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Distributed Charging Control for Electric Vehicles Considering Fair Power Allocation

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Abstract— **With the increasing penetration of intermittent renewable energy sources (e.g., photovoltaic and wind generations), more reserve energy is needed to deal with the fluctuations in power supply, which increases the cost of electricity energy. In addition, the deployment of electric vehicles (EVs) further stresses the grid. In this paper, we study a smart charging problem for a network of electrical vehicles using a distributed method to counter the fluctuations in the power supply. A three-level controller is proposed. The top-level controller provides a feasible charging schedule based on the forecast power supply, EVs' initial and target state-of-charge (SOC) levels and their required plug-off times. For the middle-level controller, we develop a distributed control algorithm that adapts the charging rate of each EV to the fluctuation of power supply while providing a fair dispatch of the available power to all EVs. The bottom-level controller uses the frequency deviations to correct the difference between the forecast power and actual available power. The features of the proposed method are demonstrated using a bank of Lithium-ion batteries with ADVISOR models.**

I. INTRODUCTION

Electric vehicles and wind energy are both green technologies intended for reducing fossil fuel consumption and environmental pollution. However, the former can significantly increase the electric grid's load during charging, which could stress generation and transmission systems. The latter is intermittent in nature and its higher penetration requires more energy reserve to counter the negative impact, which increases operation costs. Fortunately, with the development of smart grid, advanced metering and communication systems enable the development of better algorithms to deal with these problems.

Many control methods already exist for EV charging. In [1], [2] and [3], a central controller is used to coordinate the charging. In [4], [5] and [6], the charging problem is cast as an optimization problem. In both approaches, decisions are made on the basis of system-level considerations, such as mitigating the distribution system loss or maximizing the load factor, but the requirements for individual EVs are neglected. The three-level hierarchical control algorithm proposed in [7] considers users in terms of the current SOC and plug-off time. In [8], a distributed control algorithm is put forward, which adapts the charging rate of each EV to the available power to ensure that every EV receives a proportionally fair share, [9], of the available power. However, neither of them considers the heterogeneity of EVs, such as initial state of charge (SOC), target SOC and battery capacity.

Wind power is a cheap and green power source, but its intermittency has been a problem. Although wind farms help to smooth the fluctuations, [10], the grid operator may still need to procure more reserves for the wind intermittency. Researchers are tackling the wind intermittency in various ways. Some research efforts have focused on reducing prediction error of wind power to assist grid operations. Another research direction focuses on developing strategies for scheduling generation sources. Several researches included wind energy probabilities when conducting optimizations for generation scheduling, [11] and [12]. Despite of the improvement achieved by the above methods, curtailment of wind power will still happen when there is very little energy storage capacity.

Therefore, it is necessary to integrate EV charging and wind intermittency. This paper proposes a three-level controller to achieve such integration. The top-level controller schedules conventional power plants and wind power to supply enough power to EVs. Meanwhile, the power can not exceed the maximum power that all EVs can absorb. Based on $average\ consensus$, the middle-level controller allocates forecasted power supply to individual EV, according to energy need and plug-off time in a distributed fashion. Consensus and similar techniques have been adopted to design distributed/decentralized algorithms in many literatures, such as [13], [14]. The bottom-level controller corrects the power allocated to each EV according to the frequency deviation, which is caused by the difference between forecasted power supply and actual power supply. The correction of the bottom-level controller does not affect the allocation criterion of the middle-level controller and the two controllers work together without confliction because of different time scales.

The remainder of the paper is organized as follows. Section 2 presents preliminaries about EVs and average consensus. Section 3 presents the proposed control method. Section 4 exposes simulation results Concluding remarks are given in Section 5.

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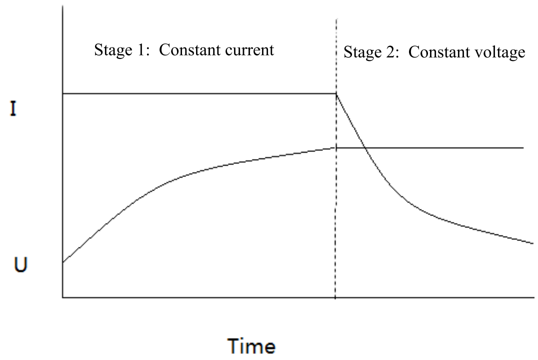

Fig. 1. CC-CV charging process of Lithium-ion batteries

II. Preliminaries

A. Elctric Vehicles

Nowadays, almost all EVs use Lithium-ion battery because of its advantages, e.g., high energy density, good load characteristics and low maintenance. SOC is the equivalent of a fuel gauge for the battery in EVs and is defined as:

$$SOC = \frac{C_R}{C} \times 100\% \tag{1}$$

with C representing the battery capacity (Ah) and C_R is the remaining battery capacity (Ah). SOC evolution, from t_1 to t_2 is formulated as:

$$SOC(t_2) = SOC(t_1) + \frac{\int_{t_1}^{t_2} I(t)dt}{C}\eta \tag{2}$$

η is the charge-discharge efficiency. It is assumed to be 1 and neglected in the following paper.

The relationship between power supply P and the charging current I is formulated as:

$$P = UI = V_{\text{OC}}I + RI^2 \tag{3}$$

where U is closed circuit voltage while V_{OC} is open circuit voltage. R is internal resistance. Actually, V_{OC} and R are dependent on SOC instead of being constant, which is considered in the model we use in Section 4.

Traditionally, constant current constant voltage (CC-CV) charging method is used to charge EVs, shown in Fig. 1. First, the EV is charged with a constant current (rated current) and when the battery voltage limit is reached, Stage 2 begins. In terms of SOC, the best work range of Lithium-ion batteries is from 20% to 85%. Actually, when Stage 1 terminates, SOC can reach 85%, so it is recommended to ignore Stage 2. The rated current is typically around 0.25C for the sake of the lifespan of batteries. See [15].

In this paper, EVs are charged with variable power to absorb the fluctuation of wind power. As regard to effects of variable charging current on Lithium-ion battery, [16] has given a detailed description in terms of capacity fade and efficiency, from which, we can conclude that Lithium-ion batteries can be charged with dynamic current. So EVs should be charged by a $smart\ charger$, which could determine the charging current of EV based on the power allocated and U. Also, smart charger can stop charging when the battery voltage limit is reached. Moreover, Lithium-ion batteries can be charged to a higher SOC with variable current than with constant current, without negative effect on batteries.

B. Average Consensus

Average consensus uses a distributed linear iteration to asymptotically compute the average of some initial values given at the nodes. We consider a network (connected graph) $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ consisting of a set of nodes $\mathcal{V} = \{1, ..., n\}$ and a set of edges $\mathcal{E}$, where each edge $\{i, j\} \in \mathcal{E}$ is an unordered pair of distinct nodes. The set of neighbors of node i is denoted by $\mathcal{N}_i = \{j | \{i, j\} \in \mathcal{E}\}$. Each node i holds an initial scalar value, $x_i(0) \in \mathbf{R}$ and $x(0) = (x_1(0), ..., x_n(0))$ denotes the vector of the initial node values on the network. The network gives the allowed communication between nodes: two nodes can communicate with each other, if and only if they are neighbors. The distributed linear iterations, shown in (4), can compute the average of the initial values, $1/n \sum_{i=1}^{n} x_i(0)$, asymptotically, using local communications only.

$$x_i(t+1) = W_{ii}x_i + \sum_{j \in \mathcal{N}_i} W_{ij}x_j(t), \quad i = 1, ...n \tag{4}$$

where $t = 0, 1, 2, ...$ is the discrete time index, and W_{ij} is the weight on x_j at node i; see [17] for the selection of the weights. The middle-level controller developed in this paper will employ an average consensus algorithm.

III. Three-level Controller

A. Objectives

We allow every EV owner to set a target SOC (SOC_{target}) and a plug-off time. The objective is to charge all EVs to their target SOC by the given plug-off time and meantime to absorb wind power fluctuation using a variable power charging approach. Only charging is permitted, i.e., at any time instant, the power allocated to each EV must be non-negative and its corresponding charging current should not exceed its rated value.

B. Approach

The controller developed in the paper consists of three levels and they work in different time scales, as shown in Fig. 2. The top-level controller provides a schedule every T_1 seconds. Its task is to determine an intermediate target SOC for each EV in the next T_1 period, based on the available long-term forecast power and the (final) targets and plug-off times for all the EVs. The middle-level controller allocates the forecast power at each time instant to the EVs in a distributed manner. This controller is updated every T_2 seconds with $T_2 = T_1/N$ for a relatively large integer N. The bottom-level controller uses frequency deviation as a feedback signal to correct the difference between the forecast power and actual available power. This difference is assumed to be relatively small. This controller runs in continuous time.

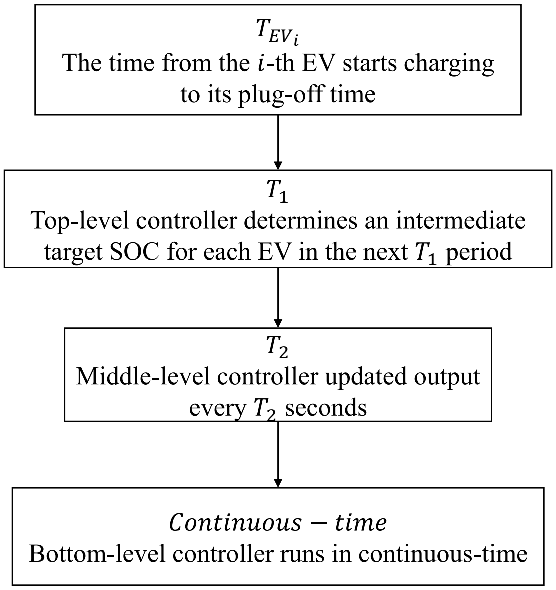

Fig. 2. Time scales of the three-level controller

1) *Top-Level Controller:* The time period for this controller is T_1. For simplicity, we assume that every EV can start charging only at the beginning of a time period. Denote by T_{EV_i} the required charging time for the i-th EV, i.e., T_{EV_i} is the time difference between the plug-off time and the starting time for charging. We also assume that $T_{EV_i} = M_i T_1$ for some integer M_i. Suppose the charging starts at kT_1 for some k and initial SOC is $SOC_i(kT_1)$. The goal of the top-level controller is to determine the intermediate SOC targets $SOC_{i,target}[(k+\kappa)T_1]$ for $\kappa = 1, 2, \ldots, M_i$ such that $SOC_{i,target}[(k+M_i)T_1] = SOC_{i,target}$. For notational simplicity, the time period T_1 will be suppressed whenever possible. We will also assume that the closed circuit voltage for each EV does not vary much during each T_1 period so that it can be assumed to be constant. This is a valid assumption because the voltage does not vary much for the SOC between 0.2 to 0.85.

The strategies for choosing the intermediate target SOCs are not the scope of this paper. This is an optimisation problem by itself. In general, we can choose according to forecast power, remaining charge time and target SOCs. And use the error between target SOCs of last batch and the actual SOCs EVs reached after last batch as a feedback signal to make the intermediate target SOCs more accurate. Moreover, moving horizon is more suitable. If intermediate target SOC is reached ahead of time, a new one can be selected. Otherwise, intermediate target SOCs are only need to updated every T_1 seconds

The supply-demand relationship when charging EVs is described with (5).

$$P_c + P_w = P_{EV} \tag{5}$$

where P_{EV} is the power demand of all EVs, P_w is the available wind power supply, which tends to be volatile,

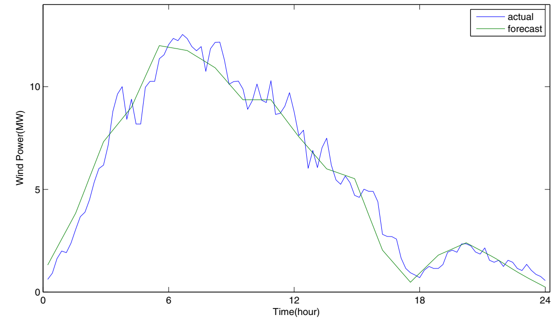

Fig. 3. A 24-h snapshot of the NREL eastern wind dataset, includes $P_{w,forecast}$ and $P_{w,actual}$

and P_c is the conventional (baseline) power supply which is assumed to have low fluctuation. We can assume that P_c is constant during each time period of T_1. The Eastern Wind Dataset, [18], from National Renewable Energy Laboratory (NREL), as shown in Fig. 3, will be used in this paper.

The constraints for the top-level control are given by

$$\begin{aligned} &\int_{kT_1}^{(k+1)T_1} P_w(t)dt + P_c(k)T_1 \geq T_1 \sum_{i=1}^{n} I_{i,\min}(k)U_i(k) \\ &\int_{kT_1}^{(k+1)T_1} P_w(t)dt + P_c(k)T_1 < T_1 \sum_{i=1}^{n} I_{i,rated}U_i(k) \end{aligned} \tag{6}$$

where n is the number of EVs that need charging from k to $k+1$, $P_c(k)$ is the available conventional power supply at time k, $I_{i,rated}$ is the rated charging current of EV_i, and $I_{i,\min}(k)$ is the minimum charging power of EV_i, given by

$$I_{i,\min}(k) = \frac{C_i[SOC_{i,target}(k+1) - SOC_i(k)]}{T_1} \tag{7}$$

2) *Middle-Level Controller:* Middle-level controller and bottom-level controller are the main work in this paper, shown in Fig. 4.

The middle-level controller is designed using an average-consensus type of algorithm which involves iterative computation and a communication network for each EV (node) to transfer information with its neighbors. For this, it is assumed that communication and computation are fast so that a large number of iterations can be done within the given time period T_1, which is needed for average consensus to converge. Accordingly, the time scale for this controller is $T_2 = T_1/M$ for a relatively large integer M. For notational simplicity, we denote mT_2 by m ($m = 0, 1 \ldots M-1$). We also assume that, for every EV, the charging current and closed-circuit voltage remain constant from m to $m+1$.

After discretizing equation (2), we get, for the i-th EV,

$$\begin{aligned} SOC_i(m+1) &= SOC_i(m) + \frac{I_i(m)T_2}{C_i} \\ &= SOC_i(m) + \frac{P_i(m)T_2}{U_i(m)C_i} \end{aligned} \tag{8}$$

Weight is designed to allocate power.

$$W_i(m) = \frac{C_i U_i(m)[SOC_{i,target} - SOC_i(m)]}{Time_i(m)} \tag{9}$$

$Time_i(m)$ is the remaining charging time of EV_i before plug-off time. If EV_i does not need charging, C_i is set to 0.

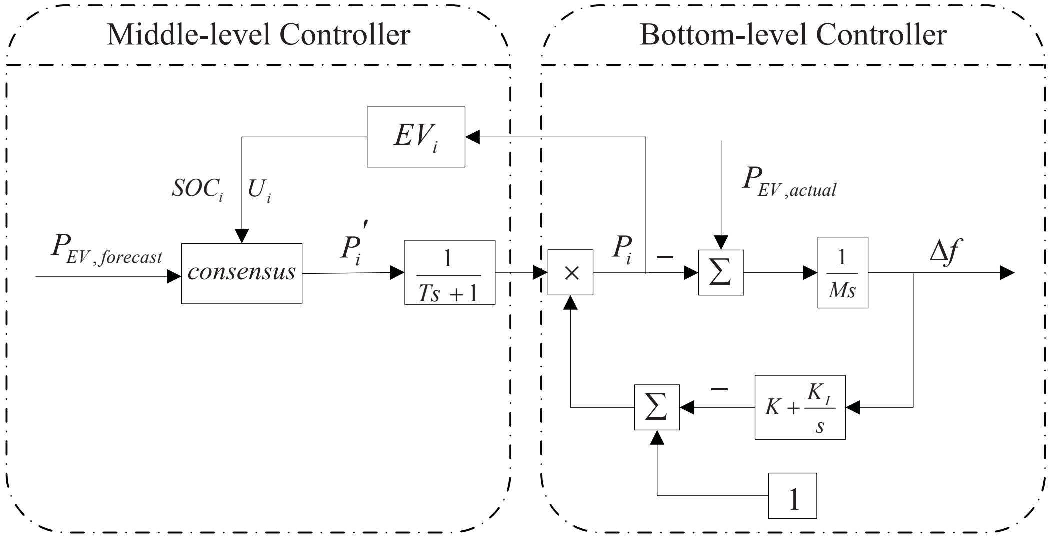

Fig. 4. Middle-level and bottom-level controllers

But the charging post is still in the network and participates in communication. Equation (9) means power is allocated according to energy need and plug-off time of different EVs.

So the power allocated to EV_i is

$$\begin{aligned} P_i(m) &= P_{EV,forecast}(m) \cdot \frac{W_i(m)}{\sum_{i=1}^{N} W_i(m)} \\ &= \frac{\frac{1}{N} P_{EV,forecast}(m)}{\frac{1}{N}\sum_{i=1}^{N} W_i(m)} \cdot W_i(m) \end{aligned} \tag{10}$$

where N, the maximum number of EVs in the network, is known to all EVs. $P_{EV,forecast}$ can be broadcast to every EV and $\frac{1}{N}\sum_{i=1}^{N} W_i(m)$ can be calculated using average consensus. Thus, $P_i(m)$ can be calculated in a distributed way. $SOC_i(m)$, $Time_i(m)$ and $U_i(m)$ are updated, which forms a closed loop and makes the allocation more precise.

However, after the allocation, $P_i(m)$ may exceed $P_{i,r}$. $P_{i,r}$ is the rated charging power of EV_i, which is regarded as a constant by the smart charger. Lithium-ion batteries had better be charged at or below $P_{i,r}$ for the sake of lifespan. So, the weight may need some adjustment. Suppose $P_p(m)$ to $P_q(m)$ surpass their rated power, weight adjustment can be done in the following way. First, set EV_p to EV_q at their rated power. After adjustment, equation (11) is established.

$$\frac{P_{EV,forecast}(m)}{[\sum_{i=1}^{N} W_i(m) - \alpha]} \cdot [\sum_{i=p}^{q} W_i(m) - \alpha] = \sum_{i=p}^{q} P_{i,r} \tag{11}$$

α is the sum of weight decrease of EV_p to EV_q and it can be calculated using average consensus too.

$$\begin{aligned} \alpha &= \frac{P_{EV,actual}(m)\sum_{i=p}^{q} W_i(m)}{P_{EV,actual}(m) - \sum_{i=p}^{q} P_{i,r}} \\ &- \frac{\sum_{i=1}^{N} W_i(m)\sum_{i=p}^{q} P_{i,r}}{P_{EV,actual}(m) - \sum_{i=p}^{q} P_{i,r}} \end{aligned} \tag{12}$$

To calculate $\sum_{i=p}^{q} W_i(m)$ and $\sum_{i=p}^{q} P_{i,r}$, just set the corresponding value of EVs to 0, except for EV_p to EV_q. Then average consensus can be used, so α can also be calculated is a distributed way. Power allocated to EV_p to EV_q has been set at its rated power and $P_j(m)$ of other EVs is calculated by

$$\begin{aligned} P_j(m) &= P_{EV,forecast}(m) \cdot \frac{W_j(m)}{\sum_{i=1}^{N} W_i(m) - \alpha} \\ & j = 1, ...p-1, q+1...N \end{aligned} \tag{13}$$

For $j = 1, ...p-1, q+1...N$, $P_j(m)$ may exceed $P_{j,r}$ because the denominator decreases from $\sum_{i=1}^{N} W_i(m)$ to $\sum_{i=1}^{N} W_i(m) - \alpha$. If this happens, set the allocated power of these EVs at their rated power, along with EV_p to EV_q, do the weight adjustment again in equation (11). Keep doing weight adjustment until every $P_i(m)$ is less than or equal to $P_{i,r}$.

3) Bottom-Level Controller: There will be inevitable imbalance between the forecast power and the actual power and also imbalance between allocated power and actually used power. To address these supply and demand imbalances, we use the frequency deviations as the feedback signal. Indeed, the power imbalances can be observed from the frequency deviation detected at each smart charger [19]. Based on this idea, the frequency deviation, Δf, works as an input signal to a proportional-integral (PI) controller. The output signal, γ, is subtracted from 1 and the result is used to multiply the power allocated by the middle-level controller to reallocate the power, which makes the sum of the power charged to each EV much close to the actual available power $P_{EV,actual}$. The output of the this controller, $P_i(m)$, is the power to be charged to EV_i at time m.

C. Algorithm

Based on the middle-level and bottom-level controllers described above, the control algorithm is developed as Algorithm 1.

IV. Case Study

The simulation in this paper is based on Matlab/Simulink and ADVISOR – the National Renewable Energy Labora-

Algorithm 1 Distributed charging control

Input: $P_{EV,forecast}(m)$, N, $U_i(m)$, C_i, $SOC_i(m)$, $SOC_{i,target}$, $Time_i(m)$, $P_{i,r}$, Δf

Output: P_i

broadcast $P_{EV,forecast}(m)$ to all EVs
if EV_i do not need to be charged **then**
    $C_i \Leftarrow 0$
end if
use average consensus to compute $\frac{1}{N}\sum_{i=1}^{N} W_i(m)$
use (10) to compute $P_i(m)$
while for all $i = 1...N$, $P_i(m) \leq P_{i,r}$ is not true **do**
    weight adjustment and compute $P_i(m)$ according to (12) and (13)
end while
$\Delta f \Rightarrow PI\ controller \Rightarrow \gamma$
$P_i \Leftarrow P_i(m)(1-\gamma)$

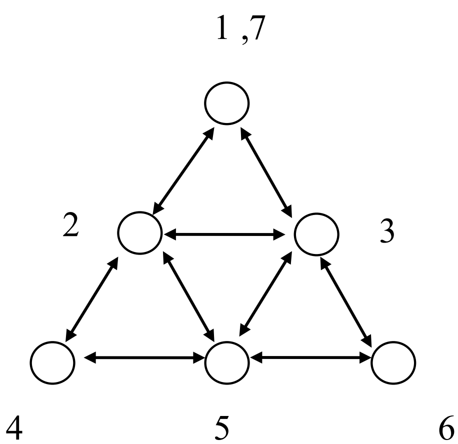

Fig. 5. Communication Network Topology of EVs

tory's advanced vehicle simulator, [20]. ADVISOR is open-source. The battery models in ADVISOR are more accurate because the parameters, like V_{OC}, R, use the data taken from battery tests and they vary with SOC and temperature. In this simulation, there are seven EVs, whose communication network topology and parameters are shown in Fig. 5 and Table I, respectively. The starting and exit times are also shown. For example, EV_7 starts charging after EV_1 finishes.

We see the communication network form a connected graph when all batteries participate in the charging process. To ensure that the communication network is connected all the time, the batteries not participating in the power dispatch will be assigned with a zero charging capacity so that they still seem to participate and maintain their communication and thus maintain the connectivity for the whole network.

In the simulation, $T_1 = 900s$, $T_2 = 10s$ and it lasts for $3600\ seconds$. In Fig. 6, $P_{EV,actual}$ is the power supply from the grid, scheduled by the top-level controller with penetration of wind power. The middle-level controller allocates $P_{EV,forecast}$ to EVs. The difference between $P_{EV,actual}$ and $P_{EV,forecast}$ causes frequency deviation, which is used as

TABLE I

PARAMETERS OF THE SEVEN EVS

NO.	Initial SOC	Target SOC	Nominal Voltage (V)	Capacity (AH)	Rated Power (KW)	Start (s)	Leave (s)
1	60%	70%	323	210	17	900	2700
2	60%	80%	305	175	13.5	0	3600
3	55%	85%	340	175	10.5	0	4500
4	70%	80%	323	245	20	900	3600
5	75%	85%	305	210	16	0	2700
6	60%	80%	340	210	18	0	4500
7	70%	85%	323	210	17	2700	5400

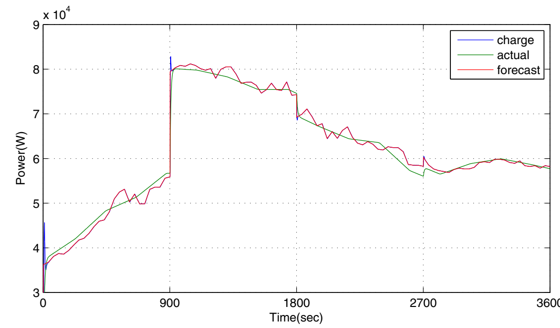

Fig. 6. Comparison of $P_{EV,forecast}$, $P_{EV,actual}$ and $P_{EV,charge}$

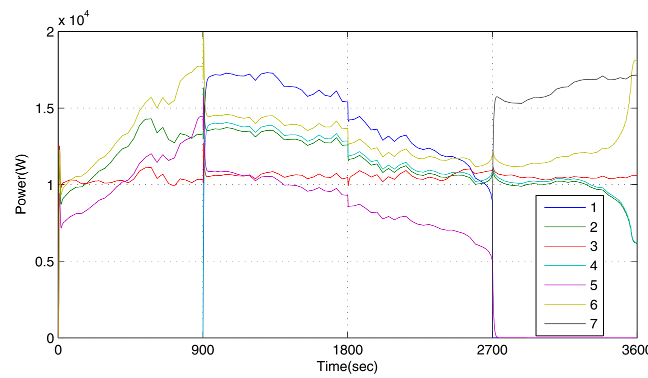

Fig. 7. Power allocated to each EV

the input signal of the bottom-level controller. The sum of the power allocated to EVs (see Fig. 7) is represented by the curve *charge* and it almost overlaps with the curve *actual*, which means the fluctuation of $P_{EV,actual}$ is well absorbed by the EVs.

It can be seen from Fig. 7 that every EV is constrained to its rated current. There is some excess caused by the reallocation of the bottom-level controller, but the amount is small and acceptable. The charging power of EV_3 almost remains the rated power during the whole simulation process because the allowed charging time is short. Fig. 7 also shows when SOC_i reaches its target SOC (see Fig. 8), the charging power decreases to 0.

Fig. 8 shows the SOC evolution of each EV. We see that every EV is charged to its target SOC before the plug-off time. Fig. 9 describes the frequency deviation, which is caused by the difference between the actual available

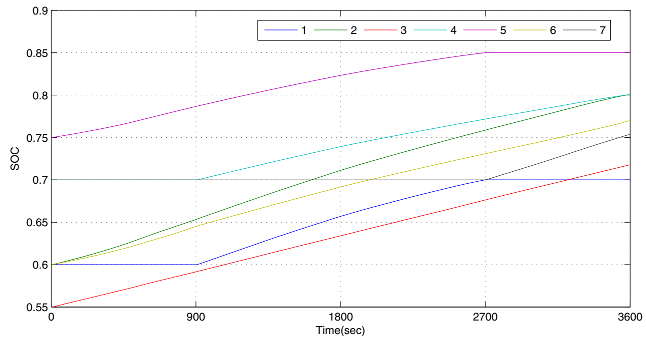

Fig. 8. SOC evolution of each EV

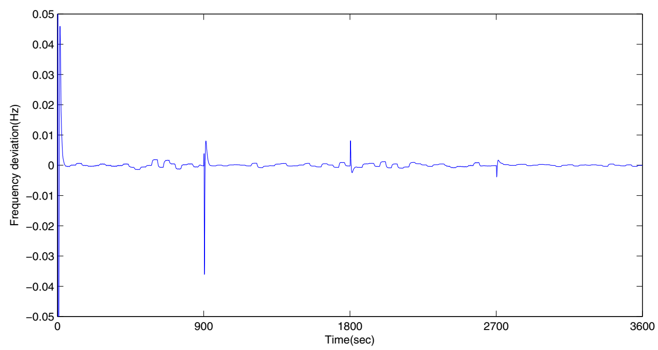

Fig. 9. Frequency deviation

power and the allocated charging power by the middle-level controller, although the two almost overlap. When the conventional power supply is changed at $900s$, $1800s$ and $2700s$, large frequency deviations occur.

V. Conclusion

This paper presents a three-level controller for smart charging of electric vehicles. The top-level controller schedules conventional power plant to provide decent power to EVs when wind power also penetrates. Based on average consensus, the middle-level controller allocates power according to the energy need and plug-off time of different EVs in a distributed way. It also guarantees that no EV exceeds its rated power. Frequency deviation is used as an input signal of the bottom-level controller to make sure the sum of power charged to every EV is as close to the power supply of the grid as possible. Simulation results show the effectiveness of our algorithm.

However, every EV may leave before its plug-off time if it has been charged to its target SOC. This can be a big problem for the top-level controller and we do not give an effective method to solve it. And if too many EVs leave, power allocated to others may exceed its rated power. So, a possible extension to our work would be to design an effective top-level controller. In addition, we can not decide when the algorithm of the middle-level controller converges. Future work may solve these problems.

References

[1] X. Gong, T. Lin, and B. Su, "Survey on the impact of electric vehicles on power distribution grid," in *Power Engineering and Automation Conference (PEAM), 2011 IEEE*, vol. 2. IEEE, 2011, pp. 553–557.

[2] J. A. P. Lopes, F. J. Soares, and P. M. R. Almeida, "Integration of electric vehicles in the electric power system," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 168–183, 2011.

[3] E. Sortomme, M. M. Hindi, S. J. MacPherson, and S. Venkata, "Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses," *Smart Grid, IEEE Transactions on*, vol. 2, no. 1, pp. 198–205, 2011.

[4] C. Ahn, C.-T. Li, and H. Peng, "Optimal decentralized charging control algorithm for electrified vehicles connected to smart grid," *Journal of Power Sources*, vol. 196, no. 23, pp. 10 369–10 379, 2011.

[5] L. Gan, U. Topcu, and S. H. Low, "Stochastic distributed protocol for electric vehicle charging with discrete charging rate," in *Power and Energy Society General Meeting, 2012 IEEE*. IEEE, 2012, pp. 1–8.

[6] Z. Ma, D. Callaway, and I. Hiskens, "Decentralized charging control for large populations of plug-in electric vehicles," in *Decision and Control (CDC), 2010 49th IEEE Conference on*. IEEE, 2010, pp. 206–212.

[7] C.-T. Li, C. Ahn, H. Peng, and J. S. Sun, "Synergistic control of plug-in vehicle charging and wind power scheduling," *Smart Grid, IEEE Transactions on*, vol. 28, no. 2, pp. 1113–1121, 2013.

[8] O. Ardakanian, C. Rosenberg, and S. Keshav, "Distributed control of electric vehicle charging," in *Proceedings of the fourth international conference on Future energy systems*. ACM, 2013, pp. 101–112.

[9] F. Kelly, "Charging and rate control for elastic traffic," *European transactions on Telecommunications*, vol. 8, no. 1, pp. 33–37, 1997.

[10] R. Doherty and M. O'Malley, "A new approach to quantify reserve demand in systems with significant installed wind capacity," *Power Systems, IEEE Transactions on*, vol. 20, no. 2, pp. 587–595, 2005.

[11] J. Hetzer, D. C. Yu, and K. Bhattarai, "An economic dispatch model incorporating wind power," *Energy Conversion, IEEE Transactions on*, vol. 23, no. 2, pp. 603–611, 2008.

[12] F. Bouffard and F. D. Galiana, "Stochastic security for operations planning with significant wind power generation," in *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*. IEEE, 2008, pp. 1–11.

[13] H. Xing, Y. Mou, M. Fu, and Z. Lin, "Distributed bisection method for economic power dispatch in smart grid," *IEEE Transactions on power systems*, vol. 30, no. 6, pp. 3024–3035, 2015.

[14] Y. Mou, H. Xing, Z. Lin, and M. Fu, "Decentralized optimal demand-side management for phev charging in a smart grid," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 726–736, 2015.

[15] Q. Wu, A. H. Nielsen, J. Østergaard, S.-T. Cha, F. Marra, and P. B. Andersen, "Modeling of electric vehicles (evs) for ev grid integration study," 2010.

[16] E. M. Krieger, "Effects of variability and rate on battery charge storage and lifespan," Ph.D. dissertation, Princeton University, 2013.

[17] L. Xiao and S. Boyd, "Fast linear iterations for distributed averaging," *Systems & Control Letters*, vol. 53, no. 1, pp. 65–78, 2004.

[18] NREL, "Obtaining the eastern wind dataset," 2013. [Online]. Available: http://www.nrel.gov/electricity/transmission/eastern_wind_dataset.html

[19] Y. Ota, H. Taniguchi, T. Nakajima, K. M. Liyanage, J. Baba, and A. Yokoyama, "Autonomous distributed v2g (vehicle-to-grid) satisfying scheduled charging," *Smart Grid, IEEE Transactions on*, vol. 3, no. 1, pp. 559–564, 2012.

[20] V. Johnson, "Battery performance models in advisor," *Journal of power sources*, vol. 110, no. 2, pp. 321–329, 2002.