377.53	1.27	14.00	5.81
Proposed	**372.17**	**375.03**	**0.75**	**20.00**	**1.54**

Bold values represent the best result.

stable robustness r of each algorithm were recorded. Equations are as follows:

$$\xi = \frac{\text{ave} - \text{best}}{\text{best}}, \tag{23}$$

$$r = \frac{m}{n}, \tag{24}$$

where ave denotes the average total mileage, best is the optimal total mileage, n is the number of experiments, and m is the number of times the optimal solution is found. The data for each of the four algorithms are shown in Table 2.

The results are presented in Table 2, which shows that the algorithm achieved the best total mileage, average total mileage, error value, robustness r, and algorithm time consumption compared to other methods tested. These findings suggest that the algorithm performs well in terms of computational complexity and robustness. This indicates that the optimal result of this paper's algorithm is better than the single ant colony algorithm, with low error, high accuracy, and stable robustness.

4.4. Comparative Analysis of Path Optimization Algorithms. In order to verify the effectiveness, stability, and convergence of the hybrid algorithm, the algorithm in this paper is compared with the other three algorithms. Table 3 shows the comparison of the four algorithms in terms of carbon emissions, total distribution time, and total distribution distance.

As can be seen from Table 3, the experimental results of the algorithm in this paper are the minimum in the above four aspects. In terms of calculation time, the proposed algorithm greatly improves the operation efficiency because the ant colony algorithm is added into the SA algorithm as the initial population.

Figure 10 shows the comparison of the convergence effect between the proposed algorithm and other algorithms. Compared with the other algorithms, the convergence speed of the proposed algorithm is significantly better than the other algorithms after 100 iterations. The figure shows that literature [22] has a long computation time and slow convergence, but its solution effect is good and its global optimization-seeking ability is strong. Literature [23] is easy to fall into the local optimal solution, with poor mining ability and short solution time. The methods of literature [24] and literature [25] converge quickly, but they are more susceptible to the influence of the individual size of the population. The algorithm in this paper has a better global convergence ability and converges faster. Therefore, the algorithm in this paper is effective for solving the proposed model.

In order to further analyze the efficiency of the proposed algorithm, this paper adopts three classical examples in TSPLIB for optimization analysis. And compared with other

Table 3: Comparison of the four path planning algorithms.

Algorithms	Carbon emissions (kg)	Total distribution time (hr)	Total distribution distance (km)
Literature [22]	280.42	27.42	671.01
Literature [23]	294.23	28.52	655.52
Literature [24]	270.21	26.34	651.64
Literature [25]	265.82	27.12	649.92
Proposed	**250.18**	**24.13**	**638.45**

Bold values represent the best result.

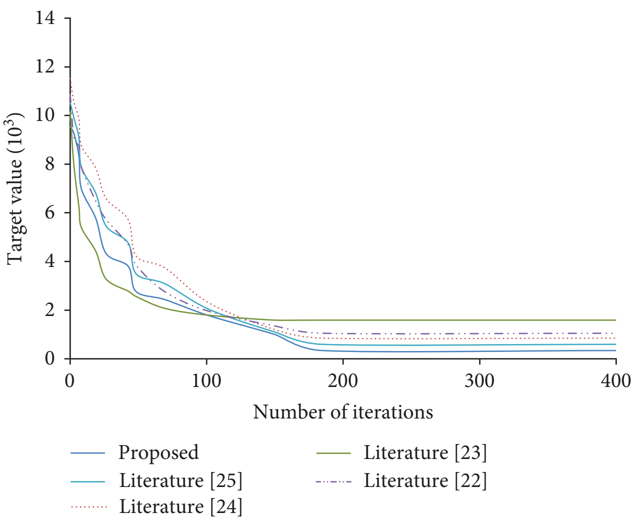

Figure 10: Comparison of convergence results.

Table 4: Comparison of the effect of TSP model algorithms.

Algorithm	Example		
	ei51 (428)	st70 (675)	Rd100 (7910)
Literatures [26]	432.2	678.6	8243.1
Literatures [27]	446.3	736.2	9132.7
Literatures [28]	424.4	684.5	8111.2
Proposed	419.1	669.9	7999.4

three state-of-the-art algorithms (literatures [26–28]), the optimization results are shown in Table 4.

As can be seen from Table 4, the algorithm in this paper has a good effect on the optimization calculation of the TSP problem.

5. Conclusion

Achieving sustainable low carbon development is an important direction for logistics technology innovation and optimization. In this paper, an optimization model is presented, focusing on minimizing carbon emissions. This model considers time, distribution distance, and carbon emissions as primary constraints within the IoT environment. The number of good genes in the population is increased by the adaptive elite individual reproduction strategy. Afterward, the multifactor operator including carbon emission is introduced to enhance the directionality of the pheromone update. The validity of the model and algorithm is verified. The assumption conditions in this paper are more ideal and have some distance from reality. For example, the distribution centers in reality may have different delivery models, different delivery temperatures for different models, different refrigerated environments for different types of fresh agricultural products, and different spoilage rates. In future research, more complex and realistic assumptions can be set to adapt the model to the real situation and make it better used in the enterprise.

Data Availability

The labeled dataset used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The author declares no competing interests.

Authors' Contributions

You-wu Liu and Ming-yue Liu contributed to the writing of the manuscript and data analysis. Bian-bian Jiao supervised the work and designed the study. Jun-long Li made contributions to the final revision and language polishing of the article, and all the authors agreed to add him to the list of authors of this article. All unanimously agreed to the above arrangement. All the authors have read and agreed the final version to be published.

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