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Low-Carbon Vehicle Routing Models and Optimization Algorithms with Hybrid Time Window

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Abstract

The large amounts of greenhouse gases generated in the logistics and transportation industry worsen global climate deterioration, jeopardizing the human living environment. A multi-objective nonlinear planning model for vehicle routing problems (VRPs) was established by considering VRPs with carbon emission constraints to realize the shortest vehicle mileage and the minimum carbon emission. An improved simulated annealing algorithm was proposed to solve the model. The farthest insertion heuristic method, combined with a relocation operator, was applied in the reinsertion operation to determine the preferred insertion back to the customer point and the optimal insertion point. The customer point with the largest minimum target increment was removed from the removed customer points and inserted into the optimal insertion point until all of them were inserted. Results demonstrate that the proposed algorithm outperforms the common genetic algorithms and forbidden search algorithms in similar studies with strong global optimization search capability. The improved algorithm could solve low-carbon VRP with high sensitivity and effectiveness.

Keywords: Low-carbon vehicle routing problem, Carbon emission, Improved ant colony algorithm, Chaotic disturbance mechanism

1. Introduction

In September 2021, China's economic transformation and technological innovation direction were discussed at the Circular Economy Development Forum with the theme of accelerating "dual-carbon" goal achievement. Moreover, carbon-neutral solutions were jointly negotiated. On October 24, 2021, China proposed Carbon Peaking and Carbon Neutrality Goals and planned to achieve "carbon peak" and "carbon neutrality" by 2030 and 2060, respectively. The "dual-carbon" goals are not only the aim of low-carbon economic development but also the only way for China to achieve high-quality development. Moreover, they are integral components to realize Chinese-style modernization. On the one hand, "dual-carbon" goals are complex and arduous projects related to China's long-term development plan. Vigorously developing a low-carbon economy can effectively optimize energy structure allocation, promote efficient energy use, and control greenhouse gas emissions. This approach is in line with China's adherence to environmentally friendly and resource-saving development concepts. Therefore, a low-carbon economy should be actively promoted in future development [1]. On the other hand, China's logistics enterprises meet new challenges and opportunities. Logistics enterprises can master the core competitiveness and stand out and walk at the forefront of the times only by adhering to the green and efficient development mode. The traditional low-efficiency logistics enterprises with high-carbon emissions can be eliminated [2]. Low-carbon economic development does not mean to reduce or give up the existing level of productivity. It intends to take the initiative to seek an efficient, environment-friendly green development, which is the inevitable requirement of high-quality development in the new development stage. Green development is an important development strategy that concerns the common destiny of the whole society, the whole nation, and even the entire humanity. Therefore, Chinese logistics enterprises should follow the development trend of the times, break the traditional logistics operation mode, and take new low-carbon and green development strategies [3].

Low-carbon logistics plays an indispensable role in developing the low-carbon economy in China. The logistics industry is one of the main industries with high carbon emissions. Actively reducing energy consumption and carbon emissions in the logistics industry can effectively accelerate low-carbon economic development and alleviate energy pressure and ecological and environmental pressure [4]. Low-carbon economic development is supported by modern logistics industry. Rational logistics distribution routing based on big data science and artificial intelligence technology is an important channel for realizing intelligent and green development in the modern logistics industry [5]. Therefore, it is of great significance to investigate low-carbon logistics, particularly logistics transportation and distribution links. This study discussed the optimization of low-carbon logistics distribution routes under the background of a low-carbon economy. Carbon emission cost was introduced into the objective function of the vehicle route optimization model with time window constraints. Combined with various conditional constraints, the distribution scheme with the lowest total distribution cost was solved. Moreover, some suggestions for healthy and green development of the low-carbon logistics industry were proposed based on practical cases. Therefore, this study has certain theoretical and practical significance.

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2. State of the art

Vehicle routing problems (VRPs) have always been a hot spot in academic circles. Scholars in China and foreign countries have conducted many relevant studies. After years of development, VRPs have evolved from initial simple traveler problems and backpack problems to different types of VRPs. For example, Duman et al. (2020) solved VRPs with load limitations based on the improved ant colony algorithm [6]. McKinnon (2010) investigated the VRPs of simultaneous collection and delivery [7]. Boukari et al. (2021) discussed VRPs with soft time windows for closed multi-warehouses [8]. Cholette et al. (2009) explored VRPs for open multi-warehouses [9]. Harris et al. (2011) put forward to limit the number of delivery vehicles in a vehicle routing model [10]. Matijašević et al. (2020) discussed multi-objective VRPs based on an improved hybrid ant colony algorithm [11]. Marinakis et al. (2015) investigated VRPs with splittable customer demands [12]. Given the limited customer idle time in the actual distribution process, improving the accomplishment of distribution tasks with time window constraints has become a new hot area. Kotb et al. (2019) solved fuzzy demand and time window problems by constructing a multi-objective function model based on a hybrid genetic algorithm and credibility measurement theory, thereby improving customer satisfaction and reducing distribution costs [13]. Chaudhuri et al. (2018) designed a route optimization model with a time window for takeaway delivery to improve customer satisfaction by considering the special characteristics of takeaway delivery and the complexity of the practitioner group. The results showed that the model can effectively enhance the service level [14]. In view of customer time window consistency, Sadjadi et al. (2016) proposed a hybrid integer linear programming model by adding a linkage operator and the consistency costs of different time window widths were analyzed [15]. Pin et al. (2017) investigated emergency material distribution in disasters and proposed to grade demands according to the degree of urgency; thus, the priority of material scheduling in the hardest-hit areas is effectively ensured, and the total cost of material scheduling is reduced [16].

As an integral part of green development, low-carbon logistics is the hot spot of the logistics industry and an important study direction of VRPs. On the basis of carbon trading, carbon tax, and mandatory emissions policy, Zhou Cheng et al. established a model and conducted simulation experiments. They found that the three policies can reduce carbon emissions under a reasonable choice of strategy. Carbon trading policy has market guidance and emission policy control advantages. With high profits but low emissions, the enterprises' emission reduction initiative can be stimulated. On the basis of supply chain management and low-carbon logistics, El-Sobky et al. (2017) constructed a low-carbon supply chain network combined with a low-carbon economy and energy-saving background to reduce enterprise costs and optimize overall resources [17]. Ahinli (2020) explored the optimization of low-carbon logistics distribution routes combined with the advantages of efficient processing of spatial data by using information visualization of GIS technology [18]. According to Álvarez-Miranda et al. (2020), irrational planning problems of coal low-carbon logistics were found in Xinjiang, and the scholars proposed to introduce third-party logistics and establish an enterprise-distribution center-user integrated coal logistics operation mode [19]. Given that customers may request to return goods during distribution, Hasan et al. (2020) used an improved genetic algorithm to optimize the low-carbon route to balance operating and carbon emission costs [20]. Yap et al. (2019) established a model considering dynamic traffic network conditions, and the results showed that the assessed total cost of distribution and carbon emissions is accurate considering real-time traffic conditions in the road network [21]. In the current trend of environmental protection and intelligence, Gelareh et al. (2018) suggested introducing intelligent network vehicle technology in low-carbon route optimization models to reduce the distribution of carbon emissions [22].

Thuerme et al. (2019) established and solved a dual-objective, low-carbon logistics route optimization model with the highest customer satisfaction and the lowest total cost. The solution performance of the discrete fireworks algorithm is better than that of other algorithms [23]. Bilisik et al. (2019) introduced high-speed access cost and distribution time cost to establish a low-carbon logistics and distribution path model with the lowest comprehensive cost, thereby increasing the randomness and directionality of the ant colony algorithm search. Chaotic initialization and chaotic perturbation were also introduced to increase the solution speed and reduce the comprehensive cost [24]. Considering the loading capacity cost and the soft time window penalty function, Simic et al. (2017) solved the low-carbon logistics distribution route model based on the genetic simulated annealing (SA) algorithm [25]. Setiawan et al. (2019) determined that carbon price is an important influencing factor in logistics distribution. A low-carbon logistics network planning model was presented based on the cloud computing platform and the high-cost problem of limited distribution route planning was discussed by effectively using massive amounts of information under the traditional information model [26]. Naderipour et al. (2019) examined carbon tax sensitivity and found that carbon tax is irrelevant to user satisfaction. However, the distribution cost gradually increased with the growth of carbon tax, and the logistics enterprises were forced to take low-carbon logistics development mode [27].

In summary, some results of low-carbon vehicle route optimization with hybrid time windows have been achieved. However, some limitations remain. First, the existing studies focus on vehicle route optimization models and algorithms with deterministic time windows. However, the studies of low-carbon vehicle route optimization problems with hybrid time windows are scarce. Second, there are few studies of the vehicle route optimization problem that consider the time window constraints. Given the above limitations, the present study established a low-carbon vehicle route optimization model with hybrid time window constraints according to the corresponding characteristics by using the trapezoidal fuzzy time window to achieve the minimum sum of the carbon emission cost, fuel consumption cost, transportation cost, and fixed departure fee. Moreover, an improved SA algorithm was designed to solve the model, and the validity of the algorithm was verified. Low-carbon logistics is a hot spot in the current academic circle. However, most studies decline at the concept of low-carbon logistics and macro countermeasures. Moreover, the scientific planning of low-carbon logistics and distribution routes is rarely studied. Therefore, it is of great significance to study low-carbon logistics route optimization.

3. Methodology

The low-carbon logistics optimization model is a variant of a vehicle route optimization model, which is a route optimization model for reducing carbon dioxide emissions based on the concept of a low-carbon economy. K vehicles are assumed to be in a distribution center, distributing materials to N different customer points in the vicinity. The location information of the distribution center and each distribution point, as well as the time window and demand of each customer, is known. The vehicles are required to start from the distribution center, arrive within the customer time window, and return to the distribution center after completing distribution tasks. The optimal distribution scheme to achieve this goal is solved. In this study, carbon emission cost was introduced into the vehicle route optimization model with time window constraints to establish a low-carbon logistics path optimization model with the lowest total cost of enterprise logistics.

3.1 Model assumption

Vehicles distribute goods to customers. Information such as the location of the customer point, service time interval, service time, vehicle capacity, and weight of goods is known. The following constraints exist during the distribution:

1) Vehicles can only provide delivery service within the time interval accepted by customers; otherwise, they can refuse to accept the service.

2) Each customer can only be visited once.

3) A vehicle may not carry more than its capacity.

4) Vehicles can only depart from and finally return to the distribution center. The objective of this problem is to find a route with the lowest cost while satisfying the above constraints.

3.2 Parameter definition

1) The sets involved in the model are explained in Table 1.

Table 1. Definition and description of sets

Set	Definition	Description
N	Set of all distribution points, n	$N = \{1, 2, .., \ n\}$
N_0	Set of distribution points and distribution centers	$N_0 = N \bigcup \{0\}$
V	Set of all vehicles, K	$V = \{1, 2, .., \ K\}$
Y	Directed grid	$Y = (P, \ Q)$
P	Set of all distribution nodes	$N = \{1, 2, .., \ n, \ n+1\}$
Q	Set of directed arcs	$Q = \{(i, j) \ i \neq j, i, j \in P\}$

2) Other parameters involved in the model are explained in Table 2.

Table 2. Parameter definitions and descriptions

Parameter	Definition
R	Rated capacity of vehicle
d_i	Cargo demand of customer i
c_{ij}	Transportation distance of vehicle from node i to node j
T_{ij}	Transportation time from distribution point i to distribution point j
Arr_{ik}	Time for the kth vehicle to reach distribution point i
$Wait_{ik}$	Waiting time after the kth vehicle arrives at delivery point i
Ser_i	Service time at customer point i
a_i	The earliest time a customer can receive service
b_i	The latest time a customer can receive service
$[a_i, b_i]$	Customer time window
F	Total cost of distribution
η_1	Cost per liter of fuel
η_2	Cost per vehicle
η_3	Environmental cost per unit of CO_2 emissions consumed
f	Fuel consumption per kilometer
U	Fuel conversion factor

3.3 Model construction

3.3.1 Objective function

The objective function of the model is as follows:

$$\min C = f\eta_1 \sum_{i \in N_0} \sum_{j \in N_0} c_{ij} \sum_{k \in V} x_{ijk} + \eta_2 \Sigma x_{ijk} + f\eta_3 \sum_{i \in N_0} \sum_{j \in N_0} c_{ij} \sum_{k \in V} x_{ijk} \tag{1}$$

where the objective function consists of three parts. The first part is the fuel consumption cost, which is positively correlated with the total transportation distance. The farther the transportation distance is, the higher the fuel consumption cost is. The second part is the vehicle cost, which is mainly linearly positively correlated with the number of enabled vehicles. The third part is the carbon emission cost. Vehicles emit carbon dioxide during fuel consumption, and carbon emission cost is positively correlated with fuel consumption.

3.3.2 Constraints

The constraints of the model are as follows:

$$\sum_{i \in N_0} \Sigma_{k \in V} x_{ijk} = 1, j \in N \tag{2}$$

$$\sum_{i\in N} d_i(\sum_{j\in N_0} x_{ijk}) \le R, k\in V \tag{3}$$

$$\sum_{j\in N} x_{0jk} \le 1, k\in V \tag{4}$$

$$\Sigma_{k=1}^{k} y_{ik} = \begin{cases} 1, i=1,2,\dots,k \\ k, i=0 \end{cases} \tag{5}$$

$$\sum_{i=0}^{n} x_{ijk} = y_{ik}, i=1,2,\dots,N; k=1,2,\dots K \tag{6}$$

$$\sum_{i=0}^{n} x_{ijk} = y_{ik}, j=1,2,\dots,N; k=1,2,\dots K \tag{7}$$

$$Arr^{ik} \le b_i, i=1,\dots,N; k=1,\dots,V \tag{8}$$

$$a_i \le Wait^{ik} + Arr^{ik} \le b_i, i=1,\dots,N, k=1,\dots,V \tag{9}$$

$$T_{ij} + Wait^{ik} + Arr^{ik} + Ser^{i} + H(1-x_{ijk}) \le Arr^{jk} \tag{10}$$

$$Wait^{0k} = Arr^{0k} = S^0 = 0 \tag{11}$$

$$Wait^{ik} = \max\{0, a_i - Arr^{ik}\} \le b_i, i=1, \quad \dots, N; k=1, \quad \dots, V \tag{12}$$

$$x_{ijk} = \begin{cases} 1, Vehicle\ k\ passes\ through\ i\ to\ j \\ 0, Vehicle\ k\ does\ not\ pass\ through\ i\ to\ j \end{cases} \tag{13}$$

$$y_{ik} = \begin{cases} 1, Vehicle\ k\ distributes\ for\ customer\ i \\ 0, Vehicle\ k\ does\ not\ distribute\ for\ customer\ i \end{cases} \tag{14}$$

where (2) indicates that each distribution point is not visited repeatedly; (3) indicates that the distribution vehicle must leave the distribution point after arriving at it; (4) indicates that overloading is not allowed; (5) represents that only one circuit exists for each vehicle, and no subcircuit exists; (6) indicates that the distribution can only be accomplished by one vehicle for each customer, and all distribution points are jointly accomplished by K vehicles; (7) and (8) indicate that only one vehicle arrives at or leaves each distribution point; (8) indicates that vehicles must arrive at the customer points before the latest time the customer can be served; (9) denotes that the service time must be within the customers' time window; (10) indicates that the service time of two customers must satisfy their corresponding time window constraints; (11) represents the nature of the distribution center; (12) is the calculation method of the waiting time; (13) and (14) are decision variables.

3.4 Algorithm design

3.4.1 Algorithm principle and realization steps

SA algorithm searches randomly in the neighborhood structure according to the Metropolis sampling stability criterion from a certain high temperature. The solution that makes the objective function increase is accepted with a certain probability according to the Metropolis criterion. The search process is iterated as the temperature decreases until the termination criterion is satisfied and an enhanced solution for the problem is obtained. SA has been theoretically proved to converge to a globally optimal solution with probability 1 at enough high initial temperature and fast temperature decrease. However, the algorithm falls into the local optimal solution. Although bidirectional stochastic search can restrain this problem to a certain extent, the algorithm spends time to jump out of the local optimal solution. Therefore, this study introduced the idea of a large-scale neighborhood search algorithm, and an improved large-scale neighborhood SA algorithm was proposed. The basic idea of the variable neighborhood search (VNS) algorithm involves changing the neighborhood structure set of the current solution in the searching process systematically to expand the search scope and find the local optimal solution through the local search algorithm. The process is repeated based on the iteration, and convergence is reached to obtain an effective solution.

This study proposed a large-scale neighborhood SA algorithm from high temperatures. A bidirectional random search based on probability was used in the current neighborhood, and a good solution in the neighborhood was found based on the Metropolis sampling stability criterion. If the optimal solution is not better than this solution, random solutions are generated in the neighborhood in the next cycle after annealing. Otherwise, the calculation is continued in the next large neighborhood. The calculation is repeated as the temperature falls until the termination criterion is met. The basic steps of the SA with variable neighborhood (SAVN) algorithm are as follows:

1) The initial temperature t_0 and the current temperature $t = t_0$ are determined; the neighborhood structure is represented as a set $\{N_k, \ k=1,2,\dots, \ k_{max}\}$, $k=1$; the initial solution s_0 is generated; the current solution is $s = s_0$, and the historical optimal solution is $s_b = s_0$.

2) Whether the solution reaches the algorithm termination criterion is determined. If the criterion is reached, (8) follows; otherwise, the current optimal solution is made to be $s_c = s$, and (3) follows.

3) Whether the sampling stability criterion is satisfied is determined. If the criterion is reached, (6) follows; otherwise, a new solution is randomly generated in the k th neighborhood structure of S, $s^* \in N_k(s)$, and (5) follows.

4) If $min\{1, exp[-(f(s^*)\text{-}f(s))/t]\} \ge randrom[0,1]$, then, $s = s^*$, and (5) follows; otherwise, (3) follows.

5) If $f(s) < f(s_c)$, then, $s_c = s$, and (3) follows; otherwise, sc is unchanged, and (3) follows. If $f(s) < f(s_b)$, then, $s_b = s_c$, and (7) follows; otherwise, $k = (k \ mod \ k_{max}) + 1$, and (6) follows.

6) In annealing, $t = update(t)$, and (2) follows.

7) The current optimal solution is output.

3.4.2 Experiments on synthetic networks

1) Initial solution generation

Before applying the metaheuristic algorithm, a high-quality, feasible solution can be obtained as the initial solution of the metaheuristic algorithm by using a small heuristic algorithm. In this study, the push-forward insertion heuristic algorithm is used. The basic steps of the algorithm are as follows:

a) $k=0$, and a new empty route, $k=k+1$, was established. According to the seed customer cost function (Formula 16), a customer with the smallest cost among all unassigned customers is selected as a seed and inserted into the current route.

b) If there are still unallocated customers, 3) follows; otherwise, the algorithm is terminated.

c) If the feasible insertion points exist in the current route k for the unallocated customers, the insertion cost is calculated according to the insertion cost function (Formula 17). The unallocated customer with the smallest insertion cost is inserted into the current route k, and (2) follows; otherwise, no feasible insertion point for any unallocated customer is inserted into the current route, and (1) follows.

The seed customer cost function is set as follows to insert customer i into the empty path:

$$c_i^{(1)}=-\alpha t_{0i}+\beta l_i+\gamma\left(\frac{|p_i-p_j|}{2\pi}\times t_{0i}\right) \tag{15}$$

where p_i is the polar angle of customer i relative to the station, p_j is the polar angle relative to the station of the last served customer j of the previous vehicle route, t_{ij} is the travel time of vehicle k on route (i,j), and l_i is the customer's latest start time of service. The three weighting factors are generally set as $\alpha=0.7,\ \ \beta=0.2,\ \ \gamma=0.1$.

As shown in Formula (16), the insertion cost function consists of four components, namely, the additional path cost, the service cost, the waiting cost, and the subsequent waiting cost variation to insert customer w into arc (i,j).

$$\begin{aligned}c_i^{(2)}&=\left(c_{iw}+c_{uj}-c_{ij}\right)+c_{wait}\times wt_i\\&+c_{serne}\times st_i+c_{wait}\times\sum_{\sigma\in V_j}\left(wt_\sigma^*-wt_\sigma\right)\end{aligned} \tag{16}$$

where c_{ij}cij is the cost of the route on arc (i,j) , w_t is the waiting time, s_t is the service time, V_j is the set of the current route and subsequent customer nodes, and w_t^* is the new waiting time of the subsequent customer nodes after the insertion of a new customer.

The initial solution obtained by the above method is feasible. However, the SAVN algorithm allows the existence of infeasible solutions. Thus, the algorithm obtains a wide search range, and the possibility that the algorithm can find a good solution is enhanced. The algorithm increases the penalty value of the time window violation when setting the objective function, gradually increasing with the decrease in temperature. Therefore, the algorithm gradually converges to a feasible solution in subsequent iterations.

2) Improved state transfer SA algorithm

The STASA algorithm replaces the greedy criterion of the state transfer algorithm with the Metropolis criterion of the SA algorithm. Thus, falling into local optimum and converging prematurely can be avoided. STASA algorithm can successfully solve combinatorial optimization problems, such as the traveler problem and the multitraveler problem. The unified form of the STASA algorithm is shown in Formula (17).

$$\begin{cases}x_{k+1}=A_kx_k+B_ku_k\\y_{k+1}=f(x_{k+1})\end{cases} \tag{17}$$

where $x_k,x_{k+1}\in R^n$ represents the current solution and the new candidate solution generated by the transformation, $x_k,x_{k+1}\in R^n$ is the transformation operator, $u_k\in R^n$ is the expression of the objective function, and $f()$ represents the objective function.

The STASA algorithm has three discrete transformation operators, namely, exchange, translation, and symmetry. The computational formulas are shown in (18) - (20).

$$x_{k+1}=A_k^{swap}(m_a)x_k \tag{18}$$

$$x_{k+1}=A_k^{shift}(m_b)x_k \tag{19}$$

$$x_{k+1}=A_k^{sym}(m_c)x_k \tag{20}$$

In the solution-updating strategy, the Metropolis criterion states that the new solution is accepted if it is better than the current one in the search process; otherwise, the new solution is accepted with the probability of $P=e^{-(f(X_{k+1})-f(X_k))/T}\geq\eta$, $\eta\in[0,1]$. As the temperature $t=t*\gamma$ decreases, the probability tends to 0, and the algorithm gradually reaches convergence.

3) Relocalization operation

This study implemented the relocation operation and performed a local search for the globally optimal solution in each generation by combining the relocation operator, the generalized exchange operator, and the correlation removal operator with the farthest insertion heuristic in LNS.

Relocation operator is an in-route search method that controls and removes some neighboring nodes in a route and reinserts them in the same route. The generalized exchange operator is an inter-route search method that controls and removes some nodes in a route and reinserts them into other routes. The overall performance and robustness of the algorithm are largely determined by the selected removal and insertion process [14].

For the correlation removal operator, a removed customer point is randomly selected, and the correlation between the selected customer point and the customer points in distribution schemes is calculated. The distribution schemes are ranked according to the correlation from high to low. The customer point ranked as $\lceil rand^D*nip\rceil$ is removed, $rand\in[0,1]$ nip is the number of customer points in the distribution scheme. The stochastic element D can work in a fairly large range, and the solution is good. The correlation is calculated, $R(i,j)=\dfrac{1}{C_y+V_y}$, and d_{ij} is the traveling distance. If customer i and customer j are served by the same vehicle, then, $V_{ij}=1$; otherwise, $V_{ij}=0$.

The farthest insertion heuristic is used for reinsertion, and the preferred insertion point back to the customer and the optimal insertion point are determined. First, the removed customer points are sequentially inserted into each location of the distribution scheme to find all the insertion points that satisfy the capacity constraints. Second, the target increments (difference in objective function before and after insertion) of these insertion points are calculated, and the corresponding minimum target increments and their insertion points are recorded. The customer point with the largest minimum target increment is selected, and the removed customer points are inserted into the best insertion point until all of them are inserted back.

4. Result Analysis and Discussion

4.1 Basic data

This study describes a low-carbon vehicle route optimization model. The data of the case model are presented in Table 3 to test the effectiveness of the proposed model and algorithm. The main content is as follows. Vehicles provide distribution services to 30 uniformly distributed customer points with known time window constraints in a certain area, and a single customer point can only be served by a distribution vehicle. The distribution vehicle models with the same approved capacity are used in the distribution process. The distribution vehicle information is shown in Table 2. Assume that the fixed cost F of each distribution vehicle is 1000 RMB/time, the vehicle driving speed is 60 km/h, the vehicle fuel consumption is 0.08 L/km, the unit cost of unit transportation of goods is 2 RMB/t*km, the unloading waiting time is 15 min, the price of fuel is 8 RMB/L, the penalty factor of early arrival is 5 RMB/h, the penalty factor of late arrival is 10 RMB/h, the carbon tax price is 0.3 RMB/kg, and CO_2 emission coefficient is 2.3 kg/L.

Table 3. Coordinate location, demand, and time window of supplier and distribution center

Customer	Coordinate X (KM)	Coordinate Y (KM)	Demand (t)	Time window (min)
B1	67	72	1.54	(0, 15, 45, 60)
B2	59	34	1.85	(0, 10, 50, 60)
B3	8	67	1.7	(0,10, 30, 40)
B4	38	25	0.59	(0, 5, 15, 20)
B5	5	20	0.6	(0, 30, 60, 70)
B6	65	90	1.4	(0, 20, 60, 90)
B7	4	45	0.77	(0, 10, 20, 30)
B8	86	72	0.76	(0, 10, 30, 40)
B9	33	90	0.56	(0, 40, 80, 120)
B10	52	69	0.56	(0, 15, 30, 45)
B11	38	41	0.93	(0, 60, 90, 120)
B12	9	16	1.43	(0, 25, 55, 80)
B13	42	95	1.5	(0, 20, 40, 60)
B14	31	57	0.63	(0, 5, 20, 30)
B15	40	75	1.19	(0, 20, 60, 80)
B16	92	7	1.41	(0, 10, 30, 45)
B17	4	46	0.76	(0, 10, 30, 40)
B18	56	49	1.75	(0, 15, 50, 70)
B19	44	41	1.44	(0, 20, 40, 60)
B20	5	87	1.82	(0, 10, 20, 30)
B21	86	16	1.7	(0, 30, 60, 90)
B22	80	0	1.82	(0, 40, 90, 130)
B23	44	39	0.83	(0, 10, 20, 30)
B24	59	4	1.97	(0, 5, 25, 40)
B25	57	76	1.7	(0, 25, 55, 80)
B26	76	26	0.76	(0, 15, 45, 60)
B27	70	3	0.67	(0, 10, 60, 70)
B28	58	12	1.92	(0, 15, 45, 60)
B29	45	100	1.99	(0, 20, 40, 60)
B30	90	88	0.97	(0, 35, 70, 105)

In this study, the Intel i7 processor and Matlab2014b were used for experiments. The genetic SA algorithm was applied for coding to realize the algorithm solution. The parameters in the algorithm are shown in Table 4.

Table 4. Algorithm parameters

Parameter	Setting value
Population size	Popsize = 100
Maximum number of iterations	Generationmax = 100
Crossover rate	pc = 0.5
Mutation rate	pm = 0.005
Initial temperature	T0 = 1 000
Cooling rate	ϕ = 0.96
Number of internal iterations	L = 200
ω1	0.6
ω2	0.4

4.2 Optimization results and analysis

In this study, the improved state transfer SA algorithm was applied to solve the low-carbon vehicle route optimization model with a hybrid time window. A mathematical model was established on MATLAB2019B. The solution results are influenced by the initial value. Thus, the computational results were taken as the initial value for iteration to find the optimal value and the corresponding scheduling scheme ultimately. The vehicle route is shown in Table 5. The total distance of seven vehicles is 980.93 km, the total cost is 8001.15 yuan, and the convergence time of the algorithm is 133.64 s. Fig. 1 shows the convergence curve of the improved state transfer SA algorithm. The optimization scheme of the low-carbon vehicle route with a hybrid time window is shown in Fig. 2.

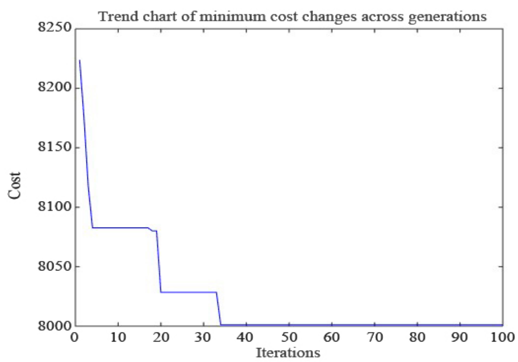

Fig. 1. Convergence curve of the improved state transfer SA algorithm

Table 5. Vehicle routes

Vehicle	Distribution route
Vehicle 1	0→11→23→4→5→12→7→17→0
Vehicle 2	0→14→19→2→18→0
Vehicle 3	0→15→13→29→9→10→0
Vehicle 4	0→25→8→30→21→26→0
Vehicle 5	0→24→22→16→27→0
Vehicle 6	0→28→1→6→0
Vehicle 7	0→3→20→0

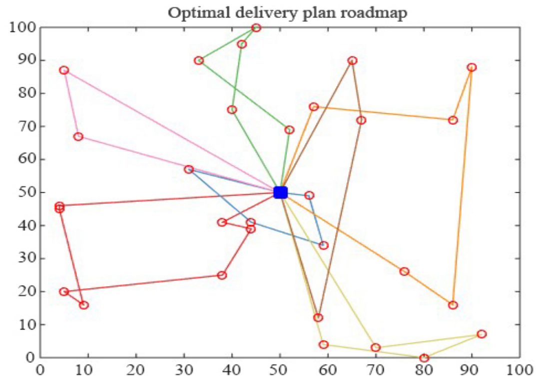

Fig. 2. Low-carbon vehicle route optimization scheme with a hybrid time window

4.3 Algorithm performance analysis

This study also used the traditional SA algorithm to verify the effectiveness of the algorithm by solving the model in the same hardware environment based on the above example data. The vehicle route is presented in Table 6. The total distance of eight vehicles is 1,138.17km, the total cost is 9,139.17yuan, and the algorithm convergence time is 197.45s. The convergence curve of the traditional SA algorithm and the low-carbon vehicle route optimization scheme with a hybrid time window are shown in Fig. 3 and Fig.4 respectively.

Table 6. Vehicle routes

Vehicles	Distribution routes
Vehicle 1	0→18→23→12→5→0
Vehicle 2	0→7→3→20→9→0
Vehicle 3	0→15→10→25→1→0
Vehicle 4	0→6→29→13→0
Vehicle 5	0→2→19→11→14→0
Vehicle 6	0→17→24→27→16→0
Vehicle 7	0→21→26→4→8→30→0
Vehicle 8	0→28→22→0

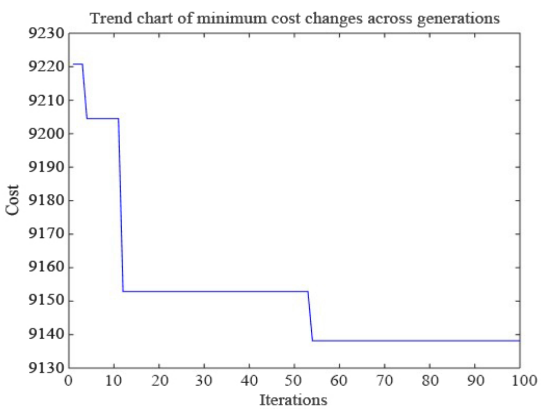

Fig. 3. Convergence curve of the traditional SA algorithm

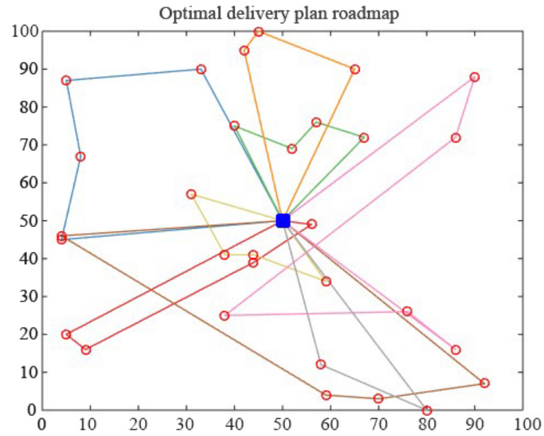

Fig. 4. Low-carbon vehicle route optimization scheme with hybrid time window

The two algorithms were compared in terms of distribution cost, traveling distance, and algorithm running time, as shown in Table 7.

Table 7. Performance comparison between the improved SA algorithm and the traditional SA algorithm

Algorithm	Total cost	Total mileage	Number of vehicles	Algorithm time
Improved SA algorithm	8001.15	980.93	7	133.64
Traditional SA algorithm	9139.17	1138.17	8	197.45

Table 7 shows that the average objective values of the improved SA algorithm are superior to those of the traditional SA algorithm in terms of total cost, traveling distance, and number of vehicles. The program running time of the improved SA algorithm and the traditional SA algorithm is 133.64 and 197.45 s, respectively. Compared with the efficiency of the traditional genetic algorithm, that of the improved genetic algorithm is improved by 32.32%. Compared with the traditional SA algorithm, the improved SA algorithm has a traveling distance and total cost decreased by 13.82% and 12.45%, respectively. This study proposed an improved SA algorithm, namely, the variable neighborhood SA algorithm, which was combined with the VNS algorithm. Thus, the convergence speed is enhanced, and the algorithm is effectively prevented from falling into local optimum. The search performance and the solution efficiency of the algorithm are improved, and the effectiveness of the improved genetic algorithm is verified.

5. Conclusions

This study introduced speed time-varying conditions to VRPs, and a segmentation function was used to represent the vehicle travel speed under different periods, enhancing the practical significance of VRPs. From the perspectives of vehicle fixed cost, travel cost, waiting cost, and delay penalty cost, a mathematical model was established by minimizing the total distribution cost as the objective function. Combined with the idea of the VNS algorithm, an improved SA algorithm, namely, the SAVN algorithm was proposed to perform the algorithm design and simulation experiments of VRPs. The comparison of the VNS algorithm, SA algorithm, and SAVN algorithm that randomly generates the initial solution indicates that the performance of SAVN algorithm is better than the performances of SA algorithm and VNS algorithm. The result verifies that SAVN algorithm can significantly improve its ability to jump out of local optimal solution. Moreover, the SAVN algorithm is superior to the SAVN algorithm that randomly generates the initial solution, indicating that the heuristic algorithms that generate initial solutions can improve the performance of the metaheuristic algorithm.

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