International Journal of Parallel, Emergent and Distributed Systems
iFirst article, 2012, 1–17

Decentralised online charging scheduling for large populations of electric vehicles: a cyber-physical system approach

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(Received 16 January 2012; final version received 16 January 2012)

As the number of electric vehicles (EVs) grows, their electricity demands may have significant detrimental impacts on electric power grid when not scheduled properly. In this paper, we model an EV charging system as a cyber-physical system, and design a decentralised online EV charging scheduling algorithm for large populations of EVs, where the EVs can be highly heterogeneous and may join the charging system dynamically. The algorithm couples a clustering-based strategy that dynamically classifies heterogeneous EVs into multiple groups and a sliding-window iterative approach that schedules the charging demand for the EVs in each group in real time. Extensive simulation results demonstrate that our approach provides near-optimal solutions at significantly reduced complexity and communication overhead. It flattens the aggregated load on the power grid and reduces the costs of both the users and the utility.

Keywords: electric vehicle charging; scheduling; vehicle-to-grid

1. Introduction

An increasing number of electric vehicles (EVs), including plug-in hybrid EVs (PHEVs) and plug-in EVs (PEVs), are emerging in the automobile market. While the EVs can incorporate multiple renewable energy sources, avoid the pollution of exhaust and reduce the emission of greenhouse gases, their charging demand may also bring detrimental impacts on the power grid, especially when it is not managed properly. It has been reported that with battery capacities varying from 15 to 50 KWh, EVs are expected to double the average household load during charging time [14]. Hence, a major challenge is how to design a charging system that supports the EVs without causing much stress to the traditional power generation and transmission systems.

A straightforward way to optimise EV charging is through a centralised approach where a central controller collects the information of all the EVs and power plants, and calculates the optimal charging schedules directly. This approach becomes computationally infeasible when the EV population becomes very large. More importantly, it faces social and legal barriers, since users are reluctant to allow the utility to directly control their devices. An alternative approach is through distributed optimisation where each user calculates its charging schedule locally based on real-time information from the utility. This approach naturally models the Smart Grid as a cyber-physical system (CPS), tightly coupling the cyber and physical components, and enabling a better coordination among communication,

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ISSN 1744-5760 print/ISSN 1744-5779 online

http://dx.doi.org/10.1080/17445760.2012.658803
http://www.tandfonline.com

control and computation inside the system. We refer to this distributed control strategy as a *CPS approach* henceforth. While taking advantage of the communication, computation and control capabilities in Smart Grid, using this CPS approach to schedule large populations of EVs still faces many challenges. First, large populations of EVs (in millions or tens of millions) can incur significant communication overhead between the EVs and the utility. Second, the EV population can be highly heterogeneous with varying charging demands and charging time preferences, so the system needs to deal with dynamic EV arrivals and optimise the charging schedule accordingly. In addition, EVs can act not only as power consumers, but also as power suppliers through vehicle-to-grid (V2G) [8,15], which may further increase the complexity of EV charging scheduling.

In this paper, we address the above problems and develop a decentralised *online* EV charging scheduling algorithm for large populations of EVs that are heterogeneous and may join the charging system dynamically. The algorithm couples a clustering-based strategy that dynamically classifies the EVs into multiple groups and a sliding-window iterative approach that schedules the charging for the EVs in real time. We evaluate the performance of our algorithm as well as the computation and communication overhead through extensive simulations, and show that our approach provides near-optimal solution at significantly reduced complexity and communication overhead. It flattens the aggregated load on the power grid, and reduces the costs of both the users and the utility.

The rest of the paper is organised as follows. Section 2 reviews related work. Section 3 describes the EV charging problem setting and the high-level approach. Sections 4 and 5 present, respectively, the grouping algorithm and the distributed online scheduling algorithm. Section 6 evaluates the performance of our algorithms through extensive simulation. Finally, Section 7 concludes the paper.

2. Related work

Several existing studies adopt centralised approaches where the controller has complete information of all the EVs. Su and Chow [24] proposed a time-of-use-based algorithm, an estimation of distribution algorithm (EDA) based charging algorithm [25] and a particle swarm optimisation method [26] for a large number of EVs at a municipal parking station. The authors in Refs [16,9,7] analysed and modelled the EV charging problem so that the controller can collect full information of all the EVs and all power plants. However, due to the high computation complexity, the above approaches can only be applicable to a limited number of EVs. Moreover, the centralised approach typically faces the social and legal barriers, as the users are reluctant to let the third party have direct control on their devices.

The drawbacks of centralised solutions have motivated several studies that adopt distributed approaches. Rotering and Ilic [22] used dynamic programming to find economically optimal solutions for PHEVs based on the forecast of future electricity and gas prices. Their work focuses solely on reducing the cost of the users, not considering the potential impact of charging load on the grid. Mets et al. [19] presented energy control strategies based on quadratic programming, aiming to minimise the peak load and flatten the overall load profile. The main idea is to charge the EVs when the predicted global base load is low. When applying this approach to large populations of EVs, the EVs can act in unison and hence the charging demand can create new load peaks. Fan suggested that the users can adapt their charging rates according to their preferences [10], where the user preference is modelled as a willingness to pay parameter, which will impact the price and charging rate. However, such business model (price bidding) is not adopted for home users by the utilities in practice. Ma et al. [18] proposed a decentralised charging control algorithm for large populations of PEVs using Nash certainty equivalence principle. The idea is that each EV interacts with the effect of the overall charging strategy of the entire population. Their scheme introduces a *tracking cost* that punishes the EVs for deviating from the average behaviour, which is not suitable to highly heterogeneous users. Our work directly takes account of heterogeneous charging characteristics, and optimises the charging schedule for every individual EV.

Several recent studies are on demand management for general electric devices [21,6,20,12,23]. Although these approaches can be applied to EV charging, they are not applicable to large populations of heterogeneous EVs. Furthermore, they do not explore the various tradeoffs in computation, communication and control. Our study differs from them in that we combine a grouping strategy and a sliding-window iterative approach that dynamically calculates the charging schedule to accommodate dynamic EV arrivals. And we explicitly take a CPS approach that exploits the various tradeoffs.

3. Problem setting and high-level approach

In this section, we first describe the various assumptions on system architecture, and then introduce the EV charging model, and the cost and pricing models. At the end, we briefly outline our high-level approach towards the EV charging scheduling problem.

3.1 System architecture

We consider a smart grid with significant penetration of EVs. The goal of the smart charging system is to schedule the charge/discharge of the EVs to reduce the strain on the power system, and to take advantage of real-time price rate to lower the cost. An example infrastructure of a smart EV charging system is illustrated in Figure 1. For simplicity and clarity, we make the following assumptions:

- All the EVs are served by the same utility[4] and are equipped with smart charging controllers (e.g. as part of a smart metering infrastructure). A smart charging controller has both computation and control capabilities – it calculates the charging schedule for an EV and can intelligently manage the charging load.
- The EVs have two-way communication capabilities (e.g. through cellular data networks, home network or power line communication) and exchange data with the information centre. Specifically, in the grouping scheme (Section 4), EVs upload the charging properties to the information centre, while the information centre broadcasts the group information to EVs; in the online scheduling algorithm (Section 5), the information centre broadcasts real-time global load/price information to the EVs, and the EVs report their charging schedules to the information centre.
- The clocks of the system participants, i.e. the utility and the EVs, are synchronised. It can be achieved using GPS or Internet time synchronisation service.
- The EVs can be equipped with bidirectional inverters so that they can act as not only power consumers but also power suppliers, delivering electricity back to the grid, known as V2G.

3.2 EV charging model

Let $\mathcal{N}$ denote the set of EVs or users (we use EVs and users interchangeably in this paper). For EV $i \in \mathcal{N}$, let B^i denote its battery capacity and η^i denote its battery charging/discharging efficiency. Without loss of generality, we assume that all the EVs

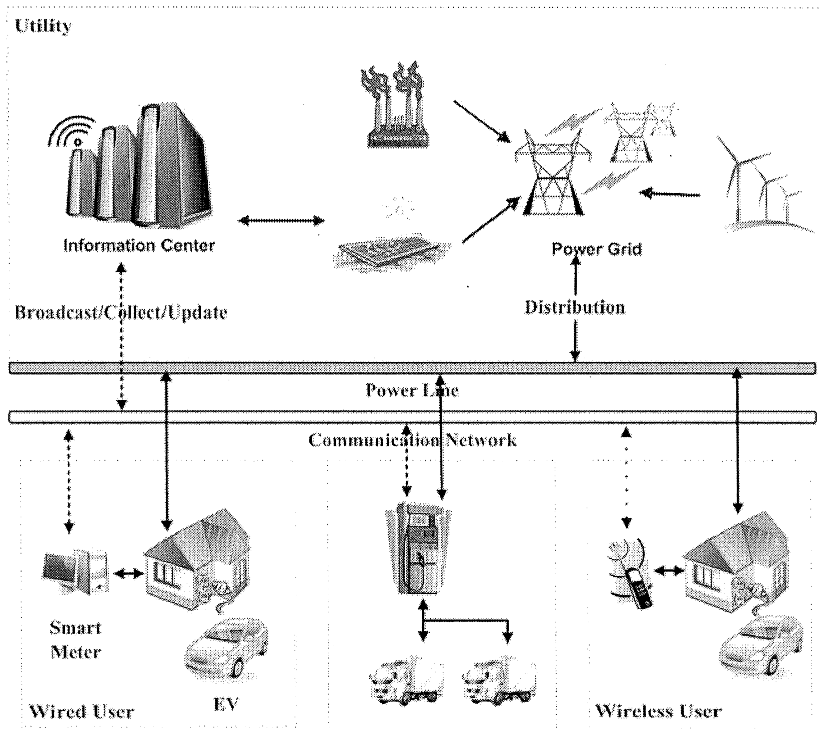

Figure 1. Infrastructure of a smart EV charging system.

are charged within a certain time period (e.g. 24 h). The charging schedule of an EV is discretised into multiple control intervals, each of length Δt (e.g. $\Delta t = 5$ min). The charging profile (i.e. the charging power for each control interval) of EV i is represented by a vector $L^i = \{l_t^i, t = 1, \ldots, T\}$, where l_t^i denotes the charging power for interval t and T is the index of the last control interval.

Let T_s^i and T_e^i denote, respectively, the start charging time and end charging time (the expected time when the EV is unplugged) for EV i. Let $l_{\max}^i$ denote the maximum charging power for EV i. Thus, $0 \le l_t^i \le l_{\max}^i$ when EV i is being charged, $l_t^i < 0$ when EV i delivers energy back to the grid (i.e. with V2G) and $l_t^i = 0$ for the non-active period.

For EV i, let $x_t^i \in [0, 1]$ denote the state of charge (SOC) at t and let E_t^i denote the amount of energy required at t (specifically, E_0^i is the initial energy requirement). Then, we have

$$E_t^i = \frac{(1 - x_t^i)B^i}{\eta^i}, \quad x_{t+1}^i = x_t^i + \frac{\eta^i l_t^i \Delta t}{B^i}. \tag{1}$$

3.3 Load demand and cost

We categorise the load on the power grid into two types: the traditional non-EV load and EV charging load. Let l_t and l_t^0 denote, respectively, the global total load and the global non-EV load at time t. Then

$$l_t = \sum_{i \in \mathcal{N}} l_t^i + l_t^0. \tag{2}$$

We assume that l_t^0 is known beforehand since current demand forecasting system [e.g. the automated load forecasting system of California ISO (CAISO) [5]] can predicate the non-EV load (or base load) accurately.

The marginal cost of generation has remarkable correlation with the total load demand [18]. Therefore, we define the cost of the utility for generating the electricity at time t as a function of the instantaneous global load l_t and denote it as $C_t(l_t)$. Clearly, the utility minimises the generation cost for the entire charging period, i.e.

$$\text{minimise}: \sum_{t=1}^{T} C_t(l_t). \tag{3}$$

The cost function can be time dependent, i.e. cost functions for different times and for the same time on different days can be varying. Furthermore, we assume that the cost will increase as the global load rises. An example of cost function is the two-step conservation rate model used by BC Hydro [1]. Also, it is possible to determine (predict) the short-term cost functions. Hence, we assume that the cost functions are known prior to the optimisation process.

3.4 Pricing and billing

Let b_i denote the bill (i.e. financial cost) of user i for EV charging. Intuitively, one may think of a pricing model that calculates the bill of user i as the summation of the instantaneous price p_t times the instantaneous load l_t^i, i.e. $\sum_t p_t l_t^i$. However, such a pricing model is not directly applicable to the decentralised charging scenario. This is because the users are non-cooperative and make independent decisions. Thus, when the price rate is announced by the utility, such a pricing model will incentivise the users to charge their EVs when the price is low (i.e. when the forecasted global load is low). In that case, a large population of EVs may act in unison, and create undesired load peaks on the grid.

The study by Mohsenian-Rad et al. [20] proposes a billing scheme where the bill of a user is proportional to its total energy consumption, i.e. $b_i \propto E_0^i$. We believe that the bill of a user should also be affected by the time of charging (since the cost of electricity varies over time). Therefore, we extend their scheme and design a *cost sharing*-based pricing model that takes the time of charging into account. In our model, the bill of a user is proportional to the weighted average energy consumption, i.e.

$$b_i \propto \alpha_i = \frac{E_0^i}{T_{\mathrm{e}}^i - T_{\mathrm{s}}^i} \sum_{t=T_{\mathrm{s}}^i}^{T_{\mathrm{e}}^i} w_t, \tag{4}$$

where we introduce the weight, $w_t \in (0, 1)$ for every time interval t ($t = 1, \ldots, T$). The weight is small for off-peak hours and large for peak hours in general. Specifically, we provide two ways to define weight w_t. The first way is to define w_t to be proportional to the non-EV load l_0^t, i.e.

$$w_t = \frac{l_t^0}{\sum_{k=1}^{T} l_k^0}. \tag{5}$$

The second way is to define w_t to be proportional to the number of users at time t, i.e.

$$w_t = \frac{\left|\{i | T_{\mathrm{s}}^i < t,\, T_{\mathrm{e}}^i > t\}\right|}{\sum_{k=1}^{T} \left|\{i | T_{\mathrm{s}}^i < k,\, T_{\mathrm{e}}^i > k\}\right|}. \tag{6}$$

In either way, the EV users are encouraged to charge their EVs during the off-peak hours (when the global load is low or when the number of active users is small). For any two users i and j, from (4) we have

$$b_j = \frac{\alpha_j}{\alpha_i} b_i. \tag{7}$$

Summing up (7) across all the users yields

$$\sum_{j \in \mathcal{N}} b_j = \frac{\sum_{j \in \mathcal{N}} \alpha_j}{\alpha_i} b_i. \tag{8}$$

Define the price-to-cost ratio [20] λ[5] as

$$\lambda = \frac{\sum_{j \in \mathcal{N}} b_j}{\sum_{t=1}^{T} C_t(l_t) - C_0}, \tag{9}$$

where C_0 denotes the cost of providing energy for non-EV load, and the denominator denotes the cost of providing energy for EV charging. Combining (2), (8) and (9), it yields

$$b_i = \frac{\lambda \alpha_i}{\sum_{j \in \mathcal{N}} \alpha_j} \left(\sum_{t=1}^{T} C_t \left(\sum_{j \in \mathcal{N}} l_t^j + l_t^0 \right) - C_0 \right). \tag{10}$$

In (10), the only variable is the charging profile $L^i = \{l_t^i, t = 1, \ldots, T\}$, for $i \in \mathcal{N}$.

Removing all the invariable components from (10), user i can minimise the bill by solving the following minimisation problem:

$$\underset{L^i}{\text{minimise}} : \sum_{t=1}^{T} C_t(l_t) = \sum_{t=1}^{T} C_t \left(l_t^i + \sum_{j \in \mathcal{N} \setminus \{i\}} l_t^j + l_t^0 \right), \tag{11}$$

which is essentially the same as (3). Therefore, under the above pricing schemes, the utility and the users have the same optimisation objective.

3.5 *High-level approach*

For large populations of EVs, obtaining the optimal charging schedule in real time will incur considerable computation and communication overhead, especially when the EVs may join the charging system dynamically. To reduce computation and communication overhead, we combine a grouping algorithm and a sliding-window iterative scheduling algorithm (see Sections 4 and 5, respectively). To accommodate dynamic EV arrivals, both algorithms run in an online manner.

Our high-level approach, as illustrated in Figure 2, is as follows. First, the information centre periodically collects the charging characteristics of the EVs that have joined the system. Based on such information, it groups those EVs into K groups dynamically, where EVs of similar charging characteristics are grouped together. Such a grouping mechanism is reasonable, as the inherent similarity of travel patterns in humans [11] can lead to similarity in charging patterns. After the EVs are grouped, the optimisation process can be carried out over the K groups instead of the individual EVs, and hence the complexity of optimisation, as well as the communication overhead, will be greatly reduced. As we shall see, the number of groups, K, is a system parameter. Intuitively, a larger K leads to higher computation and communication overhead in the distributed optimisation while it yields

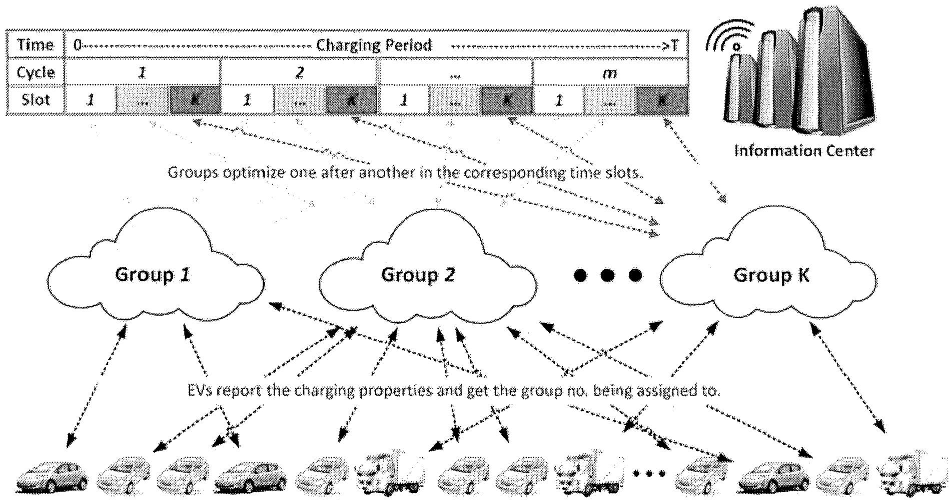

Figure 2. High-level approach for distributed online charging scheduling for large populations of EVs.

a better overall load curve. We explore the tradeoffs in choosing K through simulation in Section 6.

Second, we divide the entire charging period into m *cycles*, and equally divide each cycle into K *slots*, one for every group. Then each group optimises the charging schedule in the corresponding slot (while the charging schedules of other groups remain unchanged). After the optimisation, the EVs in a group will adjust their individual charging rates based on their energy requirements. In this way, every group optimises its charging schedule once in every cycle, and the optimisation process repeats till the end of the entire charging period.

4. Grouping large EV populations

In this section, we introduce a grouping algorithm based on K-mean clustering [17] that classifies large populations of EVs into K groups according to their charging characteristics.

The grouping algorithm (see Algorithm 1) is executed by the information centre in each cycle. At the beginning of each cycle, all the EVs that have joined the system report their charging characteristics, including the start and end charging times, the energy requirement and the maximum charging power, to the information centre. For convenience, we denote the charging attributes of EV i by a vector $x_i = (T_s^i, T_e^i, E_{t_j}^i, l_{\max}^i)$.[6] After receiving the above information, the information centre first linearly normalises the attributes into a range of $[0, 1]$ (for the calculation of the Euclidean distance) and then starts the grouping process as follows. Initially, it arbitrarily selects K EVs to be the initial centroids of the K groups, respectively. Let G denote the set of K groups formed by the algorithm. Then the algorithm proceeds by alternating between two steps:

(1) *Assignment step*. Assign an EV to the group with the shortest Euclidean distance (breaking ties arbitrarily). That is group g is the set

$$\{\mathbf{x}_i : \|\mathbf{x}_i - \mathbf{c}_g\| \leq \|\mathbf{x}_i - \mathbf{c}_h\|, \forall h \in \mathcal{G}\}, \quad \forall g \in \mathcal{G} \tag{12}$$

where $\mathbf{c}_g$ is the centroid of group g. Note that if EV i was not previously assigned to group g, then increment the counter n that counts the total number of adjustments.

Algorithm 1 Online grouping algorithm for the information centre

for cycle $j = 1$ to m **do**
  let t_j be the start time of jth cycle
  every connected EV i reports $\mathbf{x}_i = \left(T^i_{\mathrm{s}}, T^i_{\mathrm{e}}, E^i_{t_j}, l^i_{\max}\right)$ to the system
  arbitrarily pick K EVs and set them to be the centroid of the K groups, respectively
  repeat
    $n \leftarrow 0$
    for all EV i in the system **do**
      calculate the Euclidean distances $d_g = \|\mathbf{x}_i - \mathbf{c}_g\|, \forall g \in \mathcal{G}$
      find group g with the shortest distance (see (12))
      if EV i was not in group g **then**
        assign EV i to group g
        $n \leftarrow n + 1$
      end if
    end for
    update the centroids of the K groups (as in (13))
  until $n < N_t$
  sort the groups by T^g_{s} in non-decreasing order
end for

(2) *Update step*. Update the centroid of each group, i.e. calculate the new means to be the centroids of each EV group by

$$\mathbf{c}_g = \frac{1}{|g|}\sum_{\mathbf{x}_i \in g} \mathbf{x}_i, \quad \forall g \in \mathcal{G}. \tag{13}$$

The above process repeats until the total number of adjustments n in a single loop is less than the termination threshold N_t (e.g. N_t is 5% of the population in the system). At the end, we sort the groups in a non-decreasing order of T^g_{s} (such that a group with earlier start charging time is optimised first), and inform each EV to which group it is assigned.

For a group g, the group start time T^g_{s}, the group end time T^g_{e}, the group energy requirement E^g_t and the maximum charging power of the group $l^g_{\max}$ are set as follows:

$$T^g_{\mathrm{s}} = \max_{i \in g} T^i_{\mathrm{s}}, \quad T^g_{\mathrm{e}} = \min_{i \in g} T^i_{\mathrm{e}}, \tag{14}$$

$$E^g_t = \sum_{i \in g} E^i_t, \quad l^g_{\max} < \sum_{i \in g} l^i_{\max}, \tag{15}$$

where $l^i_{\max}$ is the maximum charging power of user i. By (14) and (15), the common charging time period of the group is obtained. The above algorithm runs periodically and thus, it can readily accommodate dynamic EV arrivals. Furthermore, its simplicity allows it to run efficiently over a large population of EVs.

5. Distributed online EV charging scheduling algorithm

To optimise the EVs charging, we develop a distributed charging scheduling algorithm that is run locally by the EVs. The algorithm optimises over the K EV groups (formed by the online grouping algorithm in Section 4). Thus, it can significantly lower complexity compared to the algorithms that optimise over the individual EVs.

As illustrated in Figure 2, the algorithm relies on the two-way communication between the information centre and the EVs – the information centre receives the latest charging profiles from the EVs, then updates and broadcasts the global load; the charging optimisation is performed by each EV locally based on the information received from the information centre.

The charging period is divided into m *cycles* and each cycle is divided into K *slots*. The EVs of the K groups optimise their schedules in their corresponding slots. For convenience, let $t_{g,j}$ denote the time slot for a group g in the jth cycle. Let $\{l_t^g, t = t_{g,j}, \ldots, T\}$ denote the latest charging profile of group g, where $l_t^g = \sum_{i \in g} l_t^i$ is the overall charging power of the EVs in group g at time t. Let l_t^{-g} denote the overall charging power of all the groups except group g at slot t, i.e.

$$l_t^{-g} = \sum_{h \in \mathcal{G} \backslash g} l_t^h = \sum_{h \in \mathcal{G} \backslash g} \sum_{i \in h} l_t^i, \tag{16}$$

The procedure of the information centre is summarised in Algorithm 2. Specifically, at the beginning of slot g of the jth cycle, the information centre broadcasts the non-EV load

Algorithm 2 Distributed online charging scheduling algorithm (for the information centre)

```
1: for cycle j = 1 to m do
2:    for slot g = 1 to K in the cycle j do
3:       broadcast the non-EV load {l_t^0, t = t_{g,j}, ..., T}
4:       broadcast the group energy requirement E^g_{t_{g,j}}
5:       calculate and broadcast {l_t^{-g}, t = t_{g,j}, ..., T}
6:       wait and receive charging profile {l_t^g, t = t_{g,j}, ..., T} from group g
7:    end for
8: end for
```

$\{l_t^0, t = t_{g,j}, \ldots, T\}$, the group energy requirement $E_{t_{g,j}}^g$ and the aggregated load of all the groups except group g $\{l_t^{-g}, t = t_{g,j}, \ldots, T\}$. After that, the information centre waits for the updated charging profile $\{l_t^g, t = t_{g,j}, \ldots, T\}$ from EVs in group g. The above process repeats until the end of the entire charging period.

In order to optimise the charging schedule, each EV in group g, after receiving l_t^{-g} from the information centre, optimises the group charging schedule $\{l_g^g, t = t_{g,j}, \ldots, T\}$ by solving the following minimisation problem locally.

$$\underset{L^g}{\text{minimise}} : \sum_{t=t_{g,j}}^{T} C_t\left(l_t^g + l_t^{-g} + l_t^0\right), \tag{17}$$

s.t.

$$\sum_{g \in \mathcal{G}} l_t^g + l_t^0 < L_{\max}, \quad \forall t = t_{g,j}, \ldots, T, \tag{18}$$

$$l_t^g \leq l_{\max}^g, \quad \forall t = t_{g,j}, \ldots, T, \tag{19}$$

$$l_t^g = 0, \quad \text{if } t < T_{\mathrm{s}}^g \text{ or } t > T_{\mathrm{e}}^g, \tag{20}$$

$$\sum_{t=t_{g,j}}^{T} l_t^g \Delta t = E_{t_{g,j}}^g, \quad \forall g \in \mathcal{G}, \tag{21}$$

The constraint (18) specifies that the overall EV charging power cannot exceed the capacity of the generation power grid $L_{\max}$. The constraint (19) specifies that the group charging power cannot exceed the summation of individual power constraint. The constraint (21) specifies that the optimised charging profile will meet the latest energy requirement. After solving the above problem, the EVs in group g report the updated group charging schedule $\{l_t^g, t = t_{g,j}, \ldots, T\}$ to the information centre.[7] Furthermore, each EV adjusts the individual charging schedules based on its current energy requirement $E_{t_{g,j}}^i$. Specifically, for EV i in group g, its individual charging power is adjusted to

$$l_t^i = \min\left(\frac{E_{t_{g,j}}^i}{E_{t_{g,j}}^g} l_t^g, l_{\max}^i\right), \quad \text{for } t = t_{g,j}, \ldots, T. \tag{22}$$

In this way, the group charging power l_t^g is split proportionally (without violating the power constraints) based on the individual energy requirement of each EV. The above procedure, as summarised in Algorithm 3, repeats until the end of the entire charging period.

Algorithm 3 EV charging scheduling algorithm (for each EV in group g in the jth cycle)

1: receive $\{l_t^{-g}, t = t_{g,j}, \ldots, T\}$,
2: optimise the group charging power $\{l_t^g, t = t_{g,j}, \ldots, T\}$
3: upload the new charging profile $\{l_t^g, t = t_{g,j}, \ldots, T\}$
4: determine its charging power using (22)

The above-distributed algorithm is inspired by the Gauss–Seidel method [2], where the groups run one at a time to solve the optimisation problem asynchronously. However, our approach differs from the studies [6,20,12] that adopt the Gauss–Seidel approach in the following important aspects: (1) instead of optimising the charging ahead of the actual charging period, our algorithm runs in an online manner and (2) instead of repeating until the solutions of all the groups converge, every group is optimised once in every cycle while the schedules of other groups remain fixed.

The reasons why we optimise in this way are as follows. First, it takes many (typically >10) rounds of iterations before the solutions for all the groups converge if adopting Gauss–Seidel method. Considering the communication/communication overhead, it is a very costly (sometimes even infeasible) process, especially when the number of the groups is large. Second, as EVs are assigned to groups in real time, the characteristics of the groups will change continuously from time to time. In that case, it is less useful to seek an optimal solution that is only effective for a very short period using the costly process. When the lengths of the cycles are short, the solution of our approach quickly becomes close to the optimal solution (as shown in Section 6).

With the above unique characteristics, we refer to the proposed online scheduling algorithm as a grouped-based sliding-window iterative algorithm. Coupled with the grouping algorithm, the scheduling algorithm can accommodate dynamic EV arrivals and reduce the computation/communication overhead significantly. Moreover, the above algorithm can also be applied to obtain the charging schedules when allowing V2G (i.e. delivering power back to the grid when the energy is expensive or is in severe deficiency) by allowing the charging power rate (and corresponding constraints) of a group to be negative.[8]

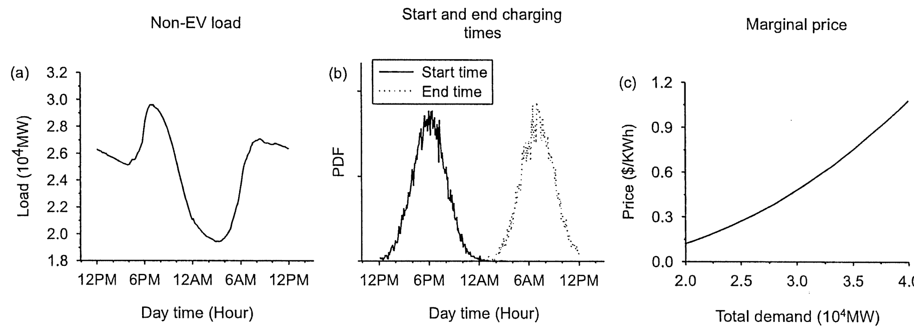

Figure 3. Simulation settings.

6. Performance evaluation

In this section, we evaluate the performance of the proposed algorithm. The simulations are based on the 5-min demand forecast published by CAISO [4]. Specifically, we captured the data from 12 pm March 1 to 12 pm March 2, which is shown in Figure 3(a). We divide this period into 24 1-h cycles. For each EV, the control interval, Δt, is set to be 5 min, which is consistent with the data from CAISO. We assume that the EV population is 3 million, which represents around 10% of the registered vehicles in California [3]. The energy requirement of an EV depends on many factors, such as battery types, charging efficiencies and driving behaviour. In the simulation, for simplicity we assume that the energy requirements of EVs follow a uniform distribution between 15 and 25 KWh.

The global maximum load constraint is set to be 4×10^4 MW and local maximum charging power is set to be 5 KW. The start and end charging times of each EV are generated following a Gaussian distribution, as shown in Figure 3(b).[9] Specifically, the mean start and end charging time are 6 pm and 7 am, respectively, with standard deviation of 2 h. Without loss of generality, we assume that the cost function of the utility is a quadratic increasing function of the instant global load, as shown in Figure 3(c), and solve the quadratic optimisation problem using CPLEX [13].

In the simulation, we consider the following three charging schemes: (i) *uniform* scheme where user i charges at a fixed rate of $l_t^i = E_0^i/(T_s^i - T_e^i)$, $\forall i \in \mathcal{N}$; (ii) *non-V2G* scheme where all users follow the proposed online charging scheduling algorithm without using V2G and (iii) V2G scheme where all users follow the proposed online charging scheduling algorithm and may use V2G (i.e. EVs can deliver energy back to grid).

The metrics we use are the utility cost, user cost (bill) and *peak-to-average ratio* (PAR) of the global load. Unless otherwise stated, the price-to-cost ratio, λ, is one. That is, the sum of the user bills equals to the cost of the utility (in other words, the system is budget balanced).

6.1 Impact of the number of groups

First, we investigate the impact of the number of groups K on the group characteristics. As stated in Section 4, a larger K leads to a better control of the EVs, since the EVs in the same group will be more 'similar' to each other. Figure 4 shows the average standard deviation of the start charging time T_s^i, end charging time T_e^i and energy requirement E_0^i of the EVs in all the groups, when varying K from 10 to 500. Observe that the standard deviations of the three properties decrease as the number of groups K grows. The standard deviations of the three properties decrease rapidly when K increases from 10 to 100 and then decrease

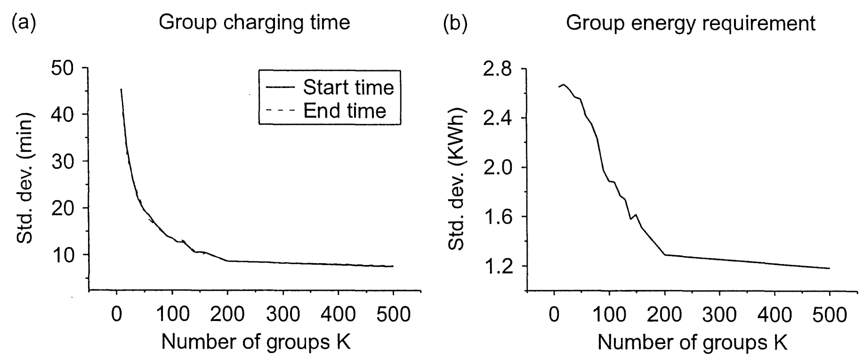

Figure 4. Average standard deviation of all the groups versus the number of groups, K.

slowly afterwards. Note that a larger K will also lead to higher communication and control overheads. In the rest of this section, we set K to be 120 and thus the length of the slot for a group is 30 s (1-h cycle divided by 120 slots), within which the optimisation can be finished by smart metres of moderate computation and communication capabilities.

6.2 *Scheduling algorithm*

In the following, we present the load results and then investigate the communication and computation overheads. The user and utility costs are evaluated at the end.

6.2.1 Load results

Figure 5(a) plots the optimised global load (including both EV and non-EV loads) curves under the non-V2G charging scheme. Observe that as more and more EVs join the system and begin charging, the global load increases correspondingly over time. As desired, the curves only rise during off-peak hours after the EV charging demand is properly scheduled, while the load at peak hours remains unchanged. The optimised EV charging load fills the forecasted global load valleys well. For clarity, we only show the selected

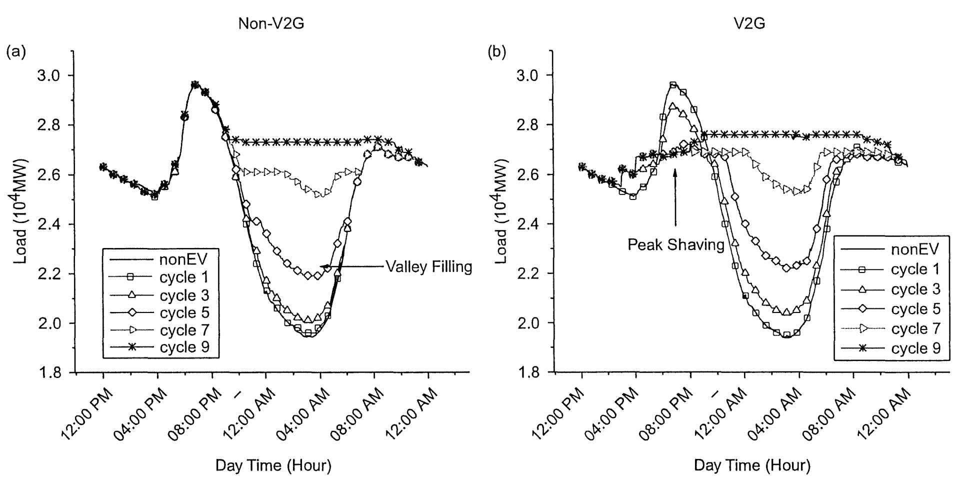

Figure 5. Load curves under different charging schemes. Cycle i represents the optimised load curve after the ith cycle. Selected curves of first nine cycles are shown.

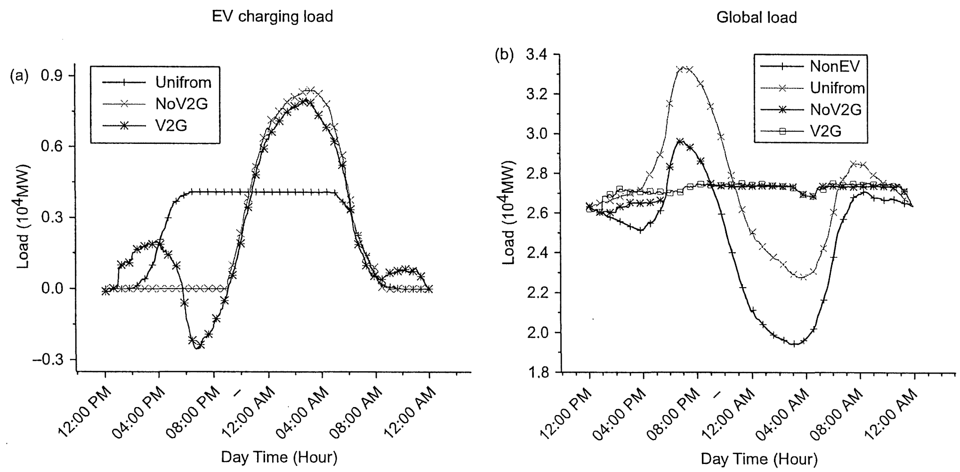

Figure 6. Overall curves under uniform, non-V2G and V2G schemes.

scheduled load curves from the first nine cycles, i.e. before 9 pm, since most EVs arrive by this time (refer Figure 3(b)) and the global load curves do not change significantly. It actually confirms the fast convergence of our scheduling algorithm.

Figure 5(b) plots the load curves under the V2G scheme. Observe that in addition to achieving the similar effect of valley filling as observed in the non-V2G scheme, it further shaves the load peak (i.e. from 6 to 9 pm) as the EVs are scheduled to deliver the charged energy back to the grid during the forecasted peak hours. In this scheme, some early arrived EVs will be recharged quickly during the first several hours (i.e. 1–5 pm) when they foresee the forecasted load peak later. Then, when it comes to the peak hours (the real-time cost/price is high as well), those EVs begin discharging certain amount of their remaining energy of the battery for gain to minimise their costs. Essentially, the EVs behave as an energy cache that can smooth the load demand over time and hence such mechanism reduces the stress on the power system.

Figure 6(a) plots the overall EV charging load demand curves in three charging schemes. In the uniform scheme, the load increases synchronously when EVs join the charging system and decreases when the EVs leave. All the EVs maintain fixed power rates during their entire charging periods. On the contrary, the scheduled load curves in non-V2G scheme and V2G scheme are much more responsive to the non-EV load, since EVs can incorporate the global load information in controlling the charging load by either throttling the charging rate or delivering energy back to the grid (as indicated by the load demand being negative in the 'V2G' curve).

Figure 6(b) plots the global load curves using the three charging schemes, respectively. When adopting uniform scheme, the EVs do not take the non-EV load and real-time cost/price into account. Consequently, as more and more EVs charge in the peak hours, the load demand from EVs exacerbates the already high load peak by around 13% (from 3.0×10^4 to 3.4×10^4 MW). Using our EV charging scheme, the EV charging load demand is properly scheduled. When adopting the V2G scheme, the EV loads in the first several hours are slightly higher than those under non-V2G scheme, indicating that some EVs will cache some amount of energy during off-peak hours, which is delivered back later to shave the load peak at the peak hours. Compared with uniform scheme, the PAR is

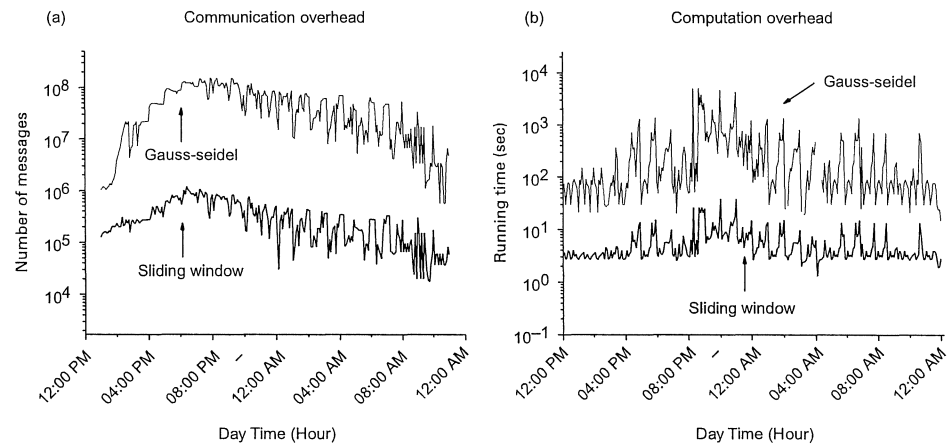

Figure 7. Communication and computation of our proposed scheme and Gauss–Seidel method.

reduced by 7.7% (from 1.178 to 1.087) under the non-V2G scheme, and is reduced by 14.2% under the V2G scheme.

6.2.2 Communication and computation overheads

Our proposed algorithm uses a sliding-window iterative method, which can significantly reduce the communication and computation overheads compared to the Gauss–Seidel method. Figure 7(a),(b) plots the communication overhead (in terms of the total number of messages sent and received) and computation overhead (in terms of running time in the simulation) in each interval using the sliding-window approach and the Gauss–Seidel approach, respectively. We observe that the communication and computation overheads under our approach are significantly lower than those under the Gauss–Seidel approach. On average, the total number of messages sent in our approach is only 1% of that in Gauss–Seidel approach. And the average total run time of the simulation is reduced from 9823 s (using Gauss–Seidel iteration) to 160 s (using our approach) on a PC with Intel Core i7 2.67 GHz and 8 G memory.

Figure 8 demonstrates the global load comparison between the sliding-window approach and the Gauss–Seidel method in both 'non-V2G' and 'V2G' charging schemes. It can be observed that the curves in the first several hours show slight differences. The reason is that by the sliding-window iterative approach, the early arrived EVs have no knowledge of the EVs that are arrived later. Correspondingly, the early EVs do not start charging immediately when they foresee the predicted load valley. The Gauss–Seidel approach runs in an off-line manner, i.e. it has the complete knowledge of the entire charging period. However, the result from Gauss–Seidel is, although optimal theoretically, not directly applicable to an online system. By comparison, we note that the load curves of sliding-window iterative approach become close to the optimal Gauss–Seidel curves quickly, and lead to similar PAR compared to the optimal Gauss–Seidel approach. When not allowing V2G, our approach leads to the same PAR as the Gauss–Seidel approach; when allowing V2G, the PAR under our approach is slightly larger (1.55%) than that under the Gauss–Seidel approach.

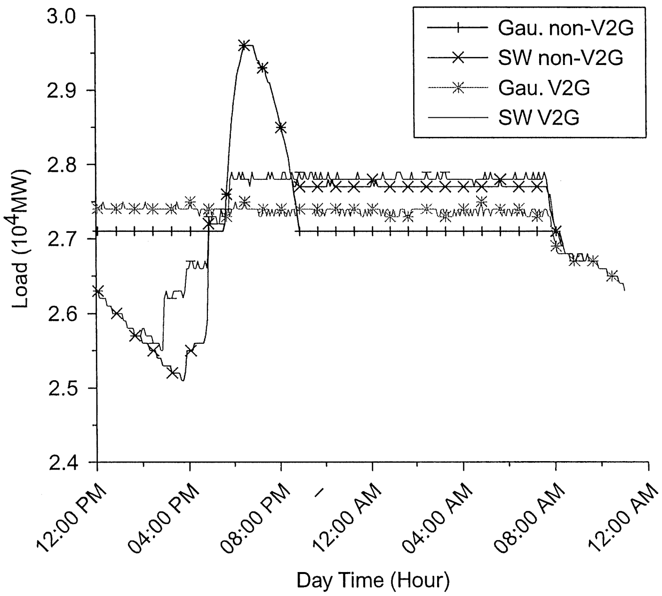

Figure 8. Overall load curves.

6.2.3 *User and utility cost*

Figure 9 plots the average user bill for the $K = 120$ groups [only the results from defining the weights using (5) are shown, as we get similar results when defining the weights using (6)]. For clarity, the results are sorted in an increasing order of the average user cost in each group using the V2G scheme. We can see that our proposed schemes reduce the average bills of the users compared to uniform charging: the average cost reduction is 5.61% under the non-V2G scheme and 11.55% under the V2G scheme. The cost of the

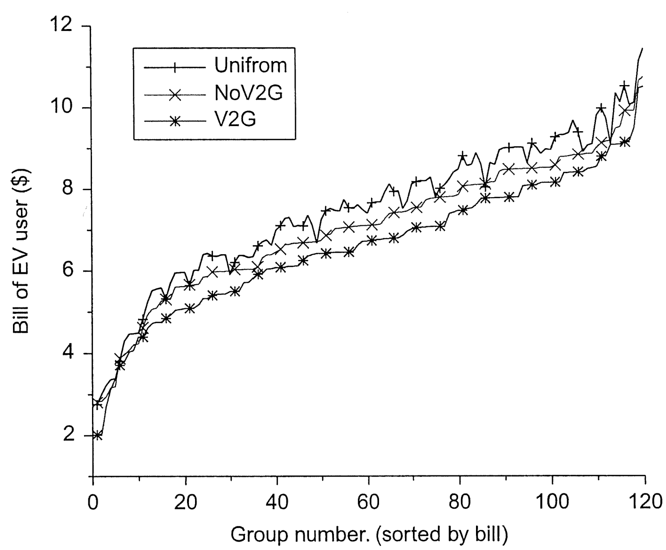

Figure 9. User bills.

utility, which is the summation of the bills of all the users in the budget-balanced system, is reduced as well.

7. Conclusion

In this paper, we developed a decentralised online EV charging scheduling algorithm for a large population of EVs with heterogeneous requirements and dynamic arrivals. The algorithm couples a clustering-based grouping method that significantly reduces the complexity of the optimisation and a sliding-window iterative approach that reduces the communication and computation overhead. Simulation results show that the optimised charging schedules can flatten the load on the grid, and reduce the PAR and the cost of both the EV users and the utility.

Acknowledgements

This work was supported in part by a USDOT-MIT-UCONN Center for Transportation and Livable Systems (CTLS) grant.

Notes

1. Email: bing@engr.uconn.edu
2. Email: peng@engr.uconn.edu
3. Email: luh@engr.uconn.edu
4. We make this assumption to simplify the communication infrastructure. The case of multiple utilities can be addressed by adding coordinators, who is responsible for information sharing among utilities.
5. Typically, the price-to-cost ratio should be greater or equal to 1 as the utility does not operate at a loss.
6. It is possible to incorporate more attributes (e.g. the geographic locations of the EVs) into the grouping algorithm, which is left as future work.
7. All the EVs in a group solve the same optimisation problem, and hence obtain the same optimal solution. For simplicity, we assume that all the EVs report their solutions. This can be further optimised by requiring only a selected number of EVs to communicate with the information centre.
8. Currently, we do not consider other indirect cost, e.g. the battery degradation cost. Incorporating other costs is left as future work.
9. We make sure that the generated time frame is feasible for each EV by eliminating the unfeasible times.

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