Vehicle Air Conditioner Temperature Regulation-based Orderly Charging Strategy for Electric Vehicles

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Abstract. Due to high power load peaks and long durations in extreme weather conditions, as well as large-scale unscheduled electric vehicles charging, it may cause “peak plus peak” loading in local areas of the power grid, moreover, lead to transformer substations overload operation in local areas, which is not good for distribution safe and stable operation of the power grid. Considering the driver’s willingness, this study proposes an orderly charging strategy based on the temperature control of electric vehicle on-board air conditioner. The proposed strategy first constructs the temperature control model for electric vehicle cabins with considering the temperature of entire electric vehicle and the special characteristics of urban roads. Then, multi-objective function is formed with minimum user charging cost and variance of grid load fluctuations. Finally, electric vehicles orderly charging period is optimized by combining with electric vehicle travel chains, charge constraints, time-of-use electricity prices, and substation capacity constraints. The results show that temperature-controlled dispatching can effectively reduce the electric vehicles disorderly charging load. It can serve the power grid “cut peaks and fill valleys” and smooth the overall grid load curve using an improved Lagrange relaxation algorithm to optimize electric vehicles charging period.

1. Introduction

Under the dual pressure on severe shortage of energy resources and increasingly environmental pollution, zero-emission electric vehicles have developed rapidly. However, with the continuous increase in the number of electric vehicles, the issue of “mileage anxiety” has received great attention. On the one hand, in the typical season of summer and winter, the mileage of electric vehicles has decreased sharply due to the use of on-board air conditioners. On the other hand, due to the randomness in the time series distribution, if a large-scale electric vehicles are connected to the power grid, it may lead to “peak plus peak [1]” of power grid loads, increase the distribution line losses [2], and overload local substation [3].

At present, there are a lot of researches on the orderly charging of electric vehicles, and fruitful results have been achieved. In terms of orderly charging strategy for electric vehicles, literature [4] proposed a distributed orderly charging control architecture for communication failures. The Monte Carlo
simulation method was used to predict the charging load of EVs connected to the power grid. The minimum distribution network load variance is the goal to formulate an orderly charging plan for electric vehicles. Literature [5] proposed a spatiotemporal distribution prediction method for EV charging load that integrates road network, traffic, weather, power grid and other multivariate information and considers users' travel demand. The concept of travel chain was introduced to evaluate the influence of EV on the power grid after being connected to the power grid from two dimensions of spatiotemporal through power flow calculation.

In terms of taking into account the temperature influencing factors, literature [6] based on the Monte Carlo method, analyzed the impact of weather and temperature on the charging demand of electric vehicles, established an electric vehicle charging demand model and analyzed the simulation examples to verify the weather and temperature changes on the demand for electric vehicle charging. Reference [7] firstly analyzed the influence of ambient temperature on additional energy consumption, battery performance and road conditions of electric vehicles. Monte Carlo simulation was used to calculate the variation of charging load at different temperatures, and an example was given to verify that temperature had a significant impact on charging load of electric vehicles.

Summarizing the above literature, the research on the temperature regulation of on-board air conditioners is basically not available. Therefore, this paper puts forward an orderly charging strategy for electric vehicles based on the temperature control of the cabin of the electric vehicle. It considers the temperature of the electric vehicle and the characteristics of the mountainous urban road, constructs a multi-objective optimization function, establishes a model of the temperature control of the electric vehicle cabin, and combines its travel chains, charge constraints, time-of-use electricity prices, and substation capacity constraints optimize the orderly charging and discharging periods of electric vehicles and serve the power grid to "cut peaks and fill valleys."

2. User characteristics analysis

2.1. Electric vehicle temperature change model
Comparing the temperature change model of the cabin of an electric car with the temperature change model of the air conditioner in a building room, the cabin is equivalent to a room. Since the space of the cabin itself is much smaller than the room, the changes of the number of people inside the car and the seats inside the car cannot be ignored. Therefore, when the temperature change model of the cabin of an electric vehicle is described using the Equivalent Thermal Parameter (ETP) [8] model, its equivalent circuit diagram is shown in Figure 1:

![Figure 1. ETP model](image)

In order to simplify the model, the first-order equivalent thermal parameter model is adopted, and its differential equation is expressed as follows:
\[
\frac{dT_i^{V}(t)}{dt} = \frac{Q_{ac}^{i}(t) + Q_{\text{humen}}^{i,q}(t) + Q_{\text{other}}^{i}(t)}{C} + \frac{T_{am}(t) - T_{i}^{V}(t)}{RC}
\]  

(1)

Where, \( T_{i}^{V}(t) \) is the cabin temperature of the \( i \)th electric vehicle at time \( t \), \( T_{am}(t) \) is the ambient temperature at time \( t \), \( Q_{ac}^{i}(t) \) is the cooling capacity of air conditioning in the \( i \)th electric car at time \( t \), \( Q_{\text{humen}}^{i,q}(t) \) is the heat dissipation of \( q \) person in the \( i \)th electric car at time \( t \), and \( Q_{\text{other}}^{i}(t) \) is the heat dissipation of other equipment in the \( i \)th electric car.

The relationship between consumption power of on-board air conditioning in electric vehicles and cooling capacity of air conditioning is as follows:

\[
P_{i}^{ac}(t) = \frac{Q_{ac}^{i}(t)}{COP}
\]  

(2)

Where, \( P_{i}^{ac}(t) \) represents the cooling power of air conditioning in the \( i \)th electric vehicle, and \( COP \) represents the energy efficiency ratio of air conditioning.

2.2. User engagement

The use of electric vehicle air conditioners is based on user decisions. The grid side cannot directly control electric vehicle air conditioners. Therefore, in order to simplify the regulation of electric vehicle air conditioners, 0 and 1 variables are used for each electric vehicle user in the area. The user is willing to participate in the temperature regulation of the power grid side, and the user opens the temperature regulation terminal by himself. 0 indicates that the electric vehicle user is unwilling to participate, which is expressed by the formula:

\[
\xi(i, j) = \begin{cases} 
0 & \text{User } i \text{ is willing to participate in temperature control at time } j \\
1 & \text{User } i \text{ is unwilling to participate in temperature control at time } j 
\end{cases}
\]  

(3)

2.3. Endurance mileage estimation model

Literature [9] used the SB factor screening method to screen the factors that have a greater impact on the range of electric vehicles. It is concluded that when the daily travel distance impact factor is 6.1667, the conversion factor for air conditioning is 3.0235. It can be seen that the use of air conditioning had a great impact on the driving range of electric vehicles. In [10], when studying other influencing factors of the total energy consumption of electric vehicles, it was stated that the consumption of auxiliary energy other than air conditioning, including lighting, audio, on-board control systems, hydraulic pumps, and other devices accounted for 6% ~ 12% of the total energy, So it cannot be ignored. From the balance equation between driving force and driving resistance, the power of the electric vehicle motor can be calculated as:

\[
P_{i}^{MT} = \frac{v_i(mg\cos \gamma + mg\sin \gamma + \frac{C_D A v_i^2}{21.15})}{3600.265 \eta_f}
\]  

(4)

Where, \( P_{i}^{MT} \) is the output power of the motor of the \( i \)th electric vehicle, \( m \) is the curb mass of the electric vehicle, \( g \) is the acceleration of gravity, \( \gamma \) is the angle of the resistance slope of the road, \( C_D \), the
The analytic mileage evaluation model is:

\[ M_i(t) = \frac{3600v_i \cdot S_{oc,i}^{pre} \cdot \varepsilon_{bat} \cdot B_i \cdot \eta_{dis}}{P_i^{MT} / \eta_M + \xi(i,j) \cdot P_i^{ac} / \eta_{ac} + P_i^{as} / \eta_{as}} \]  \tag{5}

Where, \( M_i(t) \) is the driving range of the \( i \)th electric vehicle, \( \varepsilon_{bat} \) is the battery loss coefficient of the electric vehicle, \( B_i \) is the battery capacity of the \( i \)th electric vehicle, \( S_{oc,i}^{pre} \) is the current state of charge of the \( i \)th electric vehicle battery, \( \eta_{dis} \) is the battery discharge efficiency, \( \eta_M \) and \( \eta_{ac} \) is the motor Efficiency, \( P_i^{ac} \) consumes power for the auxiliary service of the \( i \)th electric vehicle, and \( \eta_{as} \) is the efficiency for the auxiliary service of the \( i \)th electric vehicle.

The unit mileage is:

\[ \psi(t) = \frac{S_{oc,i}^{pre} \cdot \varepsilon_{bat} \cdot B_i \cdot \eta_{dis}}{M_i(t)} \]  \tag{6}

2.4. Electric vehicle travel chain
Reference [11] introduced the concept of travel chain, integrates charging process data of electric vehicles, and considers the influence of weather, journey start time, travel chain duration, travel chain distance, journey speed, initial charge status, last trip state and other factors on charging behaviour of electric vehicles from the perspective of reality. This article introduces a simple travel chain for electric vehicles. As shown in Figure 2, it is defined as "H" for Home and "W" for Work. Based on the statistical analysis of the NHTS data, the probability distribution of "H-W" and "W-H" travel time and probability of trip mileage are obtained.

![Figure 2. Simple travel chain](image)

2.5. Restrictions

2.5.1. Vehicle air conditioning temperature constraints. In the process of temperature control, in order to avoid excessive temperature adjustment, the user experience will decrease, which will affect the enthusiasm of users to participate in temperature control and scheduling, thus affecting the energy efficiency of temperature control and scheduling. According to literature [12], the comfort temperature of human body was proposed, and the temperature range of the cabin was set as:

\[ T_{min} \leq T^v \leq T_{max} \]  \tag{7}
2.5.2. Battery power constraints. In order to avoid battery loss of electric vehicles and overcharge and discharge of batteries, the current power of electric vehicles in the process of travel planning should meet:

\[ S_{oc}^{\text{min}} \leq S_{oc}^{\text{pre}} \leq S_{oc}^{\text{max}} \]  

(8)

Where, \( S_{oc}^{\text{min}} \) is the minimum value of electric vehicle battery capacity, and \( S_{oc}^{\text{max}} \) is the minimum value of electric vehicle battery capacity.

2.5.3. Charging duration constraint

\[ t_{in} \leq \frac{(S_{OC}^\text{exp} - S_{OC}^\text{pre}) \cdot E_{bat}}{P_{cha} \cdot \eta_{cha}} \leq t_{out} \]  

(9)

Where, \( S_{OC}^\text{exp} \) is the electric quantity when the EV user leaves the grid, \( P_{cha} \) is the average power charged by the EV, \( \eta_{cha} \) is the charging efficiency, \( t_{in} \) and \( t_{out} \) is the time when the EV is connected to the grid and off the grid respectively.

3. Optimal programming model

3.1. Objective function

The scheduling scenario in this article is to carry out an orderly charge planning in a research area that includes residential areas and work areas, taking full account of the focus of the power grid and users. On the user side, considering the willingness and enthusiasm of the user to participate, and taking the minimum user charging cost as the objective function. On the grid side, one is to consider the capacity constraints of the power distribution transformers in the area, and the other is to optimize the charging sequence of the electric vehicle to make the grid load curve smoother, with the minimum load variance as the objective function.

\[ \min f_1 = \sum_{i=1}^{\text{Num}} \sum_{j=1}^{T} P_{cha} \Delta t \cdot c_j SS(i, j) \]  

(10)

\[ \min f_2 = \frac{1}{T} \sum_{j=1}^{T} (P_{base}^j + \sum_{i=1}^{\text{Num}} P_{cha} SS(i, j) - \bar{P}_{avg})^2 \]  

(11)

Where, \( \text{Num} \) for a certain number of electric vehicles in 24 hours, \( T \) for the 96 time intervals in a day at 15min intervals, \( c_j \) for grid time-sharing electricity price, \( SS(i, j) \) for the charge state of the \( i \)th car at the \( j \)th moment (0 means no charging, 1 means charging), \( \bar{P}_{avg} \) for the average of the load of power grid.

3.2. Grid constraint

Since the transformer cannot be overloaded for a long time, it is assumed that the total load in the region shall not exceed the carrying capacity of the distribution network at any time, that is, it should be less than the capacity of the transformer in the region, which can be expressed as:
\[ P_{i}^{\text{base}} + \sum_{l=1}^{\text{Num}} (P_{\text{cha}} \cdot SS(i, j)) < S_N \cdot \cos \psi \]  

(12)

Where, \( S_N \) is the capacity of the transformer in the area and \( \cos \psi \) the power factor of the transformer.

3.3. Solution

In this paper, Lagrange multipliers are introduced, and the Lagrange relaxation method [13] is used to decentralize the objective function. Since the dimensions of the multi-objective optimization function are different, first, the multi-objective function is normalized, and the function is simplified as:

\[ \min G = \delta_1 f_1 / f_{1N} + \delta_2 f_2 / f_{2N} \]  

(13)

Where, \( \delta_1 \) and \( \delta_2 \) are the weight coefficients of each sub-objective function, meet \( \delta_1 + \delta_2 = 1 \), \( f_{1N} \) is the cost of unordered charging of electric vehicles, and \( f_{2N} \) is the original base load variance of electric vehicles.

For the constraint (12), the Lagrange multiplier introduced by the Lagrange relaxation principle is \( \lambda = [\lambda_1, \lambda_2, \ldots, \lambda_T] \), \( \lambda > 0 \), and the inequality constraint condition is removed and written into the objective function in the form of penalty term. The Lagrange relaxation problem of the original problem is obtained:

\[ \min G = \frac{\delta_1}{f_{1N}} \left[ \sum_{i=1}^{\text{Num}} \sum_{j=1}^{T} P_{\text{cha}} \cdot e_i \cdot SS_{i,j} \right] + \frac{\delta_2}{f_{2N}} \left[ \frac{1}{T} \sum_{j=1}^{T} \left( P_{\text{pam}} + \sum_{i=1}^{\text{Num}} P_{\text{cha}} \cdot SS_{i,j} - P_{\text{avg}} \right)^2 \right] + \sum_{j=1}^{T} \left[ P_{\text{pam}} + \sum_{i=1}^{\text{Num}} P_{\text{cha}} \cdot SS_{i,j} - S_N \cos \psi \right] \]  

(14)

The steps of Lagrange relaxation algorithm to solve dual problems are as follows:

1) Assume that the number of iterations is \( k \) and the initial value is \( k=1 \), initialize the Lagrange multiplier \( \lambda \), solve equation (14) at the given initial value, and obtain the corresponding solution \( SS(i, j) \).

2) According to the obtained solution, calculate and judge whether the accuracy meets the requirements according to equation (15). If so, it can be approximately considered as the optimal solution of the original problem. Otherwise, update the Lagrange multiplier \( \lambda \).

\[ \left\| \lambda^k - \lambda^{k-1} \right\| / \left\| \lambda^k \right\| \leq \varepsilon \]  

(15)

3) The sub-gradient method is adopted to update, and the update formula is:

\[ \lambda^{k+1} = \lambda^k + \delta^k \varphi^{k} / \left\| \varphi^{k} \right\| \]  

(16)

Where, \( \lambda \) is the step size, to ensure its convergence, the step size requirements and values are:

\[ \lim_{k \to 0} \delta^k \to 0, \delta^k = 1/(a + bk) \]  

(17)

Where, \( a \) and \( b \) are constants and require \( a < b \).

\( \varphi \) is the sub-gradient of the k iteration, \( 1 \times T \) is a column vector of, and the value is:
\[ \phi^k = P_{t}^{base} + \sum_{i=1}^{Num} P_{cha} SS(i, j) - S_N \cos \psi, j = 1, 2, \cdots, T \]  

4. Example analysis

4.1. Parameter settings

In order to analyse the travel status of private cars on this travel chain, the latest representative NHTS2017 data set obtained from the U.S. department of transportation survey was used to extract the travel time and driving distance of "car" and "SUV" users on this travel chain. The H2W and W2H oneway start time probability distribution and the H2W trip mileage probability distribution are shown in figure 3. The parameters involved in this paper are shown in table 1.

![Figure 3. H2W-W2H trip start time distribution and H2W mileage distribution](image)

| Parameter                            | Value      | Parameter                            | Value      |
|--------------------------------------|------------|--------------------------------------|------------|
| Equivalent heat resistance of cabin /({\degree}C/kW) | 13.1094    | Outdoor temperature /({\degree}C)  | 35         |
| Equivalent thermal resistance of cabin /(kJ/{\degree}C) | 183.7033   | Resistance slope Angle              | (30,0.5)   |
| Pilot/Passenger heat loss /(kW)      | 0.2/0.102  | AC energy efficiency ratio          | 2.4        |
| Reconditioning mass /Kg             | 1650       | Speed /(km/h)                        | 50         |
| Rolling resistance coefficient       | 0.02       | Driveline efficiency                | 0.9        |
| Comfort temperature range of human body /({\degree}C) | 24–28     | Air resistance coefficient          | 0.35       |
| Charging power /(kW)                | 7          | The range of SOC                    | 0.2–0.9    |

4.2. Simulation results

The grid load of a certain day in the typical season of a mountain city is selected as the research base. In this paper, the Monte Carlo method is used to the charging state of 150 electric vehicles and quantify the characteristics of mountain cities. Study the difference in charging load before and after user participation in temperature control. Based on the Lagrange relaxation method, the effect of orderly charging of electric vehicles participating in the temperature control of vehicle air conditioners in the decentralized optimization mode was studied.

(1) Influence of temperature control of disordered charging. Unordered charging is the assumption that electric vehicle users start charging immediately after arriving at work and home. Temperature controlled scheduling is to turn on and off the on-board air conditioner in consideration of user wishes to reduce battery power consumption. It is assumed that users are willing to participate in temperature control. The parameters involved in this paper are shown in table 1.
control, and its charging load is shown in Figure 4. It can be seen that the temperature control effectively reduces the charging load of electric vehicles.

![Temperature-controlled Disorderly Charging Curve](image1)

**Figure 4.** Temperature-controlled Disorderly Charging Curve

(2) Decentralized and orderly charging effect. The Lagrange multiplier is updated using the subgradient method, and the number of iterations is set to 16. The comparison diagram of the multiobjective optimized charging curve was obtained, as shown in figure 5. As can be seen from the figure that the charging load in the residential time is almost completely transferred to the load trough period, while the charging load in the working time is only reduced, but there is a certain load transfer.

![Ordered charging curve](image2)

**Figure 5.** Ordered charging curve
5. Conclusion
Considering the impact of temperature control of air conditioner on electric vehicle charging, quantifies the impact of mountain city characteristics on electric vehicle charging timing, this paper establishes a multi-objective function with the minimum user charging cost and the smallest grid load fluctuation variance and electric vehicle temperature. The control scheduling model is constructed by an improved Lagrange relaxation algorithm which can solve the multi-objective function in a decentralized manner. Through example analysis, it can be concluded that the electric vehicle temperature control can effectively reduce the charging load and provide a larger power boundary for orderly charging. The multi-objective optimization model considering both the user and the power grid can smooth the total load curve of the power grid and play a role of "peak load clipping".

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