Cabin Temperature Regulation-based Charging Strategy for Electric Vehicles Under 5G

Zhao Chenxu¹, Yang Chenggang¹, Cui Ziti¹, Zeng Xianjun², Fan Zifan³, Zhou You³,*

¹Inner Mongolia Electric Power Research Institute, Hohhot, Inner Mongolia, China
²State Grid Chongqing Electric Power Company, Chongqing, China
³Chongqing University of Posts and Telecommunications, Chongqing, China
*Corresponding author’s e-mail: longhy@cqupt.edu.cn

Abstract. As massive EVs are introduced rapidly, large-scale disordered charging loads appear in the power grid, which may lead to “peak plus peak” and overload for local substations. With the rapid development of 5G, the data transmission of large-scale EVs is suggested to help optimizing the orderly charging strategy under cabin temperature control and load control in EVs in this paper. The charging time, charging cost and substation capacity are considered as constraints, so as to optimize the charging period of EVs. It seems that the temperature control dispatching can effectively reduce the disordered charging load of EVs, smooth the overall load curve of the power grid and result “peak shifting and valley filling” of the power grid.

1. Introduction

During summer and winter, the power consumption of EVs will greatly increase due to the on-board air conditioning, so that the driving mileage of EVs will be decreased. When mass-scale electric cars come online, it can cause a situation where the grid is overloaded [1-3]. A method of electric vehicle charging load forecasting is proposed based on real-time travel and traffic conditions [4]. A forecasting method for the spatial and temporal distribution of EVs charging load is proposed [5], considering the network, traffic, weather, power grid and travel demand of users etc. A distributed ordered charging control and communication architecture is proposed in [6], which aims to minimize the load variance of distribution grid, and formulated the orderly charging plan of EVs. A remote monitoring system based on 5G technology is introduced for the charging scheduling of EVs [7]. The Internet of vehicles platform is performed to detect the conditions of various roads in real time by means of 5G communication technology [8].

As above mentioned, research on charging load scheduling with cabin temperature regulation under 5G is unavailable yet. In the text proposes an orderly charging strategy based on cabin temperature, 5G technology and car networking platform. The temperature load model of EVs’ cabin is established, and the multi-objective optimization function based on user charging cost and grid load fluctuation is constructed, which results in the orderly charging strategy with the real-time positioning of EVs location and detection of running state.

2. Electric vehicle power consumption analysis

In this paper, the EVs’ power consumption is analyzed based on cabin temperature changing.
2.1. Electric vehicle temperature change model
Comparing the EVs’ temperature change model with that of the building, the cabin is equivalent to a room. The cabin is much smaller than the room, so that the changes of the number of people and seats inside cannot be ignored. The temperature change model of the cabin is described using the Equivalent Thermal Parameter (ETP) \[^9\] model in Figure 1.

\[
\begin{align*}
\frac{dT_{in}(t)}{dt} &= \frac{Q''_{ac}(t) + T_{ext}(t) - T_{in}(t)}{R_{ro} C_{ro}} \\
\end{align*}
\]

(1)

Where, \(T_{in}(t)\) is the cabin temperature of the \(i\)th electric vehicle at time \(t\), \(T_{ext}(t)\) is the external temperature at time \(t\), \(Q''_{ac}(t)\) is the cooling(heating) capacity of the air conditioner, \(C_{ro}\) is the equivalent heat capacity of the room, \(R_{ro}\) is the equivalent thermal resistance of the room. The relationship between power consumption and cooling capacity of on-board air conditioning for electric vehicles is as follows:

\[
P''_{ac}(t) = \frac{Q''_{ac}(t)}{\eta_{ac}}
\]

(2)

Where, \(P''_{ac}(t)\) represents the \(i\)th electric vehicle’s cooling power of air conditioning at time \(t\), and \(\eta_{ac}\) represents the energy efficiency ratio of air conditioning.

2.2. Endurance mileage estimation model
Results indicate that that when the influence coefficient of travel distance is 6.1667, the conversion coefficient of air conditioning is 3.0235. It shows that the use of air conditioning had a great impact on the driving range of EVs \[^10\]. In \[^11\], In addition to air conditioning, lighting, audio, vehicle control system, hydraulic pump and other auxiliary energy consumptions seems to account for 6% ~ 12% of the total energy consumption, which cannot be ignored. By the balance equation of driving force and driving resistance, the power of the electric vehicle motor can be calculated as follows.

\[
P''\text{mot} = \frac{v (mg \sin \gamma + mg \cos \gamma + C_{ru} A v^2)}{3600 \times 265 \eta_{r}}
\]

(3)

Where, \(P''\text{mot}\) is the output power of the motor of the \(i\)th electric vehicle, \(m\) is the mass of the electric vehicle, \(g\) is the acceleration of gravity, \(\gamma\) is the grade of road slope angle, \(C_{ru}\) the coefficient of air resistance, \(A\) is the windward area, and \(v\) the speed of the \(i\)th electric vehicle , \(\eta_{r}\) is the power transmission efficiency, \(f\) is the coefficient of rolling resistance.

The mileage can be calculated as follows.

\[
M_{EV} = \frac{\frac{v \cdot S_{mot} \cdot \eta_{hev} \cdot B \cdot \eta_{dis}}{3600(P_{mot}/\eta_{mot} + P_{ac}/\eta_{ac} + P_{as}/\eta_{as})}}{3600(P_{mot}/\eta_{mot} + P_{ac}/\eta_{ac} + P_{as}/\eta_{as})}
\]

(4)
Where, $M_{EV}$ is the driving distance of the $i$th electric vehicle, $\epsilon_{bat}$ is the battery loss coefficient of the electric vehicle, $B$ is the battery capacity of the $i$th electric vehicle, $S^{pre}_{ac}$ is the current battery state of the $i$th electric vehicle, $\eta_{dis}$ is the battery discharge efficiency, $\eta_{mo}$ and is the motor efficiency, $P_{as}$ 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:

$$\psi(T) = \frac{S^{pre}_{ac} \cdot \epsilon_{bat} \cdot B \cdot \eta_{dis}}{M_{EV}}$$  \hspace{1cm} (5)

### 2.3. User engagement

It is decided by users to turn on the electric vehicle air conditioners, and the electric vehicle air conditioners cannot be directly control by the grid. In order to simplify the regulation of electric vehicle air conditioners, 0 and 1 variables are introduced. 1 indicates users agree to participate in the temperature regulation while 0 indicates that the EVs users are reluctant, which is expressed by the formula:

$$\xi(i,j) = \begin{cases} 0 & \text{User } i \text{ is unwilling to participate in temperature control at time } j \\ 1 & \text{User } i \text{ is willing to participate in temperature control at time } j \end{cases}$$  \hspace{1cm} (6)

### 3. Optimal programming of the grid

Based on the power consumption model, the minimum user's charging cost and the variance of grid load are taken as the objective function in the optimal planning model of charging, and the vehicle cabin temperature and battery state are taken as the constraint conditions for modeling.

#### 3.1. Objective function

The scheduling scheme in this paper is to carry out an orderly charging planning in the research area including residential area and working area, fully considering the focus of power grid and users. In terms of users, the willingness and enthusiasm of users to participate are taken into account, and the minimum charging cost of users is taken as the objective function. On the power grid side, firstly, capacity constraints of distribution transformers in the region are considered; secondly, charging sequence of EVs is optimized to smooth the power grid load curve.

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

$$\min f_2 = \frac{1}{T} \sum_{j=1}^{T} (P_{base} + \sum_{i=1}^{\text{Num}} P_{ac} \cdot SS(i,j) - \overline{P}_{avg})^2$$  \hspace{1cm} (7)(8)

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

#### 3.2. Restrictions

According to the appropriate temperature for human body in [12], the temperature range of the cabin was set as:

$$T_{\min} \leq T' \leq T_{\max}$$  \hspace{1cm} (9)

In order to avoid over-charging or over-discharging of batteries, the current battery state of EVs in the process of travel planning should meet:
In order to avoid long stay time of EVs at charging stations, the charging time should meet:

\[
\min S_{\text{out}} \leq S_{\text{pre}} \leq S_{\text{max}}
\]

(10)

Where, \(S_{\text{pre}}\) is the battery state when the EV user leaves the grid, \(P_{\text{cha}}\) is the average power charged by the EV, \(\eta_{\text{cha}}\) is the charging efficiency, \(t_{\text{in}}\) and \(t_{\text{out}}\) is the time when the EVs are connected to the grid and off the grid respectively. The total load in the region should be less than the capacity of the transformer in the region, which can be expressed as:

\[
P_{\text{cha}} + \sum_{i,j} (P_{\text{cha}} \cdot SS(i,j)) < S_{N} \cdot \cos \psi
\]

(11)

Where, \(S_{N}\) is the capacity of the transformer in the area and \(\cos \psi\) the power factor of the transformer.

3.3. Solution

The objective function (13) is dispersed by Lagrangian relaxation. Considering that the dimensions of multi-object optimization function are different, the multi-objective optimization function needs to be normalized first and simplified into the following form:

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

(13)

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

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:

\[
\min G = \frac{\delta_1}{f_{1N}} \sum_{i=1}^{n} \sum_{j=1}^{T} P_{\text{cha}} \cdot \Delta t \cdot c_{ij} \cdot SS_{ij} + \frac{\delta_2}{f_{2N}} \left[ \frac{1}{T} \sum_{i=1}^{n} \sum_{j=1}^{T} (P_{\text{cha}} - P_{\text{cha}_{\text{ave}}})^2 \right] + \sum_{i=1}^{T} \lambda_i \left[ P_{\text{cha}} + \sum_{j=1}^{n} P_{\text{cha}} \cdot SS_{ij} - S_N \cdot \cos \psi \right]
\]

(14)

The steps of Lagrange relaxation algorithm 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 \(\lambda\).

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

(15)

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

\[
\lambda^{k+1} = \lambda^k + \delta^i \cdot \varphi^i / \| \varphi^i \|
\]

(16)

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

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

(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:

\[
\varphi^i = P_{\text{cha}} + \sum_{j=1}^{n} P_{\text{cha}} \cdot SS(i, j) - S_N \cdot \cos \psi, j = 1, 2, \ldots, T
\]

(18)
4. Application of internet of vehicle

4.1. Technical requirements
Internet of EVs is a huge interactive network composed of information such as vehicle location, speed and route. Information about these large numbers of vehicles can be analyzed and processed so as to work out the best route for different vehicles, reported traffic conditions in a timely manner and schedule signal cycles. With the 5G and MEC (Mobile Edge Computing) technology, the network transmission delay can be reduced for the delay sensitively business, and the possibility of network congestion may be alleviated with massive EVs use.

4.2. System architecture
The overall design of the temperature control system is shown in Figure 2. The on-board terminal system gets the vehicles’ operation data, including the current precise positioning of the electric vehicle, cabin temperature, battery status and the other data. The charging station management system detects the usage data of charging piles in the station in real time.

After collecting the data, each system transmits the data to multiple MEC servers through 5G network, instead of directly sends the data to the cloud monitoring and dispatching center. MEC server then receives the relevant data and operation status of terminal system, performs compression, encryption, calculation and processing of these data. Finally, the dispatching center formulates the control strategy of grid load peak-shifting and valley-filling, generates the temperature control instruction of EVs and sends it to user client.

In this paper, EVs’ users participate in the temperature control, so as to achieve orderly charging of EVs and peak-shifting & valley-filling load. The electric power grid needs to collect real-time travel data of EVs’ users through the internet of vehicles.
5. Results & Discussion
Take the grid load of a day in a typical season as an example. In this paper, the Monte Carlo method is introduced to the charging load prediction of 150 electric vehicles, and the difference between the charging load and the grid load before and after users participate in the cabin temperature control is studied. The results are as follows:

(1) Disordered charging assumes that EVs’ users start charging immediately after they arrive at their workplace or home. The orderly charging strategy based on temperature control scheduling is to turn on or off the on-board air conditioning according to the user's intention, in order to reduce the battery power consumption and increase the travel range, thus changing the charging time. Assume that the user is willing to participate in temperature control, as shown in Figure 3. It can be found that the temperature control effectively reduces the charging load of electric vehicles.

(2) The Lagrange multiplier is updated using the subgradient method, and the number of iterations is set to 16. The comparison diagram of the multi-objective optimized charging curve is obtained in figure 4. and the charging load in the residential area is almost completely transferred to the load while the charging load in the working area is only reduced rather than a certain load transfer effect.

6. Conclusion
In this paper, the orderly charging strategy of EVs with cabin air conditioning temperature control is studied under 5G which provides data transmission and scheduling control of on-board terminal. The
influence of on-board air conditioning factors on EVs’ charging timing is quantified, so that the temperature controlling and scheduling model of EVs is established with the minimum charging cost of users. Lagrangian relaxation algorithm is adopted for decentralized optimization solution. Through the analysis of numerical examples, it is concluded that the temperature control of EVs can effectively reduce the charging load and the users’ electricity cost.

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