Optimal Scheduling and Control Techniques of Electric Vehicle Considering Flexible Grid Resources

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Abstract. With the continuous expansion of the scale of electric vehicles and the continuous development of intelligent control technology, it is of great significance for electric vehicles to participate in orderly charging and discharging to improve the efficiency of electric vehicles and ensure the safe and reliable operation of the power grid. Firstly, the behaviour aggregation model of electric vehicle is studied. Then, a two-layer optimal scheduling model is proposed for the operation management system of electric vehicles, which including the upper control model from the perspective of the operation of business operator and the lower control model from the perspective of electric system. Finally, a case study on the orderly charging and discharging of electric vehicles is carried out. The results show that the proposed model plays an important role in reducing load fluctuation and enhancing voltage stability.

1. Introduction

EV charging needs are flexible. We can control EV charging load in an orderly manner through certain control means, so as to reduce the impact of EV charging on the power grid, reduce charging cost for EV users, and improve new energy consumption [1, 2]. It is of great significance for the development of electric vehicles to study the flexibility of electric vehicles in power dispatching.

The research contents of the integration of electric vehicles and smart power grid mainly include peak load reduction, improving the stability of power system, providing auxiliary services to power grid, and promoting the consumption of new energy. EV charging network planning and operation is an interdisciplinary problem involving traffic engineering and electrical engineering [3], but the existing researches mainly focus on two directions: one is to only consider the coordination between EV and smart grid [4]. The other is to consider only the synergies between electric vehicles and the transport network. At present, there are few comprehensive studies on the collaboration of "electric vehicle -- transportation network -- smart grid", which will become an important research direction in the future.

At present, the research on interconnection of charging facilities in China is still in its infancy, and the interconnection network constructed is usually based on the traditional Internet of things architecture [5]. The traditional Internet of things system mainly consists of three layers: perception layer, network layer and application layer. In this system, the perception layer is mainly used to identify objects and
collect information, the network layer mainly transmits and processes the information obtained by
perception, and the application layer mainly meets the needs of the industry.

Based on the behavior and realization mode of EV participating in power grid dispatching, this paper
firstly models the whole process of EV behavior. Then, the sequential charge-discharge scheduling of
double-layer electric vehicles is designed. And the charge and discharge scheduling model of electric
vehicle under multi-time scale is studied. Finally, relevant cases are applied to analyze the charging and
discharging behavior of electric vehicles, and the results show that the method proposed in this paper
has a good effect.

2. Integrated model of the whole process behaviour of electric vehicles

The energy trajectory of EV over a period of time can be modeled according to the energy trajectory of
EV charging and driving behavior. We integrate the whole-process energy trajectory model according
to the mode of "charge-driving-charging". The quantity of electricity at the end of a continuous charging
process shall ensure that the next driving phase can be completed, so it shall be equal to the quantity of
electricity equivalent to discharge at the maximum power at the next driving phase until the end of the
driving exactly reaches the minimum allowable quantity. Therefore, the whole-process energy trajectory
boundary model of electric vehicles can be obtained, as shown in the figure 1.

3. A two-layer scheduling model for orderly charge and discharge of electric vehicles

A typical orderly charge and discharge scheduling system for electric vehicles is composed of two layers
of scheduling: operator (Aggregator, virtual power plant operator VPP, power distribution company
Utility, etc.) and electric vehicle integrator.

From the perspective of commercial operators, the upper dispatching optimization model is
established based on the collected conventional load and new energy output forecast, as well as the
lumped boundary information reported by the electric vehicle integrator to minimize the operation cost
of the power grid. The operating cost of the power grid includes the benefit loss caused by load removal,
the cost of purchasing power from the superior power grid and the return of surplus renewable energy
to the Internet. In order to reduce the impact on the superior power grid, the modification of the minimum
power fluctuation is added to the optimization objective. Therefore, the upper optimization objective
can be expressed as follows.

\[ f_1 = \min \left\{ \sum_i \left( c_{\text{cur}} P_i^{\text{cur}} + \pi_i^{\text{grid}} P_i^{\text{grid}} - \pi_i^{\text{ren}} P_i^{\text{ren}} \right) \Delta t + \varepsilon \sum_i \left( P_i^{\text{grid}} \right)^2 \right\} \]  

(1)

Where, \( P_i^{\text{cur}} \) is the load power to be removed at time \( t \), \( P_i^{\text{grid}} \) is the power purchased from the
superior power grid at time \( t \), \( P_i^{\text{ren}} \) is the power returned to the grid by renewable energy, \( c_{\text{cur}} \) is the
penalty for the loss caused by the removal of unit load of electricity, \( \pi_i^{\text{grid}} \) is the electricity price
purchased from the superior power grid, \( \pi_i^{\text{ren}} \) is the feed-in price of renewable energy, \( \varepsilon \) is a small
number, and \( \Delta t \) is the length of a single time period.
The lower layer optimal scheduling is the charging plan curve distributed by the ev integrator according to the dispatching center. They arrange the charging and discharging behavior of electric vehicles according to the vehicle behavior boundary. The optimal scheduling method is described in the next section.

4. A two-layer scheduling model for orderly charge and discharge of EV

For the distribution network system including EV charging load, distributed power supply and reactive power compensation device, this section proposes a specific scheme for the optimal dispatching of the lower layer. Firstly, load modeling of nodal EV is carried out, and a day-ahead optimization mixed integer second-order cone programming model is established to minimize the total power purchase cost. Within-day rolling optimization also aims to minimize the total power purchase cost, and to solve the correction of EV power when there is a deviation in the distributed power supply prediction output under the optimal action strategy of day-before reactive power compensation [6].

The energy boundary model of node charging load can be established by using specific information of electric vehicles connected to a node, such as arrival time, departure time, initial state of charge and termination state of charge.

\[
\eta \sum_{\tau=1}^{L} P_{E,V}^t \Delta t \geq E_{t,E,V}^{\text{min}}, \quad \forall t
\]  

\[
\eta \sum_{\tau=1}^{L} P_{E,V}^t \Delta t \leq E_{t,E,V}^{\text{max}}, \quad \forall t
\]

Where, \( \eta \) is the charging efficiency of EV, \( P_{E,V}^t \) is the active charging power of ev at node i at time \( \tau \), \( E_{t,E,V}^{\text{min}} \) is the total charging demand of EV leaving node i at time t and before, and is the total charging demand of EV arriving at node i at time t and before.

4.1. Day-ahead operation optimization

The day-ahead optimization model takes minimizing the total power purchase cost of distribution network as the optimization objective, namely:

\[
\min_{\eta, P_{E,V}^t, \pi_t} \sum_{i=1}^{L} \sum_{s=1}^{2} \sum_{j(b,j)s}^\Psi \pi_t P_{E,V}^t \Delta t
\]

where \( P_{E,V}^t \) is electric vehicle charging power in node i, 2 is electric vehicle charging network side load reactive power, 0-1 variables \( u_{j(s,b),t} \) is the s-th state of condenser (1, 0 means cut out) for node i at time t, \( \pi_t \) is the power purchase prices at time t, \( P_{E,V}^t \) is the root node and node j branch branch in t time between active trend, \( \Psi \) is the set of all branch, \( T \) is the time interval number, \( \Delta t \) is the length of time.

The day-ahead optimization model should meet the constraint conditions of branch power flow, node voltage, charging demand and reactive power compensation.

4.1.1. Branch power flow constraint. The active power and reactive power flow of each branch in the distribution network shall meet the power flow constraint and the power flow upper and lower bound constraint:

\[
P_{E,V}^{BR}_{g,j} - r_g \left( P_{E,V}^{BR}_{g,j} \right)^2 + \left( Q_{E,V}^{BR}_{g,j} \right)^2 \leq \sum_{(j,j)s}^\Psi \sum_{b}^\Psi \pi_t P_{E,V}^{BR}_{g,j} \Delta t
\]

\[
Q_{E,V}^{BR}_{g,j} - x_g \left( P_{E,V}^{BR}_{g,j} \right)^2 + \left( Q_{E,V}^{BR}_{g,j} \right)^2 \leq \sum_{(j,j)s}^\Psi \sum_{b}^\Psi \pi_t P_{E,V}^{BR}_{g,j} \Delta t
\]
\[
U_{ij,t}^2 = U_{ij,t}^2 + \left( \frac{P_{ij,t}^{BR}}{U_{ij,t}} \right)^2 + \left( \frac{Q_{ij,t}^{BR}}{U_{ij,t}} \right)^2 - 2 \left( \frac{P_{ij,t}^{BR} \cdot x_{ij,t} \cdot P_{ij,t}^{BR} + x_{ij,t} \cdot Q_{ij,t}^{BR}}{U_{ij,t}} \right)
\]

(7)

\[P_{ij,t}^{\min} \leq P_{ij,t}^{BR} \leq P_{ij,t}^{\max}\]

(8)

\[Q_{ij,t}^{\min} \leq Q_{ij,t}^{BR} \leq Q_{ij,t}^{\max}\]

(9)

Where \( r_{ij} \) is the resistance of the branch \( ij \), \( x_{ij} \) is a branch of the \( ij \) reactance value, \( P_{ij,t}^{BR} \) and \( Q_{ij,t}^{BR} \) respectively the \( t \) moment branch \( ij \) active and reactive power current, \( U_{ij,t} \) is voltage amplitude in node \( j \) at time \( t \), \( P_{ij,t}^{\phi} \) and \( Q_{ij,t}^{\phi} \) respectively active and reactive load in node \( j \) at time \( t \), \( P_{ij,t}^{DG} \) and \( Q_{ij,t}^{DG} \) is active and reactive power output of distributed power supply in node \( j \) at time \( t \), \( Q_{ij,t}^{C} \) is the reactive power compensation of power.

4.1.2. Charging demand constraint. The distribution network can be connected to each node of the EV, and the charging power of the node at time \( t \) shall meet the energy boundary and power upper and lower limits in the aforementioned node charging load modeling. In addition, considering that EV charging has a minimum power factor requirement (denoted as \( \lambda \)), the reactive power of the network side of the charging load needs to meet:

\[0 \leq Q_{ij,t}^{EV} \leq \frac{\sqrt{1 - \lambda^2}}{\lambda} P_{ij,t}^{EV}, \quad \forall t, \forall i
\]

(10)

4.1.3. Reactive power compensation constraint. Consider that some nodes in the distribution network are equipped with compensation capacitors that are switched on and off in different ranges. It is assumed that the capacity of each gear of the compensation capacitor is the same at the same node, but the gear and capacity of the capacitor are different at different nodes. Then the reactive compensation power of each node shall meet:

\[Q_{ij,t}^C = \sum_{s=1}^{S_i} U_{ij,t,s} \Delta Q_s, \quad \forall t, \forall i \in \Lambda
\]

(11)

Where, \( \Delta Q_s \) is the reactive capacity of each gear capacitor at node \( i \), \( S_i \) is the tap number of the switching capacitor at node \( i \), and \( \Lambda \) represents the node set connected with the graded switching capacitor.

4.1.4. Node voltage constraint. The voltage of each node in the distribution network shall meet the upper and lower limit constraint:

\[U_{ij,t}^{\min} \leq U_{ij,t} \leq U_{ij,t}^{\max}\]

(12)

Where, \( U_{ij,t}^{\min} \) and \( U_{ij,t}^{\max} \) are the voltage upper and lower limits of node \( i \) respectively.

4.2. Rolling optimization within-days.

Intraday rolling optimization goal is the same as before, that is, the minimum total purchase cost. The goals at the moment are as follows:

\[\min \sum_{r=0}^{\Delta T} \sum_{j=0}^{n} \sum_{y=0}^{y_{r}} \pi_r p_{ij,t}^{BR} \Delta t\]

(13)

Where, \( \Delta T \) is the length of time considered for rolling optimization. For a certain moment, the time length to be considered in rolling optimization is equal to the difference between the latest departure time of the EV connected to each node at the current moment and the current time.

4.2.1. Charging parameter constraint. The completed charging power of each node at each moment needs not less than the sum of the charging power demand of the vehicle leaving before:
Where, $E_{i,t_0}$ is the charging quantity completed at the moment $t_0$ in node i.

In addition, the active power and reactive power should meet the boundary requirements and power factor requirements in the node charging power model.

### 4.2.2. Distributed energy output

Distributed energy output is similar to the constraint conditions in the previous section.

### 4.2.3. Tidal constraints

Similarly, the power flow and node voltage of each branch of the distribution network shall satisfy the second-order conical power flow equation shown above, as well as the upper and lower limits of branch power flow and node voltage.

Every 15 minutes, at the beginning of each period, the real-time prediction information of photovoltaic output and EV vehicle information were updated, and the rolling optimization was carried out on the basis of which. We take the period between the current time and the latest departure time of the connected EV as the research object, and solve the aforementioned intraday rolling optimization strategy to obtain the optimal charging strategy of EV in the research period.

### 5. Case analysis

Figure 2 shows the total active load curves under four conditions: orderly charging with reactive compensation, orderly charging only, unordered charging and no EV. As can be seen from the figure, the unordered charging load of EV will be centralized charging during the peak electricity price period, especially during the evening rush hour, which not only aggravates the load pressure of the grid during this period, but also leads to a great increase in the total charging cost. The orderly charging strategy can effectively transfer the charging load from peak to valley price. Whether or not to introduce reactive power compensation has little effect on the total active power load, so the two curves are close to coincidence.

We selected the node farthest from the root node to analyze the voltage level change, and the node voltage under various circumstances is shown in figure 3. It can be seen that the introduction of EV charging load will reduce the voltage of distribution network nodes; In the case of unordered charging, the node voltage will drop sharply in the evening peak period of charging, and the possibility of voltage exceeding the limit is relatively large. Under the orderly charging strategy, the node voltage level will be improved and the node voltage fluctuation will be effectively suppressed. The introduction of reactive power compensation on the basis of orderly charging can improve the node voltage level as a whole, or even raise the voltage level above the base load level, so as to further enhance the security of power grid operation.

![Figure 2](image.png)

**Figure 2.** The total active load curve of the system in different scenarios
6. Conclusion
This paper focuses on the orderly charge-discharge scheduling model of electric vehicles, and compares and analyzes the total system load curve and the voltage change curve of the terminal node under four conditions: unordered charging, orderly charging and reactive compensation, orderly charging and no vehicle. The results show that the sequential charge-discharge model proposed in this paper can effectively reduce the system peak load, reduce the peak-valley difference and suppress the node voltage fluctuation. And the addition of reactive power compensation can further enhance the reliability of power grid.

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