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Decentralized Charging Algorithm for Electrified Vehicles Connected to Smart Grid

Changsun Ahn, Chiao-Ting Li, Huei Peng

Abstract—**Intelligent management of power generation and dispatching is important when renewable energy sources and electrified vehicles (EV/PHEV) are introduced to the grid. Intermittency of renewable power and vehicle charging loads disturbs power supply and demand and could cause instability. Fortunately, EV/PHEV can be connected as controllable load or even used as energy storage, which makes it possible to reduce their negative impact and can even be explored to improve grid resilience. By coordinating power generation and charging, it is possible to reduce power generation cost and carbon emission. To improve practicality, a decentralized charging algorithm is formulated by emulating the charging pattern identified through linear programming (LP) optimization solutions. The resulting decentralized control algorithm is a function of forecasted total power demand on the grid, estimated number of vehicles, estimated EV/PHEV plug off time, and state of charge of the vehicle battery. Simulation results are presented to demonstrate the performance of the proposed decentralized algorithm.**

I. Introduction

INCREASING electric power demand in the past were mostly met by building extra centralized power plants. The electric infrastructure is designed to meet the peak demand which only occurs a few hundred hours a year in the US [2]. The recent push for electrified vehicles, including both plug-in hybrid vehicles (PHEV) and pure electric vehicle (EV) may further increase peak electrical load if left unmitigated, resulting in more demand for generation and transmission capacities.

Fortunately, EVs can be treated as controllable loads or even power sources under extraneous situations [3]. Most EVs, due to their short range, are likely to be used for commute and are plugged-in for long hours during the night. Therefore, we have flexibility to manage the charging pattern of EVs by reducing or delaying their power demand. V2G (vehicle-to-grid) [4] has been studied to explore their potentials [4, 5]. A number of studies [6-9] focused on regulation capability of EV batteries and many results show that V2G may be beneficial to the grid operators at the expense of reduced battery charging completion. Furthermore, most of those approaches are based on short time horizon and did not fully explore long-term behavior such as valley-filling. Ma [10] and Callaway [11] showed that a demand dependent pricing scheme drives a unique Nash equilibrium that results in a valley-filling effect. The valley-filling algorithm works in a decentralized way but requires that each vehicle have access to all information of every vehicle and power generation. So the developed algorithm is not really distributed. Furthermore it does not provide a closed form charging algorithm. In theory, a centralized controller can collect full information of all EVs and all power plants, utilizing future power demand and control all vehicles/plants simultaneously for optimal performance. Such an approach, however, requires extensive bi-directional communication and heavy computation and thus is not as desirable as a decentralized approach. A decentralized charging controller requires small amount information from the grid and from other vehicles.

In our vision, a practical decentralized charging controller receives simple command from the grid and only has access to information from the local vehicle (e.g., battery state of charge, SOC). A decentralized charging controller that achieves near-optimal performance (compared with a centralized controller) is the goal of this paper. This paper presents a sub-optimal control algorithm based on the one-way (G2V) power flow—and no V2G power flow is envisioned. The charging control balance among multiple objectives: minimization of the negative impacts of increased electric loads, reduction of carbon dioxide emission; and reduction of the power generation cost. The near-optimal decentralized control algorithm is formulated by emulating the optimal charging pattern obtained from a Linear Programming (LP) technique that solves a centralized optimization problem. The optimal decentralized control algorithm is formulated as a function of few pieces of information from the grid operator and forecasted total power demand of the grid, estimated plug off time, and the battery SOC of the local vehicle. The performance of the decentralized controller is then verified using simulations.

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C. Ahn is a research fellow in the Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109, USA (phone: 734-647-9732; e-mail: sunahn@umich.edu).

C. Li is a graduate student in the Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109, USA (phone: 734-647-9732; e-mail: ctli@umich.edu).

H. Peng is a professor of the Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI 48109, USA (e-mail: hpeng@umich.edu).

II. PROBLEM DESCRIPTION

A. Target Grid

In this paper, the area supported by DTE Energy in Michigan is used to size the power generation and load. The electric power demand in the DTE area varies from around 5000MW to 8000MW and the electric load in summer is usually higher than the winter load due to air-conditioning. Peak electric demand occurs around 2pm in the summer and 7 pm in the winter. Lowest demand occurs around 4 am. The hourly power demand for typical summer and winter days is shown in Fig. 1, where the load below about 5500 MW is defined as base load, the load between 5500~7200 MW is defined as intermediate load, and above 7200 MW is defined as peak load. The summer demand profile will be used for the design of controller as a base power demand. The same design process of course can be used for the winter load.

B. Electric Vehicles and Commuting Patterns

The target electrified vehicle is assumed to be designed for commuting. The number of electrified vehicles is assumed to be two million, which is about 25% of the number of registered passenger vehicles in Michigan. The commuting pattern is assumed as follows: the owners leave home for work on average at 7:20 am with 2 hours of standard deviation; the owners return home 4:30 pm with a standard deviation of 4.3 hours; the battery state of charge (SOC) when plugged-in is also assumed to be described by a normal distribution with a mean of 0.5 and a standard deviation of 0.1; the vehicles are charged only during the night (not at work). The mean and standard deviation of the commute patterns are based on observed traffic flow data acquired from Interstate Highway 5 [12]. The battery capacity is assumed to be 16kWh [13], the charger capacity is assumed to be 120V/15A (Level I) [14] which represents a more challenging scenario for controls, and the allowed SOC range is assumed to be 0.3~0.85 [14].

If we simulate a scenario where every EV starts charging unmitigated at the moment they are plugged in, the electric power demand is as shown in Fig. 2. The vehicle charging demand increases the peak electricity demand and it will require the peak load power plants to operate, which have significantly higher electricity generation cost because they are usually use fuels that have higher cost.

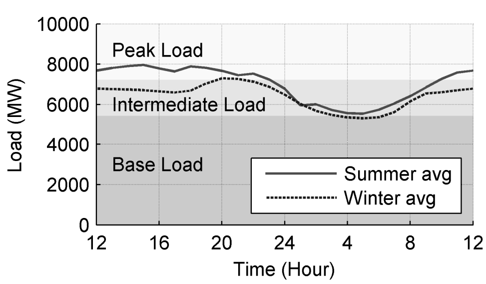

Fig. 1. Average base power demand of DTE service area [1]

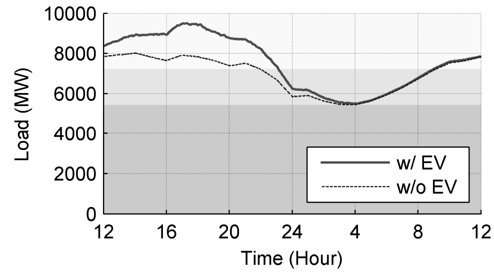

Fig. 2. Power demand profile when 2M EVs are charged with no control (start charging at the maximum power the moment they plug in)

C. Objective and Constraints

The objective is to develop a decentralized charging control algorithm that minimizes generating cost and/or carbon dioxide emission of power plants, and in the meantime the batteries should be fully charged for those vehicles that are plugged-in to the grid long enough. To accomplish the objective, the EV loads should be shifted to the valley (valley-filling) to minimize the operation of the peak load plants, and in the meantime the charging power should be distributed in such a way that those vehicles with lower SOC or earlier plug-off time will receive higher charging power.

III. CONTROL ALGORITHM DESIGN

The design process begins by solving an optimal control problem where all information is available and a central controller determines the charging power of each EV. The solution of this control problem is centralized and is not very practical. However, it serves as a benchmark, and its control pattern serves as a role model for a decentralized control algorithm. A decentralized charging control algorithm can be derived by emulating the optimal control behavior using only the information broadcasted by the plant operator and the local information from the EV. The remaining contents of this chapter include: formulation of an optimal control problem and the solution; analysis of the optimal control patterns; and, derivation of a decentralized control algorithm.

A. Formulation of the Optimal Control Problem

The cost function to be minimized is the electricity generation cost and total carbon dioxide emissions. The generation cost curves are based on economic dispatch rules of the service providers. A service provider typically manages many types of plants and the plants can be categorized into base load plants, intermediate load plants, and peak load plants. Nuclear and coal power plants are designated for the base load; combined cycle power plants for the intermediate load; and gas turbines for the peak load.

An instantaneous cost curve for the target grid is derived using the method reported in [15], as shown in Fig. 3 (a). The carbon dioxide emission curve is achieved using the tables of carbon dioxide emission by fuel types [16] and by plant types [17, 18], as shown in Fig. 3 (b). To achieve the

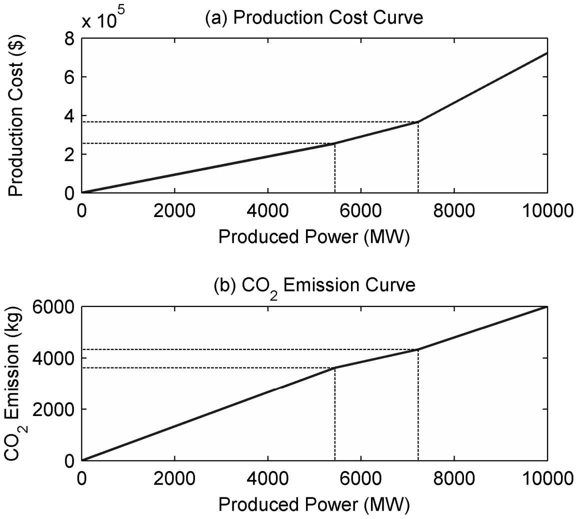

Fig. 3. Power generation cost curve (a) and CO_2 emission curve (b)

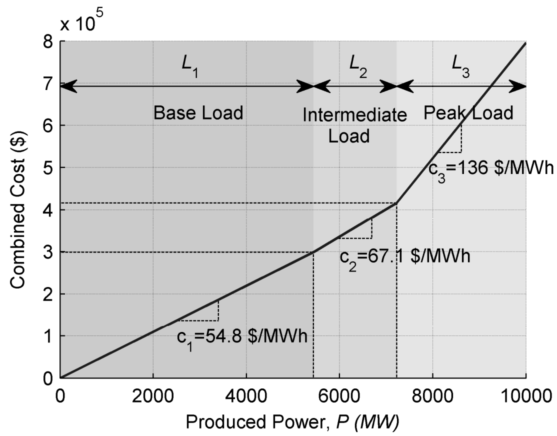

Fig. 4. Combined cost curve, $C(P(t))$, (Generation cost + CO_2 emission), The carbon tax of \$12/tCO_2 is used.

minimization of production cost and carbon dioxide emission, we combined these two curves using a carbon tax concept [19]. The combined cost curve for a carbon tax of \$12/tCO_2 is shown in Fig. 4.

Given the cost curve, $C(P(t))$, shown in Figure 4, the optimal control problem is defined as follows:

$$\min_{P_{EV}(t,n)} \sum_{t=0}^{T} C\left(P(t)\right), \tag{1}$$

where

$$P(t) = \sum_{n=1}^{N} P_{EV}(t,n) + P_{base}(t), \tag{2}$$

$P_{base}(t)$ is base grid load (the non-EV electric load) and $P_{EV}(t, n)$ is the control variable for t=0,1,2,…,T, n=1,2,3,…,N. The constraints are

$$\sum_{t=0}^{T} P_{EV}(t,n) \cdot \Delta t = B(n), \tag{3}$$

$$0 \le P_{EV}(t,n) \le P_{EV\,\mathrm{lim}}(t,n), \tag{4}$$

where $B(n)$ is the total energy to fully charge the battery # n, for n=1,2,3,…,N, and $P_{EV\mathrm{lim}}(t)$ is the charging power limit of the battery determined as follows:

$$P_{EV\,\mathrm{lim}}(t,n) = \begin{cases} P_{EV\,\max}, & \textit{when the vehicle } n \textit{ is on-line} \\ 0 & , \textit{when the vehicle } n \textit{ is off-line} \end{cases}. \tag{5}$$

If the combined cost curve is linear, then the optimization problem is trivial and can be solved by using Linear Programming (LP). However, the cost curve is not linear and a nonlinear optimization problem with a large number of control variables requires tremendous computation load. Fortunately, the cost curve is piece-wise linear and has increasing convexity. Therefore, we can use a LP technique by adding more control variables and constraints. Details are shown in the following section.

B. Solution through Linear Programming

The optimization problem with a piece-wise linear function that has increasing convexity can be solved by modifying the cost function, as follows:

$$\min_{P_{EV}(t,n)} \sum_{t=0}^{T} \left(c_1 \cdot q_1(t) + c_2 \cdot q_2(t) + c_3 \cdot q_3(t)\right), \tag{6}$$

where $0<c_1<c_2<c_3$ are defined in Fig. 4. The constraints consist of linear constraints and conditional constraints. The linear constraints are

$$P(t) = q_1(t) + q_2(t) + q_3(t) = \sum_{n=1}^{N} P_{EV}(t,n) + P_{base}(t), \tag{7}$$

$$\sum_{t=0}^{T} P_{EV}(t,n) = B(n), \tag{8}$$

$$0 \le P_{EV}(t) \le P_{EV\,\mathrm{lim}}(t), \tag{9}$$

$$0 \le q_1(t) \le L_1,\ 0 \le q_2(t) \le L_2,\ 0 \le q_3(t) \le L_3. \tag{10}$$

The conditional constraints are

$$\begin{aligned} &\textit{if}\ \ P(t) < L_1:\ \ q_1(t) = P(t),\ q_2(t) = 0,\ q_3(t) = 0, \\ &\textit{if}\ \ L_1 \le P(t) < L_2:\ \begin{cases} q_1(t) = L_1, \\ q_2(t) = P(t) - L_1,\ q_3(t) = 0, \end{cases} \\ &\textit{if}\ \ P(t) \ge L_1 + L_2:\ \begin{cases} q_1(t) = L_1,\ q_2(t) = L_2, \\ q_3(t) = P(t) - L_1 - L_2, \end{cases} \end{aligned} \tag{11}$$

where $q_1(t)$, $q_2(t)$, and $q_3(t)$ vary only in the linear ranges of the piece-wise linear cost curve. The new control variables transform the nonlinear cost function to a linear cost function but they impose the conditional constraints. However, these conditional constraints are not active (the optimal solution does not exist in the hyper-plane defined by the conditional constraints) because the expensive resources would not be used unless the cheaper resources are used up completely. Therefore, we can ignore the conditional constraints and the problem can be solved using a LP technique.

C. Optimal Results and Analysis

The parameters in the optimization problem are as follows: T = 48 (48 hour time horizon with 1 hour step size), N=100 (100 vehicle fleet each representing 20,000 EVs with similar level of SOC). The plug-in times, plug-off times, and the initial SOCs are randomly generated based on the commute pattern but are known to the centralized controller. The problem is solved using the LP solver in MATLAB (linprog) and the results are shown in Fig. 5. In the optimal solution, the additional load due to EV charging fills the valley of demand profile during the night so that no additional peak power plant needs to operate. If we compare the power demand profile in Fig. 5 (b) with Fig. 2, we see the demand at evening moves to early time in the morning. Fig. 6 shows some cases of charging patterns. The EVs begin to charge their batteries as soon as the valley period begins, which is defined as the time that the base demand curve decreases below the peak load line, where we do not need turn on peak load plants. The EVs also finish their charging when the valley period ends, which is defined as the time that the base demand curve increases above the peak load line. The charging power depends on the energy to charge the battery. The EV that has a lower initial SOC shows higher charging power. The charging power closely depends on the base load and the amount of "cheap power", defined as power available from the "lower cost plants" minus the base loads.

D. Derivation of Decentralized Control Algorithm

To analyze the charging pattern, the EVs are grouped by the plug-off time. As shown in Fig. 7, the charging power of EVs with the same plug-off time shows linear dependency in SOC and the sensitivity changes over time. As a result, the charging power can be expressed as follows:

$$P_{EV}(t,n) = K(t,n)\cdot\left(SOC_{\max} - SOC(t,n)\right) \tag{12}$$

The gradient, $K(t, n)$, is computed and plotted over time and plug-off time, and shown in Fig. 8. The gradient increases as the time to plug-off decreases, or the time to valley-end decreases. Also it was found that grid congestion also affects $K(t, n)$. To extract the function of $K(t, n)$ from the optimal solution, more various demand profiles are required.

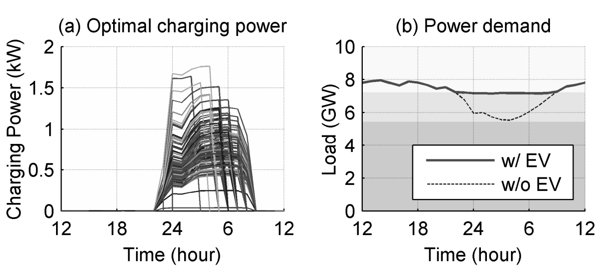

Fig. 5. Optimal results obtained from LP: the charging pattern of EVs (a) and resulted electric power demand (b).

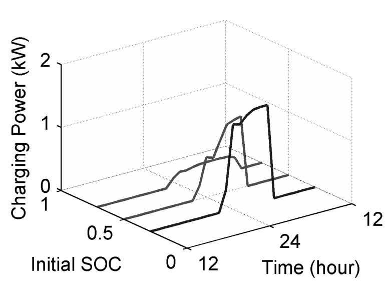

Fig. 6. Example charging patterns from the optimal solution.

Another approach to derive $P_{EV}(t, n)$ is based on the observation that charging power is highly related to available power reserve, which is defined as the difference between the peak load and the base demand profile, $L_1+L_2-P_{conv}(t)$. From the observation that the charging power is proportional to the available power, another candidate charging power pattern can be expressed as

$$P_{EV}(t,n) = R(t,n)\cdot PR_{grid}(t) \tag{13}$$

where $R(t, n)$ is a charging gain. $PR_{grid}(t)$ is the available charging power for each EV and is computed from:

$$PR_{grid}(t) = \max\left(L_1 + L_2 - P_{conv}(t),\, 0\right) / N_{EV}(t), \tag{14}$$

where $N_{EV}(t)$ is the number of EVs that are plugged in. Because the EV's battery should be fully charged the following equation must hold:

$$\begin{aligned} SOC_{\max} - SOC(t,n) &= \frac{1}{C}\int_t^{T_{end}} P_{EV}(\tau,n)\cdot d\tau \\ &= \frac{1}{C}\int_t^{T_{end}} R(\tau,n)\cdot PR_{grid}(\tau)\cdot d\tau, \end{aligned} \tag{15}$$

where T_{end} = min($t_{plug\text{-}off}$, $t_{valley\text{-}end}$) and C is the battery capacity. Because we do not know future $R(\tau, n)$, it is assumed to be constant and calculated from:

$$R(t,n) = \frac{C\left(SOC_{\max} - SOC(t,n)\right)}{\int_t^{T_{end}} PR_{grid}(\tau)\cdot d\tau}. \tag{16}$$

This calculated $R(t, n)$ is assumed to be constant over t, but it is only constant until $PR_{grid}(t)$ is updated, at which point $R(t, n)$ is recalculated using new SOC and new $PR_{grid}(t)$.

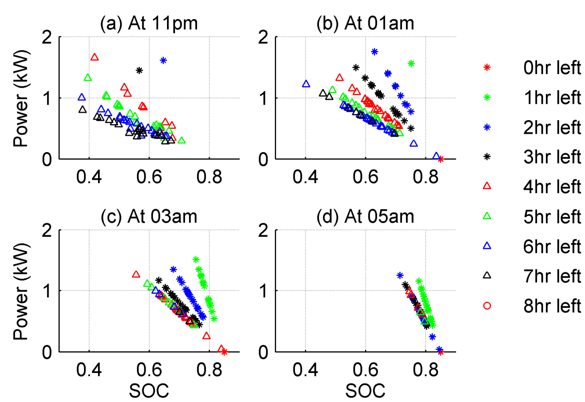

Fig. 7. Optimal charging power from the LP solutions was found to be proportional to "SOC deficit".

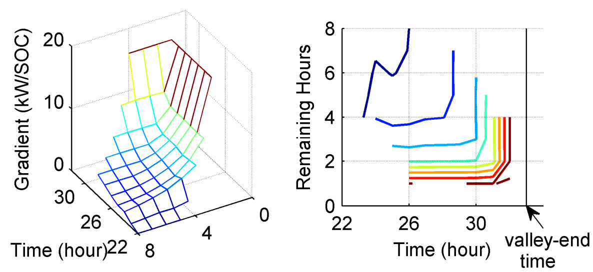

Fig. 8. Charging gain function extracted from the optimal solutions.

Plug (16) into (13), we have

$$P_{EV}(t,n)=\frac{C\cdot PR_{grid}(t)}{\int_t^{T_{end}} PR_{grid}(\tau)\cdot d\tau}\left(SOC_{\max}-SOC(t,n)\right). \quad (17)$$

which is the equation for decentralized charging algorithm. It is interesting to point out that $K(t, n)$ in (12) can be identified by comparing (12) and (17):

$$K(t,n)=\frac{C\cdot PR_{grid}(t)}{\int_t^{T_{end}} PR_{grid}(\tau)\cdot d\tau}. \quad (18)$$

The control algorithm in (17) can be implemented in a decentralized fashion, and it consists of two parts: gain and SOC deficiency. The gain becomes larger when the time to plug-off is shorter, and when the power reserve is high. The dependency on SOC deficiency ensures that vehicles with lower SOC receive higher charging power. And it is interesting to note all these dependency show simple proportional relations.

To implement the proposed controller in (17), predicted future power reserve from current time to the end of the valley hours, and the plug-off time of the vehicle are required. Accurate forecast of base grid load is already available and used in the power transmission industry, thus, the end of the problem horizon (end of valley hours) can be calculated from the forecasted demand data. The plug-off time of individual EV needs to be estimated, perhaps from user input or learned from past behaviors. Also, we assume that the number of EVs connected to the grid can be estimated from historical data, or from collection of binary on-off data from their "smart meters" or "interruptible meters". Therefore, the controller is implementable in a decentralized way. The control algorithm has a simple form and the computation can be done locally. Information from vehicle to grid is not required—except the binary plug-in data which again can be estimated and this is optional. The only information that needs to be broadcast from the grid to the vehicles is the predicted power reserve trajectory.

IV. Simulations

The decentralized controller is verified through simulations of four scenarios. Scenario 1 uses the electric demand profile of the Detroit area and Scenario 2 uses a modified electric demand profile. Scenario 3 uses the same demand profile as Scenario 1, but the estimation of $N_{EV}(t)$ is inaccurate: the estimated $N_{EV}(t)$ is assumed to be 1-hour delayed from the true value. Scenario 4 also uses the same demand profile as Scenario 1 but the total number of EVs is 25% higher than the expected. The plug-in, plug-off and initial SOC distributions are the same for all simulations.

A. Simulations without Uncertainties

Scenarios 1 and 2 are designed to verify the performance when there is no uncertainties in forecasted demand profiles and estimated $N_{EV}(t)$. In both scenarios, we assume that the base load is perfectly forecasted. The baseline controller

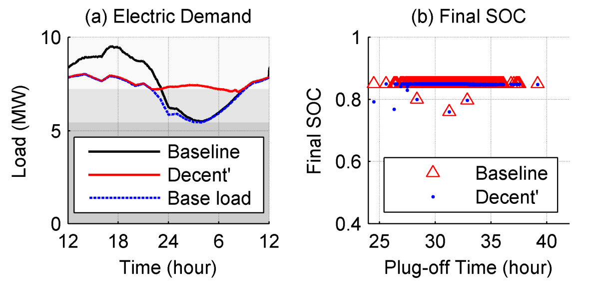

Fig. 9. Demand profile managed by the decentralized controller (a) and charging performance comparison to baseline controller (b), Simulated with the demand profile of DTE area.

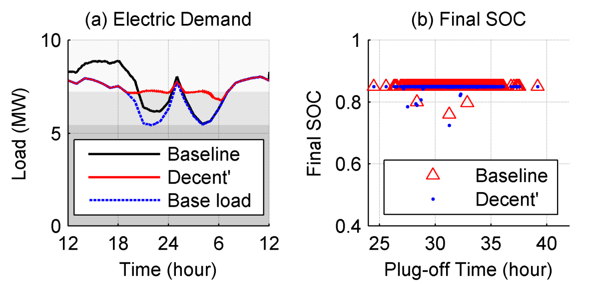

Fig. 10. Demand profile managed by the decentralized controller (a) and charging performance comparison to baseline controller (b), Simulated with the modified demand profile of DTE area.

allows un-mitigated charging behavior, and starts charging the battery with maximum power immediately at plug-in. The baseline controller achieves highest full-charging performance but because it uses the peak power sources, the power generation cost is much higher. The centralized optimal controller is the implementation of the LP optimization results, which achieves best valley-filling performance because of its non-causal control ability. Its performance was shown in Fig. 5 for the first scenario.

Simulation results of the decentralized control algorithm for Scenario 1 are shown in Fig. 9. The charging load is shifted to the valley hours, reducing the cost function without deteriorating the battery charging performance. Simulation results of Scenario 2 are shown in Fig. 10. The decentralized controller designed using the optimization results of Scenario 1, works well, which shows that the proposed decentralized controller is robust under base load profile variances. The performances of the three controllers are compared in Table I. The cost of the decentralized controller is close to the cost of the optimal controller, i.e., the decentralized controller is near-optimal.

B. Simulations with Uncertainties

Scenario 3 is designed to test the robustness against error in estimated number of electrified vehicles $N_{EV}(t)$. In this scenario, we assume that the estimated vehicle number is a time delayed version of the actual number. Scenario 4 is designed to see the effect of many more EVs than expected. The total charging energy is larger than the energy available in the valley hours so it is necessary to turn on the peak power plant. However, battery charging still happens orderly. The results of these two scenarios demonstrate the

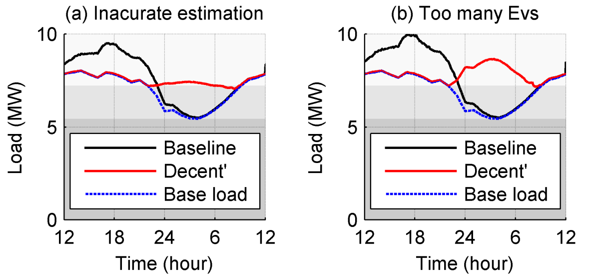

Fig. 11. Simulation results with uncertainties: (a) when $N_{EV}(t)$ estimation is inaccurate; (b) number of total EVs are more than expected.

TABLE I
PERFORMANCE OF THE DECENTRALIZED CONTROLLER COMPARED TO THE BASELINE AND THE CENTRALIZED OPTIMAL CONTROLLERS

Scenario	Controller	Generation Cost	CO_2 Emission	SOC Charging
1	Baseline	1	1	100 %
	Centralized	0.907	0.969	100 %
	Decentralized	0.923	0.976	99.99 %
2	Baseline	1	1	100 %
	Centralized	0.908	0.970	100 %
	Decentralized	0.948	0.985	99.98 %
3	Baseline	1	1	100 %
	Decentralized	0.923	0.976	99.93 %
4	Baseline	1	1	100 %
	Decentralized	0.925	0.976	99.92%

advantage of the optimal problem formulation: generation cost and CO2 emission are to be minimized but SOC charging is a hard constraint that must be satisfied.

V. CONCLUSION

This paper presents a design process for a decentralized charging algorithm for electrified vehicles. The algorithm mimics the behavior from a global optimal solution obtained through the linear programming technique which minimizes overall generation cost and carbon dioxide emission. The developed algorithm requires four pieces of information: forecasted base load profile, the estimated number of plugged vehicles, the estimated plug-off time, and the battery SOC of the vehicle being charged (the last piece of information is used locally). The performance of the proposed algorithm is compared to the centralized optimal controller (from Linear Programing) and the baseline controller (unmitigated charge). The proposed algorithm achieves a cost function very close to the centralized optimal controller and SOC charging performance similar to the baseline controller.

Uncertainties in renewable energy source and inaccuracy of base load forecasting were not studied in this study. The possibility of V2G, i.e., energy from the vehicle battery flows to the grid, was not considered. Development of the decentralized control algorithm considering these scenarios is left for future studies.

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