An Ant Colony Algorithm for Electric Vehicle Routing Problem with Load Energy Consumption

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For solving the impact of load energy consumption in electric vehicle routing problem, an ant colony algorithm is realized in this paper. By adjusting three different pheromone update methods, the solution speed of the algorithm is improved, and the solution result is obtained when the objective function is minimized. The comparative simulation experiment analysis shows that the pheromone is initialized once, the incremental method is one step by step, and the volatilization method is global volatilization. The optimal route length value of this pheromone update strategy is at least 19% better than the strategy of other combinations in the paper.

Keywords: Load energy consumption, Ant colony algorithm, Pheromone update strategy, Electric vehicle routing problem

1. INTRODUCTION

1.1. Research Background and Significance

Vehicle Routing Problem (VRP) was first put forward by Dantzig and Ramser in 1959 [1], referring to a certain number of customers with different quantities of goods, and the distribution center provides goods to customers with a fleet organizing the appropriate route, which is to meet the needs of customers and minimize the objective function.

There are many VRPs in the actual logistics, distribution and transportation scenarios. For example, the well-known JD Logistics Distribution Center distributes express packages; manufacturers deliver goods to various retailers; the logistics department collects the upstream suppliers in the vehicle production link; hazardous goods transportation planning, etc. Thus, the study of VRP is very important and necessary.

Compared with fuel vehicles, the emergence of electric vehicles (EV) can reduce environmental pollution and has been recognized by the world. It is developing quickly, which has led to the birth of electric vehicle routing problem (EVRP). Compared with VRP, it is necessary to consider power consumption and battery life. When solving the EVRP, many people ignore the energy consumption of electric vehicles by load. Through the experiments of other people, we have learned that this part of the loss is actually very large and cannot be ignored, so the energy consumption of load is studied and the impact on the path planning of electric vehicles is studied in this paper. And name this question electric vehicle routing problem considering load energy consumption (EVRLP).

1.2. Current Status of Electric Vehicle Path

EVRP refers to a certain number of customers with different quantities of goods needs. The distribution center provides goods to customers, and an electric vehicle team is responsible for distributing the goods, organizing the appropriate driving route. The goal is to meet the needs of consumers, and achieve the purposes such as the minimum journey, minimum cost and minimum time consuming under certain constraints. The EVRP in existing studies can be divided into two parts, namely EVRP allowing charging and EVRP with battery capacity limit.

Minfang Huang, Jing Liu, Qiong Guo considered the electric vehicle routing problem with soft time window and charging station positioning[3]. Xianlong Ge, Ziqiang Zhu considered the problem of electric vehicle path planning with soft time windows[4]. Pengwei Zhang, Ying Li, Qi Cheng considered Electric vehicle path optimization problem with multiple distribution centers and charging locations [5]. Guiqin Xue, Xianlong Ge analyzed the constraints of electric vehicles compared with fuel vehicles[6]. Bingshan Ma, Dawei Hu, Xiqiong Chen, Hui Hu considered the semi-open electric vehicle path planning problem with multiple distribution centers with time windows [7]. Wanchen Jie, Ying Shi, Jun Yang, Chao Yang considered electric vehicle path planning problem based on vehicle mileage, demand restriction, and separate distribution [8]. Decheng Li, Yanru Chen, Zongcheng Zhang considered the problem of electric vehicle path planning with time windows [9].

In conclusion, some scholars considered the EVRP by considering time window changes or dynamic demand changes in EVRP, but ignoring the load energy consumption of EV which is considered in this paper.

2. RELATED WORK

2.1. Analysis of the Motor Load Problem

As early as October 2018, someone compared the range of EV through actual measurements. The test vehicle used in the test is Tengshi 400, to test power consumption in two states in the same route, only one driver at empty load and about additional 330kg at full load. Finally, the test results are shown in Table. 1.

Table. 1 No-load and full-load battery life comparison

Vehicle status	endurance mileage(km)
No load	361.7
Full load	330

Obviously, the load has a very great impact on the energy consumption of electric vehicles, about 9% of the total empty load. Thus, it also confirms the necessity and the importance of this paper. Next content is the derivation process of energy consumption formula for load and path for different environmental factors.

The literature [2] considers multiple factors of an electric vehicle, including engine efficiency e_f, vehicle dead weight $W(t)$, vehicle acceleration $a(m/s^2)$, gravitational coefficient $g(m/s^2)$, road slope θ_{ij}, vehicle front area $A(m^2)$, air density $\rho(kg/m^3)$, rolling resistance coefficient C_r, air resistance coefficient C_d, etc. Construction of mathematical model: for the instantaneous emission rate of greenhouse gases $E(g/s)$ is directly related to the rate of gas use $F(g/s)$, here we adopt an expression $E=\alpha_1 F+\alpha_2$ for the greenhouse gas α_1 and α_2 specific emission index parameters. Because this calculation is complicated, this calculation is simplified and the final results are given:

$$F \approx (KNV + (P_t/\varepsilon + P_a)/w)U \tag{1}$$

In this formula k is the engine friction coefficient, N is the engine speed, V is the engine displacement, P_t is the total traction power demand watts placed on the vehicle $(W = kgm^2/s^3)$, ε is the vehicle transmission system efficiency, P_a is the engine power demand related to the engine operation loss (W) such as air conditioning, $w=0.45$ is a measure of diesel engine efficiency, U depends on the value of some constant. The parameter P_t is further calculated as follows:

$$P_t = \left(Mav + Mgv\sin\theta + 0.5C_d \mathrm{A}\rho v^3 + MgC_r\cos\theta \mathrm{v}\right) \tag{2}$$

For practical reasons, we assume that all the parameters will remain unchanged on a given arc (but the load and speed may vary from one arc to another). In other words, we assume that the vehicle will be driven at an average speed in the arc, the route is straight , the total load at the road angle $\theta=\theta_{ij}$ is $M=W+f_{ij}$. W is the empty vehicle weight. f_{ij} is the load the vehicle carries on that arc. The total energy consumed on this arc can be approximately as:

$$P_{ij} \approx P_t\left(\frac{d_{ij}}{v_{ij}}\right) \approx \alpha_{ij}\left(W+f_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij} \tag{3}$$

Then the energy consumption function is simplified as

$$b_{ij} = \frac{P_{ij}}{e_f} = \frac{\alpha_{ij}\left(W+f_{ij}\right)d_{ij} + \beta v_{ij}^2 d_{ij}}{e_f} \tag{4}$$

In the formula above (4)

$$\alpha_{ij} = a + g\sin\theta_{ij} + gC_r\cos\theta_{ij} \tag{5}$$

$$\beta = 0.5C_d \mathrm{A}\rho \tag{6}$$

This paper approximates the total energy value consumed on a given route, as the parameters required for the latter as well as the denominator are vehicle-specific. Remain constant when a specific vehicle is selected for travel. The resulting approximation yields the energy demand of the Joule, which translates directly into fuel consumption.

2.2. Ant Colony Algorithm

2.2.1. Basic Definition

Ant Colony Optimization (ACO) is a group intelligence algorithm, and also a bionic algorithm, inspired by ant foraging behavior in nature. In nature, ant groups are always able to find an optimal path from the nest and food source after a period of foraging.

2.2.2. Determination of the Ant Selection Behavior

Initialization parameters are constructed as follows:

Name	Physical meaning
Information	A two-dimensional matrix of pheromone for all ant routes
information_add	A two-dimensional matrix of pheromone increments on all ant routes
VisitedList	A two-dimensional matrix of points that each ant has visited in a loop
Route	A two-dimensional matrix of the route that each ant has gone to in a loop
UVL	A one-dimensional matrix that has not been to the point
UVL_weight	A one-dimensional matrix that has not been visited and has a weight limit
UVL_weight_light	A one-dimensional matrix that has not been visited and has weight and power restrictions
UVL_weight_light_limit	One-dimensional matrix of the current point (charging piles or starting point)
Subscript_all	Store a valid (charging piles or starting point) one-dimensional matrix
sum_powder_ele	A one-dimensional matrix that stores the power consumption of each step

The weight of the initialized load is 450kg (the initialized load weight is set to the maximum of 450kg. Setting it to 450kg is to calculate the current load situation during the subsequent load energy consumption, if we study the problem, we can set the initial load weight to 0kg). Initialized EV power consumption is 0W (max. 30,000 W). With the number of initialization cycles set to 100 times and the number of ants set to 30, for each ant in each loop, the most important thing is how to go to the next position point while determining the current position point.

The logic description of the algorithm is as follows: first, the most basic and most important thing is to load the known information into the program, read the position coordinate information of 31 demand points, read the load information of 31 demand points and read the position coordinate information of 6 charging piles. After that, the physical quantity needs to be initialized elements, setting the number of cycles, number of ants, ant colony algorithm parameters, etc. In the case of the number of cycles and the number of ants. For each ant, select the subscript of the next demand point to go from the roulette group in UVL_weight_light and put it into the VisitedList matrix. Prove that the ant completes the task when all the demand points are traversed. If the wheel group turns to the number above the sum of the probability also need to judge whether the current group can return to the initial position or the charging piles. The specific architecture of the ant selection method is shown in Fig.1 below.

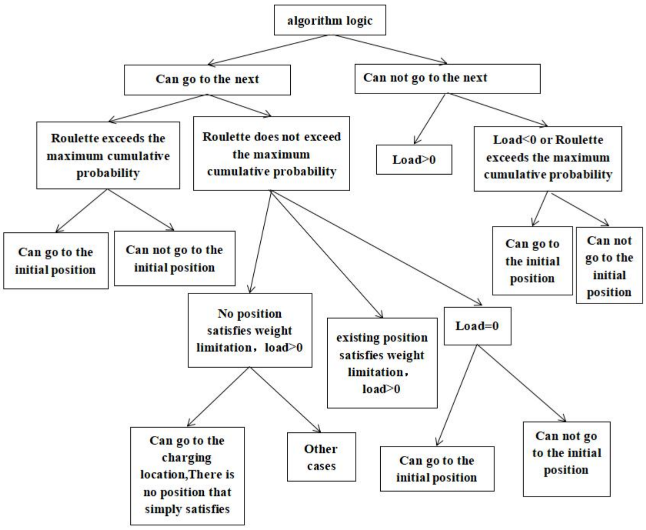

Fig. 1 Schematic diagram of the algorithm logic.

It is worth mentioning that if you want to change to the initial position, the battery power consumption changes back to 0w, weight changes back to 450kg. If you want to change to a charging pile, the battery power consumption returns to 0w, weight remains unchanged.

3. EVRLP MODELING

3.1. Problem Description

A simple description of the EVRLP is shown in Fig. 2. The green triangle is the distribution center (initial point position), the red dot represents the position of the demand point, and the batteries and power above directly reflect the current power situation of the electric vehicle. The four path plans of "ONE, TWO, THREE, FOUR" correspond to four different scenarios. Take route "ONE" as an example for explanation.

Route 1："distribution center- -demand point 6- -demand point 7- -demand point 8- -demand point 9- -distribution center", means that the electric vehicle goes to the nearest charging facilities when it needs electricity, and then continues to visit the next demand point until the load constraint or power factor do not meet the requirements.

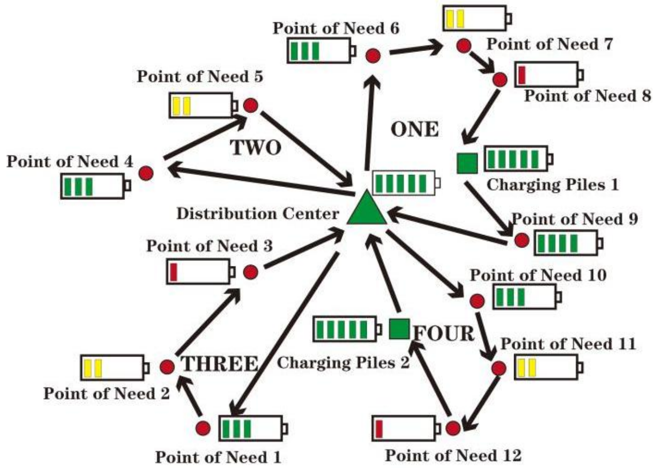

Fig. 2 EVRLP model sample diagram.

3.2. Mathematical Model Construction

3.2.1. Basic Assumption

- The road slope is all consistent, and it is 0.
- The electric vehicle travels at a uniform speed of about 24.44m/s.
- Air resistance coefficient is 0.25 and rolling resistance coefficient is 0.019.
- The air density is 1.205kg per cubic meter.
- When the electric vehicle is dead, if it is determined to arrive at the charging piles rather than the starting position, the charging piles nearest to the current demand point is chosen.
- Only consider the delivery problem of logistics vehicles, do not consider the problem of logistics vehicles pickup.
- Only one initial location (which is also a termination position).
- There is no priority and no time window limit.
- The distance between the two demand points is the straight line distance between the two demand points, excluding the road bending factor.

3.2.2. Variable Settings

When consider the path planning of the electric vehicle load, the core of the whole problem construction is to get a path that minimizes the total cost (i. e. time and energy consumption costs) while meeting the needs of all demand points. Based on the assumption that electric vehicles travel at a uniform speed, the time cost is considered proportional to the energy consumption cost, and both costs are positively correlated to the distance value. Therefore, the EVRLP can be transformed into a path that minimizes the total distance by obtaining a requirement for all the demand points. The relevant parameters and variables are defined as follows:

$N = (N_1, \cdots, N_{31})$	Collection of demand points (with 31 demand points)
$F = (F_1, \cdots, F_6)$	Collection of charging piles (6)
$G = N \cup F$	Collection of all coordinate points (with a total of 37)
d_{ij}	Distance from i to j(in km)
v_{ij}	The speed of the EV driving on the point i-to-point j path
L_{ij}	The total weight of the vehicle as the electric vehicle leaves from point i to point j
b_{ij}	Electricity consumed from point i to point j
B_{ij}	At the point i away, the total amount of electricity consumed by EV starts from full power
x_{ij}	When the vehicle is driven from point i to point j, it is 1; otherwise, 0
Po_i	Current location of the EV
0	Initial position tag
Final	Last position mark
p_{ij}	Transfer probability of ants from current point i to point j
T_{ij}	The pheromone concentration between point i to point j
P_i	Demand point i of demand for goods
W	EV dead weight
l_{ij}	EV leaves the point i at the moment of the weight of the cargo
b_i	The nearest charging pile or initial position accessible from the point i
l_{max}	The maximum cargo weight value that the EV can carry is 450kg

3.2.3. Model Building

$$\min \sum d_{ij} * x_{ij}; \forall i, j \in G \tag{7}$$

Subject to

$$\sum_{j \in N} x_{ij} = 1, \forall \mathrm{i} \in \mathrm{N} \tag{8}$$

$$\sum_{j \in G} x_{ip} = \sum_{j \in G} x_{pj}, \forall p \in G \tag{9}$$

$$0 \le l_{ij} \le l_{max}, \forall i, j \in G \tag{10}$$

$$\sum_{j \in N} l_{ji} - \sum_{j \in N} l_{ij} = P_i, \forall i \in N \tag{11}$$

$$\sum_{j \in N} l_{0j} = l_{max} \tag{12}$$

$$B_{0j} = 0, \forall j \in N \tag{13}$$

$$B_{ij} + b_{ij} = B_{jk}, \forall i, j, k \in G \tag{14}$$

$$b_i \ne [\,], \forall i \in N; \tag{15}$$

$$Po_0 = Po_{final} \tag{16}$$

$$B_{ij} \le 30KW \tag{17}$$

Formula (7) is the objective function, which is the minimum total distance. Formula (8) is used to ensure that every point of demand will be visited and accessed only once. Formula (9) is the flow conservation formula that the number of electric vehicles entering each point of demand is equal to the number of electric vehicles coming out from each point of demand. Formula (10) is the load limit constraint of each electric vehicle. Formula (11) indicates that the difference between the outbound load and the inbound load at the node i is equal to the pickup demand of the node i. Formula (12) indicates that the maximum load of each electric vehicle from the initial point. Formula (13) indicates that power consumption of each electric vehicle is 0w coming out from the initial point or charging piles. Formula (14) indicates that the power consumption of the electric vehicle at the point j is equal to the power consumption of the electric vehicle from the point i plus the power consumption between the two points. Formula (15) indicates that the electric vehicle has sufficient power to reach the next demand point on the route planned for it and is able to successfully return to the starting point or charging piles. Formula (16) indicates that the final coordinate point of the electric vehicle is the starting point. Formula (17) indicates that the power consumption at any time is less than 30KW.

4. SIMULATION EXPERIMENT AND ANALYSIS

Firstly this chapter gives the basic information of the calculation example, and then compares the different ant colony algorithm solution methods of the calculation example through the T test method. Finally, it obtains the best solution method.

4.1. Experimental Setup

4.1.1. Simulation Calculation Examples

Two simulation examples are proposed to prevent the contingency of one example and ensure the real reliability of the algorithm effect. Both examples have 31 demand points and 6 charging piles. 31 demand points have different position coordinates, but the requirements of the corresponding coordinate points are the same, and the 6 charging piles are exactly the same positions.

First, the initialization of the parameters in the ant colony algorithm is performed. The transfer probability

α (pheromone importance factor) and β (enlightening function importance factor) are all initialized to 1. The volatile factor of pheromone ρ is 0.1, and the update method is set to section update, and the pheromone and pheromone increment are set to cumulative mode. The number of iterations is set to 200, and the number of ants is set to 30.
The 2-dimensional schematic diagram of example 1 is shown in Fig. 3. The 2-dimensional schematic diagram of example 2 is shown in Fig. 4.

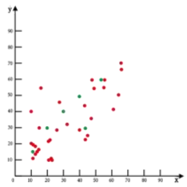
Fig. 3 The 2 D schematic diagram of Example 1.

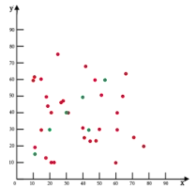
Fig. 4 The 2 D schematic diagram of Example 2.

4.1.2. Verify Mode

The subsequent results of this paper need to distinguish the advantages between the two experiments, so the T test is chosen.

4.2. EVRLP Simulation Experiment

4.2.1. Analysis of the Experimental Results of the Pheromone Update Cycle

Using the control variable method, ensure that other parameters and methods are unchanged ($\rho = 0.1$, $\beta = 1.0$, pheromone volatile mode choose full volatile mechanism , pheromone incremental mode step by step, iteration number set to 200), two examples were independent and each performed ten experiments to prevent experimental contingency. Compared the algorithm effect of two different pheromone update cycles on ant colony algorithm, namely each iteration update (method 1: Initialize once per iteration) and global update (method 2: Initialize only once).
Ten cycle analysis table of example 1 is shown as table. 2.

Table. 2 Example 1 ten cycle analysis table

Test count	Method 1	Method 2
1	748	497
2	706	492
3	657	523
4	743	529
5	761	526
6	614	530
7	676	549
8	717	527
9	742	472
10	622	490
average value	698.6	513.5
standard deviation	53.59	24.06

The T test results is 9.44007E-09<0.01, Proof method 2 is better. The best comparison route result of method 1 and method 2 in example 1 is shown as follows.

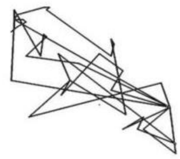
Fig. 5 Each iteration update.

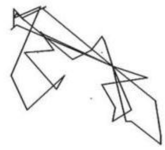
Fig. 6 global update.

4.2.2. Analysis of Experimental Results in Pheromone Incremental Methods

Using the control variable method, ensure that other parameters and methods are unchanged ($\rho = 0.1$, $\beta = 1.0$, pheromone volatile full volatile mechanism, pheromone global update cycle, iteration times set to 200 times), two examples were independent and each performed ten experiments to prevent experimental contingency. Compared the algorithm effect of two different pheromone incremental methods on ant colony algorithm, namely, pheromone one increase (method 3) and pheromone one step by step (method 4).
Ten increment analysis table of example 1 is shown as table. 3.

Table. 3 Example 1 ten increment analysis table

Test count	Method 3	Method 4
1	779	497
2	892	492
3	736	523
4	753	529
5	749	526
6	836	530
7	789	549
8	951	527
9	687	472
10	819	490
average value	799.1	513.5
standard deviation	78.28	24.06

The T test results is 1.94111E-9<0.01. Proof method 4 is better. The best result of the method 3 route of example 1 is shown below.

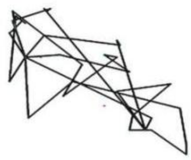
Fig. 7 pheromone one increase.

4.2.3. Analysis of the Experimental Results of the Pheromone Volatilization Method

Using the control variable method, ensure that other parameters and methods are unchanged ($\beta = 1.0$, $\rho = 0.1$, pheromone update cycle selection global increase, pheromone incremental mode, number of iteration set to 200 times), two examples were independent and each performed ten experiments to prevent experimental contingency. Compared the algorithm results of two different pheromone volatile methods on the ant colony algorithm, namely, pheromone global volatilization (method 5) and pheromone local volatilization (method 6).

Ten increment analysis table of example 1 is shown as table. 4. The T test results is 0.001892082<0.01. Proof method 5 is better.

Table. 4 Example 1 ten volatilization analysis table

Test count	Method 5	Method 6
1	497	646
2	492	540
3	523	684
4	529	601
5	526	749
6	530	506
7	549	694
8	527	527
9	472	542
10	490	631
average value	513.5	612
standard deviation	24.06	82.23

The best result of local volatilization of pheromones is shown below.

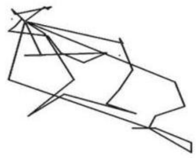

Fig. 8 Pheromone local volatilization.

4.2.4. Optimal Results

The optimal solution 403 is obtained by adjusting parameters, with specific position coordinates: 21-15-23-12-29-20-34-30-17-19-16-16-22-21-25-14-6-13-7-27-35-8-21-28-9-24-21-4-5-3-18-0-1-2-32-11-10-26-21, bringing route coordinates into the C + + drawing program to obtain Fig. 9.

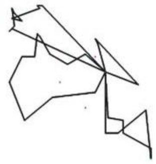

Fig. 9 The optimal solution.

Due to limited space and the results of example 2 are the same as example 1, the results of example 1 are mainly explained. And make the result clearer through drawing.

Later, three different pheromone update methods are considered in this paper, namely different update cycles, different incremental methods, different volatile methods. Analyze the algorithm effect of ant colony algorithm respectively, and each different way makes two examples ten times to ensure the universality of different methods. After that with T test, test each different experimental method and each T test results are far less than 0.01, indicating that the obvious difference is great. At the same time, it proves that the global update effect of the update cycle selection is better than one iteration and one update, the way of pheromone incremental selection of ants step by step is better than the overall increase after each walk, and the Pheromone global volatilization effect is better.

Finally, the optimal solution of example 1 is given and shown by image, showing that the current route is divided into four regions.

5. CONCLUSION

The electric vehicle routing problem with load energy consumption and charging piles has been presented in this paper and has analyzed the model based on ant colony algorithm. The specific work is summarized as follows:

(1) A model with charging piles has considered the energy consumption of transportation distance and load.

(2) The basic concept and detailed process of the ant colony algorithm has been introduced and the algorithm logic to adapt to the studied problem has been designed in this paper.

(3) The effects of three different pheromone update methods in ants on the overall performance of ant colony algorithm have been analyzed.

Many problems have been simplified in this paper and the time cost of the charging process and the queue time cost when charging have not been considered. Besides more dynamic factors needs to be considered.

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