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Two Approaches for Coordination of Electric Vehicle Charging and the Comparison

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Abstract: A large population of Electric Vehicles (EVs) will have a significant impact on the power grid if the charging of EVs is left uncontrolled. It is necessary to design optimal charging approach for Evs. In this study, we propose two optimal approaches for EV charging. They are congestion game-based centralized optimal approach and learning theory of game-based decentralized optimal approach. The objective of two approaches is to minimize the charging cost of each EV and meanwhile to flatten the total load profile. Under the approach based on congestion game, the problem of EV charging is described as a congestion game which solves the problem of EV acceptance that other centralized approaches have. Howerver, when there are high penetration of EVs, this approach requires significant computational capability. To develop a more practical approach, we propose the approach based on learning theory of game, where the optimized charging strategies are made locally and directly by EVs through learning in a repeated process. With the IEEE 33-bus case as the test system, results show that both approaches can flatten the total load profile, optimize power losses and improve voltage regulation effectively compared with the uncoordinated scenario.

Key words: Electric vehicle, congestion game, learning theory of game, optimal charging

INTRODUCTION

With an increased societal awareness of environmental issues and petroleum scarcity, large-scale use of EVs has been the trend for many countries. However, the charging of high penetration of EVs will have a significant impact on the power grid if it is left uncontrolled. This is because that EVs charging consumes a large amount of electrical energy and this demand of electrical power can lead to extra large and undesirable peaks in the electrical consumption (Luis, 2011; Qian *et al*., 2011; Moura *et al*., 2011; Mitra and Venayagamoorthy, 2010).

A number of studies have been undertaken to control the charging of EVs which can be divided into two categories: centralized optimal approach and decentralized optimal approach. Centralized approach requires a utility or system operator to control the charging of EVs while decentralized approach means that charging strategies are determined by EVs.

Many centralized optimal approaches for EV charging have been proposed. Different centralized optimial approaches have different objectives, such as to minimize generation costs (Zhao *et al*., 2012), power losses (Clement-Nyns *et al*., 2010; Deilami *et al*., 2011) and load variance (Sortomme *et al*., 2011), or maximize load factor (Sortomme *et al*., 2011) and supportable EV penetration level (Richardson *et al*., 2012). However, centralized approach has the defect that EV owners would not like to accept it. In order to let EV owners obey the grid, fair and attractive policies need to be made. What's more, considering large and growing number of EVs in the future, the centralized approach will ran into the curse of dimensionality and needs much more effective solution agrithom.

On the other hand, so far, few decentralized optimal approaches for EV charging have been presented. Ma *et al*. (2010) proposes a decentralized charging strategy which is only effective in the case where all EVs consume the same amount of energy at the same charging power. Gan *et al*. (2011) gives two decentralized algorithms, one synchronous and one asynchronous, of which the latter is more practical but its the convergence rate is lower and its performance is likely to be affected by communication delays and failures. Vaya and Andersson (2012) proposes a decentralized scheme based on node tariff, the amount of calculation of the scheme increases with the number of nodes in grid.

In this study, two optimal approaches for EV charging are proposed, one is the centralized optimal approach based on congestion game and the other is the decentralized optimal approach based on the learning theory of game. Firstly, the congestion game model of EV charging is built and the equilibrium solution of the game

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is attained by solving a optimal problem. Because the solution is a Nash equilibrium, each EV would like to accept it, for no one can get less cost by changing its charging schedule. However, the approach based on congestion game belongs to the category of centralized approach, the computational amounts of which increases with the increasing number of EVs. To develop a more practical approach, the approach based on learning theory of game is proposed, where the optimized charging strategies are made locally and directly by EVs to minimize their costs through learning in a repeated process. The learning model of EV charging is built and the solution procedure is given. Through simulations, the performance of both approaches are validated and compared.

SYSTEM MODEL

The charging period during a day is evenly divided into T intervals, the length of each interval is 1 h. It is assumed that the base load which represents the load of all electricity consumptions except EV charging, keeps constant in an interval.

In order to encourage EVs to charge during load valley, the dynamic charging price is proposed in this study which is modeled as a monotone increasing linear function of the total load including non-EVs base load and EVs charging load on the grid. The charging price model is given as follows:

$$\begin{cases} p_t = kq_t \\ q_t = s_t + l_t \end{cases} \tag{1}$$

where, t is charging interval, p_t is the charging price at interval t, k is price coefficient, q_t is the total load at interval t, s_t is the total charging load at interval t, l_t is the base load at interval t.

Based on Eq. 1, the charging cost of EV i is:

$$c_i = \sum_{t=1}^{T} \omega_t k q_t \tag{2}$$

where, ω_t is the charging power of EV i at interval t.

CENTRALIZED OPTIMAL APPROACH BASED ON CONGESTION GAME

Basics of congestion game: A congestion game model (Monderer and Shapley, 1996) can be defined as a tuple $(N, E, (S_i)_{i\in N}, (c_e)_{e\in E})$.

Where:
N = {1, 2,..., n} denotes the set of player
E = {1, 2,..., r} denotes the set of resource

Each player i has a strategy space S_i in which each specific strategy $s_i \in S_i$ is the set of resource that is $S_i \subseteq 2^E$.

The congestion cost of resource $e \in E$ is determined by a function $c_e(\ )$ that depends on the congestion level.

The cost of player i under the strategy combination of $s = \{s_1,..., s_n\}$ is:

$$c_i(s) = \sum_{e\in s_i} c_e(n_e(s)) \tag{3}$$

where, $n_e(s)$ denotes the number of players using resource e under the strategy combination of s and is called the congestion level of resource e.

If a congestion game admits a real function Φ: S→R ($S = \times_{i\in N} S_i$) with argument of strategy combination and when any player i change its strategy from s_i to s'_i and the others' strategies s_{-i} keep constant, the function always satisfies the follwing:

$$\text{sign}\left[c_i(s_i, s_{-i}) - c_i(s'_i, s_{-i})\right] = \text{sign}\left[\Phi(s_i, s_{-i}) - \Phi(s'_i, s_{-i})\right] \tag{4}$$

then the congestion game is called a potential game (Monderer and Shapley, 1996), Φ is potential function.

Theorem 1: Every potential game has at least one pure Nash equilibrium (Monderer and Shapley, 1996)

Theorem 2: When a potential game reach Nash equilibrium, the potential fuction attains the minimum (Monderer and Shapley, 1996)

Congestion game model of EV charging: It is assumed that EVs charge at constant power. EV charging can be described as the following congestion game:

- The players are N EVs
- The resources are T charging intervals t during charging period, t = {1, 2,..., T}
- The strategy of EV i is the set of charging strategy at every interval $s_i = \{s_{i,t}\}$, $s_{i,t}$ only has two values that "0" means no charging and "1" means charging

Under the strategy combination of $s = \{s_1,..., S_N\}$, the charging cost of EV i is:

$$c_i(s) = \sum_{t=1}^{T} s_{i,t}\omega_i k q_t(s) \tag{5}$$

where, ω_i is the charging power of EV i, $q_t(s)$ is the congestion level of the resource t.

In the game, each EV defines its opimal charging strategy to minimize its charging cost.

Existence of the nash equilibrium solution of EV charging game: The potential function of the EV charging game model is formulated as follows:

$$\Phi(s) = \sum_{t \in \cup_{i=1}^{N} s_i} k q_t^2(s) \tag{6}$$

The proof of the potential function is given in Appendix. It indicates the EV charging game is a potential game. We can then use Theorem1 to guarantee the convergence of the game to a pure Nash equilibrium.

Solution procedure of EV charging game: According to Theorem 2, the solution of EV charging game can be attained by solving the following optimazation problem:

- Objective function:

$$\min_{s_i} \sum_{t=1}^{T} k q_t^2 \tag{7}$$

- Subject to:

$$q_t = \sum_{i=1}^{N} s_{i,t}\omega_i + l_t \tag{8}$$

$$\lambda \sum_{t=1}^{T} s_{i,t}\omega_i = (1 - soc_i)C_D \tag{9}$$

$$s_{i,t} = 0 \text{ or } 1 \tag{10}$$

where, λ is the conversion efficiency of the charger, soc_i is the initial state of charge of EV i, C_D is the battery capacity. Equation 9 gurantees the battery of every EV to be full at the end of the charging.

The above optimazation problem can be easily solved by interior point method combined with branch and bound method (Boyd and Vandenberghe, 2004). The solution provides the charging strategies for Evs. Because the solution is a Nash equilibrium, none of EVs will change its charging strategy, thus, compared with other centeralized optimal approaches, this approach can be accepted willingly by EVs. However, the difficulty of finding the solution still increases with the increasing number of EVs.

DECENTRALIZED OPTIMAL APPROACH BASED ON LEARNING THEORY OF GAME

Here, the approach based on learning theory of game is proposed which will not be affected by the number of EVs. Under this approach, the charging strategy is made locally and directly by EV and the utility is just as a guider not a decision maker. EV learns its charging strategy by iterations.

Learning model of EV charging and the solution: Different with the congestion game-based approach, the learning theory of game-based approach assumes that the charging power of EV at every interval is variable, the charging strategy of EV i is the set of the charging power at every interval.

We assume that the charing power of EVs are constant in an interval and the output power of the charger can be adjustable.

The charging power of EV i at t in iteration m and m-1 are denoted by $s^{m}_{i,t}$ and $s^{m-1}_{i,t}$, EV i revises its strategy according to the following learning algorithm:

$$s_{i,t}^{m} = s_{i,t}^{m-1} + \beta_1\left(b_{i,t}^{m-1} - s_{i,t}^{m-1}\right) + \beta_2\left(\bar{s}_t^{m-1} - s_{i,t}^{m-1}\right) \tag{11}$$

where, $b^{m-1}_{i,t}$ is the best reply of EV i in iteration m-1, the $\bar{s}^{m-1}_{t}$ is average charging power of the other EVs in iteration m-1. β_1 and β_2 are learning parameters.

The implementation process is as follows:

Step 1: Initializations. Each EV proposes initiazed charging strategy stochasticly when m = 0

Step 2: The utility broadcasts charging price to all Evs. Each EV solves the following optimization problem to attain its $b^{m-1}_{i,t}$:

$$\min_{b_{i,t}} \; c_i = \sum_{t=1}^{T} b_{i,t}^{m-1} p_t \tag{12}$$

Subject to:

$$0 \le b^{m-1}_{i,t} \le s_{max} \tag{13}$$

$$\lambda \sum_{t=1}^{T} b_{i,t}^{m-1} = (1 - soc_i)C_D \tag{14}$$

where, s_{max} is the maximum charing power of EV.

Each EV revises its charging power at every interval according to Eq. 11 and then reports it to the utility.

Step3: Repeating step 2 until the iteration number arrives

In the above procedure step 1-3, each EV independently updates its own optimal charging strategy. The local computational complexity is therefore independent of the EV population size N.

RESULTS AND ANALYSIS

The radial network used for this analysis is the IEEE 33-node test feeder. The total load of the network on peak is 3715 kW+j2265 kVAR. The basevalue of power is 10 MVA and the basevalue of voltage is 12.66 kV. The base load profile is a typical day load profile of some region of guangdong of china in winter of 2010. The charging period takes place between 20:00 pm to 05:00 am. The charging period is evenly divided into 10 intervals. Each interval has a length of 1 h.

The total number of the EVs is set to 200 by default and we assume EVs uniformly distribute at every node. Half of the EVs have a 32 kW h battery and half have a 16 kW h battery. The initial soc of EV is 0.2 and the battery of each EV must be full before departure. The energy conversion efficiency of the charger is 0.9 and the maximum output power is 7 kW. In congestion game-based approach, EV charges at the constant power of 7 kW.

The price coefficient k is 2×10^{-4} yuan kW^{-1} h^{-1}/kW and the learning parameter $\beta_1 = 0.05$, $\beta_2 = 0.06$.

The congestion game-based approach and the learning theory of game-based approach are compared with the free chaging scheme in which the charging strategy of an EV at an interval is defined based on the electricity price on the previous day.

The variation of the charging power in each interval in different scenarios are shown in Fig. 1. It can be seen from Fig. 1 that in three scenarios, EVs charge at the intervals with a lower base load to achieve a low cost.

The variation of the total load in each interval in different scenarios are shown in Fig. 2. It can be seen from Fig. 2 that in three scenarios, "valley-filling" achieve, however, under the approaches proposed in this study, the total load profiles are much flatter while the load fluctuation brought by the free charging is larger and there is even a new load peak at 03:00.

The voltage profile of a node in different scenarios are given in Fig. 3. Node 17 that is at the end point of the grid feeder is choosen as the subject. It can be seen that the voltage cuts down when EVs charge, free charging leads to large voltage drop at load peak and two optimal charging approaches flatten the fluctuation of voltage.

The power losses during the charging period in three scenarios are given in Fig. 4. It is clear that the free charging brings larger power losses.

The comparison of the total charging costs of EVs with different EV numbers in different scenarios is given in Fig. 5. We can see from Fig. 5 that under two optimal approaches, EVs will pay the utility almost the same cost, which are less than that under the free charging scheme. Furthmore, compared with the free charging scheme, the

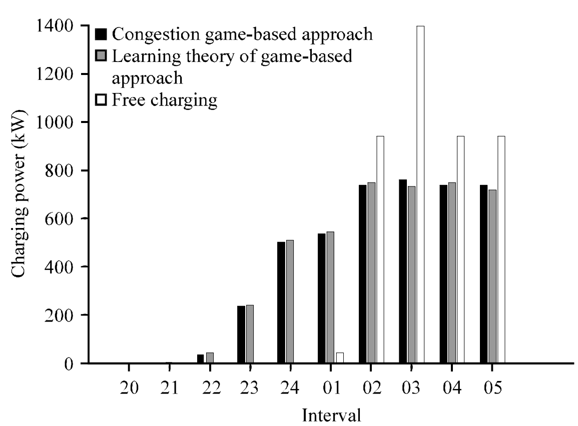

Fig. 1: Charging power of EVs in different scenarios

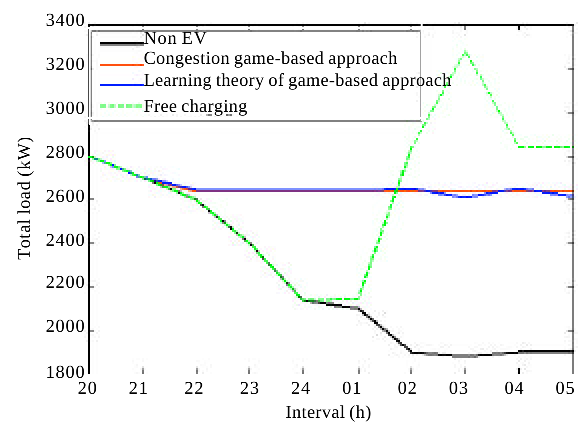

Fig. 2: Load profiles in different scenarios

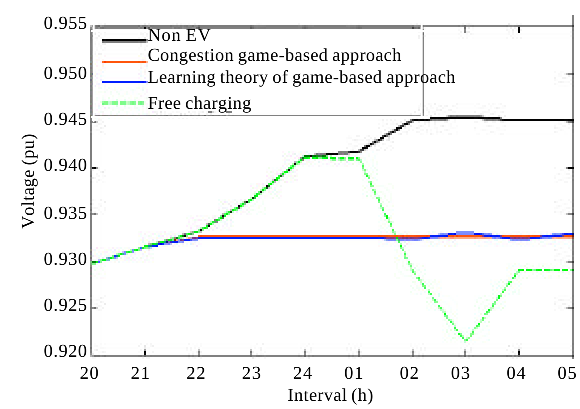

Fig. 3: Voltage curves of node 17 in different scenarios

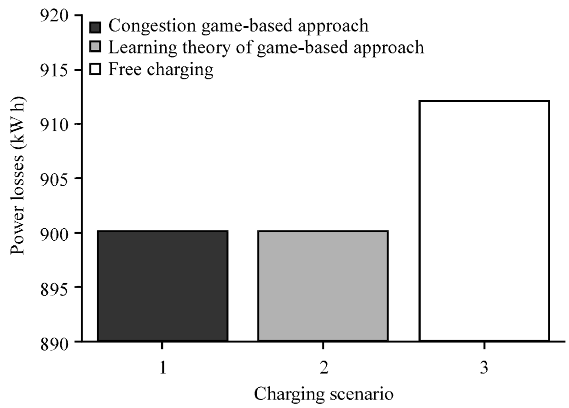

Fig. 4: Power losses in different scenarios

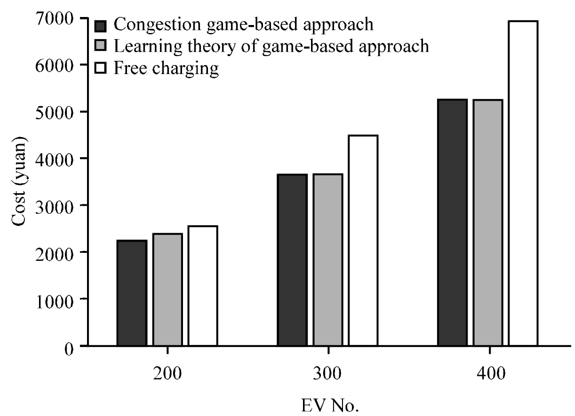

Fig. 5: Total charging costs in different scenarios

optimal approaches will get more cost saving when the number of EV increases. When the number of EV is 200, 300 and 400, the corresponding saving is 11.53, 18.81 and 24.54%.

CONCLUSION

In this study, we propose two optimal approaches for electric vehicle charging. They are congestion game-based approach and learning theory of game-based approach. The objective of two approaches is to minimize the charging cost of each EV and meanwhile to flatten the total load profile. The congestion game-based approach that belongs to the category of centralized approach can solve the problem of EV acceptance that other centralized approaches have but it still requries the utility to have strong calculation capability when the number of EVs is very large. To develop a more practical approach, we formulate the learning theory of game-based approach which is scalable to a large EV population. Simulations results show that the approach based on learning theory of game can achieve a close performance compared to the approach based on congestion game. Future works will focus on the optimal approach of EV charging and discharging.

APPENDIX

Proof: Because the battery of EV must be full after the end of the charging,when EV changes its strategy, if it will not charge at one interval, it has to charge at another interval.

We assume that there are k changes when the charging strategy of EV i changes from si to s'_i and the other EVs' strategies keep s_{-i}, for example that EV changes from charging at t_1 to charging at t_2 means once change. The charing load at t except EV i is denoted by Q_t.

Considering No. m changes which EV changes from charging at t_1 to charging at t_2, the changed cost of EV i at t_1 is:

$$\Delta c_{i,t_1}(s) = k\left(Q_{t_1} + \omega_i + l_{t_1}\right)\omega_i$$

The change of potential function of resource t_1 is:

$$\Delta\Phi_{t_1}(s) = k\left[\left(Q_{t_1} + \omega_i + l_{t_1}\right)^2 - \left(Q_{t_1} + l_{t_1}\right)^2\right] = k\left(2\omega_i Q_{t_1} + 2\omega_i l_{t_1} + \omega_i^2\right)$$

The changed cost of EV i at t_2 is:

$$\Delta c_{i,t_2}(s) = -k\left(Q_{t_2} + \omega_i + l_{t_2}\right)\omega_i$$

The change of potential function of resource t_2 is:

$$\Delta\Phi_{t_2}(s) = -k\left[\left(Q_{t_2} + \omega_i + l_{t_2}\right)^2 - \left(Q_{t_2} + l_{t_2}\right)^2\right] = -k\left(2\omega_i Q_{t_2} + 2\omega_i l_{t_2} + \omega_i^2\right)$$

So, when EV i changes its strategy from charging at t_1 to charging at t_2, the changed cost of EV i is:

$$\Delta c_i^m(s) = \Delta c_{i,t_1}(s) + \Delta c_{i,t_2}(s) = k\left(Q_{t_1} - Q_{t_2} + l_{t_1} - l_{t_2}\right)\omega_i$$

The change of potential function is:

$$\Delta\Phi^m(s) = \Delta\Phi_{t_1}(s) + \Delta\Phi_{t_2}(s) = 2k\left(Q_{t_1} - Q_{t_2} + l_{t_1} - l_{t_2}\right)\omega_i$$

Thus $\Delta\Phi^m(s) = 2\Delta c_i^m(s)$.

Because:

$$\Delta\Phi(s) = \sum_{m=1}^{k}\Delta\Phi^m(s), \Delta c_i(s) = \sum_{m=1}^{k}\Delta c_i^m(s)$$

Therefore, $\Delta\Phi(s) = 2\Delta c_i(s)$.

So:

$$\text{sign}[c_i(s_i, s_{-i})\text{-}c_i(s'_i, s_{-i})]. = \text{sign } [\Phi(s_i, s_{-i})\text{-}\Phi (s'_i, s_{-i})]$$

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REFERENCES

Boyd, S. and L. Vandenberghe, 2004. Convex Optimization. Cambridge University Press, Cambridge, UK., ISBN-13: 9780521833783, Pages: 716.

Clement-Nyns, K., E. Haesen and J. Driesen, 2010. The impact of charging plug-in hybrid electric vehicles on a residential distribution grid. IEEE Trans. Power Syst., 25: 371-380.

Deilami, S., A.S. Masoum, P.S. Moses and M.A.S. Masoum, 2011. Real-time coordination of plug-in electric vehicle charging in smart grids to minimize power losses and improve voltage profile. IEEE Trans. Smart Grid, 2: 456-467.

Fernandez, L.P., T.G.S. Roman, R. Cossent, C.M. Domingo and P. Frias, 2011. Assessment of the impact of plug-in electric vehicles on distribution networks. IEEE Trans. Power Syst., 26: 206-213.

Gan, L.W., U. Topcu and S. Low, 2011. Optimal decentralized protocol for electric vehicle charging. Proceedings of the 50th IEEE Decision and Control and European Control Conference, December 12-15, 2011, Orlando, FL., USA., pp: 5798-5804.

Ma, Z.D., D. Callaway and I. Hiskens, 2010. Decentralized charging control for large populations of plug-in electric vehicles. Proceedings of the 49th IEEE Conference on Decision and Control, December 15-17, 2010, Atlanta, GA., USA., pp: 206-212.

Mitra, P. and G.K. Venayagamoorthy, 2010. Wide area control for improving stability of a power system with plug-in electric vehicles. IET Gener. Transm. Distrib., 4: 1151-1163.

Monderer, D. and L.S. Shapley, 1996. Potential games. Games Econ. Behav., 14: 124-143.

Moura, S.J., H.K. Fathy, D.S. Callaway and J.L. Stein, 2011. A stochastic optimal control approach for power management in plug-in hybrid electric vehicles. IEEE Trans. Control Syst. Technol., 19: 545-555.

Qian, K.J., C.K. Zhou, M. Allan and Y. Yue, 2011. Modeling of load demand due to EV battery charging in distribution systems. IEEE Trans. Power Syst., 26: 802-810.

Richardson, P., D. Flynn and A. Keane, 2012. Optimal charging of electric vehicles in low-voltage distribution systems. IEEE Trans. Power Syst., 27: 268-279.

Sortomme, E., M.M. Hindi, S.D.J. MacPherson and S.S. Venkata, 2011. Coordinated charging of plug-in hybrid electric vehicles to minimize distribution system losses. IEEE Trans. Smart Grid, 2: 198-205.

Vaya, M.G. and G. Andersson, 2012. Centralized and decentralized approaches to smart charging of plug-in vehicles. Proceedings of the Power and Energy Society General Meeting, July 22-26, 2012, San Diego, CA., USA., pp: 1-8.