A scenario of vehicle-to-grid implementation and its double-layer optimal charging strategy for minimizing load variance within regional smart grids

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A B S T R A C T

As an emerging new electrical load, plug-in electric vehicles (PEVs)’ impact on the power grid has drawn increasing attention worldwide. An optimal scenario is that by digging the potential of PEVs as a moveable energy storage device, they may not harm the power grid by, for example, triggering extreme surges in demand at rush hours, conversely, the large-scale penetration of PEVs could benefit the grid through flattening the power load curve, hence, increase the stability, security and operating economy of the grid. This has become a hot issue which is known as vehicle-to-grid (V2G) technology within the framework of smart grid. In this paper, a scenario of V2G implementation within regional smart grids is discussed. Then, the problem is mathematically formulated. It is essentially an optimization problem, and the objective is to minimize the overall load variance. With the increase of the scale of PEVs and charging posts involved, the computational complexity will become tremendously high. Therefore, a double-layer optimal charging (DLOC) strategy is proposed to solve this problem. The comparative study demonstrates that the proposed DLOC algorithm can effectively solve the problem of tremendously high computational complexity arising from the large-scaled PEVs and charging posts involved.

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1. Introduction

Plug-in electric vehicles (PEVs) which are also known as grid-enabled EVs, can be generally categorized into battery EVs (BEVs), plug-in hybrid EVs (PHEVs), and extended-range EVs (EREVs) [1]. BEVs are usually equipped with large capacity batteries, which can be charged by connecting into power grid via on-board charging circuit or specialized ac–dc charging device. BEVs are wholly propelled by electric power through the electromechanical conversion of traction motors. On the contrary, in PHEVs and EREVs, both the internal combustion engine (ICE) and the electric motor are combined together. From the EV development point of view, EREVs more originate from BEVs for solving the “range anxiety problem” of BEVs [2], and PHEVs are likely derived from traditional hybrid EVs (HEVs). The key difference lies in that PHEVs are equipped with larger capacity battery packs, and their batteries can be charged by plugging into power grid. Thus, PHEVs are able to be operated with the charge–depletion mode, just like the BEVs, as well as the charge–sustained mode, which is similar to traditional HEVs [3].

With serious concerns on global warming and energy crisis, plenty of motivations for developing and commercializing PEVs have come out, such as reducing the greenhouse gases emission and the dependence on fossil fuel, increasing the energy efficiency and the utilization of renewable energy, and so on. At the same time, the impact of PEVs as an emerging new electrical load on the power grid has drawn more and more attention worldwide. The possible challenge for power grid lies in that the penetration of large number of PEVs may trigger extreme surges in demand at rush hours, and therefore, harm the stability and security of the existing power grid. Nevertheless, there are potential opportunities for power grids as well. It is predicted that if PEVs are charged at off-peak hours, the existing U.S. power grid can support the conversion of 84% of light duty vehicles to PEVs in U.S. without significantly adding investment [4]. An optimal scenario is to dig the potential of PEVs as moveable energy storage devices, which means PEVs withdraw power from grid at off-peak hours and then feedback energy deposited in the onboard batteries to grid at peak hours. This concept is also termed as vehicle-to-grid (V2G) technology [5,6]. It has been demonstrated that the V2G option can aid to flatten the power load curves [7–10], reduce power losses,
improve voltage profile [11–13], and integrate renewable energy sources [14,15]. Consequently, the implementation of V2G is believed to be able to improve the efficiency and reliability of the power grid, as well as reduce its overall operating cost and carbon emission.

The key to the implementation of V2G is how to effectively integrate information into energy conversion, transmission and distribution. V2G should be carried out within the framework of smart grid [16–18], so that the status information of power grid can be perceived. In addition, the demand information of PEV owners should also be taken into account, so that the function of PEVs as transportation means can be guaranteed. The problem formulation and mathematically modeling concerning all this crucial information can lead to the optimal charging strategies for PEVs, which aim at maximizing the benefits of V2G. Recently, several studies on the economic issues related to the V2G implementation [19–21] have been made. The basic idea is to encourage EV owners to manage their energy consumption and regulate their charging profile by using financial incentives, such as floating electricity pricing or subsidy mechanism. Nevertheless, in our opinion, these are much more complicated problems which involve quite difficult aspects, such as, the regulation of electricity production, the utilization of intermittent renewable energy, the deployment of energy storage systems, and so on. In some region, for example, in China, the design and application of floating electricity pricing is a rather crucial issue even concerned with upper-level economic reform and government policy making.

The purpose of this paper is to discuss a possible scenario of V2G implementation within regional smart grid. The related mathematical formulation is also analyzed. It is essentially an optimization problem, and the objective is to minimize the overall load variance. With the increase of the scale of PEVs and charging posts involved, the computational complexity will become tremendously high. Therefore, a double-layer optimal charging (DLOC) strategy is proposed to solve this problem.

2. A scenario of V2G implementation within regional smart grid

V2G is a rather sophisticated concept. It involves new technique patterns, innovative business models and even novel industrial rules. Although consensus has not been reached on how to define V2G to date, it can still be explicitly understood in the view of its essential missions that are expected can be achieved in the future: (1) PEVs are either being connected to grid or running on the way; (2) When PEVs are plugged into grid, they exchange electric energy with grid and try to bring positive effects to grids by functioning as energy storage devices; (3) The energy exchange between PEVs and power grid should guarantee that PEVs have sufficient electric energy left in a battery compared with the energy it has when it is fully charged [22,23]. In order to extend the lifetime of batteries, upper limit and lower limit for the Soc value of battery should be set to avoid over charging and deep discharging, which both can harm the physical constitution of batteries.

2.2. Registering the plug-in electric vehicles involved

The CCC should also understand the necessary information on PEVs involved. Vehicle owners who are willing to associate their PEVs with V2G in the regional smart grid should register their vehicles in advance by, for example, submitting the registration form online to the CCC as illustrated in Fig. 2. Then, CCC will allot a unique identity number for each PEV that are successfully registered. Consequently, CCC builds data tuples on its server to record every PEV involved:

$$CP = [CP_{ID}, CP_{Loc}, P_{CP}^{max}, Flag]$$ (1)

where the entities represent: $CP_{ID}$ is the identity number of the PEV, $CP_{Loc}$ is the location of the CP, $P_{CP}^{max}$ is the allowed maximum charging power of the CP and $Flag$ is the to indicate whether the CP is available for public use, $Flag = 0$ means this is a public CP, while, $Flag = 1$ represents this is a private CP.

2.3. Proposing request for joining V2G Operation

Normally, the CCC plans the charging schedule for every 24 h (one-day cycle), such as from 06:00 am to 05:59 am (next day). Thus, each vehicle owner who intends to join V2G operation for the coming one-day cycle should propose request to the CCC before the deadline (06:00 am), and tell when and where their PEVs will be connected to grid. This can be conducted by logging into the online application system as shown in Fig. 3.

For our mathematical modeling which will be presented in Section 3 and 4, some key information should be reported to the CCC: (1) The estimated latest moment that this PEV can be connected into grid; (2) The estimated earliest moment that this PEV will be detached from grid; (3) Which charging post this PEV will be connected to; (4) The estimated battery Soc value when this PEV connected into grid; (5) The required battery Soc value when this PEV detached from grid. For point 3), if the vehicle owner plans to connect his/her PEV into his/her private charging post, he/she reports the ID No. of the charging post directly. Otherwise, he/she reports the location or area where the PEV will stop, and request the CCC to allocate a public charging post for the PEV. For point 4), the battery Soc value when the PEV connected into grid is affected by many factors, such as, the energy efficiency of the PEV, the initial Soc when the last charging is completed, the travel point 4), the battery Soc value when the PEV connected into grid is affected by many factors, such as, the energy efficiency of the PEV, the initial Soc when the last charging is completed, the travel...
vehicle owner exactly estimate the battery SOC when his/her PEV connected into grid.

2.4. Request confirmation and data preparation

After the vehicle owner submits his/her request, the CCC attempts to include the proposed PEV into the V2G operation by allocating an available charging post for it. On the server of the CCC, there is a database to record the mappings between the location where PEV stops and all the charging posts installed nearby. The charging posts are available on first-proposed first-served. The allocation may be failed for two reasons: (1) There is not any charging post located within the area where the PEV will stop; (2) The charging posts nearby have all been allocated to other PEVs. The CCC feedbacks its allocation results to the vehicle owners and asks for their confirmation by the interface as shown in Fig. 4. If the plan is confirmed, this case will be included into the V2G operation.

Next, the CCC conducts data preparation for mathematical formulation according to the confirmed allocation plans. Firstly, it generates a set of the active charging posts as:

\[
S_{ACP} = \{A_1^{CP}, A_2^{CP}, A_3^{CP}, \ldots, A_N^{CP}\}
\]

where \(A_n^{CP}, n = 1, 2, 3, \ldots, N\), represents the \(n\)-th active charging post that is assigned to offer charging services in the next 24-h, and \(N\) is the number of the active charging posts.

Secondly, the CCP builds up a 2D data tuple for each charging post \(A_n^{CP}\) as given by (4).
In practice, the one-day cycle is evenly divided into T time-slots, and the length of each time-slot is given by $\Delta t$. For example, we can assume $\Delta t = 15$ min, and there are totally 96 time-slots in the 24 h period. Therefore, the quantities in (4) are: $\Gamma_{ACP,n}^{t}$ is the $k$-th charging service offered by $A_{CP}^{n}$, $A_{CP}^{n}$ will start at the beginning of the $\Gamma_{ACP,n}^{t}$ time-slot, $\Gamma_{ACP,n}^{t-1}$ is the $k$-th charging service offered by $A_{CP}^{n}$, $\Gamma_{ACP,n}^{t}$ will finish at the ending of the $\Gamma_{ACP,n}^{t}$ time-slot, $E_{ACP,n}^{t}$ is the ID No. of the PEV connected to $A_{CP}^{n}$ during the $k$-th charging service offered by $A_{CP}^{n}$, $B_{ACP,n}^{k}$ is the battery capacity of the PEV connected to $A_{CP}^{n}$ during the $k$-th charging service offered by $A_{CP}^{n}$, $S_{ACP,n}^{upper,k}$ is the allowed battery SOC upper limit of the PEV connected to $A_{CP}^{n}$ during the $k$-th charging service offered by $A_{CP}^{n}$, $S_{ACP,n}^{lower,k}$ is the allowed battery SOC lower limit of the PEV connected to $A_{CP}^{n}$ during the $k$-th charging service offered by $A_{CP}^{n}$, $\text{upper}_{ACP,n}^{k}$ is the estimated battery SOC value of PEV when the $k$-th charging service offered by $A_{CP}^{n}$ starts, $\text{lower}_{ACP,n}^{k}$ is the estimated battery SOC value of PEV when the $k$-th charging service offered by $A_{CP}^{n}$ ends, and $k(n)$ is the Charging post $A_{CP}^{n}$ is assigned to offer $k(n)$ times charging service in the coming one-day cycle.

Up till now, the CCC gets enough information on the PEVs, the charging posts, and the vehicle owners’ desires. Some other key points should be gotten known before the CCC can carry out optimal charging planning for every charging service, and this will be elaborated in the following sections. We must make it clear that the scenario of V2G implementation herein presented is come out by focusing on the essential functions V2G operation, it does not concern any considerations on economic incentives, business models or government policy makings.

3. Problem formulation

The optimal charging planning is to determine the charging power at each time slot for every charging post when it is offering charging services for PEVs. For each charging post, its charging power in the same time slot is kept unchanged. The objective is to minimize the overall load variance of the regional grid during the coming one-day cycle. Hence, the problem can be formulated as:

$$\min \sum_{t=1}^{T} \left( \frac{1}{T} \left( \sum_{n=1}^{N} \left( P_{Cap}.n - P_{Con} + \sum_{n=1}^{N} P_{ACP,n}^{t} \right) \right)^{2} \right)$$

Subject to:

$$P_{Cap} + \sum_{n=1}^{N} P_{ACP,n}^{t} \leq P_{max}^{t}, \quad t \in [1, T]$$

$$P_{Con} = \sum_{t=1}^{T} \left( \sum_{n=1}^{N} P_{ACP,n}^{t} \right) / T$$

$$P_{Cap} = \sum_{t=1}^{T} \left( \sum_{n=1}^{N} P_{ACP,n}^{t} \right) / T$$

$$P_{Con}^{t} = \sum_{t=1}^{T} \left( \sum_{n=1}^{N} P_{ACP,n}^{t} \right) / T$$

$$P_{Cap}^{t} = \sum_{t=1}^{T} \left( \sum_{n=1}^{N} P_{ACP,n}^{t} \right) / T$$

$$A_{CP}^{n} = \begin{cases} 1 & \text{if } i - K^{t} - 1 \in [\Gamma_{ACP,n}^{t} - \Gamma_{ACP,n}^{t-1}] \\ 0 & \text{otherwise} \end{cases}, \quad n \in [1, N]$$

4. Double-layer optimal charging strategy

In order to solve the problem of tremendously high computational complexity arising from large-scaled PEVs and charging posts involved, a double-layer optimal charging (DLOC) strategy is proposed. The basic idea is to categorize all the charging posts in the regional grid under the administration of several charging stations. In the first layer optimization, the CCC plans the optimal operating power schedule for each charging station as a whole aiming to minimize the overall load variance. Then in the second layer optimization, the station control server plans the charging power for each charging post under its governance, aiming to meet the instructions ordered by CCC which has been generated in the first layer optimization. Fig. 5 illustrates both the energy flow and the information flow in the proposed DLOC strategy.

The charging posts located in the same area, or connected to the same node transformer can be classified into the same charging station, such as those installed on the same streets, in the same parking lot, or in the same residential community.

4.1. First layer optimization

After the induction of charging stations, the data tuple given by (1) should be updated to:

$$CP = [CPID, CPloc, CPmax, CSID, Flag]$$

where the newly added entity CSID denotes the identity number of charging station to which this charging post is associated. Then, the set given by (3) evolves into:

$$S_{ACP}^{th} = \left[ \{ A_{CP}^{th}, A_{CP}^{th}, A_{CP}^{th}, \ldots, A_{CP}^{th} \} \right]$$
where \(S_{\text{ACP}}^{h} \) is the set of the active charging posts in the \( h \)-th charging station, \( h \in [1,H] \), and \( H \) is the number of the active charging station in the V2G operation for the coming one-day cycle. \( A_{\text{ACP}}^{h} \) denotes the \( n \)-th active charging post in the \( h \)-th charging station, \( n \in [1,N(h)] \), \( N(h) \) is the number of the active charging post in the \( h \)-th charging station. \( A_{\text{ACP}}^{h} \) is also a 2D data tuple with the same structure as illustrated in (4), but the entities are updated into:

\( \Gamma_{\text{ACP}}^{h} : \) the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \) will start at the beginning of the \( \Gamma_{\text{ACP}}^{h} \)-th time-slot;

\( \Gamma_{\text{ACP}}^{h} : \) the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \) will finish at the ending of the \( \Gamma_{\text{ACP}}^{h} \)-th time-slot;

\( \text{EV}_{\text{ACP}}^{h,k} : \) the ID No. of the PEV connected to \( A_{\text{ACP}}^{h} \) during the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \);

\( \text{BAT}_{\text{ACP}}^{h,k} : \) the battery capacity of the PEV connected to \( A_{\text{ACP}}^{h} \) during the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \);

\( \text{SoC}_{\text{ACP}}^{h,k} : \) the allowed battery SoC upper limit of the PEV connected to \( A_{\text{ACP}}^{h} \) during the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \);

\( \text{SoC}_{\text{ACP}}^{h,k} : \) the allowed battery SoC lower limit of the PEV connected to \( A_{\text{ACP}}^{h} \) during the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \);

\( \text{SoC}_{\text{ACP}}^{h,k} : \) the estimated battery SoC value of PEV when the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \) starts;

\( \text{SoC}_{\text{ACP}}^{h,k} : \) the required battery SoC value of PEV when the \( k \)-th charging service offered by \( A_{\text{ACP}}^{h} \) ends.

In the first layer optimization, the target variables become the operating power of charging stations at every time slot. Thus, the objective function given in (5) can be changed to:

\[
\min \sum_{t=1}^{T} \left[ \frac{1}{T} \left( P_{\text{Con}}^{t} - P_{\text{Arg}}^{t} + \sum_{h=1}^{H} P_{CS,h}^{t} \right) \right]^2
\]  

(15)

where \( P_{CS,h}^{t} \) is the operating power of the \( h \)-th charging station at the \( t \)-th time slot. The restraints (6) and (7) can be changed to:

\[
P_{\text{Con}}^{t} + \sum_{h=1}^{H} P_{CS,h}^{t} \leq P_{\text{Max}}^{t} \quad t \in [1,T]
\]  

(16)

\[
P_{\text{Arg}}^{t} = \frac{\sum_{t=1}^{T} \left( P_{\text{Con}}^{t} + \sum_{h=1}^{H} P_{CS,h}^{t} \right)}{T}
\]  

(17)

Moreover, restraints (8) and (9) can be rewritten as:

\[
- \sum_{n=1}^{N(h)} v_{n}^{(h)}(P_{\text{Max}}^{t,h} - P_{CS,h}^{t}) \leq \sum_{n=1}^{N(h)} v_{n}^{(h)}(P_{\text{Max}}^{t,h}) - P_{\text{Max}}^{t,h} \quad t \in [1,T]
\]  

(18)

\[
v_{n}^{(h)}(t) = \begin{cases} 0 & \text{if} \quad t \in [1,T] \backslash \{ \cup_{k=1}^{K(h)} \Gamma_{\text{ACP}}^{h,k} \} \\ 1 & \text{if} \quad t \in \cup_{k=1}^{K(h)} \Gamma_{\text{ACP}}^{h,k} \end{cases}
\]  

(19)

where \( P_{\text{Max}}^{h} \) is the allowed maximum working power of the charging post \( A_{\text{ACP}}^{h} \).

The restraints (10)–(12) are set to guarantee the demanded charging quantities of each charging service, and to make sure that the batteries are neither over charged nor deeply discharged. Considering the \( k \)-th charging service that going to be offered by the charging post \( A_{\text{ACP}}^{h} \), the charging process can be illustrated by the change of battery SoC versus time as shown in Fig. 6. As long as the battery SoC value is located in the shadow area, the restraints (10)–(12) can be satisfied.

Denoted by \( W_{h,k}^{t,h} \) the accumulated charging quantity from the first time slot to the \( t \)-th time slot offered by the charging post \( A_{\text{ACP}}^{h} \) in its \( k \)-th charging service, it can be known from Fig. 6 that the lower boundary and upper boundary of \( W_{h,k}^{t,h} \) are given by (20)–(23).
Specifications of cases simulated.

<table>
<thead>
<tr>
<th>Case</th>
<th>Number of plug-in EVs</th>
<th>Number of charging posts</th>
<th>Number of charging stations</th>
<th>Number of charging/discharging services</th>
<th>Computing time consumed (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1</td>
<td>100</td>
<td>100</td>
<td>10</td>
<td>336</td>
<td>0.38</td>
</tr>
<tr>
<td>Case 2</td>
<td>500</td>
<td>500</td>
<td>22</td>
<td>1738</td>
<td>1.27</td>
</tr>
<tr>
<td>Case 3</td>
<td>1000</td>
<td>1000</td>
<td>31</td>
<td>3433</td>
<td>3.26</td>
</tr>
<tr>
<td>Case 4</td>
<td>2000</td>
<td>2000</td>
<td>44</td>
<td>6919</td>
<td>6.17</td>
</tr>
</tbody>
</table>

Fig. 7. Power load and connected PEVs. (a) Case 1. (b) Case 3. (c) Case 4. (d) Case 5.

Thus, the accumulated charging quantity from the first time slot to the t-th time slot offered by the h-th charging station as a whole has the lower boundary and the upper boundary, given by:

\[
W^h_{ACP-e_i} (t) = \sum_{n=1}^{N(h,k)} W^h_{ACP-e_i} (t) \bigg|_{\text{lower}}
\]

\[
W^h_{ACP-e_i} (t) = \sum_{n=1}^{N(h,k)} W^h_{ACP-e_i} (t) \bigg|_{\text{upper}}
\]
Hence, the following restraint can be derived:

\[ W^h(t)_{\text{lower}} \leq \sum_{t=1}^{m} (\Delta t \cdot P_{CS-h}^t) \leq W^h(t)_{\text{upper}}, \quad m \in [1, T] \]  

Finally, the first layer optimization problem is obtained. Its objective function is given by (15), and the restraint conditions are given by (16)–(26).

### 4.2. Second layer optimization

In the second layer optimization, the station control server plans the charging power for each charging post under its governance, aiming to meet the instructions ordered by CCC which has been generated in the first layer optimization. The problem can be formulated as:

\[
\min \sum_{t=1}^{T} \left[ \frac{1}{T} \sum_{h=1}^{H} (P_{ACP-n}^t - P_{CS-n}^t)^2 \right], \quad h \in [1, H] 
\]

Subject to:

\[
-\left( P_{ACP-n}^t - P_{ACP-n}^t \right) \leq \sum_{h=1}^{H} (\Gamma_{h} - k_{n}^{t-h}) \leq \sum_{h=1}^{H} (\Gamma_{h} - k_{n}^{t-h}), \quad n \in [1, N(h)] 
\]

\[
P_{ACP-n}^t = 0, \quad t \in [1, T] - \sum_{h=1}^{H} (\Gamma_{h} - k_{n}^{t-h}) \leq \sum_{h=1}^{H} (\Gamma_{h} - k_{n}^{t-h}), \quad n \in [1, N(h)] 
\]
The proposed DLOC strategy can effectively reduce the computational complexity. For the first layer, the number of variables depends on the number of charging stations, which is dramatically shrunk compared to the number of all charging posts in the regional grid. For the second layer, the optimization program can be executed at the same time for all the charging stations. The results and performance will be presented in the following section.

5. Results and discussions

Several cases are studied to assess the performance of the proposed V2G and the DLOC strategy. A set of programs are designed to randomly generate the data needed for simulation studies. The one-day cycle starts at 06:00 am and ends at 05:59 am (next day). The time slot $D_t = 15$ min, and there are totally 96 time-slots in the 24 h period. Some practical situations are taken into account when designing the random data generation programs, for example, the conventional load is likely to reach peak values at noon and in the evening, the PEVs are likely to be connected to grid at night and at noon, and so forth. Limited by the length of the article, the details on data generation are not included herein.

Totally six cases with different problem scales are simulated. Table 1 lists the specifications of these cases. For each case, two models are employed. One is the single-layer model (Model 1) introduced in Section 3, and the other is the double-layer model (Model 2) proposed in Section 4. Fig. 7 gives the performances of V2G operation in several selected cases. It can be observed that the overall load curves are successfully flattened with the help of the PEV loads. Moreover, it can also be found

\[ \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h} \right] = \left( \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \right) \cdot \text{BAT}_{ACP-n}^{C-h} \cdot k \in [1, K(n)] \]  
\[ n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \leq \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \]  
\[ k \in [1, K(n)], \quad n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} + \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h}/\text{BAT}_{ACP-n}^{C-h} \right] \]

The proposed DLOC strategy can effectively reduce the computational complexity. For the first layer, the number of variables depends on the number of charging stations, which is dramatically shrunk compared to the number of all charging posts in the regional grid. For the second layer, the optimization program can be executed at the same time for all the charging stations. The results and performance will be presented in the following section.

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\[ n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \leq \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \]  
\[ k \in [1, K(n)], \quad n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} + \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h}/\text{BAT}_{ACP-n}^{C-h} \right] \]

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\[ n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \leq \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \]  
\[ k \in [1, K(n)], \quad n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} + \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h}/\text{BAT}_{ACP-n}^{C-h} \right] \]

The proposed DLOC strategy can effectively reduce the computational complexity. For the first layer, the number of variables depends on the number of charging stations, which is dramatically shrunk compared to the number of all charging posts in the regional grid. For the second layer, the optimization program can be executed at the same time for all the charging stations. The results and performance will be presented in the following section.

\[ \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h} \right] = \left( \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \right) \cdot \text{BAT}_{ACP-n}^{C-h} \cdot k \in [1, K(n)] \]

\[ n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \leq \text{Soc}_{ACP-n}^{C-h} - \text{Soc}_{ACP-n}^{C-h} \]  
\[ k \in [1, K(n)], \quad n \in [1, N(h)] \]  
\[ \text{Soc}_{ACP-n}^{C-h} + \sum_{t=1}^{r+1} \left[ \Delta t \cdot P_{ACP-n}^{C-h}/\text{BAT}_{ACP-n}^{C-h} \right] \]
that the peak value of the total load is slightly lower than that of the conventional load, attributed to the energy feedback of the PEVs. This demonstrates that power grid is able to contain newly added PEV loads to some extent without boosting its capacity, if the V2G operation can be effectively carried out.

The obtained PEV load curves by using two modeling methods are the same. This implies that the proposed DLOC strategy agrees very well with the design objectives. Nevertheless, this does not mean that Model 2 is exactly equivalent to Model 1. Fig. 8 gives the optimal charging schedules of the 10 charging stations in Case 1, in which, the red curves are the results of the first layer optimization of Model 2, and the blue curves are obtained by summing up the charging schedules of all the charging posts in the same charging station calculated in Model 1. It can be found that there are tiny differences between the results obtained by using these two models.

Moreover, Figs. 9 and 10 gives the optimal charging schedules of two selected charging post in Case 1 obtained by using two models, the charging post Nos. 8 and 69. Both charging posts are assigned to offer five charging services (I–IV) in the coming 24-h. The upper part of each plot gives the resulted optimal charging power provided by the corresponding charging post. With these regulated charging profiles, the electricity charging demand of the PEV connected can be guaranteed, moreover, the minimized overall load variance can be achieved. The lower part of each plot illustrates the battery SOC curve of the PEV connected to the corresponding charging post by engaging the optimal charging pattern. Subtle distinctions can also be observed in the results of the two models.

The two models are solved on the same workstation (CPU 3.20 GHz, RAM 6 GB), and the computing time consumed are listed in Table 1. For Model 2, the time consumed in the first layer optimization plus the longest time consume in the second layer optimization is given for comparing with that consumed by calculating the Model 1. Fig. 11 visually illustrates the comparison between the two models. It is worth noting that, for Case 6, the Model 1 is failed to be solved due to the running out of the RAM. Both Table 1 and Fig. 11 demonstrate that the proposed DLOC strategy can dramatically reduce the computational complexity.

6. Conclusions

In this paper, a possible scenario of V2G implementation within regional smart grid is discussed. The key information on the power grid, the charging posts, the PEVs and the vehicle owners’ demands should be perceived by the central control center, so that it can generate optimal charging schedules to fulfill the demands of each charging services, and to minimize the overall load variance in the regional grid. Next, the problem concerning V2G operation is mathematically formulated. With the increase of the scale of PEVs and charging posts involved, the computational complexity will become tremendously high. Therefore, a double-layer optimal charging (DLOC) strategy is proposed to solve this problem. Case studies demonstrated that the V2G operation can help flatten the overall power load curves and it enables power grid to contain newly added PEV loads to some extend without boosting its capacity. Comparative study shows that the proposed DLOC strategy can dramatically reduce the computational complexity. The outstanding performance on reducing overall load variance of regional power grid implies that tremendous economic and social interests can be derived from V2G implementation, which demonstrates the reasonability and necessity of developing V2G. In future work, a lot more practical issues, such as financial incentives, will be taken into account, and could be estimated and testified by using the DLOC strategy presented in this paper.

References


