A Distributed Electric Vehicle Charging Management Algorithm Using Only Local Measurements

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***Abstract*—With the uptake of electric vehicles (EVs) promoted by many governments, the impact of electric vehicles on electricity grids will become significant in the near future. In Australia, charging a typical EV battery puts the same demand per day on the grid as an average household, which could lead to a sizeable increase in peak demand. However, the negative impacts of EVs can be mitigated if their charging is scheduled during times of otherwise low demand, such as overnight. The majority of studies trying to achieve this require a certain level of coordination among EVs and/or a central controller. In many countries, however, the hardware and infrastructure required for central charging methods do not exist. Here EV charging is approached from a distributed point of view, and a protocol in which charging decisions are made individually at each household, without any access to full network state is proposed. The decision making process is conducted in real time, using both instantaneous and historical local voltage measurements to estimate present network load. The overall goal is to maximally use grid capacity at all times, while still ensuring fairness of charging for all users. The proposed algorithm ensures both charging efficiency and fairness among all EVs across the network. At the same time, peak demand in the grid is minimally affected. Simulations based on a realistic suburban network using real demand data and vehicle travel profiles is presented to illustrate typical performance.**

***Keywords*—Distributed control, Electric vehicles, Power system planning, Smart grids, Voltage measurements**

I. Introduction

Electric vehicles (EVs) have many advantages over internal combustion engine vehicles technically, environmentally and financially [1]. However, due to the high capacity of EV batteries, if every house had an EV to be charged, the current load in grids would be nearly doubled [2]. Many studies have shown that without any control over the charging, failures or unacceptable electricity quality will occur in the grid frequently even with a small EV penetration rate [3], [4]. On the other hand, for most of the time during the day, the installed capacity of distribution networks are not fully utilized. In Australia, Victorian customers use less than 50% of grid capacity for more than 50% of the time especially during off-peak hours [2]. The huge spare capacity caused by uneven demand in networks has inspired many energy management algorithms for smart grids to deal with the charging problem.

There are two approaches to address the charging problem from the demand side. One is to manage the distribution network in a centralized way where a central controller communicates with each EV and calculates a suitable charging profile for each vehicle based on the global information [5], [6]. The other is for each EV charger to calculate its own charging profile in a distributed manner [7]–[14]. The centralized approach requires all agents to participate in the decision making process and this incurs a large communication and computational cost, especially if the network is large. The distributed approach is simpler and less costly, but also less effective especially if it only makes use of limited information.

Distributed algorithms can be formulated in several ways. The recent works [12]–[14] adopt a similar approach to ours and study Additive Increasing Multiplicative Decreasing (AIMD) alike algorithms, which are proven to be an effective way of deciding the charging rate for EVs. Although the decision is made at each household, [12]–[14] and most of the distributed algorithms in the literature require active or passive communication with central agents. However, such communication infrastructures are not immediately available in most countries and building new infrastructure incurs huge costs. A conceptual product named nPlug is introduced in [15] which manages the demand of home appliances based on only local voltage measurements. It has been shown that the nPlug performs effectively in alleviating peak demand in India. The nPlug is designed for home appliances with on and off settings. This approach leads a trend towards a demand management solution that requires as little communication as possible.

In this paper, we present a distributed algorithm based only on local voltage measurements, as similar to [15], to control EV charging, and hence demand. The algorithm uses varying charging power and passive back-off strategy to ensure grid safety and to maintain supply quality. Our algorithm also aims to address the fairness issue among EVs via self correction of each participant. The performance of the algorithm is studied through realistic simulations and compared to centralized and uncontrolled charging.

The rest of the paper is organized in the following way. Section II describes our research model as well as some background information. Section III introduces the algorithm and the analytical principals behind it. Section IV presents simulations of our algorithm on an actual Australian suburban distribution network. Section V concludes this paper and talks about the future plans.

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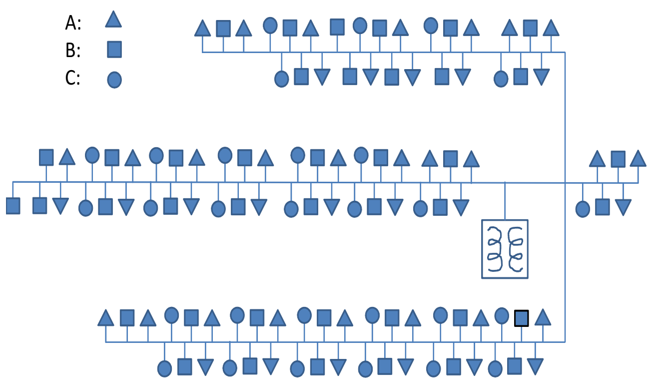

Figure 1. A diagram of an Victorian suburban distribution network of 114 houses fed by a 300kVA distribution transformer. Triangles denote houses on phase A; rectangles denote houses on phase B and circles on phase C.

II. Model

A. The Grid and EV model

We focus on the low voltage distribution networks which consist of transformers and all households along the distribution lines. Figure 1 shows the low voltage (LV) distribution network we used for simulation based on actual Victorian suburban networks. Houses including EVs are modelled as resistive inductive capacitive (RLC) loads which consume both real power and reactive power. Backbones and service lines are modelled as RL loads based on actual data.

It is assumed that each EV charger has a digital controller embedded which is able to read local voltages, battery State of Charge (SOC) in percentage and perform calculations to give charging instructions.

There are some inputs a controller requires from the users. The charging start time t_s is the time when the EV is plugged in. The user needs to input an expected finish time t_e which is when the EV needs to be ready for departure. We assume in this paper that users behave rationally and do not cheat by setting a finish time that occurs long before they need to depart. The users' behaviours can be regulated by introducing price incentives, which is an ongoing research topic.

The required SOC level S_e is usually 100% upon finishing but a user could overwrite such a value. The controller also records the initial SOC level S_s when the vehicle is plugged in. The sensing of controllers are executed in a slotted manner with equal slots of several minutes. The slots for each EV are equal in length, but they are not synchronized across EVs. At the beginning of each slot, each controller monitors the SOC level $S(t)$, the local voltage $V(t)$ and calculates a charging level which is maintained for the duration of that slot.

EV travelling models are based on real data from the Victoria Government EV trial project [1]. A typical average workday EV travel profile in Victoria is shown in Figure 2. We only examine residential networks in this paper where EVs can only be charged at home and charging in the workplace is not considered.

[1]data available at http://www.transport.vic.gov.au/projects/ev-trial

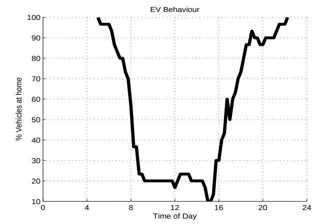

Figure 2. An average workday EV travelling profile generated from a sample of size 100 from of EV trial project database.

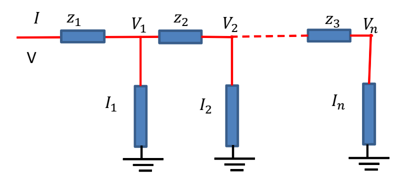

Figure 3. A model of a three phase resistive network

B. Local voltage model

Ideally, it is desirable to make charging decisions based on the average amount of spare capacity in the network for each EV, such that the total demand does not go beyond the limit. However, the total spare capacity information is not available at each household and it is not possible from local measurements to know the number of EVs that are charging. In such circumstances, we will use local voltage to estimate such values. It has been explained in [15] that it is possible to indicate spare capacity in the grid using local voltage. We will explore this method in more detail.

Consider the one phase of a radial distribution line connecting a n houses as depicted in Figure 3. Even though most houses are creating complex loads, the power factor in a modern grid is close to 1 so that the resistive components dominate the power flow in a grid. We therefore simplify our grid as a resistive DC network. In Figure 3, z_n, $n = 1, 2, ...$ represents line impedances and V is the constant voltage level that the transformer supplies. I is the total demand of current in the network and I_n, $n = 1, 2, ...$ denotes the current in the nth branch which may consist of several houses or sub-branches. With this simplified DC model, we shall see that at any time

$$\begin{aligned} V_1 &= V - Iz_1 \\ V_2 &= V_1 - (I - I_1)z_2 = V - I(z_1 + z_2) + I_1 z_2 \\ V_n &= V_{n-1} - (I - I_1 - ... - I_{n-1})z_n \\ &= V - I(z_1 + ... + z_n) + I_1(z_2 + ... + z_n) + ... + I_{n-1}z_n \end{aligned} \quad (1)$$

Let I_{max} be the threshold supply current, the available spare current or discrete current $I_d = I_{max} - I$. Therefore, from line 1 of (1), the spare capacity in terms of current is proportional to the voltage level at house 1. As for houses located further from the transformer, the proportional relationship will become weaker due to the demand of preceding houses in location. Therefore, we cannot accurately calculate total spare capacity from local voltages. However this weak proportional relationship can still be used by controllers to estimate spare capacity and make preliminary decisions. In addition, when total demand is too high, local voltage at each house will be low compared to its own voltage profile. Therefore, we can use a low local voltage level as a triggering message telling controllers to stop or slow down.

III. Distributed Algorithm

Algorithm 1 Fair EV charging with local measurements

Require: t_s, t_e, τ, k, $V(t)$, V_{min}, V_{max}, S_e, $S(t)$, S_s, r_{max}

1: $r(t) = 0$ ▷ initialization
2: $S_{wanted} = S_e - S_s$, $T = t_e - t_s$
3: $B = S_{wanted}/T$ ▷ average charging rate
4: **if** $S_e - S(t) \leq 0$ **then** ▷ check if fully charged
5:     **charge** (OFF)
6: **else if** $V(t) - V_{min} \leq 0$ **then**
7:     $r(t) = 0.5r(t-1)$ ▷ drop to half
8:     **charge** (ON)
9: **else**
10:     $C \leftarrow (S_e - S(t))/(t_e - t)$ ▷ required charging rate
11:     $\Delta r(t) \leftarrow k * r_{max} * (V(t) - V_{min})/(V_{max} - V_{min})$
12:     $r(t) \leftarrow (r(t-1) + \Delta r(t)) * (C/B)$
13:     **charge** (ON)
14:     **charge rate = min**$\{r(t), r_{max}\}$
15: **end if**
16: **keep charging for** (τ)
17: **goto** (step 4)

The proposed distributed EV charging algorithm for each individual EV is summarized in Algorithm 1. Accordingly, each EV controller will independently execute the Algorithm 1 as soon as the EV is plugged in. The parameter τ denotes the time slot which can be a few minutes and the constant k controls the power increment step size (with a large k, the charging profile will exhibit more spikes). The constants V_{min} and V_{max} are the threshold values on local voltages which will be used to regulate the total demand in the grid, i.e. when the total demand is too high, the local voltages will drop below the threshold and EVs will decrease their charging rate. V_{min} and V_{max} can be obtained from historical data. V_{max} can be calculated simply as the average of maximum voltages over the last 10 workdays and V_{min} can be a certain portion of V_{max} for each EV. Note that data on weekends, weekdays, holidays will be classified in different sets since the demands behave differently. The variable $V(t)$ is the local voltage sensed and r_{max} denotes the maximum charging power. The charging start time is t_s and finish time is t_e. The SOC start, finish and current level is S_s, S_e and $S(t)$ respectively. We assume all EVs use identical batteries such that $dS(t)/dt = r(t)/c$ where c is a constant relating energy to battery percentage change.

While controlling EV charging from a distributed point of view, it is very difficult for individual EV controllers to coordinate or communicate with others without additional complexity and infrastructure. Therefore, it is natural for each EV to take power greedily if it is safe to do so. By greedily, we mean that each EV tries to make charging rate as high as possible such that the set of all charging profiles at t is close or equal to a solution of (2). And we will show the performance via realistic simulation.

$$
\begin{aligned}
\underset{r_1(t),...,r_N(t)}{\text{minimize}} \quad & \left(C(t) - \sum_{n=1}^{N(t)} r_n(t) \right)^2 \\
\text{subject to} \quad & 0 \leq r_n(t) \leq e_n(t)\overline{r}_n(t),\ n = 1, ..., N(t), \\
& S_n(t) \leq S_e^n \ n = 1, ..., N(t).
\end{aligned}
\tag{2}
$$

The parameter $e_n(t)$ which is either 0 or 1 is the travelling profile for EV n at time t denoting whether the EV is away or at home respectively and r_n is the charging profile for vehicle n which is the main dependant variable for our system. S_e^n is the intended SOC level upon finishing the charging for EV n. $\overline{r}_n$ is the maximum charging power limit for EV n. Also the total number of EVs plugged in at time t is $N(t) = \sum_{n=1}^{N} e_n(t)$ where N is the total number of houses with EVs. T_n is the total charging time for EV n and $C(t) = max\{0, E(t) - D(t)\}$ is the spare capacity where $E(t)$ is the greedy threshold and $D(t)$ is the total non-EV demand in the distribution network.

In (2), $C(t)$ is not directly measurable and the equations show an ideal case of our intent. However, each EV could estimate the spare capacity in the grid using local voltage as explained in (1). Generically, the minimum voltage threshold corresponds to the maximum level of power $E(t)$ the transformer is willing to supply. Each EV gradually increases its charging power asynchronously to others till the network threshold is reached. The charging power increments are determined in proportional to the spare capacity in the grid as in (3). When the grid limit is about to be reached, the increment of power for each EV will be smaller and smaller to avoid sudden violation of grid constraints.

$$\Delta r(t) = k r_{max} \frac{V(t) - V_{min}}{V_{max} - V_{min}} \tag{3}$$

Fairness is important while developing EV charging algorithms. Due to location and load conditions, when using the greedy algorithm, it is always the case that some vehicles have charging advantages over the others. However, we do not want any EVs to be unduly disadvantaged. Though it is not possible to communicate with other households, EV n has an average charging rate, $S_e^n - S_s^n / t_e^n - t_s^n$, calculated from user settings which can be used as a benchmark charging speed. In this paper, we assume there is a price incentive such that users plug in their EVs as soon as they get home and set the finish time as late as possible to avoid paying extra. At time t, we apply (4) to calculate a correction factor $p(t)$ which is used to manipulate the current charging rate to keep it consistent with benchmark charging speed. What (4) does for EV n at time t is to determine how much faster/slower it has to be charged after t such that S_e^n can be achieved right at t_e^n. Note that discontinuous and varying rates of charging will be used in our work which potentially increases batteries lifespan since it does not produce as much accumulated heat in batteries as charging with full power [16]. These steps will be repeated until local voltage reaches the threshold value in which case, the power will be dropped to half to ensure safety and electricity quality across the grid.

$$p(t) = \frac{S_e^n - S_n(t)}{t_e^n - t} \Big/ \frac{S_e^n - S_s^n}{t_e^n - t_s^n} \tag{4}$$

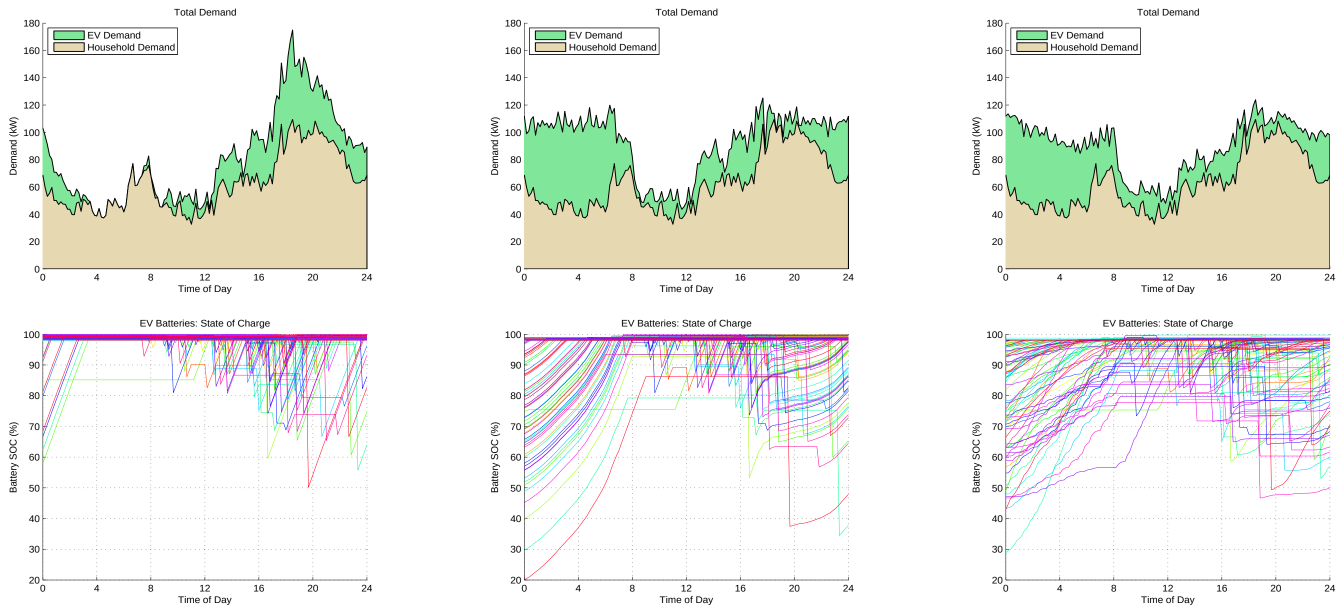

Figure 4. The performance comparison of the uncontrolled charging(first column), centralized charging (second column) and distributed greedy fair charging (third column). The first row shows the demand of households and EVs over a particular day, the second column shows the battery SOC level of all EVs in the network where each colour represents a vehicle. Sudden drops indicate vehicles arriving at home and gradients of curves denote the charging rate. Long horizontal lines before dropping indicate the EV being away.

IV. Case studies and results

We ran simulations for our algorithm on a real Victoria suburban distribution network with $300kW$ installed capacity and 114 households as in Figure 1. In order to really test the algorithm, the simulations assume an EV penetration rate of 80% with real demand profile and EV travelling profiles. The software packages used were MATLAB SimPower toolbox for load flow calculation and POSSIM Simulator [2] which provides an interface to MATLAB for control actions.

We present three sets of simulations in this paper. The first set is the grid operating with no control over EVs. The second set is an implementation of (2) where the central controller has perfect knowledge of how much spare capacity the grid has and how many EVs are plugged in. Therefore the controller is able to distribute spare capacity equally among all agents. This algorithm is a centralized version of the greedy algorithm presented in [17]. The last set is our distributed greedy fair charging algorithm.

Here we use the average of maximum historical local voltage over 20 days as V_{max} for each household. Then V_{min} is calculated as $V_{min} = j * V_{max}$ where j is a constant relating to the greedy threshold E. Since a direct calculation for E from voltages is not accurate, we will need simulations to assist voltage level setting and can be done easily with a few simulation trials. In our experiments, the greedy threshold $E(t)$ is set to $110kW$ to simulate grid behaviour under limited resource and the corresponding j is 0.97.

Figure 4 consists two categories of diagrams. The top set shows the aggregated demand of all EVs, aggregated household non-EV demand and their sum. The lower set shows how the SOC level of each EV changes over time. During the middle of the day, most EVs are out and there is not much EV demand in the grid. Since controllers do not have access to SOC levels while EVs are travelling, the SOC levels are therefore shown as constants when EVs are away and adjusted as soon as the vehicles are plugged in. We can see that without control, additional EV load will cause significant peak increase which affects not only electricity price but also electricity quality. The centralized algorithm makes very good use of spare capacity in the grid and the total demand when most of EVs are plugged in oscillates between $100kW$ and $120kW$. The oscillation is caused by the synchronous behaviour in simulation. The distributed fair charging algorithm also controls peak load well and moves the majority of EV demand to the overnight valley. Almost all EVs are charged to above 80% in our algorithm. Even though it is not as good as the centralized algorithm, the results for the distributed algorithm are still impressive given the difference in the amount of information used in two strategies. It is worth noting that due to fairness correction, in early morning, EVs with high battery level reduces their charging power and those with low battery level tend to have a steep charging profile.

Figure 5 shows the local voltage on each phase for each house. Phase A in the uncontrolled case drops below distribution code regulated level $216V$. Both the centralized and distributed algorithms keep the voltage within range. There are more voltage fluctuations in the distributed algorithms and this is because we used 50% power back-off to ensure safety. In practice, the issue can be resolved by asynchronous decision making among EVs and a smaller power back-off size. However, the voltage is already well within limits.

V. Conclusion and Future Work

In this paper, we have proposed a distributed greedy fair charging algorithm for EVs in a smart grid. Unlike all other

[2]available at www.possim.org

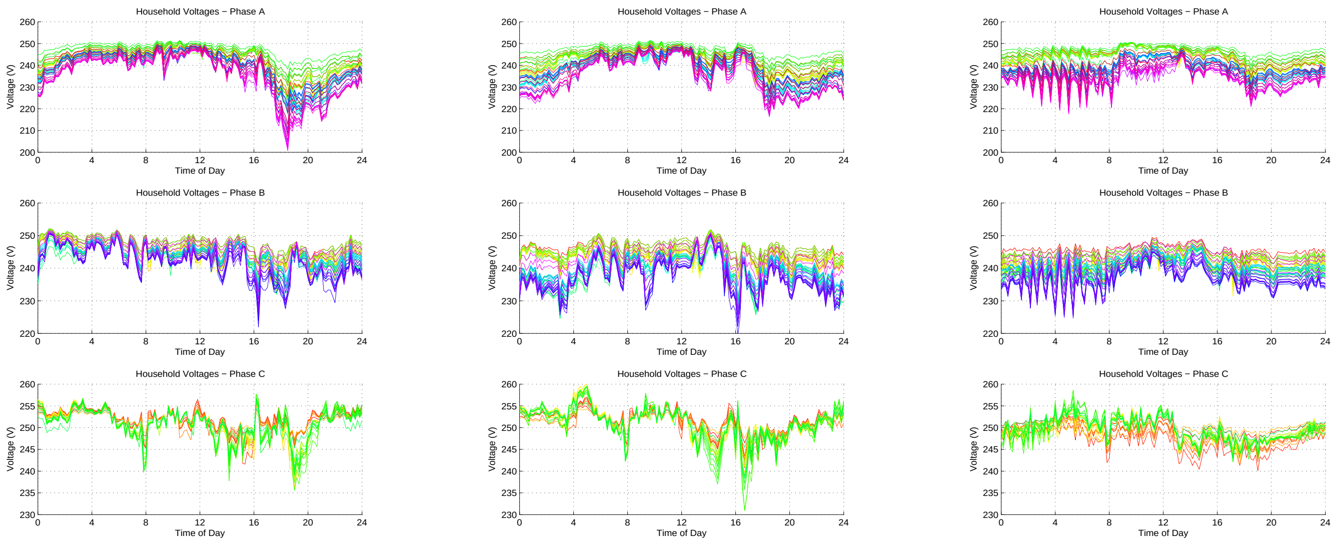

Figure 5. The household local voltage levels of the uncontrolled charging(first column), centralized charging (second column) and distributed greedy fair charging (third column). The first three rows show the voltage of individual houses on individual phases; each color denotes a house.

algorithms, our method is based totally on local information. By simulating an actual distribution network, we have shown that, even with a high 80% penetration rate, the distributed greedy fair algorithm successfully mitigates peak demand, ensures battery level and fairness without breaking any grid constraints. Even though the performance is not as efficient as a centralized solution, given the amount of information used in our algorithm, the result is remarkable. What's more, our solution is in a ready to use state and requires no upgrade of the current grids' infrastructure. In the future, when smart grid communication facilities are well developed, our algorithm can be easily modified to generate more accurate outcomes. There are several projects that our group is currently working on. One is the investigation of how to manage the behaviour of EVs and home appliances given local smart meter data; another direction is the price incentive for customers and their EV charging behaviours. We also would like to investigate analytically differences in the results from a distributed approach and a centralized algorithm.

References

[1] R. Sharma, C. Manzie, M. Bessede, R. Crawford, and M. Brear, "Conventional, hybrid and electric vehicles for australian driving conditions. part 2: Life cycle co2-e emissions," *Transportation Research Part C: Emerging Technologies*, vol. 28, no. 0, pp. 63 – 73, 2013.

[2] I. Mareels, D. Thomas, and M. Brazil, "On smart grid technology to support a high uptake of electric vehicles - preliminary observations," in *Control Methodologies and Technology for Energy Efficiency*, vol. 1, no. 1, 2010, pp. 19–23.

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

[4] L. Kelly, A. Rowe, and P. Wild, "Analyzing the impacts of plug-in electric vehicles on distribution networks in british columbia," in *Electrical Power & Energy Conference (EPEC), 2009 IEEE*. IEEE, 2009, pp. 1–6.

[5] P. Richardson, D. Flynn, and A. Keane, "Optimal charging of electric vehicles in low-voltage distribution systems," *Power Systems, IEEE Transactions on*, vol. 27, no. 1, pp. 268–279, 2012.

[6] S. Sojoudi and S. H. Low, "Optimal charging of plug-in hybrid electric vehicles in smart grids," in *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011, pp. 1–6.

[7] 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.

[8] L. Gan, U. Topcu, and S. Low, "Optimal decentralized protocol for electric vehicle charging," in *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*. IEEE, 2011, pp. 5798–5804.

[9] N. Li, L. Chen, and S. H. Low, "Optimal demand response based on utility maximization in power networks," in *Power and Energy Society General Meeting, 2011 IEEE*. IEEE, 2011, pp. 1–8.

[10] Z. Fan, "Distributed charging of phevs in a smart grid," in *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*. IEEE, 2011, pp. 255–260.

[11] C. Ahn, C.-T. Li, and H. Peng, "Decentralized charging algorithm for electrified vehicles connected to smart grid," in *American Control Conference (ACC), 2011*. IEEE, 2011, pp. 3924–3929.

[12] S. Studli, E. Crisostomi, R. Middleton, and R. Shorten, "Aimd-like algorithms for charging electric and plug-in hybrid vehicles," in *Electric Vehicle Conference (IEVC), 2012 IEEE International*. IEEE, 2012, pp. 1–8.

[13] M. Liu and S. McLoone, "Enhanced aimd-based decentralized residential charging of evs," *Transactions of the Institute of Measurement and Control*, 2013.

[14] 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.

[15] T. Ganu, D. P. Seetharam, V. Arya, J. Hazra, D. Sinha, R. Kunnath, L. C. De Silva, S. A. Husain, and S. Kalyanaraman, "nplug: An autonomous peak load controller," *Selected Areas in Communications, IEEE Journal on*, vol. 31, no. 7, pp. 1205–1218, 2013.

[16] R. C. Cope and Y. Podrazhansky, "The art of battery charging," in *Battery Conference on Applications and Advances, 1999. The Fourteenth Annual*. IEEE, 1999, pp. 233–235.

[17] J. de Hoog, D. A. Thomas, V. Muenzel, D. C. Jayasuriya, T. Alpcan, M. Brazil, and I. Mareels, "Electric vehicle charging and grid constraints: Comparing distributed and centralized approaches," in *Proceedings of the IEEE Power and Energy Society General Meeting*, July 2013.