Distribution Route Optimization of Electric Vehicles

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Abstract—From the perspective of low carbon logistics, we take into account the environmental costs caused by the carbon emissions of battery electric vehicles. In addition, according to the customer's certain requirements for the delivery time during the actual delivery process, this paper introduces the penalty cost of the time window, thus constructing a delivery route optimization model with the goal of minimizing the total delivery cost. Then, this problem is solved by using the Ant Colony Algorithm. Finally, the case design is used for empirical analysis.

1. Introduction
To protect the ecological environment and reduce dependence on fossil energy, it is urgent to promote green logistics in urban distribution. Due to the immaturity of all aspects of battery electric vehicles, logistics companies will face some problems in electric vehicle technology when using battery electric vehicles for distribution tasks. Therefore, optimizing the distribution path of battery electric vehicles can improve the vehicle utilization rate of logistics companies and reduce distribution costs.

The problem of vehicle distribution route planning was first proposed by Dnatzig and Rmaser in 1959, This problem quickly received the attention of experts in related disciplines and became the frontier and research focus in the field of combination optimization\cite{1}. In 2018, Grosso established a vehicle path optimization model with access time windows and compared and analyzed the modified savings algorithm, genetic algorithm and tabu search method. The performance of the solution is discussed due to the impact of time constraints on transportation costs \cite{2}. Erdoğan et al. \cite{3} firstly proposed the vehicle routing problem for electric vehicles in 2012. They took the shortest vehicle driving distance as the optimization goal and constructed a GVRP (Green Vehicle Routing Problems) model that took into account the cruising range limitation and the allocation of routes and other factors. On the basis of considering the charging needs of electric vehicles, Conrad and Figliozzi \cite{4} took the minimum total distribution cost as the optimization goal, and established an electric vehicle path planning problem model that included customer time window requirements Jane Lin et al. \cite{5} considered the effect of vehicle load on a battery electric vehicles and established a model that minimizes the total cost. Worley et al. \cite{6} comprehensively considered the problem of electric vehicle path planning and the location of the charging station, and constructed a model on the constraints of travel distance and cargo load, but the charging time factor was ignored in the model time constraints.

In view of this, from the perspective of low-carbon logistics, according to the customer's certain requirements for the delivery time in the actual distribution process, this article introduces a time window penalty cost, and constructs a distribution path optimization model that aims to minimize the total distribution cost, and then solves the problem through the ant colony algorithm Problem, and finally carries out empirical analysis through case design.
2. Distribution Model of Battery Electric Vehicles

2.1. Problem Description
This paper aims at the minimum total cost and builds a logistics electric vehicle routing optimization problem model based on battery electric vehicles. The total cost in the optimization goal includes fixed transportation cost, variable transportation cost, electricity cost and carbon emission cost, this chapter also adds a time window penalty cost when considering the total electric delivery cost, which can be closer to the real city distribution situation.

2.2. Model Establishment
The goal of this article is to minimize the distribution cost and establish a battery electric vehicles distribution path optimization model:

\[
\begin{align*}
\min & \quad c_1 k + c_2 \sum_{k \in K, i,j \in N} X_{ik} d_{ij} \\
& + c_3 \sum_{k \in K, i,j \in N} X_{ik} d_{ij} \zeta \\
& + c_4 \gamma \lambda \sum_{k \in K, i,j \in N} X_{ik} d_{ij} \zeta + \sum_{i \in C} \sum_{k \in K} c^2_{ik} (t_{ik})
\end{align*}
\]

(1)

where \( c_1 \) represents the set of customer points that need service; \( k (k=1,2, \cdots, n) \) represents the set of electric vehicle. \( c_2 \) represents the variable cost of electric vehicle unit mileage transportation; \( X_{ik} \) represents that electric vehicle \( k \) travels from point \( i \) to point \( j \) otherwise it is 0; \( d_{ij} \) is the distance between customer points \( i \) and \( j \); \( c_3 \) is the unit cost per k·Wh; \( \zeta \) is the electric energy consumption per unit mileage of electric vehicle; \( c_4 \) is the environmental cost caused by unit carbon emissions; \( \gamma \) is the carbon emission coefficient of electricity production; \( \lambda \) is the proportion of thermal power generation per unit of electricity. \( c^2_{ik} \) is the time penalty cost for electric vehicle \( k \) reaching customer point \( i \); \( t_{ik} \) is the time for electric vehicle \( k \) reaching customer point \( i \).

\[
c^2_{ik} (t_{ik}) = etc \times \max (e_i - t_{ik}, 0) + \max (t_{ik} - l_i, 0)
\]

(2)

Formula (2) represents the penalty cost to be paid for a pure electric logistics vehicle \( k \) earlier or later than the customer's point of receipt window. Where \( etc \) represents the waiting cost incurred by the electric vehicle arriving at the customer's point in time window in advance; \( ltc \) represents the penalty cost incurred by the electric vehicle after the customer's time window; \( e_i \) represents the latest time to serve customer point \( i \); \( l_i \) represents the earliest time to serve customer point \( i \); The pure electric distribution route optimization model established in this section comprehensively considers the following constraints:

2.2.1. Distribution node constraints
The main node types involved in the model constructed in this section include: distribution centers and customer sites. Formula (3) indicates that each customer point can be served and can only be served once; Formula (4) indicates that the inbound and outbound volumes at each fixed point are equal; Formula (5) indicates the number of vehicles exiting from the distribution center Less than the total number of electric vehicles owned.

\[
\sum_{j \in N} X_{ijk} = 1 \quad \forall k \in K, \forall i \in C
\]

(3)
\[ \sum_{i \in K} \sum_{j \in C} X_{ij} \leq n \]  

where \( X_{ij} \) represents the electric logistics vehicle \( k \) driving from point \( j \) to point \( l \).}

\[ \forall k \in K, \forall i \in N, \forall j \in N, \forall l \in N, i \neq j \neq l \]

2.2.2. Load constraint

Formula (6) indicates that the weight of the electric vehicle exiting the distribution center is less than its rated load.

\[ 0 \leq u_{ik} \leq W \]  

where \( u_{ik} \) represents the load (not unloaded) when electric vehicle \( k \) reaches customer point \( i \).

2.2.3. Time constraints

Formula (7) indicates that the electric vehicle will be delivered from time 0; formula (8) indicates that if the battery electric vehicle \( k \) starts from point \( i \) to point \( j \), the time to point \( j \) is equal to the time from point \( i \) plus the time of road delivery. If it does not go to point \( j \), the constraint does not hold; formula (9) indicates that the time of any node in the distribution process meets the distribution network time window constraint; formula (10) indicates the consumption of electric vehicle \( k \) from point \( i \) to point \( j \). Time is equal to the ratio of the distance between two points to its average speed.

\[ t_{ik}^2 = 0 \quad \forall k \in K \]  

\[ t_{ij}^1 \geq t_{ik}^2 + t_{ik} X_{ij} - T_{\text{max}} (1 - X_{ij}) \]  

\[ \forall i, j \in N, \forall k \in K \]

where \( T_{\text{max}} \) is the longest time allowed in the entire delivery process; \( t_{ik}^2 \) is the time when electric vehicle \( k \) leaves customer point \( i \); \( t_{ik} \) is the time consumed by electric vehicle \( k \) from customer point \( i \) to customer point \( j \); \( 0 \leq t_{ij}^1, t_{ik} \leq T_{\text{max}} \) \( \forall i \in N, \forall k \in K \).

2.2.4. Power constraints

Formula (11) indicates that the weight of the electric vehicle is equal to the weight of the empty vehicle plus the weight of the loaded cargo; formula (12) indicates that the rotation resistance is equal to the product of the rotation friction coefficient and the weight of the electric vehicle. Formula (13) represents the mechanical energy required by electric vehicle \( k \) from customer point \( i \) to customer point \( j \), which is equal to the product of rotational resistance and its average speed. Formula (14) is the battery energy required by the electric vehicle \( k \) from customer point \( i \) to customer point \( j \), which is equal to the mechanical energy multiplied by the corresponding electric energy efficiency regression coefficient; The formula (15) represents the corresponding relationship between the electric energy consumption coefficient of the electric vehicle \( k \) from the customer point \( i \) to the customer point \( j \) and the battery energy; Formula (16) indicates that the electric vehicle \( k \) has \( q \) when the battery leaves the distribution center (the state is fully charged) Formula (18) represents the electric energy of electric vehicle \( k \) reaching...
point \( i \), which is equal to the amount of electricity it left before divided by the amount of electricity consumed during driving; formula (19) indicates that the electric energy of electric vehicle \( k \) at any point should be between 0 and rated power.

\[
m(u) = m_e + m_u \cdot u
\]

(11)

\[
F_r = c_r \cdot m(u) \cdot g
\]

(12)

where \( u \) is the total demand of customer points on the driving path of the electric vehicle; \( m(u) \) represents the total weight of the cargo carried by the electric vehicle; \( c_r \) represents the rotation friction coefficient; \( g \) represents gravity factor. \( m_e \) is the empty weight of the electric vehicle; \( m_u \) represents the weight of unit cargo;

\[
P_{ijk}(u_{jk}) = c_r \cdot m(u_{jk}) \cdot g \cdot u_{ijk}
\]

\( \forall i \in N, \forall j \in C, \forall k \in K \)

(13)

where \( u_{jk} \) represents the load when the electric vehicle \( k \) arrives at the customer point \( j \) (unloaded); \( P_{ijk} \) represents the mechanical energy required by electric vehicle \( k \) from customer point \( i \) to customer point \( j \);

\[
r_{ijk}(u_{jk}) = \varphi_d \cdot \varphi_e \cdot F_r \cdot X_{ijk}
\]

\( \forall i \in N, \forall j \in C, \forall k \in K \)

(14)

where \( r_{ijk} \) represents the battery energy required by electric vehicle \( k \) from customer point \( i \) to customer point \( j \); \( \varphi_d \) represents the regression coefficient of electric energy efficiency in automobile mode; \( \varphi_e \) represents the regression coefficient of generator model electrical energy efficiency; \( F_r \) represents the rotation resistance;

\[
b_{ijk}(u_{jk}) = r_{ijk}(u_{jk}) / X_{ijk}
\]

\( \forall i \in N, \forall j \in C, \forall k \in K \)

(15)

\[
p_{ik}^1 = p_{ik}^2 \quad \forall i \in C, \forall k \in K
\]

(16)

where \( p_{ik}^1 \) represents the remaining power of electric vehicle \( k \) when it reaches customer point \( i \); \( p_{ik}^2 \) represents the remaining power of electric vehicle \( k \) when leaving customer point \( i \); \( b_{ijk} \) represents the electric power consumption coefficient of electric vehicle \( k \) from customer point \( i \) to customer point \( j \);

\[
p_{ik}^2 = Q \quad \forall i \in O, \forall k \in K
\]

(17)

where \( Q \) represents the rated power of the electric vehicle;

\[
p_{ik}^1 \leq p_{ik}^1 - b_{ijk}(u_{jk}) \cdot X_{ijk} + Q(1 - X_{ijk})
\]

\( \forall i \in N, \forall j \in C, \forall k \in K, i \neq j \)

(18)

\[
0 \leq p_{ik}^1, p_{ik}^2 \leq Q \quad \forall i \in N, \forall k \in K
\]

(19)

In summary, the situation of battery electric vehicles in urban distribution is complex, and the model needs to consider multiple factors when it is constructed.
3. ANT COLONY OPTIMIZATION ALGORITHM

There are many ways to solve the problem of vehicle distribution route optimization, including genetic algorithm, particle swarm optimization, ant colony greedy algorithm, etc., and ant colony algorithm[7] is a simulated evolutionary algorithm which is effectively used to solve the Traveling Salesman Problem (TSP), vehicle scheduling and other issues. The basic idea of the ant colony algorithm is that ants rely on the released pheromone to guide the actions of each ant under the action of positive feedback, so that the more ants pass on a certain path, the greater the probability that the latter ants choose the path. Finally, when the entire ant is concentrated on this optimal path, the corresponding path at this time is the optimal solution of the optimal solution of the problem to be optimized.

4. Case Study

4.1. Case Description

There is an organic vegetable distribution company that distributes supermarkets in a certain area of the city. The company uses the H-type battery electric vehicles with a cruising range of 150 kilometers. The empty mass of the electric vehicle is 1800 kg and the maximum load capacity is 1600 kg. After online inquiries and field investigations, certain costs and related symbols in the battery electric vehicles distribution route model are given certain values, as shown in Table I.

| parameter | Parameter meaning | Parameter value |
|-----------|-------------------|----------------|
| $v$       | Electric vehicle speed | 50km/h         |
| $n$       | Maximum number of vehicles available | 10             |
| $m_u$     | Unit weight | 2.4kg          |
| $c_1$     | Fixed cost of electric vehicle transportation | 42Yuan/car    |
| $c_2$     | Variable cost of electric vehicle unit mileage transportation | 0.60 Yuan  |
| $c_3$     | Unit cost per kWh | 0.82 Yuan      |
| $c_4$     | Environmental costs caused by unit carbon emissions | 0.315 Yuan  |
| $\zeta$   | Electric vehicle power consumption per unit mileage | 0.5kw.h/km   |
| $\lambda$ | Carbon emission factor for electricity production | 0.94          |
| $\gamma$  | Percentage of thermal power generation per unit of electricity | 0.72         |
| $T_{max}$ | The maximum time allowed during the entire delivery process | 14h          |
| $etc$     | Penalty coefficient for electric vehicles arriving earlier than time window | 0            |
| $ltc$     | Penalty factor for electric vehicles arriving later than the time window | 300          |

4.2. Problem Description

This plan takes the actual operation status of an organic vegetable distribution company as an example and abstracts it. Assuming that the coordinates of the distribution center are the origin, the vehicle starts at 5:00 in the morning and departs from the distribution center before 19. The coordinate position, demand, specified time window and service time data of each customer point are shown in Table II.
TABLE II. CUSTOMER-RELATED DATA

| No. | Coordinate  | Demand (kg) | Time Window   | Service time (min) |
|-----|-------------|-------------|---------------|-------------------|
| 1   | (20,6.7)    | 270         | (9:30-11:00)  | 17                |
| 2   | (40,6.7)    | 310         | (10:00-11:30) | 38                |
| 3   | (33.3,33.3) | 370         | (8:30-10:30)  | 21                |
| 4   | (13.3, 46)  | 350         | (10:00-11:30) | 23                |
| 5   | (-6.7,26.7) | 220         | (8:00-10:00)  | 15                |
| 6   | (-46.7,-6.7)| 340         | (8:00-9:00)   | 30                |
| 7   | (-20,-13.3) | 240         | (7:30-9:30)   | 26                |
| 8   | (0, -40)    | 210         | (7:00-9:00)   | 18                |
| 9   | (20, -20)   | 240         | (7:00-10:00)  | 13                |
| 10  | (-33.3,33.3)| 340         | (7:30-9:00)   | 28                |

4.3. Algorithmic Solution

The text adopts MATLAB (R2016a) to solve the battery electric vehicles distribution path model considering carbon emissions and time window requirements. According to the characteristics of electric vehicles, when designing the algorithm to solve, it comprehensively considers the impact of vehicle range limit and load on electricity. The parameters required for the ant colony algorithm solving step are shown in Table III.

TABLE III. ANT COLONY ALGORITHM PARAMETER SETTINGS

| Parameter | Parameter meaning                | Parameter value |
|-----------|----------------------------------|----------------|
| NC<sub>max</sub> | Maximum number of iterations     | 200            |
| α         | Pheromone important factor       | 1              |
| β         | Heuristic function importance factor | 5             |
| ρ         | Pheromone global volatilization factor | 0.5 |
| Q         | Total pheromone release         | 100            |

The running image shows that the optimal solution can be considered when the number of iterations is close to 90 generations. Iteration curves and experimental results are shown in Figures 1 and 2.
The optimal distribution route is: 0→5→3→4→0; 0→10→1→0; 0→8→9→2→0; 0→7→6→0.

TABLE IV. PATH OPTIMIZATION PLAN FOR BATTERY ELECTRIC VEHICLES

| Delivery route | Delivery distance (km) | Deadweight (kg) |
|----------------|------------------------|-----------------|
| 0-5-3-4-0      | 140                    | 940             |
| 0-10-1-0       | 135                    | 610             |
| 0-8-9-2-0      | 142                    | 760             |
| 0-7-6-0        | 98                     | 580             |
| total          | 515                    | 2890            |

TABLE V. COST BREAKDOWN OF BATTERY ELECTRIC VEHICLES

| Distribution route | Fixed cost | Variable cost | Electricity cost | Carbon emission | Penalty cost |
|--------------------|------------|---------------|------------------|-----------------|--------------|
| 0-5-3-4-0          | 42.00      | 84.00         | 57.40            | 14.92           | 0            |
| 0-10-1-0           | 42.00      | 81.00         | 55.35            | 14.39           | 0            |
5. Summary

In the context of low carbon logistics, from the perspective of urban distribution and low carbon logistics, this paper analyzes the advantages of using battery electric vehicles in urban distribution and the factors that need to be considered in the distribution process, and constructs a battery electric vehicles distribution path optimization model. Then, the VRP is solved by the ant colony algorithm. Finally, the effectiveness of the optimization model is verified through practical cases.

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