Research on Low Carbon Distribution Supply Chain of Multi-product of Pure Electric Vehicles

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Abstract. In view of the issue of carbon emissions generated by vehicles in the distribution link of supply chain, a low carbon supply chain distribution model is established considering collaborative optimization of production scheduling and distribution paths, taking the carbon emissions of pure electric trucks at different speeds under the time-varying network as the key variable. In this model, firstly, it is considering constraints such as product type, customer demand time window, vehicle load rate, loading and unloading time and service time. Secondly, an improved ant colony algorithm, a hybrid algorithm combining simulated annealing algorithm with ant colony algorithm, is proposed to improve the ability of searching and jumping out of local optimum. Finally, through the simulation optimization and comparative analysis of a random numerical example, it is verified that it can effectively reduce carbon emissions in the process of distribution using collaborative optimization model of supply chain production and distribution with minimizing optimization of carbon emissions and total travel time under the time-varying network, and the effectiveness of the algorithm is also verified.

1. Introduction

The transportation industry is one of the important sources of carbon emissions. It is exacerbated air pollution by exhaust emissions of a large number of distribution vehicles. Carbon emission trading will also affect the transportation costs of enterprises. The number of pure electric freight vehicles is gradually increasing in major cities, and the disadvantages of pure electric trucks are gradually reduced with the development of technology. It is very necessary to study how to optimize the distribution scheduling scheme of pure electric trucks in supply chain, to reduce the electricity consumption of pure electric trucks under the condition of minimum disturbance to production of transport, so as to reduce carbon emissions and optimize the production time and distribution path of enterprises.

At present, there are a few researches having been studied by domestic and foreign scholars to add the constraints of carbon emissions in distribution process under the time-varying network. Figliozzi [1][2] earlier studied the modeling of Vehicle Routing Problem (VRP) related to carbon emissions in the time-varying network. Arigliano et al. [3] studied the Traveling Salesman Problem (TSP) under the time-varying network in a complete network graph, and proposed a branch-and-bound algorithm. Wang et al. [4], from the perspective of low carbon and environmental protection, proposed and solved the green vehicle routing scheduling problem under the time-varying network with the optimization goal of minimizing the total carbon emissions and operating costs.
It has also attracted the attention of domestic and foreign researchers on how to conduct reasonable electric vehicle dispatch and distribution path planning under the limitation of technical conditions. The routing problem of electric vehicles is the extension and expansion of the traditional vehicle routing problem. Zhao Z. X. and Li X. M. [5] built an optimization model of urban fresh delivery path of electric vehicles under the time-varying traffic by considering the constraints of minimum freshness of fresh products by customers, on-board restrictions and electric vehicle quantity constraints comprehensively. Hiermann et al. [6] studied the rational allocation of fleet structure for distribution according to difference of energy consumption and load of different types of electric vehicles. Afroditi et al. [7] built a path planning model of electric vehicles considering constraints such as vehicle loads, charging mode and electric quantity and so on.

At present, there are less researches studying on carbon emission problem of pure electric trucks, under the time-varying network, but the above results of researching provide reference theory and method for exploration in this field. In this paper, it proposes a low carbon distribution model of multi-product of pure electric vehicles to optimize the whole supply chain to reduce vehicle carbon emissions using pure electric trucks for distribution under the time-varying network, with arranging production plan and delivery plan of a factory within a certain time window comprehensively, taking minimum of carbon emissions and costs as optimization objectives, adjusting product processing time and completion time.

2. Problem Description

2.1. Problem specification

The problem studied in this paper is to optimize the production scheduling of a variety of products under time variation, and to arrange pure electric trucks for distribution according to traffic congestion. Vehicles will depart from the distribution center, provide delivery services to different customers, and finally return to the distribution center. A distribution task is completed under the service time window required by customers, which multiple transport vehicles are used to deliver different products to multiple customers in cities. Among the model, carbon emissions of pure electric vehicles are a function of driving speed and driving time of vehicles. Due to different traffic jams in different periods of time in cities, electric trucks consume less energy at a slower speed, but the slower the speed, the longer the delivery time, which is corresponding to increase costs of transportation. The relationship between the speed of an electric truck with a load of 2.1 tons and its carbon emissions is shown in Figure 1.

![Figure 1 Relationship between the speed of an electric truck and its carbon emissions](image)

As can be seen from Figure 1, the faster the electric truck travels, the more power it consumes per unit time and the more carbon emissions it generates. Under conditions with same driving time and mileage, the more the speed changes, the greater the power consumption is and the more carbon emissions are increased.

| Speed (km/h) | Unit carbon emission (g/km) | Time (h) | The total carbon emissions (g) | Rate of change |
|--------------|-----------------------------|----------|-------------------------------|---------------|
| 20           | 88.5                        | 1        | 12774                         | 29.08%        |
| 60           | 183.4                       | 1        | 12774                         |               |
| 40           | 123.7                       | 2        | 9896                          |               |

Table 1 Speed variation and constant carbon emissions of pure electric trucks
As can be seen from Table 1, there are two types of driving, the speed changes from 20km/h to 60km/h, and the speed remains unchanged at 40km/h, with same driving time and mileage which are 2 hours and 80 km, respectively, the total carbon emissions differ by 29.08%. Therefore, the vehicle's electricity consumption can be effectively saved and carbon emissions can be reduced, if the change of speed can be kept as small as possible.

Cities are generally congested in the peak of morning and evening. In the period between traffic congestion, the average speed of vehicles varies slightly, which is the best time period for pure electric trucks to distribute. As customers generally have requirements of demand time window, it will increase costs if delaying in delivery. Generally, vehicles will be arranged to deliver products within the time demand window period of customers, after a certain amount of products is processed by the processing factory. Therefore, it considers the cooperative arrangement of production and distribution scheduling in this paper, the distribution of vehicles is carried out between morning and evening traffic peaks as far as possible, so as to reduce power consumption and the total carbon emissions of vehicles, under the condition that there are little changes of window periods and the total travel time.

2.2. description of symbols

Network: $G = (E, S)$ is a complete graph, which is a distribution and transportation network, where the set of nodes is $E \in \{1, 2, \ldots, B\}$, set $E = 1$ as the origin of distribution, and $E = (2, \cdots, B)$ represents customers; $S$ for the arc set in the network diagram, the $i, j$ node for any two customers, $S = \{(i, j)\mid (i, j \in E \text{ and } i \neq j)\}$; $v_{ij}^r$ represents the average traveling speed from node $i$ to node $j$ under the $r$-th speed change.

Distribution and processing center: $N$ represents the collection of product types of processing and distribution. For any product $n \in \{1, 2, \ldots, N\}$, $n_h$ represents that product $n$ has $h$ processing procedures; $M$ represents the collection of processing machines; $O_m$ represents the time from the beginning of processing to completion of machine $m$ in the processing of this batch of products, $\forall m \in M$; $K$ represents the collection of all vehicles, $k$ represents a certain distribution vehicle, and $\forall k \in K$; $q$ represents the real-time load of a vehicle, and $Q$ represents the maximum load of a vehicle.

Customer nodes: $[\bar{\theta}_j, \underline{\theta}_j]$represents the earliest and latest delivery time window of customer node $j$; $g^r_j$ represents the demand for product $n$ from customers at node $j$, and $G_j$ represents the demand for all types of products at node $j$.

Decision variables: $x_{ij}^k = [0,1]$ represents decision variables of road section where vehicles travel, $x_{ij}^k = 1$ represents the path between customer node $i$ and $j$ where the vehicle $k$ passes, otherwise $x_{ij}^k = 0$.

2.3. Conditional Assumptions

(1) There are enough same types of pure electric trucks in processing and distribution center;

(2) There is a maximum load limit for any distribution vehicle. The vehicle will start from the distribution center and return to the distribution center after completing a task;

(3) After a vehicle arrives at a customer, the service time includes the formalities handover time and the unloading time which is related to the unloading quantity;

(4) In production scheduling, there are process constraints between processes of the same process, and the processing of the next process can only be started after the processing of the previous process is completed;

(5) In production scheduling, each process can only be processed on the designated machine, and one machine can only process one process at the same time.

3. Modelling

The model is optimized with the total carbon emissions and the total travelling time of vehicles as two
objectives. Carbon emission is a function of vehicle driving speed and mileage. The calculation of carbon emissions in this paper mainly refers to the electricity consumed at a given speed by all-electric trucks translates into carbon emissions. In addition to the travel time of vehicles, the total travel time also includes the service time of vehicles arriving at the customer node. Labor costs can be reduced, vehicle utilization and customer service satisfaction can be improved by minimizing the total travel time of vehicles.

3.1. Carbon emission calculation of pure electric trucks

The power consumption of an electric vehicle is closely related to its speed. When driving on a flat road, its operating power is:

\[ P(v) = (M_g \cdot g \cdot f + C_d \cdot A \cdot v^2 / 21.25) / 3600 \eta \]

In the formula (1), \( M_g \) represents the total mass of a vehicle, and \( g \) represents the gravitational acceleration; \( \eta \) represents the mechanical efficiency of the transmission system; \( f \) represents the rolling resistance coefficient of a vehicle, \( C_d \) represents the air resistance coefficient, and \( A \) represents the windward area of a vehicle. Then, the carbon emissions of an electric vehicle \( k \) from path \( i \) to \( j \) is:

\[ C_{eq} = \mu \phi e \sum_{r=1}^{k} p(v_{eqr}) \cdot r_{eqr} \]

where, \( r \) represents the number of speed changes in the time-varying network, \( \mu \) represents the battery energy conversion rate, and \( \phi \) represents the carbon emissions is produced by per unit of electricity.

3.2. Service hours

The service time includes the loading and unloading time of an electric truck as well as the formalities and handover time with customers. The loading time of a vehicle is completed at the origin of distribution, and the loading time is not included in the vehicle running scheduling model. The service time \( e_{uj} \) of vehicle \( k \) at customer \( j \) only needs to consider unloading time \( e_{uj} \) and formalities handover time \( e_{pj} \). Unloading time is related to the demand of customer \( j \), \( G_j \), and unit unloading time \( q_i \) (hour/ton), that is, \( e_{uj} = G_j / q_i \). The service time of Customer \( j \) is shown in Formula (3).

\[ e_{jk} = e_{uj} + e_{pj} = G_j / q_i + e_{pj} \quad (3) \]

3.3. Model establishment

In this paper, a Job-shop Scheduling Problem (JSP) model, which is in line with production practice, is used to study the production scheduling of multiple products. The carbon emissions of vehicles in the distribution network are related to the speed and distance of travelling. In the urban distribution environment, the vehicle speed is closely related to the congestion peak period. Therefore, the departure time of vehicles should try to avoid the peak period, and the arrangement of production scheduling is directly related to the departure time of distribution vehicles, under the condition of satisfying the demand time window of customer distribution.

Objective function:

\[ \min \sum_{i=0}^{B} \sum_{j=0}^{R} \sum_{k=1}^{K} \left( \sum_{l=1}^{S} \frac{d_{ij}}{v_{ij}} + e_{ij}^k \right) X_{ij}^k + \min(\sum_{m=1}^{M} O_m) \]

\[ \min \sum_{i=0}^{B} \sum_{j=0}^{R} \sum_{k=1}^{K} \left( \sum_{l=1}^{S} C_{ij} \left( v_{eql}^k \right)^r X_{ij}^k \right) \]

The former part of Formula (4) represents the minimum total travel time of delivery vehicles, while the latter part represents the minimum total production time of machines. Formula (5) represents the minimum carbon emissions function during the driving of delivery vehicles.
\[ \sum_{j=2}^{B} \sum_{k=1}^{K} \sum_{s=1}^{S} x_{ij}^{ks} = 1, i \in \{1, \cdots, B\} \quad (6) \]

\[ \sum_{n=1}^{N} g_{i}^{n} = G_{i}, i \in \{2, \cdots, B\} \quad (7) \]

\[ t_{j}^{k} \leq \theta_{j} - \overline{\theta}_{j}, j \in \{2, \cdots, B\}, k \in K \quad (8) \]

\[ \sum_{j=1}^{B} G_{i} \sum_{j=1}^{B} x_{ij}^{k} \leq Q_{i}, k \in K \quad (9) \]

\[ \sum_{j=1}^{B} x_{ij}^{k} = \sum_{i=1}^{B} x_{ii}^{k} = 1, k \in K \quad (10) \]

\[ x_{ij}^{k} = [0, 1], (i, j) \in \{1, 2, \cdots, B\} \quad (11) \]

where, Formula (6) indicates that all customer nodes are visited only once; Formula (7) represents the demand of all products of customer nodes; Formula (8) indicates that vehicle \( k \) must arrive within the delivery demand window of customers; Formula (9) is the maximum load limit of vehicles; Formula (10) indicates that the distribution vehicle only starts from the processing and distribution center once, and must return to the starting point after completing the task; Equation (11) is the decision variables of paths.

4. Algorithm design

It has an obvious effect in solving VRP problems with Ant Colony Optimization (ACO) \[9\]. In this paper, in order to enhance the global search ability of the algorithm and avoid the difficulty of jumping out of the algorithm due to too fast convergence speed or being trapped in the local optimal, it proposes to add the search method of simulated annealing algorithm and Metropolis sampling criterion to the ACO process, so as to increase the search space of the algorithm and strengthen the ability of jumping out of the local optimal. The calculation of Metropolis probability is shown in Equation (12), where \( \Gamma \) is the control parameter of temperature drop, which is inversely proportional to the number of iterations of the algorithm, that is, the probability of accepting changes is high at the beginning of the algorithm, and the acceptance probability gradually decreases with the iteration of the algorithm.

\[ \Psi = \exp\left(-\frac{f(S(t)) - f(S(t))}{\Gamma}\right) \quad (12) \]

Algorithm flow:

Step 1: Code and generate the initial population;

Step 2: Calculate the individual fitness value \( f[S(t)] \) of the population, and update \( S(t) \) to \( S(t) \) according to pheromone concentration;

Step 3: Determine if \( \Delta f = f[S(t)] - f[S(t)] \) is greater than 0. If so, go to step 4; If not, determine whether the Metropolis sampling criterion is accepted; if so, go to step 4; if not, go to step 5;

Step 4: let \( S(t) = S(t) \);
Step 5: Update the individual pheromone concentration value;
Step 6: Determine whether to break out of the inner loop or not. If so, go to step 7. If not, go to step 2;
Step 7: Determine whether to break out of the outer loop or not. If so, the algorithm is ended. If not, the temperature \( \Gamma \) drops, and go to step 2.
4.1. Algorithm coding mode

The population of the algorithm is coded by real number, which is coded in two stages, as shown in Figure 3. In the first stage, the distribution path and time information are encoded. The first real number in the distribution information of each vehicle represents the loading time of vehicle \( k \) at the origin of distribution, and the following number represents the node through which the distribution path passes. The second stage is to encode the production scheduling information, taking \([3,2,3,1,2...]\) as an example, the first number "3" represents the first procedure of the third process, the second number "2" represents the first procedure of the second process, and so on.

4.2. Update mode

In the improved ACO, the single-point update method is adopted, that is, a random point \( Rand \) is generated in the feasible solution of a path. The part before the random point is copied and retained directly, and the part after the random point is reconstructed according to the update method of pheromone concentration in ACO. In the iteration process, the real number after the particle \( Rand \) point is recoded. The probability \( \rho_{kj}^s(t) \) is that electric vehicle \( k \) reaches node \( j \) through node \( i \), and the path \( s \) is selected, and its calculation is shown in Formula (13).

\[
\rho_{kj}^s(t) = \left\{ \begin{array}{ll}
\frac{[\tau_{kj}^s(t)]^\alpha \times [\eta_{kj}^s(t)]^\beta}{\sum_{j \in \text{allowed}_j} [\tau_{kj}^s(t)]^\alpha \times [\eta_{kj}^s(t)]^\beta}, & j \in \text{allowed}_j, \\
0, & \text{others}
\end{array} \right.
\]

In the Formula (13), \( \text{allowed}_j \) represents the node customers are not visited after the random point. \( \eta_{kj}^s(t) \) represents visibility, which is the reciprocal of the total production time of all products in the production scheduling stage. In the distribution stage, \( \eta_{kj}^s(t) \) is the reciprocal of the sum of carbon emissions, travel time and service time of node \( j \) when electric vehicle \( k \) selects path \( s \) to drive from node \( i \) to node \( j \). \( \tau_{kj}^s(t) \) represents the pheromone concentration of the path \( s \) selected by vehicle \( k \) from node \( i \) to node \( j \). The updating method of \( \tau_{kj}^s(t) \) is shown in Formula (14).

\[
\tau_{kj}^s(t) = (1 - \mu)\tau_{kj}^s + \sum_{w=1}^{W} \Delta \tau_{kj}^{kw}
\]

In the Formula (14), \( W \) represents the number of ants in ACO, \( \mu \) represents the evaporation rate of pheromone on the path, \( 0 < \mu \leq 1 \). If the \( w \) ant chooses path \( s \) and vehicle \( k \) from node \( i \) to node \( j \), then \( \Delta \tau_{kj}^{kw} = \gamma_1 (C_w)^{-1} + \gamma_2 (T_w)^{-1} \). Otherwise, \( \Delta \tau_{kj}^{kw} = 0 \). Where, \( C_w \) and \( T_w \) represent the total carbon emissions and total travel time of ant \( w \) after all paths respectively, and \( \hat{\lambda}_1 \) and \( \hat{\lambda}_2 \) are the weight coefficients of adjustment order of magnitude.

4.3. Fitness function

It adopts a fitness function \( f(t) \) with adaptive way to adjust the order of magnitude relationship, as shown in Formula (15). In the formula, \( C \) and \( T \) represent the total carbon emissions, total travel time and total travel path length of feasible solution \( t \).

\[
f(t) = \lambda_1 \frac{C(t) - C_{\max}}{C_{\max}} + \lambda_2 \frac{T(t) - T_{\max}}{T_{\max}}
\]

(15)
5. Simulation example

5.1. Example data

The data of the example in this paper are randomly generated by computer. Within a region with a diameter of 30 kilometers, coordinates of 30 nodes are randomly generated, among which node 1 is the distribution center, and coordinate (15, 15) is in the center of the region. The other 29 nodes are customer nodes, whose demands follow the uniform distribution $U(0.1, 0.8)$, whose product types follow the integer uniform distribution $DU(1, 6)$, and whose category numbers follow $DU(1, 2)$, as shown in Table 2.

| No. | Product type/quantity required | Coordinates | Time window | No. | Product type/quantity required | Coordinates | Time window |
|-----|--------------------------------|-------------|-------------|-----|--------------------------------|-------------|-------------|
| 1   | Distribution of origin        | 15, 15      | -           | 16  | P2/0.3, P5/0.4                 | 3, 4        | [12, 21]    |
| 2   | P3/0.2, P6/0.1                | 24, 2       | [14, 21]    | 17  | P3/0.3                         | 28, 20      | [12, 20]    |
| 3   | P1/0.3                        | 6, 15       | [10, 17]    | 18  | P1/0.4, P3/0.2                 | 27, 29      | [12, 21]    |
| 4   | P3/0.2, P5/0.4                | 6, 6        | [12, 21]    | 19  | P5/0.1                         | 11, 25      | [12, 20]    |
| 5   | P1/0.4, P4/0.1                | 28, 2       | [10, 17]    | 20  | P2/0.7, P6/0.4                 | 11, 16      | [14, 20]    |
| 6   | P2/0.2                        | 10, 1       | [12, 21]    | 21  | P1/0.3, P4/0.6                 | 14, 29      | [10, 19]    |
| 7   | P4/0.1, P6/0.4                | 0, 8        | [14, 21]    | 22  | P1/0.2, P5/0.2                 | 4, 19       | [12, 20]    |
| 8   | P2/0.3                        | 21, 29      | [12, 21]    | 23  | P2/0.2, P4/0.3                 | 24, 28      | [12, 21]    |
| 9   | P1/0.2, P3/0.6                | 17, 8       | [12, 20]    | 24  | P2/0.4, P3/0.7                 | 2, 15       | [12, 20]    |
| 10  | P3/0.6                        | 7, 24       | [12, 20]    | 25  | P4/0.4, P5/0.1                 | 0, 26       | [12, 20]    |
| 11  | P5/0.7                        | 17, 18      | [12, 20]    | 26  | P1/0.3                         | 4, 4        | [10, 19]    |
| 12  | P2/0.2, P4/0.2                | 21, 18      | [12, 21]    | 27  | P2/0.2, P4/0.2                 | 8, 26       | [12, 20]    |
| 13  | P2/0.6, P4/0.4                | 18, 6       | [12, 21]    | 28  | P4/0.6                         | 18, 7       | [10, 17]    |
| 14  | P4/0.8, P6/0.4                | 0.6         | [14, 21]    | 29  | P3/0.2, P5/0.4                 | 27, 24      | [12, 21]    |
| 15  | P4/0.7                        | 28, 23      | [10, 19]    | 30  | P2/0.2, P5/0.4                 | 28, 3       | [12, 21]    |

In the production stage, there are 6 machines and 6 products being used, and each product contains 4 to 6 processes. The normal distribution $N(0.9, 10)$ is followed by the constraint of production time of the product process. The integer distribution $DU(1, 6)$ is followed by the constraint of the processing machines. The starting time of each product processing is (6, 7, 6, 5.5, 7, 6), as shown in Table 3.

| Product | Machine/Time (Hours) | Product | Machine/Time (Hours) |
|---------|----------------------|---------|----------------------|
| P1      | 3/0.8 1/0.6 2/1.5 4/1.5 6/0.7 2/0.6 | P4      | 2/1.1 1/0.5 3/1.1 4/0.6 5/1.2 6/0.4 |
| P2      | 2/1.5 3/1.2 5/0.6 6/1.1 - - | P5      | 3/0.9 2/0.6 5/1.4 6/0.8 1/0.6 - |
| P3      | 3/0.7 4/0.6 6/0.7 1/0.8 2/0.8 5/0.7 | P6      | 2/0.8 4/1.4 6/0.7 - - |

The time-varying network of urban traffic and the average speed of vehicles are as follows: 5:00 ~ 7:00, 55km/h; 7:00 ~ 9:00, 25km/h; 9:00-17:30, 40km/h; 17:30 ~ 19:30, 25km/h; 19:30 ~ 24:00, 55km/h. The values of relevant parameters in the model are shown in Table 4.

| Parameter | Parameter value | Parameter | Parameter value | Parameter | Parameter value |
|-----------|-----------------|-----------|-----------------|-----------|-----------------|
| $q_t$     | 0.5h/t          | $M_g$     | 4.5t            | $C_d$     | 0.6             |
| $\epsilon p^1$ | 0.33h        | $g$       | 9.81m/s²        | $A$       | 6m²             |
| $Q$       | 2.1t            | $\eta$   | 1.46            | $\mu$     | 0.89            |
| $M$       | 6               | $f$       | 0.0015          | $\varphi$ | 0.785kwh/kg     |

5.2. Simulation results

Matlab2019a version is used for modeling optimization, and the population size is 500. In the algorithm parameters, the initial annealing temperature $T_0 = 800$, the number of inner cycles is 100, and the condition of algorithm termination (jumping out of outer cycles) is the fitness of the optimal
solution of the algorithm will not change within 1000 iterations. The value of $\alpha$ and $\beta$ in the probability function of path selection algorithm is 1, and the evaporation rate of pheromone $\sigma$ is 0.58. The simulation is conducted for 30 times in three ways: the separated scheduling of production and distribution respectively, the coordinated scheduling of production and distribution, and the shortest path scheduling (without considering carbon emissions), and the average value is obtained. The results are shown in Table 5.

Table 5 Comparison of simulation results of different optimization methods

|                  | Collaborative optimization | Optimization separately | Shortest path |
|------------------|---------------------------|-------------------------|--------------|
| Carbon emissions | 55.72                     | 64.34                   | 86.44        |
| Travel time      | 36.23                     | 36.08                   | 35.77        |
| Total production time | 7.25               | 7.19                   | 7.25         |
| Number of vehicles | 10.2              | 10.1                   | 9.8          |

As can be seen from Table 5, when production and distribution are coordinated, carbon emissions are reduced by 15.5% compared with optimizing respectively, and 55.1% compared with the shortest path scheduling (carbon emissions are not taken into account). However, the differences in travel time, the total production time and the number of vehicles are little. It takes one of the feasible solutions from collaborative scheduling of production and distribution as an example. The total production time is 7.23, and the Gantt chart of production scheduling is shown in Figure 4. The distribution path of pure electric trucks is shown in Table 6.

Figure 3 Production scheduling Gantt chart

Table 6 Optimized time of departure and return and distribution paths of vehicles

| Vehicle | Path     | Time of departure | Time of return | Vehicle | Path     | Time of departure | Time of return |
|---------|----------|-------------------|----------------|---------|----------|-------------------|----------------|
| 1       | 0-15-21-26-0 | 11.9              | 16.24          | 6       | 0-12-18-13-0   | 14.3             | 18.38          |
| 2       | 0-3-5-28-0   | 11.9              | 15.38          | 7       | 0-20-6-16-4-0  | 14.3             | 19.05          |
| 3       | 0-29-23-8-0  | 14.3              | 17.38          | 8       | 0-10-19-22-0   | 14.3             | 17.11          |
| 4       | 0-9-11-17-0  | 14.3              | 17.98          | 9       | 0-20-0         | 15.3             | 16.72          |
| 5       | 0-25-27-24-0 | 14.3              | 18.40          | 10      | 0-14-7-2-0     | 15.3             | 19.73          |

To sum up, it is comprehensively considered factors and variables such as time-varying network and collaborative optimization of production and distribution in the model, the carbon emissions can be significantly reduced while the time of total travel time production have little change, under the condition that requirements of customer time window are met.

6. Conclusion
Aiming at how to reduce carbon emissions in the process of pure electric vehicles in the distribution problems, coordinated scheduling of production and distribution of low carbon supply chain model is established in the time-varying network. It reduces carbon emissions in the process of the entire transport from the optimization objectives, combining with the actual production transportation, considering the loading and unloading service time in the process of optimization, dynamic load and other factors. An improved ACO search method using simulated annealing algorithm is proposed to enhance the global search ability and the ability to jump out of local optimal. Through the comparative analysis of the simulation calculation of an example, it is verified that the total carbon emissions are significantly reduced in the time-varying network if taking carbon emissions and travel time as double optimization objectives, and considering the collaborative optimization of production scheduling and distribution in the model, which is compared with the one considering production and distribution.
optimization separately, and the delivery method only taking the shortest path as objective. Integration of loading and unloading also occupies a high proportion in production and transportation. In the future, transportation scheduling problems of low-carbon supply chain can also be studied under the constraints of integration of loading and unloading. The proportion of third-party cold chain distribution in production and transportation is gradually increasing. We can also consider to study the transportation scheduling problem of low-carbon supply chain under the time constraints of the transportation of new energy freight vehicles.

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