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Research Article

Optimization of Vehicle Paths considering Carbon Emissions in a Time-Varying Road Network

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Regarding the study of the time-dependent green vehicle path problem (TDGVRP), most of the literature uses the step function to represent the vehicle speed change in order to reduce the computation, ignoring the continuity of vehicle speed, which leads to the lack of accurate carbon emissions measurement. This study represents the vehicle speed variation as a continuous function to make the constructed model more consistent with the actual situation, in order to promote the reduction of carbon emissions generated in the logistics and distribution process, improve the greenhouse effect and ecological environment, and ultimately promote sustainable development. In this paper, a simulated annealing-genetic hybrid algorithm (GA-SA) is proposed to solve the constructed optimization model, and two sets of comparison experiments are designed. The experimental results show that compared with the two classical algorithms, the simulated annealing-genetic hybrid algorithm (GA-SA) has better solution performance, inherits the robustness and potential parallelism of the genetic algorithm, and has a higher practical value. Meanwhile, although the total driving distance of the vehicle path considering carbon emissions increases by 3.52 km, the carbon emission cost and the total cost decrease by 5.6% and 3.4%, respectively, which confirms that the path optimization model considering carbon emissions constructed in this study can not only play the role of restraining carbon emissions but also reduce the total distribution cost and the waste of resources. In this study, a continuous function is used to represent the vehicle speed variation, and two classical optimization algorithms (the genetic algorithm and simulated annealing algorithm) are combined and parameter-optimized, and certain innovations are made in the processing of vehicle speed and the solution algorithm. Finally, the effectiveness of the model and algorithm is verified by experiments.

1. Introduction

Global ecological conditions have become increasingly hostile in recent decades, with global CO_2 emissions reaching a record 36.7 billion metric tons of CO_2 in 2019. According to Statista, in 2020, a reduction in global CO_2 emissions by 5% to 34.81 billion metric tons due to the COVID-19 outbreak emissions is expected to rebound in 2021 as the embargo is eased. Figure 1 shows the change in global CO_2 emissions from 2000 to 2021 according to Statista, where carbon emissions in 2021 are projected. This has drawn the attention of countries worldwide to the issue of carbon emissions, and energy conservation and emissions reduction have become primary issues in the world's economic and social development.

China, as a major carbon emitter, has reached 10.6 billion tons of carbon emissions in 2020. However, China's report on the two sessions of the National People's Congress in 2021 clearly states that it will achieve no further growth in carbon dioxide emissions by 2030. Globally, low carbon is also a major direction advocated and pursued by countries worldwide. According to Statista, global carbon emissions by sector in 2020, as shown in Figure 2, the transport sector is the main source of carbon dioxide emissions, accounting for 7.29 billion metric tons of carbon emissions, accounting for 20.5% of global carbon emissions, and according to Statista, road emissions account for 41% of the total transport emissions. In this context, it is of theoretical and practical importance to examine the issue of vehicle pathways that considers carbon emissions.

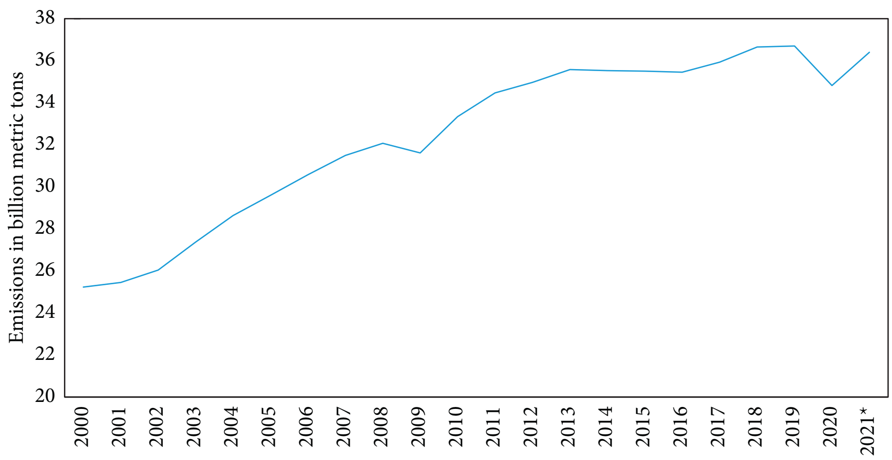

Figure 1: Annual CO_2 emissions worldwide from 2000 to 2020.

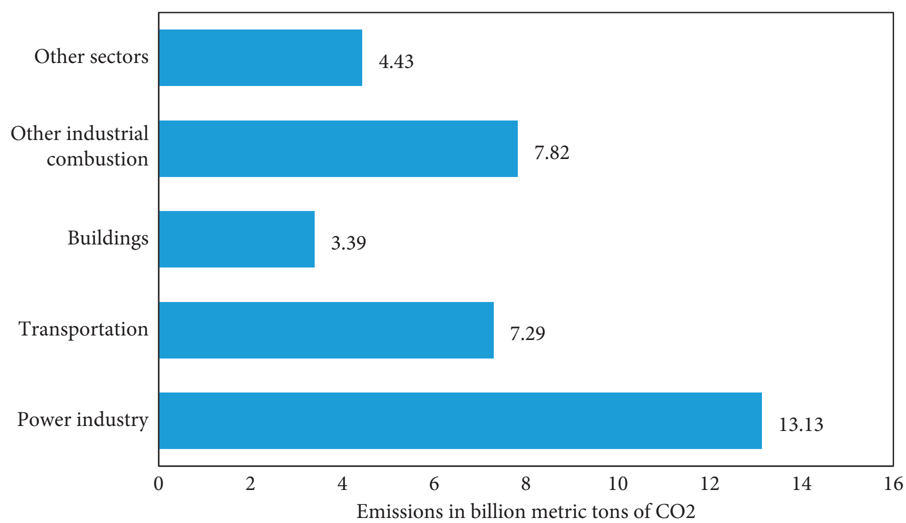

Figure 2: Global carbon emissions by sector in 2020.

2. Review of the Literature

vehicle routing problem (VRP) is a classical class of combinatorial optimization problems, which was first proposed by Dantzig and Ramser in 1959 with the main purpose of reducing transportation cost and transportation distance [1]. On this basis, later research models were optimized continuously [2, 3]. Since then, due to the increasingly serious pollution caused by road transportation to the ecological environment, the green vehicle routing problem (GVRP) was proposed and became a very important research direction [4, 5]. Scholars from various countries began to pay attention to this research direction and conducted more in-depth research on the basis of the GVRP [6, 7].

In this article, we study the time-dependent green vehicle path problem (TDGVRP) and define it as follows: under the condition of changing road traffic conditions, while meeting the service time requirements of customers and vehicle capacity constraints, we take the reduction of operation costs, energy consumption, and carbon emissions as the optimization objectives and scientifically plan the number of departures, departure times, and vehicle routes to achieve economic benefits. The number of departures, departure times, and vehicle routes are scientifically planned to achieve coordinated optimization of economic, environmental, and social benefits.

The main feature of TDGVRP is that it considers environmental factors such as fuel consumption and carbon emissions of the vehicle under changing road traffic conditions, considering economic and environmental benefits, which is the main difference between TDGVRP and traditional VRP. TDGVRP does not seem to be fundamentally different from traditional VRP on the surface; only optimization objectives such as fuel consumption/carbon emissions have been added to the objective function. However, fuel consumption and carbon emissions are affected by various factors such as load weight, vehicle speed, vehicle characteristic parameters, road gradient, and traffic congestion [8–10], leading to much more complicated modeling and optimization of TDGVRP than traditional VRP.

Considering the effect of load weight on fuel consumption and carbon emissions, the heavier the vehicle load weight, the more fuel consumption and carbon emissions per unit distance traveled [11–13]. TDGVRP cannot just consider the shortest travel distance or the least distribution cost like traditional VRP when performing vehicle path planning. It must consider road traffic conditions, giving priority to customers with heavier demanded cargo weight to reduce fuel consumption and carbon emissions.

Considering the effect of vehicle speed on fuel consumption and carbon emissions, because the fuel consumption rate and carbon emissions rate are lowest when the vehicle is running at the optimal speed, and deviating from that speed, its fuel consumption rate and carbon emissions rate will increase [14]. Therefore, the vehicle should consider the effect of vehicle speed on multiple optimization objectives, such as fuel consumption, carbon emissions, and vehicle usage cost, in an integrated way when performing path planning. These optimization objectives affect each other and may even conflict with each other.

In addition, considering the effects of road gradient, traffic congestion, and vehicle characteristics on vehicle fuel consumption and carbon emissions, TDGVRP is more difficult to model and optimize than traditional VRP. Therefore, TDGVRP brings new challenges to the modeling and optimization of traditional VRP, and it is a topic worthy of in-depth study. TDGVRP contains two hot problems of current VRP research: time-dependent vehicle path problem and green vehicle path problem. For these two problems, more scholars have conducted research.

For the time-dependent vehicle path problem, Sabar et al. developed a mathematical model to minimize the total distribution cost for dynamic VRP with different road traffic conditions at different times. They proposed an adaptive evolutionary algorithm using variable parameters to solve such dynamic VRP more effectively [15]. Jaballah et al. solved the dynamic speed-based shortest path problem with a simulated annealing metaheuristic algorithm and demonstrated by example that ignoring time-dependent traffic information leads to inaccurate estimates of travel times [16]. Gmira et al. argued that the time-dependent vehicle path problem should relate travel speed to the road network and proposed a taboo search heuristic to solve such vehicle path problems [17].

Similarly, Wei et al. fully considered the time-varying speed and time window of the vehicle and proposed a heuristic-based nondominated ranking genetic algorithm to find the Pareto optimal solution in a reasonable time [18]. Liu Zhang constructed an urban cold chain transportation model, with the objective function of minimizing the total cost in view of the time-dependent nature of urban cold chain transportation and the time-varying nature of urban road speed, and an artificial immune particle swarm optimization algorithm to solve the model [19].

In addition, Xu and Li proposed an unconventional path optimization method for dynamic road conditions and traffic congestion and a fission ripple diffusion algorithm based on coevolutionary path optimization to solve the problem [20]. Liu et al. considered the effect of vehicle travel speed on carbon emissions, proposed a calculation method across the time domain and a method to avoid traffic congestion during peak hours, and designed an improved ant colony algorithm to solve this problem [21].

In summary, scholars mostly use classical or improved algorithms to solve the model when studying TDGVRP. In this study, two classical optimization algorithms (the genetic and simulated annealing algorithm) are combined and parameter optimized to propose a hybrid algorithm.

For the speed processing method, Chen et al. established a vehicle speed matrix of the urban distribution networks based on the analysis of the spatiotemporal dynamics of distribution vehicles in the urban road networks and cut the distribution periods and the road sections in the distribution networks separately [22]. Franceschetti et al. argued that the vehicle travel process could be divided into normal driving periods and congestion periods according to whether the traffic is congested or not. The different periods of vehicle speed are different, but all are moving at a uniform speed [23].

Similarly, Ge and Ran used the same treatment to divide the speed into three segments and introduced a waiting strategy for travel time calculation to solve time-varying traffic congestion conditions [24]. Wang considered that the driving speed of electric vehicles may vary in different periods and divided the speed into four segments [25].

In summary, in treating speed, most of the literature uses the step function to represent the change of vehicle speed without considering the problem of continuity of vehicle speed. Yildirim and Catay argued that because TDGVRP proposed in most of the literature cannot capture some real features of real road networks and therefore cannot be used well to solve the associated shortest path problem, the authors propose to use real-life road networks and velocity data to generate real velocity data and demonstrate its applicability in TDGVRP in their paper [26]. To address this problem, Elomri et al. proposed that the vehicle speed during traffic congestion continuously changes according to a certain rule rather than uniform motion [27]. A similar treatment of vehicle speed was carried out by Fan et al. who considered that the vehicle travel speed satisfies a specific trigonometric relationship equation [28]. In this study, we combined the treatment of Xu et al. and Franceschetti et al. and argued that the vehicle is moving at a uniform speed during the normal driving period but at a speed that varies according to a certain rule during the traffic congestion period.

For GVRP, how to measure the carbon emissions of vehicles is the basis of its research. According to the different factors affecting carbon emissions, different carbon emissions measurement models are established, and then carbon emissions are reduced. In terms of measuring carbon emissions, some literature has carried out a simpler treatment [29–31]. In order to make the carbon emissions measurement closer to reality, some literature has considered more factors in measuring carbon emissions. Kuo proposed a load and speed-based fuel consumption model to calculate carbon emissions for fuel consumption minimization [32], which is widely cited in path optimization considering carbon emissions. Yao and Zhang [33] and Zhang and Li [34] used a load and speed-based fuel consumption model to calculate carbon emissions and construct a path optimization model considering carbon emissions.

Hickman et al. proposed the MEET carbon emission measurement model, which not only considered the load but also included the vehicle speed and road slope [35]. Some studies have cited MEET models in their carbon emissions measurement models; for example, Zhou et al. [36] and Wang and Yan [37] used the MEET model to measure carbon emissions generated during vehicle travel and used the total cost as the objective optimization function. The vehicle load constraint was modified on the basis of the MEET model by Du and Zhang to ensure that the carbon emission calculation is closer to the real value [38]. Similarly, Jamshidian and Tirkolaee incorporated load, vehicle speed, road gradient, and traffic conditions into the model in the green vehicle path problem [39].

In addition, Younglove and Scora proposed a transient fuel consumption model, which mainly considered the effects of load, speed, acceleration, road gradient, and vehicle characteristic parameters on fuel consumption [40]. Assogba et al. invoked the transient fuel consumption model to calculate carbon emissions and constructed a dual-objective model to minimize the total carbon emissions and transportation costs [41]. Yang et al. [42] and Yu and Wang [43] used the instantaneous fuel consumption model to measure carbon emissions and constructed a multi-vehicle model with vehicle number constraints and a simultaneous delivery multi-vehicle model, respectively.

Although scholars have considered as many factors as possible in calculating carbon emissions, there are few papers in GVRP that consider the effects of factors such as road and fuel types, and this paper integrates these two factors in the calculation of carbon emissions based on previous studies.

3. Research Gaps

First of all, regarding the study of the vehicle path problem under the time-varying road network, the existing study of road speed change is mostly expressed as a step function without considering that the vehicle speed is continuous, which is not consistent with the actual situation, and this paper addresses this in the previous research based on a continuous function to express the change of vehicle speed. Neither generalized that the vehicle has been driving at a uniform speed nor all the vehicles have been in the speed change state. Rather, it is considered that the vehicle is traveling at a certain speed uniformly in the normal driving period, whereas the vehicle is changing at that speed according to a certain law in the congestion period.

Secondly, in terms of carbon emission measurement for the green vehicle path optimization problem, although some literature considers factors such as load, speed, road gradient, and vehicle characteristic parameters, the existing literature mainly studies the effects of vehicle speed and load on fuel consumption and carbon emissions, and the factors considered are not comprehensive enough, thus leading to a large error between the measurement of carbon emissions and the actual situation. In this field, few studies mention factors such as fuel type and road type. In this study, we consider two factors (fuel and road types) based on previous studies to make the carbon emission measurement more accurate.

In addition, existing literature has conducted a more in-depth study on how the average, optimal, time-varying, and uncertain speeds affect the fuel consumption and carbon emissions of vehicles. The results show that different types of speed affect the fuel consumption and carbon emissions of vehicles to different degrees. This indicates that treating time-varying speed in TDGVRP is crucial and directly affects whether the model can be realistically applied in practice.

Finally, scholars have mostly used classical metaheuristic algorithms or improved algorithms to solve the TDGVRP model problems and less often combined the two algorithms to solve this type of problems. In this study, a hybrid simulated annealing-genetic algorithm is constructed by combining two classical optimization algorithms (the genetic and simulated annealing algorithms) with parameter optimization for the constructed model. A set of experiments is conducted to compare the solution results of the hybrid algorithm with the above two classical optimization algorithms, proving that the hybrid algorithm has better solution performance.

In summary, the main contributions of this study are as follows: (1) a continuous function is used to represent the variation of vehicle speed with road conditions; (2) fuel and road types are considered in measuring vehicle carbon emissions; and (3) a hybrid algorithm with better solution performance is designed. In conclusion, this study constructs a continuous function to represent the speed variation, considers various factors that affect the carbon emissions during the vehicle driving process, constructs a corresponding carbon emissions calculation formula, designs a hybrid algorithm, and confirms the scientific validity of the algorithm through simulation experiments.

4. Problems and Models

4.1. Problem Description. A certain number of distribution vehicles depart from the same distribution center and deliver to 60 customer demand points belonging to the range of the distribution center, where the location and demand quantity of each demand point are known. Under the premise of satisfying customer demand, the total distribution cost (vehicle dispatch, transportation, carbon emissions, overload penalty, and overtime penalty costs) is minimized to solve for an appropriate distribution path, considering the load limit, time window limit, and variation of vehicles' speed of the distribution vehicles. The specific symbol descriptions are shown in Table 1.

4.2. Model Assumptions. The load capacity of each distribution vehicle is known and identical, and the vehicle departs from and must return to the distribution center 12; the demand at the demand point and the acceptable delivery service time are known, and each demand point must and can only be served by one vehicle 42. The distribution center has the size capacity to meet all demand points and has

Table 1: Description of symbols for path optimization problems.

Notation	Definition
N	The set of serial numbers of all demand points, $N = \{0, 1, \ldots, n\}$, where 0 denotes the distribution center and the rest nodes denote demand points
S	The set of originating nodes
E	The set of final arrival nodes
SC	The set of originating nodes and demand nodes
DE	The set of demand nodes and final arrival nodes
B	An infinite number
K	The set of all vehicles, $K = \{l, 2, \ldots, n\}$
F	Denotes the fixed cost of dispatching a vehicle
Cij	The unit transportation rate from point i to point j
qi	The quantity demanded at demand point i
Q	Maximum load capacity of a dispatching vehicle
[ET, LT]	The left and right time windows of the distribution center
[ai, bi]	Left and right time windows for demand point i
Dij	Distance from demand point i to distribution center j
Wik	Time when vehicle k arrives at demand point i
Si	Service time of demand point i
Tijk	Travel time of vehicle k from demand point i to demand point j
ϒ	Price per unit of carbon emissions
Yik	0-1 variable, yik = 1 when the kth vehicle is in service, otherwise yik = 0
P	Overload penalty factor
R	Overtime penalty factor
SD	Any subset of the set of demand points
|SD|	Number of demand points in the set S
Xijk	0-1 variable, xijk = 1 when the kth vehicle passes from point i to point j, otherwise xijk = 0

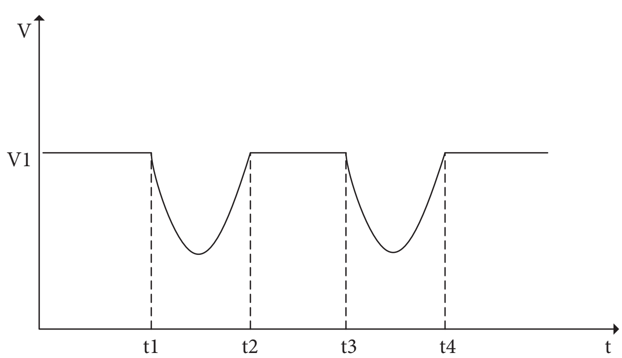

Figure 3: Variation of speed with time.

multiple vehicles but limited vehicles 44. Only carbon emissions from vehicle transportation are considered 45.

4.3. Vehicle Speed Processing. Most of the existing literature deals with vehicle travel speed as a function in segmented form, and the speed is mostly treated as a sudden change at the segmentation point; however, this is not realistic, and in fact, the vehicle speed varies continuously rather than abruptly.

Fan et al. proposed that the relationship between vehicle speed (v) and time (t) during peak hours is $V = \alpha \mathrm{Sin}\,(\mathrm{yt}) + \delta$ (where α, y, and δ are coefficients related to road conditions) [10, 20]. Franceschetti et al. argued that the vehicle travel process can be divided into normal and congested periods according to whether the traffic is congested or not, and the vehicle speed in different periods is different, but all are in uniform motion [23–25].

This study combines the treatments of Xu et al. and Franceschetti et al. and represents the continuous variation of vehicle speed during a day in Figure 3, with the normal driving period with a stable speed V1 (variable) during time t1 and the peak hours during time periods t1–t2 and t3–t4, the vehicle speed during this period starts from V1 with $V = \alpha \mathrm{Sin}\,(\mathrm{yt}) + \delta$ (where α, y, and δ are coefficients related to road conditions) with a regular variation, and the t2–t3 time period is the normal driving period for the recovery of the steady speed V1 (variable).

4.4. Calculation of Carbon Emissions. Factors such as speed, vehicle type, load capacity, road gradient, and fuel type all affect the carbon emissions of the vehicle driving process. This study calculates fuel consumption based on the MEET model proposed by Assogba et al. [41] and refers to the carbon emission model of Demir et al. [11] and the relevant parameters determined by Zhou et al. [44], combined with the actual research of this situation; the formula for calculating the carbon emissions of vehicle K from point i to point j is determined as follows. When the vehicle is always running at a constant speed,

$$E_{ijk} = E_r * GC * LC * d_{ij}. \tag{1}$$

When the vehicle is always moving at variable speed,

$$E_{ijk} = \int_{t_2}^{t_1} \left(E_r * GC * LC * V\right) d_t. \tag{2}$$

When the vehicle is between a constant speed and a variable speed,

$$E_{ijk} = E_r * GC * LC * V\Delta t + \int_{t_f}^{t_c} (E_r * GC * LC * V)d_t. \quad (3)$$

Here,

$$E_r = 110 + 0.000375V^3 + \frac{8702}{V}, \quad (4)$$

$$GC = \exp\left[\left(0.0059V^2 - 0.00775V + 11.936\right)\varepsilon\right], \quad (5)$$

$$LC = 0.27W_r + 1 + 0.0614\varepsilon W_r - 0.0011\varepsilon^3 W_r\varsigma \quad (6)$$

where E_r is carbon emissions per kilometer, GC is the road gradient correction factor, LC is the vehicle load correction factor, ε is the road gradient, and W_r is the ratio of the loaded cargo weight to the rated load.

4.5. Model Construction

(1) Vehicle dispatch cost:

$$C_1 = \sum_{k\in K}\sum_{j\in N} Fx_{0jk}. \quad (7)$$

(2) Transport costs:

$$C_2 = \sum_{i\in N}\sum_{j\in N}\sum_{k\in K} c_{ij}x_{ijk}d_{ij}. \quad (8)$$

(3) Cost of carbon emissions:

$$C_3 = \gamma\sum_{i\in N}\sum_{j\in N}\sum_{k\in N} E_{ijk}x_{ijk}. \quad (9)$$

(4) Overload penalty costs:

$$C_4 = \beta\max\left\{\sum_{i\in N}\left(q_i y_{ik}\ldots Q\right), 0\right\}. \quad (10)$$

(5) Overtime penalty cost:

$$C_5 = r\max\left\{\sum_{i\in N}\sum_{k\in K}\left(W_{ik} - b_i\right), 0\right\}. \quad (11)$$

In summary, a distribution center path optimization model is constructed to minimize the sum of total distribution and carbon emission costs as follows:

$$\min C = C_1 + C_2 + C_3 + C_4 + C_5. \quad (12)$$

Subject to

$$\sum_{k\in K}\sum_{i\in N} x_{ijk} = 1, \quad j\in N, i\neq j, \quad (13)$$

$$\sum_{k\in K}\sum_{i\in N} x_{ijk} = 1, \quad i\in N, i\neq j, \quad (14)$$

$$\sum_{j\in N} x_{ijk} - \sum_{j\in N} x_{jik} = 0, \quad i\in N, k\in K, \quad (15)$$

$$\sum_{j\in N}\sum_{k\in K} x_{0jk} = \sum_{i\in N}\sum_{k\in K} x_{i0k}, \quad (16)$$

$$\sum_{k\in K}\sum_{i\in N} d_i x_{ijk} \leq Q, \quad (17)$$

$$\begin{aligned}&\max\left(a_i, w_{ik}\right) + s_i + T_{ijk} \leq LT,\\ &E \leq w_{ik} \leq L, \quad \forall k\in K, \forall i\in\{0, n+1\},\end{aligned} \quad (18)$$

$$\sum_{i\in N}\sum_{j\in N} x_{ijk} \leq |SD| - 1, \quad SD\in N, \quad (19)$$

$$\begin{aligned}&\sum_{i=1}^{k} k\left(y_{ik} - yik\right) \leq B\left(1 - \sum_{k=1}^{k} \text{xijk} - 1\right),\\ &i\in SC,\ j\in DE,\ i\neq j,\end{aligned} \quad (20)$$

$$\sum_{i=1}^{k} k\left(y_{ik} - \text{yik}\right) \geq B\left(\sum_{k=1}^{k} x_{ijk} - 1\right), \quad i\in SC,\ j\in DE,\ i, \quad (21)$$

$$x_{ijk}\in\{0, 1\}, \quad \forall k\in K, \forall (i, j)\in N. \quad (22)$$

Objective (12) is the optimization objective, indicating that the sum of total distribution cost and carbon emissions cost is minimized, where the default transportation rate per unit distance is 1. Constraints (13) to (15) restrict each demand point to be assigned to only one path; it can only be served by one vehicle once. Constraint (16) indicates that all distribution vehicles must return to the distribution center after completing the distribution task, and the number of departure vehicles is equal to the number of return vehicles. Constraint (17) indicates that the vehicle load cannot exceed the maximum load. Constraint (18) is a time window constraint, and the time point of arrival at the demand point cannot be greater than the right time window of that point. Constraint (19) indicates the time window limit for distribution vehicles to return to the distribution center. Constraint (20) is used to eliminate subloops that do not contain the distribution center. Constraints (21) and (22) indicate that the same route distribution point is served by the same vehicle. Constraint (23) indicates the relevant decision variables.

5. Algorithm Design

5.1. Genetic Algorithm Solving Process. The genetic algorithm transforms the problem-solving process into a process similar to the crossover and mutation of chromosome genes in biological evolution using mathematics and computer simulation. The flowchart is shown in Figure 4.

5.2. Simulated Annealing Algorithm Solving Process. The simulated annealing algorithm is a random optimization algorithm based on Monte Carlo iterative solution strategy. Its starting point is based on the similarity between the annealing process of solid matter in physics and general combinatorial optimization problems. The flowchart of the conventional simulated annealing algorithm is shown in Figure 5.

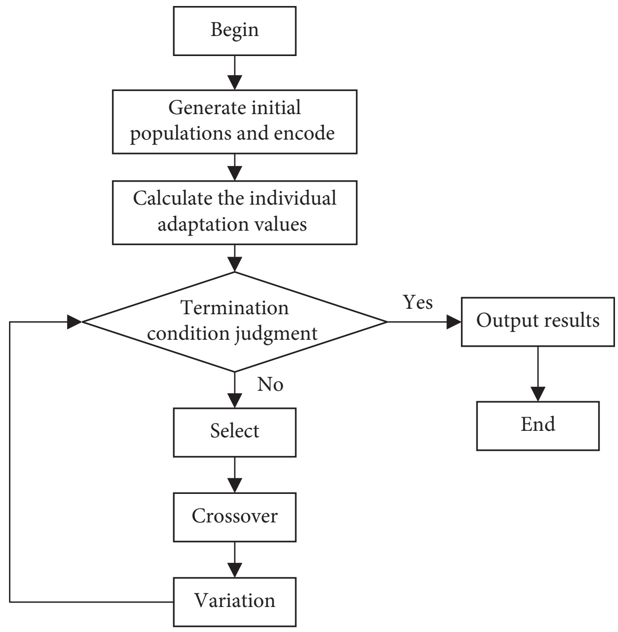

Figure 4: Flowchart of the genetic algorithm.

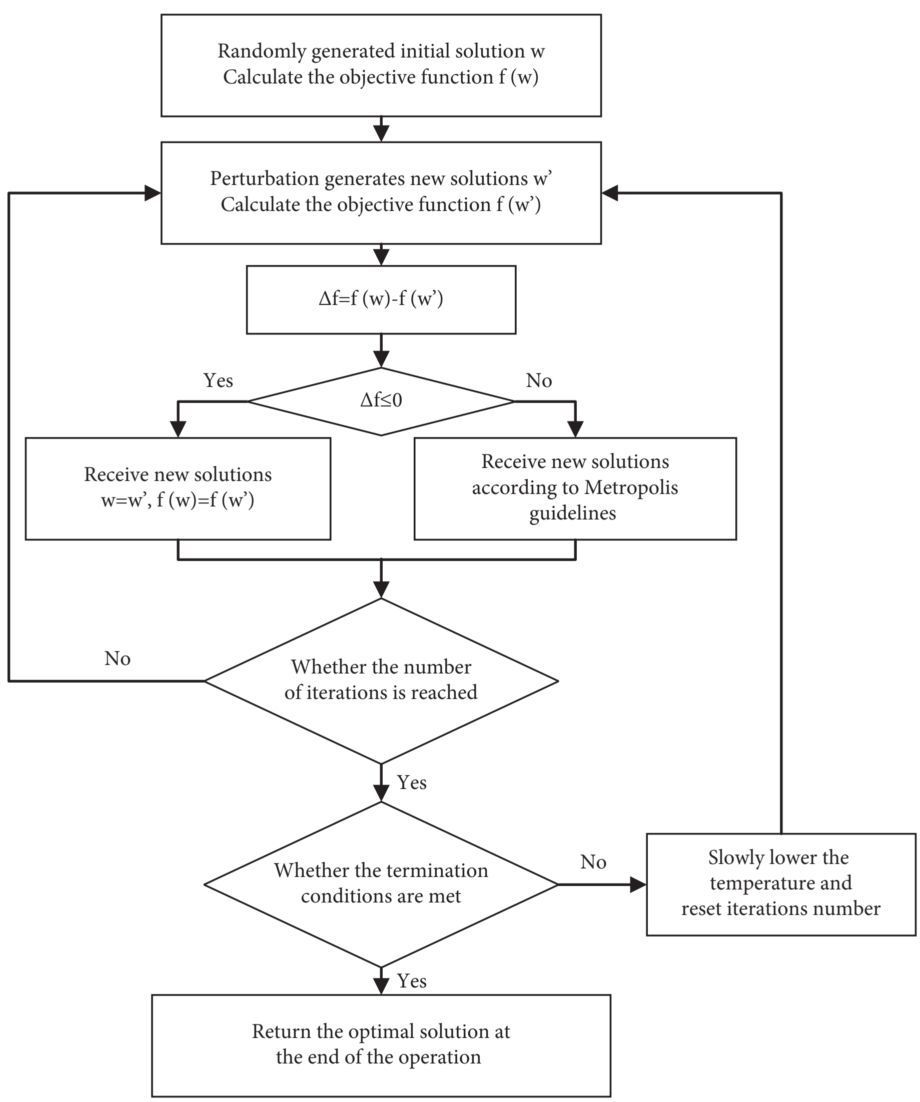

Figure 5: Flowchart of the simulated annealing algorithm.

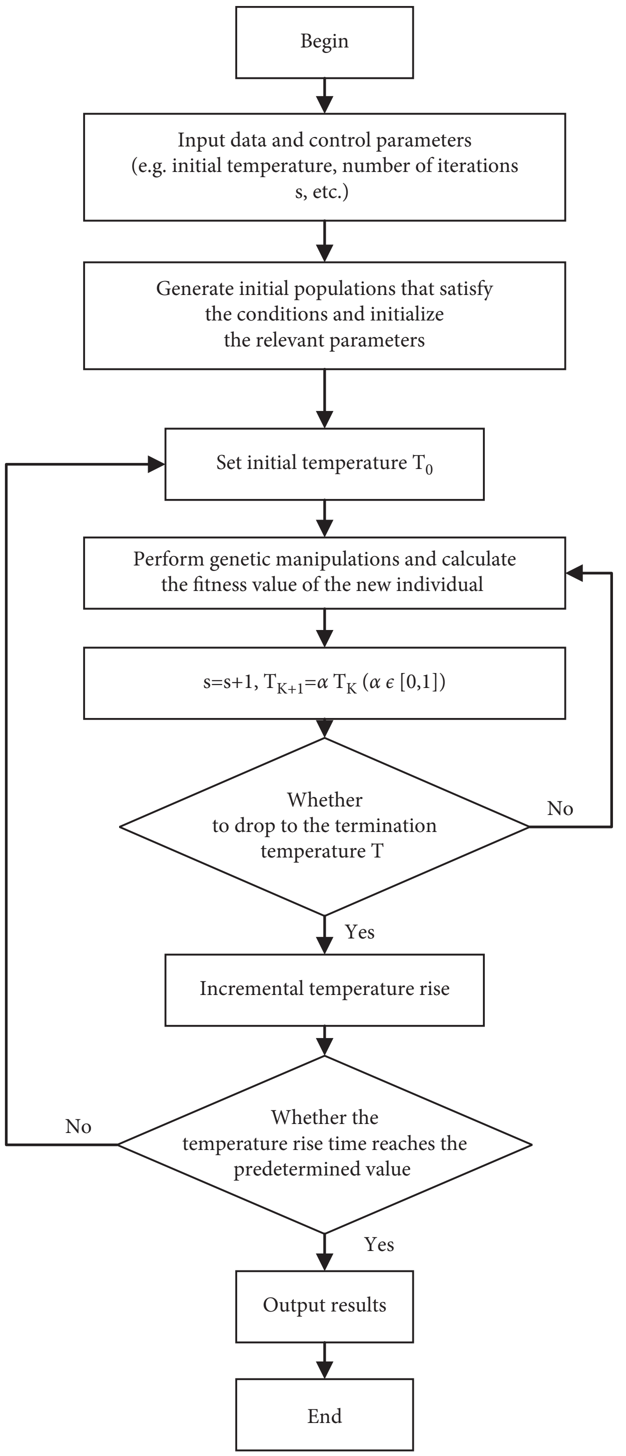

Figure 6: Flowchart of the simulated annealing-genetic hybrid algorithm.

5.3. Hybrid Simulated Annealing-Genetic Algorithm Solution Process. The simulated annealing-genetic hybrid algorithm is a compromise between the simulated annealing and the genetic algorithms. The specific flowchart is shown in Figure 6, and the specific computational process is as follows:

(1) An integer encoding approach is used to construct chromosomes to encode the paths that satisfy the constraints.

(2) An initial population consisting of an initial set of individuals is randomly generated in the solution space.

(3) Here, the metropolis criterion from the simulated annealing algorithm is combined with the selection, crossover, and mutation from the genetic algorithm to generate a new population and recalculate the fitness function values.

(4) Cooling down. Decrease gradually and converge to 0, then turn to step 3.

(5) Output optimal solution. One optimal solution is selected from the N population optimal solutions as the final global optimal solution obtained.

The classical genetic algorithm uses greedy rules to select chromosomes, which is more destructive to chromosome diversity, whereas the simulated annealing-genetic hybrid algorithm (SA-GA) constructed in this study selects chromosomes based on probability and also has a certain selection probability for poor chromosomes, which can effectively improve chromosome diversity and the algorithm's tojump out of the local optimum. In addition, the simulated annealing-genetic hybrid algorithm (SA-GA) replaces the variation operation in the classical genetic algorithm with the simulated annealing algorithm. The scale of population selection, the probability of individual crossover, and the probability of performing simulated annealing for each individual of the population are set dynamically so that the simulated annealing-genetic The hybrid SA-GA algorithmhas a large global search range in the early stage of execution and can perform a large number of iterations of optimization for a relatively fixed population in the middle and late stages of execution, thus providing good performance in terms of both search range and solution accuracy. However, on the contrary, the intelligent optimization method is designed to expand the search range and improve the solution accuracy, which inevitably increases the computing power, so the hybrid algorithm is a trade-off between the search range and the search accuracy while maintaining the same order of magnitude of computing power.

6. Experimental Design and Analysis of Results

6.1. Experimental Design. The coordinates of a distribution center are (0, 0), and there are 60 customer points within the service area. The relevant information of customers is shown in Table 2. The distribution center has a limited number of distribution vehicles of the same type, and the maximum load capacity of the distribution vehicles is 5t. Let the unit carbon emissions price be 0.1 yuan/kg.

6.2. Solving and Analysis of Results. In order to verify the solution efficiency and accuracy of the simulated annealing-genetic hybrid algorithm, 25 simulations were conducted using both the traditional genetic algorithm and the simulated annealing algorithm, where the parameters were set as shown in Table 3.

Figures 7–9 show the distribution path diagrams solved by the three algorithms, the specific driving routes are shown

Table 2: Customer information sheet.

Serial number	Horizontal coordinates (km)	Vertical coordinate (km)	Demand (t)	Left time window (min)	Right time window (min)	Service time (min)
0	80	100	0	0	1005	0
1	90	136	0.2	912	942	8
2	84	130	0.2	15	45	6
3	80	138	0.4	621	651	1
4	80	132	0.4	170	200	7
5	76	136	0.4	255	285	2
6	76	140	0.2	534	564	5
7	70	132	0.2	357	387	9
8	40	160	0.8	384	414	9
9	40	170	0.8	475	505	10
10	36	150	0.4	99	129	9
11	30	150	0.4	179	209	1
12	30	160	0.2	278	308	6
13	60	100	0.2	10	40	1
14	60	104	0.4	914	944	7
15	56	104	0.4	812	842	4
16	56	110	0.2	732	762	7
17	50	100	0.2	65	95	3
18	50	104	0.8	169	199	8
19	40	100	0.2	358	388	9
20	40	110	0.2	449	479	5
21	20	70	0.4	200	230	6
22	20	80	0.6	31	61	9
23	16	80	0.8	87	117	10
24	16	90	0.4	751	781	9
25	10	70	0.2	283	313	7
26	70	64	0.2	166	196	5
27	66	64	0.4	68	98	8
28	66	70	0.2	16	46	8
29	64	60	0.2	359	389	4
30	60	60	0.2	541	571	9
31	60	64	0.6	448	478	3
32	60	70	0.2	966	996	3
33	56	60	0.2	632	662	4
34	56	70	0.2	856	886	10
35	52	64	0.2	815	845	6
36	50	60	0.2	725	755	8
37	50	70	0.2	912	942	6
38	76	10	0.6	471	501	3
39	70	10	0.4	562	592	2
40	100	60	0.2	531	561	7
41	100	70	0.4	262	292	1
42	100	80	1	171	201	3
43	94	70	0.2	826	856	7
44	94	80	0.2	12	42	8
45	106	60	0.2	450	480	9
46	106	70	1	353	383	3
47	90	130	0.4	889	919	3
48	180	70	0.2	203	233	2
49	176	60	0.2	574	604	4
50	176	70	0.4	109	139	9
51	170	50	0.2	769	799	1
52	140	116	0.4	458	488	2
53	136	120	0.6	555	585	7
54	130	120	0.6	645	675	5
55	120	120	0.2	836	866	2
56	134	170	0.4	368	398	4
57	124	160	0.6	196	226	4
58	120	160	0.2	95	125	2

Table 2: Continued.

Serial number	Horizontal coordinates (km)	Vertical coordinate (km)	Demand (t)	Left time window (min)	Right time window (min)	Service time (min)
59	120	170	0.6	561	591	4
60	110	170	0.4	647	677	2

Table 3: Algorithm parameter settings.

Solution method	Name	Parameter values	Solving methods	Name	Parameter values
Genetic algorithms	Population size	100	Simulated annealing algorithm	Initial temperature	100
	Number of iterations	100		Cooling rate	0.99
	Crossover probability	0.9		Max number of iterations of the inner cycle	300
	Probability of variation	0.05		Maximum number of iterations of the outer loop	2000
	Generation gap	0.9		Probability of selecting a swap structure	0.2
				Probability of selecting a reversal structure	0.5
				Probability of choosing the insertion structure	0.3

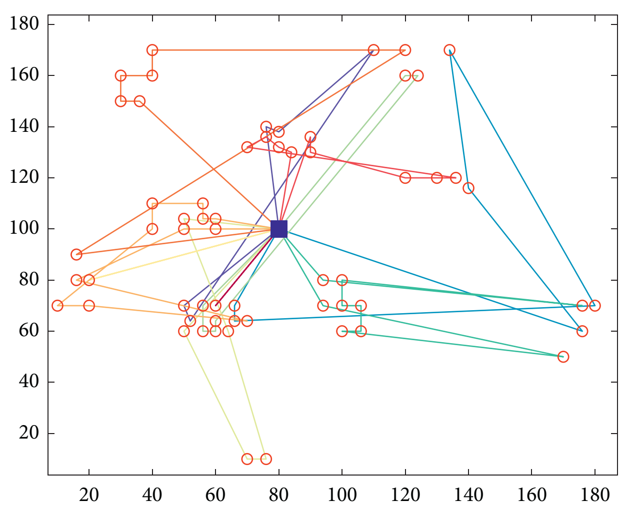

Figure 7: Optimal route for the genetic algorithm.

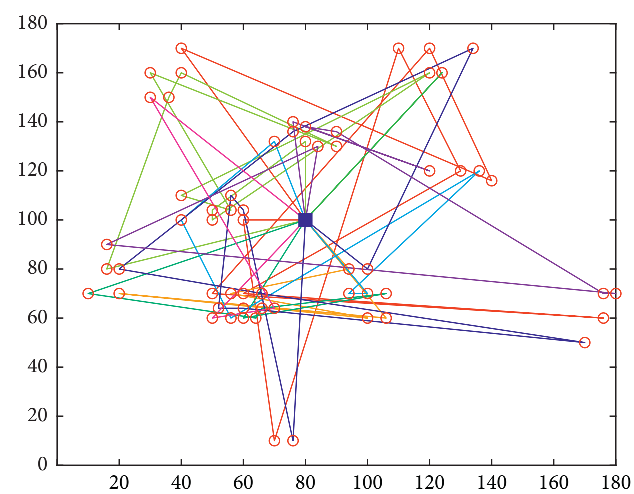

Figure 8: Optimal route for the simulated annealing algorithm.

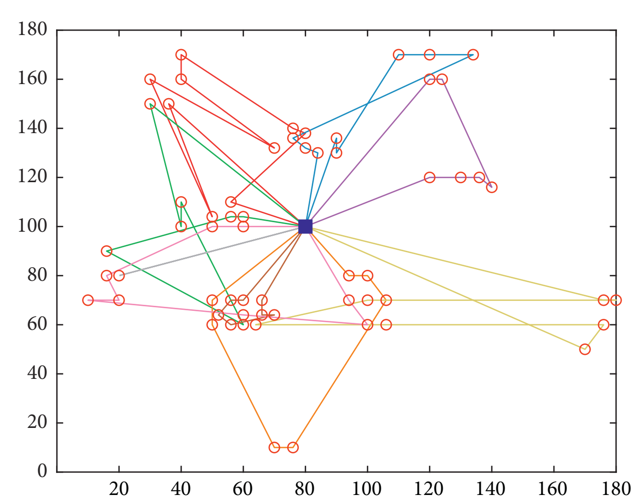

Figure 9: Optimal route for the simulated annealing-genetic hybrid algorithm.

in Tables 4–6, respectively, and Table 7 compares the solution results of the three algorithms.

Based on the distribution route map solved by the three algorithms, the specific driving route, and the comparative data in Table 7, check the following:

(1) The response time of the simulated annealing-genetic hybrid algorithm is shorter in the same number of experiments than the two traditional algorithms, which have a smaller average number of iterations, indicating that the improved simulated annealing-genetic hybrid algorithm search efficiency is higher, and from the optimal solution standard deviation, the optimal solution simulated annealing-genetic hybrid algorithm found is more stable.

Table 4: Distribution path by genetic algorithm.

Vehicles	Number of clients	Distribution routes
Vehicle 1	5	0 -> 6 -> 3 -> 60 -> 35 -> 37 -> 0
Vehicle 2	6	0 -> 28 -> 27 -> 48 -> 56 -> 52 -> 49 -> 0
Vehicle 3	9	0 -> 44 -> 50 -> 42 -> 41 -> 46 -> 45 -> 40 -> 51 -> 43 -> 0
Vehicle 4	6	0 -> 58 -> 57 -> 31 -> 30 -> 33 -> 34 -> 0
Vehicle 5	5	0 -> 18 -> 29 -> 38 -> 39 -> 36 -> 0
Vehicle 6	1	0 -> 22 -> 0
Vehicle 7	11	0 -> 13 -> 17 -> 23 -> 26 -> 21 -> 25 -> 19 -> 20 -> 16 -> 15 -> 14 -> 0
Vehicle 8	7	0 -> 10 -> 11 -> 12 -> 8 -> 9 -> 59 -> 24 -> 0
Vehicle 9	9	0 -> 2 -> 4 -> 5 -> 7 -> 53 -> 54 -> 55 -> 47 -> 1 -> 0
Vehicle 10	1	0 -> 32 -> 0

Table 5: Distribution paths from simulated annealing algorithm.

Vehicles	Number of clients	Distribution routes
Vehicle 1	9	0 -> 27 -> 50 -> 49 -> 52 -> 57 -> 26 -> 48 -> 55 -> 45 -> 0
Vehicle 2	8	0 -> 8 -> 3 -> 33 -> 13 -> 40 -> 47 -> 58 -> 7 -> 0
Vehicle 3	3	0 -> 23 -> 31 -> 30 -> 0
Vehicle 4	3	0 -> 21 -> 25 -> 16 -> 0
Vehicle 5	6	0 -> 4 -> 2 -> 59 -> 54 -> 5 -> 22 -> 0
Vehicle 6	13	0 -> 41 -> 19 -> 10 -> 17 -> 36 -> 12 -> 56 -> 46 -> 44 -> 32 -> 14 -> 39 -> 29 -> 0
Vehicle 7	4	0 -> 15 -> 28 -> 18 -> 43 -> 0
Vehicle 8	5	0 -> 9 -> 6 -> 20 -> 11 -> 35 -> 0
Vehicle 9	9	0 -> 38 -> 42 -> 60 -> 51 -> 34 -> 37 -> 1 -> 53 -> 24 -> 0

Table 6: Distribution paths by the simulated annealing-genetic hybrid algorithm.

Vehicles	Number of clients	Distribution routes
Vehicle 1	9	0 -> 2 -> 10 -> 11 -> 12 -> 8 -> 9 -> 16 -> 15 -> 14 -> 0
Vehicle 2	7	0 -> 58 -> 57 -> 56 -> 52 -> 49 -> 51 -> 0
Vehicle 3	4	0 -> 4 -> 59 -> 60 -> 1 -> 0
Vehicle 4	8	0 -> 28 -> 27 -> 26 -> 29 -> 31 -> 30 -> 33 -> 34 -> 0
Vehicle 5	6	0 -> 18 -> 5 -> 7 -> 6 -> 3 -> 47 -> 0
Vehicle 6	10	0 -> 13 -> 17 -> 23 -> 21 -> 25 -> 19 -> 20 -> 53 -> 54 -> 55 -> 0
Vehicle 7	10	0 -> 44 -> 42 -> 41 -> 46 -> 38 -> 39 -> 36 -> 24 -> 35 -> 37 -> 0
Vehicle 8	1	0 -> 22 -> 0
Vehicle 9	6	0 -> 50 -> 48 -> 45 -> 40 -> 43 -> 32 -> 0

Table 7: Comparison of results of simulation experiments.

Algorithms	Optimum solution	Standard deviation of optimal solution	Average number of convergence iterations	Average response time (s)
Genetic algorithms	6441.3524	76.4259	90.25	24.97
Simulated annealing algorithms	6389.4405	24.9054	92.85	15.55
Hybrid simulated annealing-genetic algorithm	6268.1007	22.8065	74.78	11.23

Table 8: Vehicle distribution routes considering the cost of carbon emissions.

Vehicles	Number of clients	Distribution routes
Vehicle 1	9	0 -> 2 -> 10 -> 11 -> 12 -> 8 -> 9 -> 16 -> 15 -> 14 -> 0
Vehicle 2	7	0 -> 58 -> 57 -> 56 -> 52 -> 49 -> 51 -> 0
Vehicle 3	4	0 -> 4 -> 59 -> 60 -> 1 -> 0
Vehicle 4	8	0 -> 28 -> 27 -> 26 -> 29 -> 31 -> 30 -> 33 -> 34 -> 0
Vehicle 5	6	0 -> 18 -> 5 -> 7 -> 6 -> 3 -> 47 -> 0
Vehicle 6	10	0 -> 13 -> 17 -> 23 -> 21 -> 25 -> 19 -> 20 -> 53 -> 54 -> 55 -> 0
Vehicle 7	10	0 -> 44 -> 42 -> 41 -> 46 -> 38 -> 39 -> 36 -> 24 -> 35 -> 37 -> 0
Vehicle 8	1	0 -> 22 -> 0
Vehicle 9	6	0 -> 50 -> 48 -> 45 -> 40 -> 43 -> 32 -> 0

Table 9: Vehicle distribution routes considering transport costs only.

Vehicles	Number of clients	Distribution routes
Vehicle 1	8	0 -> 44 -> 42 -> 41 -> 29 -> 38 -> 49 -> 51 -> 43 -> 0
Vehicle 2	7	0 -> 58 -> 57 -> 56 -> 9 -> 59 -> 60 -> 1 -> 0
Vehicle 3	5	0 -> 10 -> 11 -> 6 -> 3 -> 47 -> 0
Vehicle 4	13	0 -> 28 -> 27 -> 26 -> 21 -> 25 -> 8 -> 20 -> 39 -> 36 -> 24 -> 35 -> 34 -> 37 -> 0
Vehicle 5	1	0 -> 22 -> 0
Vehicle 6	1	0 -> 32 -> 0
Vehicle 7	5	0 -> 50 -> 48 -> 46 -> 45 -> 40 -> 0
Vehicle 8	12	0 -> 13 -> 17 -> 23 -> 18 -> 12 -> 19 -> 31 -> 30 -> 33 -> 16 -> 15 -> 14 -> 0
Vehicle 9	8	0 -> 2 -> 4 -> 5 -> 7 -> 52 -> 53 -> 54 -> 55 -> 0

Table 10: Cost comparison of two distribution options.

Distribution solutions	Fixed start-up costs for vehicles	Transport distance	Cost of carbon emissions	Cost of time window violation	Total cost
Distribution options that consider carbon emissions	1,800	2,438.6254	2,080.4259	2.3011	6,221.3524
Distribution options that consider transport costs only	1,800	2,435.1007	2,204.5037	2.3011	6,441.9055

(2) The optimal solution obtained by the simulated annealing-genetic hybrid algorithm is better, meaning that the simulated annealing-genetic hybrid algorithm has a larger search range and a higher search accuracy in each solution domain, resulting in a stronger global search capability.

6.3. Comparison Test before and after considering Carbon Emissions. In order to prove that the model considering carbon emissions can restrain carbon emissions, the simulated annealing-genetic hybrid algorithm is used to carry out the comparative test before and after considering carbon emissions. Table 8 shows the vehicle distribution route considering carbon emissions, and Table 9 shows the vehicle route results considering only transportation cost. The comparison of the results of the two distribution schemes is shown in Table 10.

According to Tables 8–10, the following conclusions can be drawn: the difference in transport distance between the two distribution options is nonsignificant, but there is a more obvious difference in the distribution route. Although the distribution option that considers carbon emissions increases the transport distance by 3.52 km, the carbon emissions costs and total costs decrease by 5.6% and 3.4%, respectively. This is mainly because the carbon-emission-considered delivery solution prioritizes the delivery of customers with long distances and large loads, which increases the transport cost but significantly reduces the carbon emissions cost. Therefore, the experiment proves that considering carbon emissions in vehicle route optimization can reduce the actual carbon emissions cost and the total distribution cost, which is of value in achieving low carbon emissions. [45].

7. Conclusion

In this study, we take the premise of considering traffic congestion, consider carbon emissions in the vehicle path optimization problem, treat the speed as a segmented continuous function in the calculation of carbon emissions, construct a vehicle path optimization model considering carbon emissions under the time-varying road network, and design a simulated annealing-genetic hybrid algorithm for the model. Two sets of comparative experiments are designed. The first set of experiments compares and analyzes the results of the hybrid algorithm and the above two classical algorithms to solve the simulation experiments. The second set of experiments compares and analyzes the vehicle path optimization before and after considering the effect of carbon emissions based on the hybrid algorithm. The following conclusions are drawn from the two comparative simulation experiments:

(1) The simulated annealing-genetic hybrid algorithm designed in this study has better search capability in solving NP-hard problems such as TDGVRP, higher search accuracy, and better solution performance than the traditional genetic algorithm and simulated annealing algorithm. Meanwhile, the simulated annealing-genetic hybrid algorithm is simple to implement, inherits the robustness and potential parallelism of the genetic algorithm, and has high practical value. This is because the hybrid algorithm expands the search range as much as possible in the early stage of execution to avoid the algorithm falling into local optimal solutions and stabilizes the population as much as possible in the middle and late stages of execution according to the dynamic probability setting so that the simulated annealing algorithm has the largest possible number of executions for each individual to improve the search accuracy in the individual domain. Because the search in each individual domain is independent, it can also guarantee the algorithm in the middle and late stages. The search range of the algorithm can also be guaranteed in the middle and later stages.

(2) The distribution scheme considering carbon emissions is distributed to the customer demand points slightly far away but with larger load capacity first. Although the increased transportation distance causes the transportation cost to increase, the increased transportation cost is much smaller than the reduced carbon emissions cost, thus realizing the reduction of carbon emissions cost and total distribution cost, which, on the one hand, shows that the simulated annealing-genetic hybrid algorithm proposed in this study can effectively solve the vehicle path problem considering carbon emissions under time-varying road networks. On the other hand, it proves that path optimization considering carbon emissions has a certain inhibiting effect on carbon emissions, which has certain practical significance and can reduce not only carbon emissions but also the total distribution cost and the waste of resources.

Although some meaningful conclusions are drawn in this study, there are some limitations to the research. First, this study did not further design relevant experiments to verify the optimization effect brought by treating vehicle speed as a segmented continuous function, so future research can consider designing a set of comparison experiments to verify and further optimize the model. Secondly, this study only considers the path optimization of a single distribution center, but, in reality, there are multiple distribution centers for common distribution, so the subsequent research can consider studying the green path optimization of multiple distribution centers.

For the future research direction, in the existing research of TDGVRP, the model establishment is based on conditional assumptions, and the setting of constraints differs greatly from the actual logistics scenario, such as when the existing TDGVRP literature considers customer demand. Most of them only consider the static demand and less consider the dynamic demand situation. In fact, customer demand is dynamic, existing orders may be canceled, their demand or delivery address may change, and the system may receive new orders at any time. In terms of the model-solving algorithm research, most of the algorithms proposed in the existing TDGVRP literature only apply to small-scale logistics and distribution networks. There is a large gap between the realistic application needs and the theoretical model and research method, which should promote and complement each other. Therefore, future research can consider the dynamic needs of customers and improve the algorithms to apply to large-scale logistics distribution.

Data Availability

This experiment includes hypothetical experimental data.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

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