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A Snowmelt Optimization Algorithm Applied to Green Low Carbon Logistics Pathways Optimization Problems

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Abstract

INTRODUCTION: Efficient and accurate optimization of green and low-carbon logistics paths, as one of the key technologies of green and low-carbon logistics, can not only promote the high-quality development of the economy, but also reduce the negative impacts of logistics on the environment and increase the cost of logistics delivery.
OBJECTIVES: To address the problems of slow convergence and easy to fall into local optimization in the current performance prediction research on talent team building.
METHODS: This paper proposes a snowmelt heuristic optimization algorithm to solve the green low-carbon logistics path optimization problem. Firstly, the objective function of green low-carbon logistics path optimization is designed by analyzing the optimization cost and conditional constraints of the green low-carbon logistics path optimization problem; then, a method based on intelligent optimization algorithm is proposed by designing the position-order array coding and fitness function, combined with the snow-melting optimization algorithm; finally, the validity and superiority of the proposed method are verified by simulation experiments.
RESULTS: The results show that the proposed method not only improves the convergence speed but also increases the optimization fitness value.
Conclusion: The problem of slow convergence and easy to fall into local optimum in the solution of green low-carbon logistics path optimization problem is solved.

Keywords: green low-carbon logistics path optimization, snow-melt optimization algorithm, position-order array coding, distribution path scheme

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1. Introduction

With the development of society, the quantity and quality of logistics demand continues to increase and improve, the impact of logistics on the environment has become more and more serious [1]. With the continuous increase in global greenhouse gas emissions, the world energy crisis and other issues continue to appear, low carbon, green and other concepts gradually deepened into people's hearts, the logistics industry as a link to connect the various links in the national economic activities, the development of green and low-carbon logistics has become the mainstream [2]. As the research hotspot and key technology of green low-carbon logistics, the optimization of efficient and fast green low-carbon logistics path can promote the high-quality development of the economy, and also reduce the negative impact of logistics on the environment and increase the cost of logistics delivery [3].

Green low-carbon logistics path optimization is essentially a Vehicle Routing Problem (VRP) [4]. Green low-carbon logistics path optimization technology is under certain constraints, in order to minimize the driving distance, carbon emissions and other costs as the goal, for the logistics vehicle planning from the warehouse to each customer point of the best driving route [5]. The goodness of the green low-carbon logistics path depends entirely on the design of the path optimization algorithm, how to use an algorithm to quickly and accurately plan the distribution path from the warehouse to each customer point [6], is the global optimization and fast convergence problem. Commonly used logistics path optimization methods include exact optimization algorithms and heuristic algorithms [7]. Exact algorithms include A* algorithm [8], branch-and-bound method [9] and simplex method [10]. As the size of VRP increases, the computation of exact algorithms increases exponentially, so it is difficult for exact algorithms to find a satisfactory solution in a short period of time as the size of logistics and distribution increases [11]. Heuristic algorithms mainly include Genetic Algorithm (GA) [12], Particle Swarm Optimization (PSO) [13] and other heuristic algorithms based on population and individual solutions. Literature [14] combines the firefly algorithm with local search method and genetic algorithm to solve the VRP with capacity (Capacitated Vehicle Routing Problem, CVRP) problem, which solves the problem of firefly algorithm falling into the local optimum to a certain extent; Literature [15] solves the VRP based on the cold chain through the improvement of the artificial fish swarm algorithm problem by introducing a variation operator and a crossover operator to enhance the global and local search performance of the artificial fish swarm algorithm; Literature [16], in order to improve the search efficiency of the squid algorithm, proposed a discrete squid algorithm by introducing an elite measurement class, which successfully solves the Green VRP (GVRP, GVRP) problem; Literature [17] proposed a GVRP (GVRP with Fuzzy Demand) algorithm with fuzzy demand based on an improved Bat algorithm; Literature [17] proposed a GVRP with Fuzzy Demand based on the improved Bat algorithm. GVRP (GVRP with Fuzzy Demand, GVRPFD) method; Literature [18] proposed a multi-objective multi-time-window VRP method based on hybrid pigeon flocking algorithm and water droplet algorithm by combining pigeon flocking algorithm and water droplet algorithm. The logistics path optimization method based on heuristic algorithm converges quickly and is easy to implement, but it is also easy to fall into the local optimum problem [19]. In addition, there are fewer studies on logistics path optimization models for green low-carbon economy, and the existing studies consider the constraints are incomplete and the objectives are not objective enough [20].

Aiming at the defects of the current green low-carbon logistics path optimization method, this paper proposes a green low-carbon logistics path optimization method based on snow melting heuristic algorithm. Firstly, we analyze the characteristics of the green low-carbon logistics path optimization problem and construct a logistics path optimization model considering green low-carbon; then we use the snowmelt heuristic algorithm to solve the logistics path optimization problem considering green low-carbon. The algorithm testing results show the feasibility of the proposed method. Compared with other optimization algorithms, the proposed snowmelt heuristic algorithm shows better performance in the green low-carbon logistics path optimization problem.

2. Green low-carbon logistics path optimization model

2.1. Description of the problem

Green low-carbon logistics is the direction and trend of the future development of the logistics industry, which is widely welcomed by governments and logistics enterprises. In order to achieve green low-carbon logistics and distribution, electric vehicles have become the protagonist of green low-carbon with the advantages of zero pollution, low noise and energy saving [21]. Logistics in general should consider the type of logistics nodes and the nature of time, this paper studies the electric vehicle path problem with time window and simultaneous pickup and delivery with charging station. The electric vehicle path problem with time window and simultaneous pickup and delivery with charging station is based on the energy constraints of power constraints, mileage constraints, and customer allowable service time window constraints, to realize the simultaneous pickup and delivery needs of all customers at the smallest distribution cost [22].

Electric Vehicle Path Assumptions with Time Window and Simultaneous Pickup and Delivery and Including Charging Stations:

(1) The electric vehicle departs from the distribution center and returns to the distribution center after serving the customer;

(2) The trolley is fully charged at the time of departure, the power consumption is positively correlated with the distance traveled, and the distribution process can be ignored for some unexpected factors;

(3) Complete delivery of goods within the time allowed by the customer while picking up the goods from the customer back to the distribution center in accordance with the pickup requirements, with penalties for deviation from the time window;

(4) Only one electric vehicle will be visited by each customer and the number of visits will be one;

(5) May visit each charging station one or more times;

(6) Charging stations have a fixed charging rate, and the vehicle's charge is proportional to the time it takes to

recharge, so an electric vehicle cannot wait until it runs out to recharge;

(7) The number of electric vehicles used in the distribution process cannot exceed the total number of vehicles available.

2.2. Optimization model construction

In order to achieve low carbon and green, this optimization problem considers the fixed dispatch cost, vehicle travel cost, time penalty cost, and charging cost as the objective function [23].

Time window penalty costs

For the timeliness factor in the process of goods distribution, time window constraints are added to the model, while it is known from the assumptions that this section investigates the problem with soft time window and simultaneous pickup and delivery of electric vehicles, i.e.: in the process of goods distribution, the goods are delivered within the time window stipulated by the customer, but the customer allows the electric vehicle to deviate from the time window when it performs the service, and the corresponding penalties are given. The time window penalty cost is calculated as follows:

$$p_i(t_i) = \begin{cases} Max & 0 \le t_i < S_i \\ ep \cdot (e_i - t_i) & S_i \le t_i < e_i \\ 0 & e_i \le t_i \le l_i \\ lu \cdot (t_i - l_i) & l_i < t_i \le K_i \\ Max & t_i > K_i \end{cases} \tag{1}$$

$[e_i, l_i]$ where the EV delivery time window is . $[S_i, e_i)$ $(l_i, K_i]$ $(0, S_i]$ $[K_i, +\infty)$ Max Within the event window, the cost is 0; within the time window , it means that the goods are delivered early and the EV will have to wait, thus the cost cost is determined by the time of early delivery, which decreases as time moves backwards; within the time period , it means that the goods are delayed and the EV will be penalized for being late, and the penalization cost increases as the time moves backward; and the cost of the number of times penalization within the customer's allowable time horizon or is .

In summary, the specific expression for the time window penalty cost is as follows:

$$p_t = ep \cdot \sum_{i=1}^{N} \max(e_i - t_i, 0) + lu \sum_{i=1}^{N} \max(t_i - l_i, 0) \tag{2}$$

Objective function construction

According to the description of the green low-carbon logistics path optimization problem in Section 1.1, the objective function of the EV path optimization problem with time window and simultaneous pickup and delivery and containing charging stations is expressed as follows:

$$\min Z = z_{dispatch} + z_{drive} + z_{cha} + p \tag{3}$$

$$z_{dispatch} = c_0 \cdot \sum_{f \in F} x_0^f \tag{4}$$

$$z_{drive} = c_1 \cdot \sum_{f \in F} \sum_{i \in \wedge} \sum_{j \in \wedge} d_{ij} \cdot x_{ij}^f \tag{5}$$

$$z_{cha} = c_2 \cdot \sum_{f \in F} \sum_{i \in \wedge} y_j^f \cdot w_i^f \tag{6}$$

Z $z_{dispatch}$ z_{drive} z_{cha} p where denotes the total cost of EVs to complete the distribution task, denotes the fixed dispatch cost of EVs, denotes the cost of vehicle traveling, denotes the cost of vehicle charging, and denotes the cost of penalties paid by vehicles exceeding the time window allowed by the customer. c_0 F x_0^f denotes the EV fixed cost; denotes the number of EVs available; denotes the vehicle f being dispatched. c_1 $\wedge$ $\wedge = \Omega \cup \{0\} \cup \Delta$ Ω $\Omega = \{1, 2, \cdots, N\}$ Δ $\Delta = \{1, 2, \cdots, B\}$ d_{ij} $i \in \Omega, j \in \Omega, i \ne j$ x_{ij}^f denotes the cost per unit distance; denotes the set of all nodes (customers, distribution centers, and charging stations) within the distribution network, , denotes the set of customers ( ), denotes the number of charging stations available ( ); denotes the distance from node i to node j, ; denotes the driving of vehicle f from node i to node j. c_2 y_j^f w_i^f denotes the cost of charging per unit time, denotes the charging of vehicle f at charging station i; and denotes the amount of electricity replenished by electric vehicle f at charging station point j.

Constraints

According to the description of the green low-carbon logistics path optimization problem in Section 1.1, the constraints of the EV path optimization problem with time window and simultaneous pickup and delivery and containing charging stations are expressed as follows:

1) Carrying capacity and customer service demand constraints

a) Relationship between EV carrying capacity and demand services:

$$0 \le p_i^f \le p_i^f - p_i^f x_{ij}^f + Q(1 - x_{ij}^f), \forall i \in \wedge, \forall j \in \wedge, i \ne j, f \in F \tag{7}$$

p_i^f Q Where, denotes the customer point i demand; denotes the maximum loading capacity of the EV.

b) Maximum carrying capacity of the electric vehicle f:

$$0 \le p_0^f \le Q, f \in F \tag{8}$$

p_0^f where denotes the capacity of EV f in the distribution center.

2) Electricity constraints

a) Electric vehicle power relationship at each distribution node:

$$q_j \le q_0 - hd_{0j}x_{0j}^f + Q\left(1 - x_{0j}^f\right), \forall j \in \wedge, f \in F \quad (9)$$

$$0 \le q_{j1}^f \le q_j^f q_{j2}^f + w_j^f - hd_{ij}x_{ij}^f + Q\left(1 - x_{ij}^f\right), \forall i \in \wedge, \forall j \in \Omega, i \ne j, f \in F \quad (10)$$

q_j q_0 h d_{0j} x_{0j}^f q_{j1}^f q_{j2}^f w_j^f Where, denotes the power of EV arriving at node j, denotes the power at the distribution center, denotes the battery energy consumption coefficient, denotes the driving distance from the starting point to the node j, denotes the distribution variable of EV f from the starting point paired with the node, denotes the residual power of the vehicle when EV f arrives at the node i, denotes the residual power of the vehicle when EV f leaves the node i, and denotes the charging node j where the EV f is the replenished power.

b) The residual power of the tram should generally not be negative, and the specific constraints are expressed as follows:

$$0 \le q_{j1}^f \le C, \forall j \in \wedge, f \in F \quad (11)$$

C Where indicates the maximum battery capacity of the EV.

c) The maximum capacity of the battery of an electric vehicle should be greater than the charge of the charging station:

$$0 \le q_{i2}^f + w_j^f \le C, \forall i \in \wedge, \forall j \in \Delta, f \in F \quad (12)$$

d) The electric vehicle's power remains unchanged during the period of service to the customer, i.e., before and after the service to the customer:

$$q_{i1}^f = q_{i2}^f, \forall i \in \wedge, f \in F \quad (13)$$

3) Time constraints

a) The EV waiting time should have to satisfy the following constraints:

$$td_i = \max\left[0, \left(e_i - t_i^1\right)\right], i \in \Omega \quad (14)$$

e_i l_i Where, denotes the earliest service time of client node i and denotes the latest service time of client node i.

b) The time for an electric vehicle f to leave customer i is composed of the arrival time at i and the service and waiting time:

$$t_{i2} = t_{i1} + tf_i + td_i, i \in \Omega \cup \wedge \quad (15)$$

t_{i1} t_{i2} tf_i where denotes the time when the EV arrives at customer i, denotes the time when the EV leaves customer i, and denotes the EV service time.

c) The time required for the electric vehicle f to travel from node i to node j:

$$t_{ij} = \frac{d_{ij}}{v}, \forall i, j \in \wedge \quad (16)$$

d) The time the EV is at customer j is composed of the time it leaves customer i and the time it takes to get from customer i to j:

$$t_{j1} = \sum_{i \in \wedge} \sum_{j \in \wedge, i \ne j} x_{ij}^f \left(t_{i2} + t_{ij}\right), \forall f \in F \quad (17)$$

4) Variable constraints

x_{ij}^f y_i^f a) The values of and are constrained as follows:

$$x_{ij}^f = \begin{cases} 1 & \text{vehicle f from i to j} \\ 0 & \text{else} \end{cases} \quad (18)$$

$$y_i^f = \begin{cases} 1 & \text{vehicle f charging at station i} \\ 0 & \text{else} \end{cases} \quad (19)$$

b) Motorized vehicles are serviced only once per customer:

$$\sum_{j \in \Omega, i \ne j} x_{ij}^f = 1, \forall i \in \Omega, f \in F \quad (20)$$

c) Only one distribution route is scheduled for each electric vehicle:

$$\sum_{j \in \wedge, i \ne j} x_{ij}^f \le 1, f \in F \quad (21)$$

d) The same number of times an EV enters to leaves a node:

$$\sum_{i \in \Omega, j \in \wedge} x_{ij}^f = \sum_{i \in \Omega, j \in \wedge} x_{ij}^f, f \in F \quad (22)$$

5) Other constraints

a) Time window constraints:

$$e_i \le G_i \le l_i . i \in \wedge \quad (23)$$

$$t_i + g_i \ge S_i . i \in \wedge \quad (24)$$

$$t_i + g_i \le K_i . i \in \wedge \quad (25)$$

G_i g_i where denotes the time when the vehicle is allowed to perform the service at customer point i, and denotes the waiting time after the vehicle arrives at customer point i.

b) The relationship between the time the EV arrives at the customer, the time it waits for the customer, and the time it finishes servicing the customer:

$$t_i + g_i + G_i = \phi_i . i \in \wedge \quad (26)$$

ϕ_i where denotes the time the vehicle left customer point i.

c) The same number of EVs are sent from the distribution center as returned:

$$\sum_{i=0}^{N} x_{ij}^{f} - \sum_{j=0}^{N} x_{ij}^{f} = 0 \tag{27}$$

3. Snowmelt optimization algorithm

3.1. Inspiration mechanisms

Snow is one of the most fascinating and beautiful natural phenomena. In winter, snowmelt plays an important role in the ecosystem, affecting crop growth and human health. From the physical point of view, it is known that snow can be transformed into two forms: liquid and vapor, which correspond to the physical processes: melting and sublimation. The snow melting process and optimization mechanism are given in Figure 1. From Figure 1, it can be seen that during the melting process, snow is converted into liquid water, or through the sublimation process snow is directly converted into vapor. Meanwhile, liquid water can be converted into steam through transpiration.

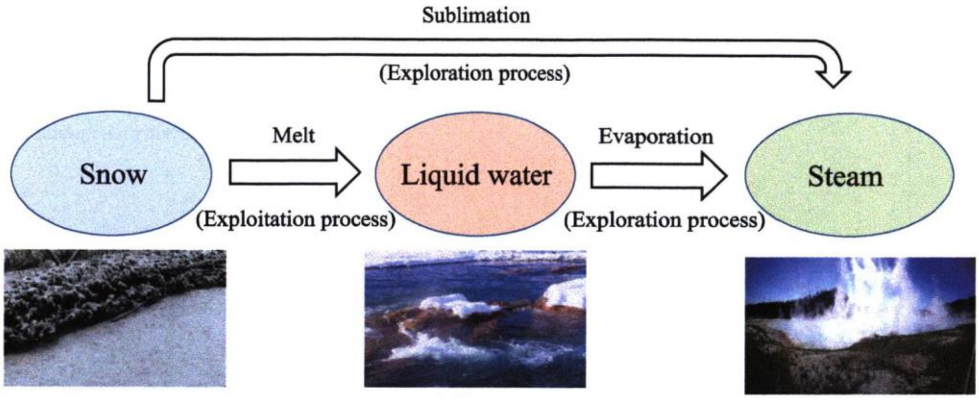


Figure. 1 Illustration of snow melting inspiration

Based on snow melting and sublimation behaviors, Snow ablation optimizer (SAO) [25] was proposed, which includes initialization, exploration phase, exploitation phase and dual population mechanism. The snow melting behavior simulates the exploitation phase of the optimization process, and the sublimation and transpiration behaviors simulate the exploration phase of the optimization process.

3.2. Optimization Strategies

Initialization phase

In the SAO algorithm, the population initialization is done using a stochastic strategy, which is modeled as follows:

$$Z = L + \theta \times (U - L) \tag{28}$$

L U θ $[0,1]$ where and denote the lower and upper bounds of the spatial solution and denotes the random number between .

Exploration phase

In the exploration phase, when snow or liquid water is transformed into vapor water, the searching intelligences show highly dispersed characteristics and have irregular movement characteristics. In the exploration phase, Brownian motion is used to simulate the behavioral situation, and Brownian motion can search for areas with potential. The position update formula in the exploration phase is as follows:

$$Z_i(t+1) = Elite(t) + \boldsymbol{BM}_i(t) \otimes \left(\theta_1 \times \left(G(t) - Z_i(t)\right) + (1-\theta_1) \times \left(\vec{Z}(t) - Z_i(t)\right)\right) \tag{29}$$

$Z_i(t)$ $\boldsymbol{BM}_i(t)$ $\otimes$ θ_1 $[0,1]$ $G(t)$ $Elite(t)$ $\vec{Z}(t)$

Where, denotes the ith individual in the tth iteration number, denotes the random vector of Gaussian distribution based on Brownian motion, denotes the dot product notation, denotes the random number between , denotes the current optimal solution, denotes the randomly selected individuals among the elite individuals, and denotes the location of the form center of the population. $\vec{Z}(t)$ The specific calculation formula is as follows:

$$\vec{Z}(t) = \frac{1}{N} \sum_{i=1}^{N} Z_i(t) \tag{30}$$

$Elite(t)$ The elite groups to which they belong are indicated below:

$$Elite(t) \in [G(t), Z_{second}(t), Z_{third}(t), Z_c(t)] \quad (31)$$

$Z_{second}(t)$ $Z_{third}(t)$ $Z_c(t)$ where and denote the second and third best individuals, respectively, and denotes the location of the morphology centers of the individuals ranked in the top 50% of the fitness values.

$$Z_c(t) = \frac{1}{N_1}\sum_{i=1}^{N_1} Z_i(t) \quad (32)$$

N_1 where indicates the number of individuals in the elite group, which is generally half the number of individuals in the population.

$\theta_1 \times (G(t) - Z_i(t))$ $(1-\theta_1)\times(\bar{Z}(t) - Z_i(t))$ The behavioral diagram of the exploration stage is shown in Figure 2. and reflect the relationship between individuals in the exploration behavior.

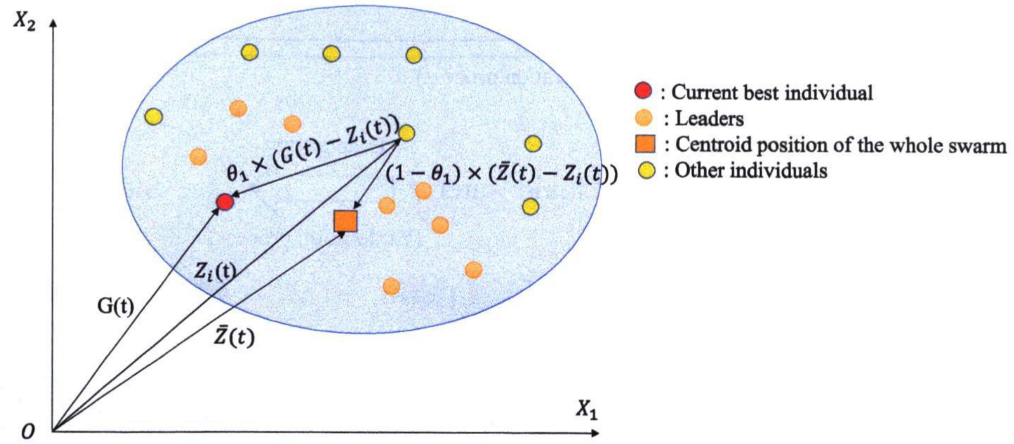


Figure. 2 The exploration stage of the snow melting algorithm

Development phase

In the development stage, relative to the highly dispersed features, the search intelligences adopt a high quality development strategy around the optimal solution, which mainly simulates the conversion of snow into liquid water behavior, i.e., snow melting behavior. In the SAO algorithm, the snow melting rate is calculated as follows:

$$M = \left(0.35 + 0.25 \times \frac{e^{\frac{t}{t_{\max}}} - 1}{e - 1}\right) \times T(t) \quad (33)$$

$$T(t) = e^{\frac{-t}{t_{\max}}} \quad (34)$$

During the SAO development phase, the locations were updated as follows:

$$Z_i(t+1) = M \times G(t) + BM_i(t) \otimes \left(\theta_2 \times (G(t) - Z_i(t)) + (1-\theta_2) \times (\bar{Z}(t) - Z_i(t))\right) \quad (35)$$

M θ_2 $[-1,1]$ Where denotes the snowmelt rate and denotes a random number between $\theta_2 \times (G(t) - Z_i(t))$ $(1-\theta_2)\times(\bar{Z}(t) - Z_i(t))$ In this stage, under the effect of individuals search through the current optimal search particles and population shaped centroids to develop potential regions.

Dual Stock Mechanism

The balance between exploitation and exploration is very important. Liquid water is converted to steam to model the exploration phase. The algorithm gradually converges to the exploration search solution space as the irregular motion dispersion feature increases. In order to balance the exploration and exploitation phases, a two-population search mechanism is proposed in this section. P P_a P_b At the initial stage of the algorithm, the population is divided into two equal population sizes respectively, and are used to represent the whole population and divide the population. P_a P_b Population is mainly used for exploration and population is mainly used for exploitation. P_a P_b As the number of iterations increases, the number of populations will decrease and the number of populations will increase, and the two-population mechanism is illustrated in Figure 3.

```
Algorithm: Dual-population mechanism
Initialization: t=0, tmax, Na=Nb=N/2, where N denotes the population size
while t<tmax do
    if Na<N then
        Na = Na +1, Nb = Nb – 1
    end if
    t = t+1
end while
```

Figure 3 Pseudo-code diagram of the two-species mechanism

2.3. Algorithm flow and pseudo-code

According to the algorithm heuristic mechanism and optimization strategy, the flowchart of SAO algorithm is shown in Figure 4, and the specific steps are as follows:

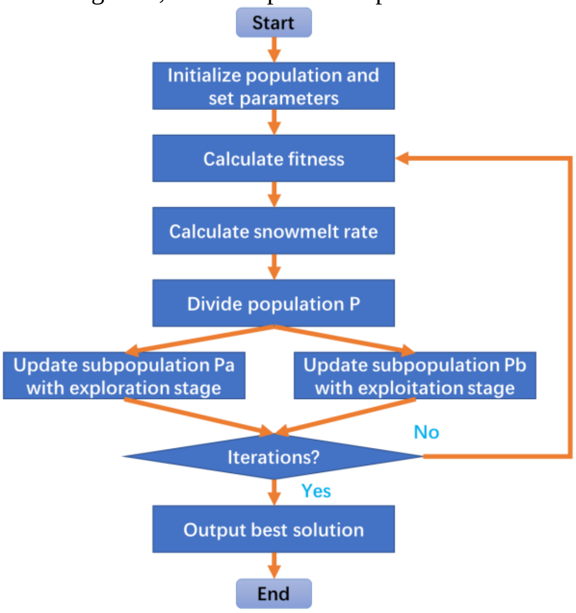


Figure 4. Flowchart of SAO algorithm

Step 1: Initialize the population parameters as well as the population position, set the maximum number of iterations and other parameters;

Step 2: Calculate the fitness value and record the current optimal individual;

Step 3: Calculate the snowmelt rate M;

Step 4: Randomly divide the population into two sub-populations based on the number of sub-populations;

Step 5: Subpopulation a carries out the exploration behavior phase through snow or liquid water conversion to vapor water, and subpopulation b carries out the exploitation behavior phase through snow conversion to liquid water behavior;

Step 6: Calculate the fitness value and update the optimal individual;

Step 7: Determine whether the number of iterations reaches the maximum number of iterations. If the maximum number of iterations is reached, proceed to output the optimal solution and optimal value; otherwise, go to step 4.

According to the SAO algorithm steps, the SAO algorithm pseudo-code is shown in Figure 5.

```
Algorithm Snow ablation optimizer (SAO)
Initialization: the swarm Z, t=0, tmax,Na=Nb=N/2
Fitness evaluation
Record the current best individual G(t)
while t<tmax do
    Calculate the snowmelt rate M;
    Randomly divide the population P into two subpopulations Pa and Pb;
    for each individual do
        Update each individual's position;
    end for
    Fitness evaluation
    Update G(t)
    t = t+1
end while
Return G(t)
```

Figure 5. Pseudo-code diagram of SAO algorithm

4. A green and low-carbon logistics path optimization method based on snow melting optimization algorithm

4.1. Optimizing solutions

In the SAO algorithm for solving the electric vehicle path problem with time window and simultaneous pickup and delivery with charging station, the population individuals are the feasible solutions of the problem to be solved. Therefore, the optimal solution obtained by solving the electric vehicle path problem with time window and simultaneous pickup and delivery with charging station is the optimal position of the SAO algorithm [27].The relationship between the SAO algorithm and the electric vehicle logistics and distribution planning problem is shown in Figure 6. From Figure 6, it can be seen that the population individual position in the electric vehicle path problem corresponds to the feasible path traversing the target distribution node and charging station, the change of the population individual position corresponds to the change of the path passing through the distribution node and the charging station or the planning optimization process, and the fitness value corresponds to the value of the objective function.

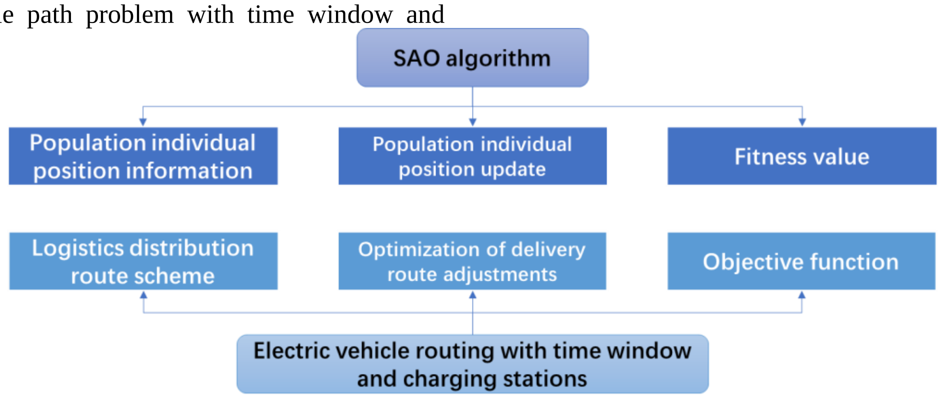


Figure 6. The optimized solution

4.2. Coding Design

$2\times\dim$ From the correspondence between the SAO algorithm and the EV problem with time window and simultaneous pickup and delivery with charging station in Fig. 6, it can be seen that in this paper, the population individual position indicates the feasible path traversing the target distribution node and charging station, and an array coding method is used to explain the structure of the population individual position, i.e., , where the dim dimension indicates the number of distribution nodes and charging stations, and the structure of the solution is shown in Figure 7. From Figure 7, it can be seen that the distribution centers, customer points and charging stations are discrete points, and the position-order array coding method is introduced to encode the SAO algorithm for solving the EV problem with a time window and simultaneous pickup of delivery and charging stations. The location-order coding expression formula is as follows:

$$Y_i(x)=\left(Y_{i1}(x),Y_{i2}(x),\cdots,Y_{in}(x)\right) \tag{36}$$

$$R(x)=\left(order\left(Y_{i1}(x)\right),order\left(Y_{i2}(x)\right),\cdots,order\left(Y_{in}(x)\right)\right) \tag{37}$$

$Y_i(x)$ $order\left(Y_{i1}(x)\right)$ $\left(Y_{i1}(x),Y_{i2}(x),\cdots,Y_{in}(x)\right)$ $R(x)$ Where, denotes the position of the ith individual in the xth generation of the SAO algorithm, denotes sorted in ascending order, and denotes the EV path code.

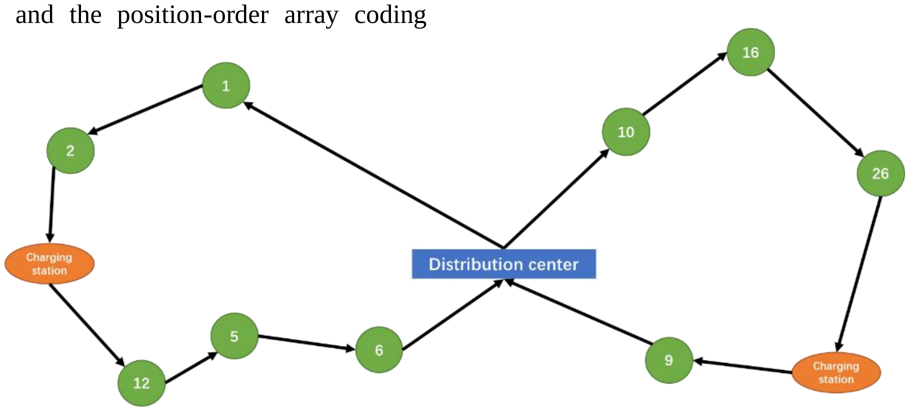


Figure 7. The solution structure

$1,2,\cdots,N$ From Figure 7, it can be seen that the distribution center number dimension 0, the customer point is , and the EV returns to the distribution center after serving a certain number of customers. According to the battery capacity, loading capacity and other constraints of each EV, Figure 7 gives the structure of two sets of solutions, the first set of solutions indicates that the first EV returns to the distribution center after serving customer nodes 1, 2, charging station, 12, 5 and 6 from the distribution center, and the different EVs carry out the distribution service without repetition.

4.3. Adaptation function design

Individual fitness function is used to analyze the constraints of the green low-carbon logistics path optimization problem, combined with the total cost of electric vehicles to complete the distribution task, to generate the fitness value used to evaluate the individual advantages and disadvantages of the distribution scheme. In this paper, the individual fitness function is specified as:

$$f\left(Y,R\right)=z_{dispatch}+z_{drive}+z_{cha}+p \tag{38}$$

Y,R where denotes the distribution node and order of the distribution scheme, respectively.

4.4. Green low-carbon logistics path optimization process

The essence of the green low-carbon logistics path optimization problem is to solve the optimal solution problem with multiple constraints and multiple objectives, i.e., the electric vehicle path optimization problem with a time window and simultaneous delivery pickup and delivery and containing charging stations. The application process of snow melting optimization algorithm in green low-carbon logistics path optimization is shown in Figure 8, and the specific steps are as follows:

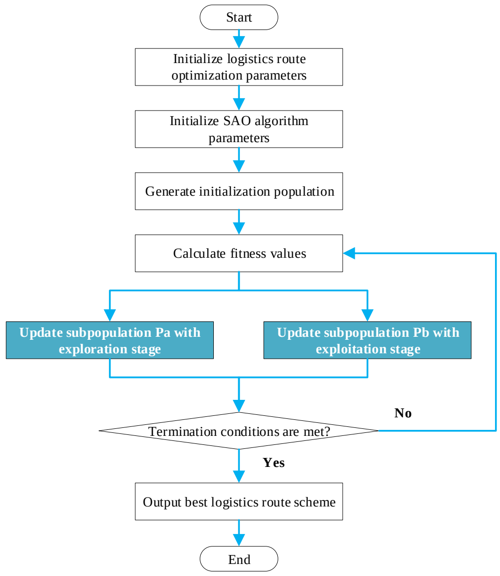


Figure 8. Flow chart for optimization of green and low-carbon logistics paths

Step 1: Initialize the green low-carbon logistics path optimization parameters, including the parameters of the green low-carbon logistics path optimization mathematical model and the SAO algorithm parameters. The parameters of the green low-carbon logistics path optimization model include the relevant constraints, and the parameters of the SAO algorithm include the population size and the maximum number of iterations.

Step 2: Initialize the search population. Select the search population randomly and uniformly using the given boundary constraints.

Step 3: Individual encoding mapping. The mapping between population individuals to the problem solution is accomplished using the position-order array encoding approach.

Step 4: Calculate the fitness value of the individual. The adaptation degree value is mainly used to assess the quality indicator of the individual relative to the whole group. In this paper, we use the total cost of the electric vehicle to complete the delivery task as a function of the fitness value, the smaller the fitness value is, the better the quality of the individual and the better the solution is.

Step 5: Snowmelt optimization strategy search for updated populations. Optimize and update the individuals of the logistics delivery scheme according to the exploration phase, development phase and dual population mechanism of the SAO algorithm.

Step 6: Determine whether the algorithm termination conditions are satisfied. If the number of search iterations is greater than the maximum number of iterations, terminate the search and output the optimal green low-carbon logistics path distribution scheme; otherwise, continue with **steps 4** to **6**.

5. Experimental results and analysis

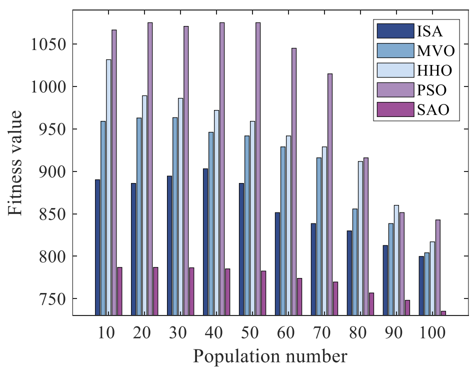
In order to verify the effectiveness of the green low-carbon path optimization method based on the snow-melt optimization algorithm, using the R101 test data, five analysis algorithms were selected for comparison in this paper. MATLAB 2021a was used to write the program, and the test environment was a Windows 10 system, the processor was AMD Ryzen 9 5900HX with Radeon Graphics, and the RAM was 16.0 GB.The parameters of each algorithm are shown in Table 1.

Table 1. Parameter settings of green low-carbon logistics path optimization algorithm

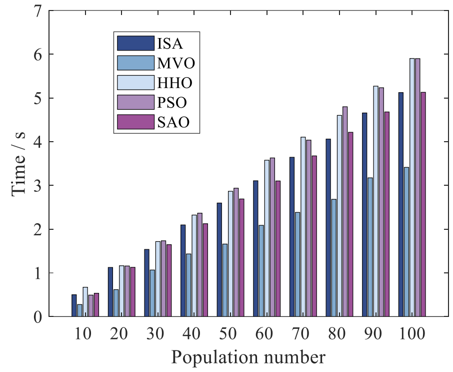
arithmetic	parameterization
ISA	α = 0.2
MVO	WEPmax=1, WEPmin=0.2
HHO	E0 in the range (-1, 1)
PSO	Vmax=30, Vmin=-30, r=0.5
SAO	Parameter-free optimization

5.1. Algorithm Parameter Analysis

In order to investigate the impact of SAO algorithm parameters on the optimization performance of green and low-carbon road logistics routes, this paper analyzes the population size and the number of iterations of the ISA algorithm. Figure 9 gives the effect of different population sizes on the performance of green low-carbon road logistics path optimization based on intelligent optimization algorithms. From Figure 9(a), it can be seen that the fitness value of each algorithm has a tendency to decrease as the population size increases, and when the population increases to a certain size, the fitness value does not change much and fluctuates around a certain fitness value. From Figure 9(b), it can be seen that the elapsed time of each algorithm increases as the population size increases. Therefore, in a comprehensive analysis, the population size should take the value of 50 in order to fairly compare the optimization performance of each algorithm.



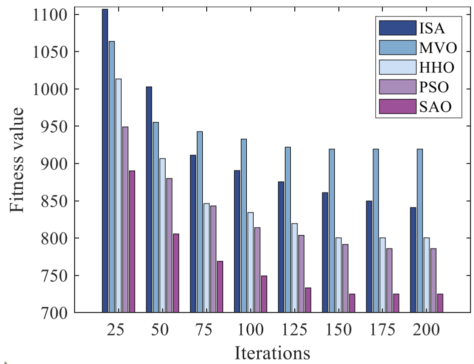
(a) Optimal adaptation value results



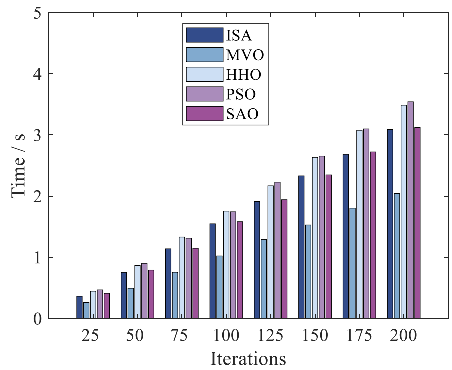
(b) Time-consuming results

Figure 9. Effect of population size on the performance of logistics path optimization methods

Figure 10 gives the effect of different iteration numbers on the performance of green low-carbon road logistics path optimization based on intelligent optimization algorithms. From Figure10(a), it can be seen that with the increase in the number of iterations, the fitness value of each algorithm decreases, and when the number of iterations reaches a certain value, the fitness value no longer changes; after the number of iterations of the SAO algorithm reaches 150 times, its fitness value no longer changes. From Figure 10(b), it can be seen that the elapsed time of each algorithm increases with the increase in the number of iterations; the slope of the change in the elapsed time of the optimization of the SAO algorithm is the minimum.



(a) Optimal adaptation value results



(b) Time-consuming results

Figure 10. Impact of the number of iterations on the performance of logistics path optimization methods

5.2. Analysis of path optimization results

Based on the above parameter analysis, this subsection compares and analyzes the five compared optimization algorithms from three perspectives such as optimization convergence curve, fitness value, and time consuming, etc., and each algorithm is run 20 times, and the specific results are shown in Figures. 11, 12, and 13.

Figure 11 gives the results of the distribution of the optimal fitness values of each algorithm in the four working conditions. From Figure 11, it can be seen that the SAO algorithm has the highest convergence accuracy and the fastest convergence speed; in terms of convergence accuracy, SAO is the best, and then PSO, HHO, ISA, and MVO algorithms in that order.

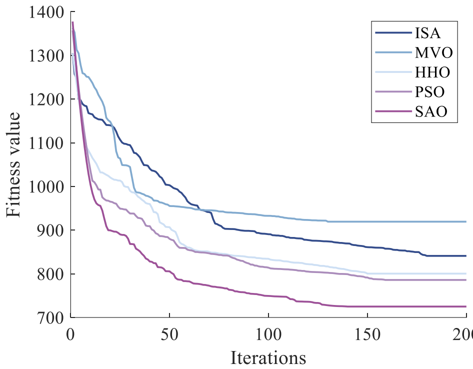


Figure. 11 Iterative convergence curve of green low-carbon logistics path optimization based on each algorithm

Figure 12 gives the results of the distribution of the optimal fitness values of each algorithm. From Fig. 12, it can be seen that SAO algorithm is better than other algorithms in terms of optimal fitness value for distribution path optimization, and the standard deviation of optimal fitness value is also the smallest, and the robustness is better than the other algorithms.

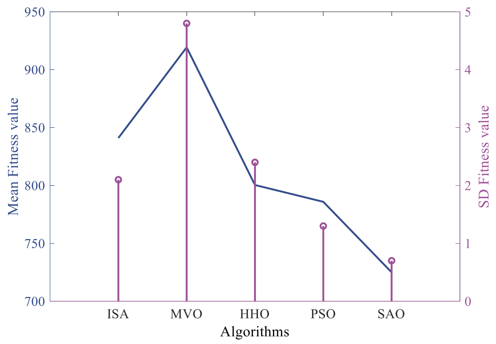


Figure 12. Comparison results of adaptation value of green low-carbon logistics path optimization methods based on each algorithm

Figure 13 gives the results of the time-consuming optimization process of each algorithm. From Figure 13, it can be seen that SAO algorithm is better than the other algorithms in terms of optimization time-consumption, MVO algorithm based logistics and distribution path optimization has the smallest standard deviation of time-consumption, followed by SAO algorithm.

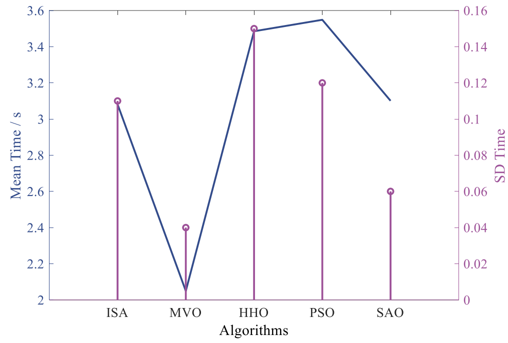


Figure 13. Comparison results of time-consuming green low-carbon logistics path optimization methods based on each algorithm

According to the SAO algorithm running 20 times the optimal results, this section gives the results of the optimal distribution scheme with the schematic diagram, the specific results are shown in Figures 14 and 15.Figure 14 gives the results of the optimal distribution scheme for logistics. From Figure 14, it can be seen that the four-vehicle distribution path passes through the nodes more evenly and is charged once or twice.

Delivery routes	Delivery routes	Charging stations
#1	0->28->30->18->17->5->6->0	17
#2	0->27->27->19->7->8->17->12->16->14->13->0	27、12
#3	0->1->9->20->27->11->0->37->26->21->15->2->0	27、37
#4	0->12->3->29->24->25->4->53->23->22->0	53

Figure 14. Green and low-carbon logistics and distribution vehicle routes based on SAO algorithm

A schematic diagram of the optimal distribution scheme is given in Figure 15. From Figure 15, it can be seen that the travel paths of each vehicle start from the distribution center, pass through the customer node, charging station, and finally return to the starting point; the third vehicle departs and returns to the starting point after passing through five points, and then there are departures and finally return to the starting point.

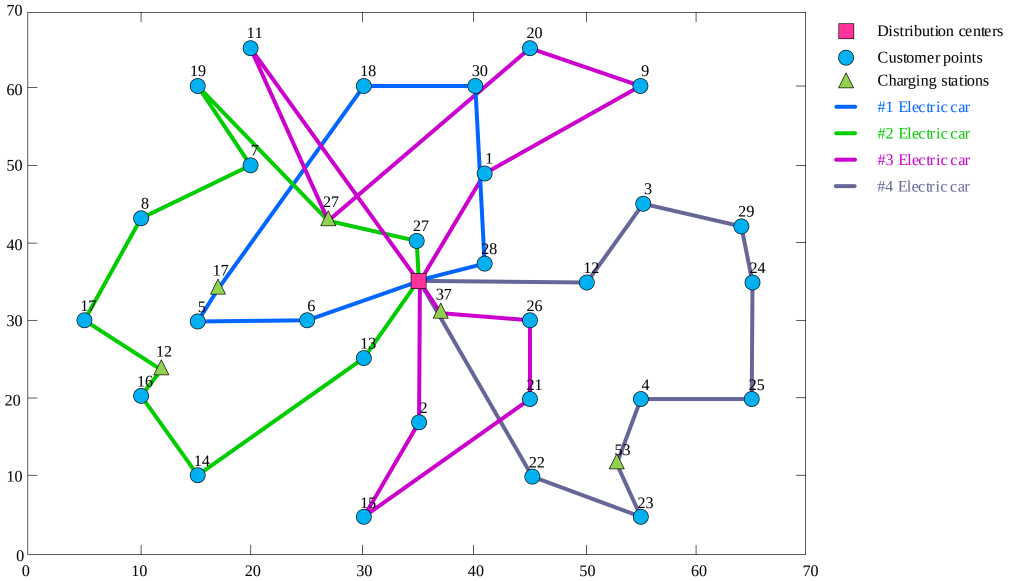


Figure 15 Green low-carbon logistics distribution path based on SAO algorithm

6. Conclusion

Distribution path optimization solution is one of the key technologies for the green low-carbon logistics path optimization problem. Aiming at the defects of the current distribution path optimization method, such as slow convergence speed and easy to fall into local optimization, this paper proposes a snow-melting heuristic optimization algorithm to solve the green low-carbon logistics path optimization problem. By analyzing the optimization cost and conditional constraints of the green low-carbon logistics path optimization problem, designing the objective function, and constructing the green low-carbon logistics path optimization model; combining the position-order array coding method and the fitness function, the snow-melting optimization algorithm is used to search for the optimal solution of the distribution problem using the snow-melting optimization algorithm search strategy. The experimental results show that the green low-carbon logistics path optimization method proposed in this paper can find the optimal solution of green low-carbon logistics distribution path in a shorter time, with higher node coverage and more stable performance.

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