Electric Vehicle Charging and Grid Constraints: Comparing Distributed and Centralized Approaches

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Abstract—**The expected rise of electric vehicles will lead to significant additional demand on low voltage (LV) distribution systems. Uncontrolled charging could lead to problems such as thermal overload of transformers and lines, voltage deviation, harmonics, and phase unbalance. We propose two electric vehicle charging algorithms, one centralized and one distributed, and compare their performance in simulations that use real vehicle data, on a model based on a real LV network in northern Melbourne, Australia. Our experiments confirm that the locations of the vehicles in the network are an important factor in predicting adverse effects. Furthermore, our coordinated charging solutions allow penetrations of electric vehicles approximately 3-6 times higher than is possible using uncoordinated charging, in our network.**

Index Terms—**Centralized control, Distributed control, Electric vehicles, Power system planning, Smart grids**

I. INTRODUCTION

Governments and manufacturers around the world are promoting electric vehicles (EVs) as a green alternative to conventional fossil fuel based transport. Every major automaker has released a fully or partially electric vehicle model, and several countries have seen the rise of new players in electricity markets that cater to the growing demand of EVs. An emerging model is that of an aggregator providing electric vehicle charging across home and public charge spots in return for a monthly fee [1].

Electric vehicles, when charging, act as significant loads in the grid. Today's vehicles typically draw between 3-4 kW (roughly equivalent to the demand of a full household), and upcoming models are expected to be capable of drawing twice that, or more. The resulting impact on low voltage distribution systems can be significant, with potential problems including transformer or line overload [2], harmonics [3], voltage drop [4], and phase unbalance [5].

The time of day at which vehicles are charged has a strong influence on how they affect the grid, and it is in the interest of the entity responsible for charging (whether aggregator, distributor, or other) to ensure that negative effects of charging

are minimal. To this end, several charging algorithms have been proposed and examined.

A significant difference between uncontrolled and controlled charging is demonstrated in [4]. In a neighbourhood of approximately 8,500 households, an additional load of only 10% EVs is found to be sustainable before voltages drop below acceptable levels. Using a controlled charging algorithm, this rises to 52%. In [6], uncontrolled charging is compared to quadratic and dynamic programming methods that aim to minimize power losses and voltage deviations. At EV penetrations of 30%, losses are at 6% and voltage deviation at 10.3% in the worst case of uncontrolled charging. The coordinated charging method reduces these to 5.8% and 9.1%, respectively. Linear programming is used in [7] to coordinate charging. With uncontrolled charging, only 21 vehicles could be added to the modeled network (16%), whereas the linear programming approach allows for over 60 vehicles to be charged (45%) without adverse effects on the network.

This work aims to contribute to the existing work on aggregated electric vehicle charging. We focus on a more extensive range of specific constraints in the grid, including voltage deviation, cable overload, transformer overload, phase unbalance, and power factor. Real data underpin all of our simulations: our grid model is based on a real neighbourhood in northern Melbourne, Australia; our household demand model uses data obtained from a distribution transformer serving this neighbourhood; our cable impedances are based on spec sheets for cables used in this neighbourhood; our vehicle demand model uses traffic survey data specific to the area this neighbourhood is located in; and our battery model uses a charging profile based on a real electric vehicle battery.

We propose two new charging algorithms. The first, a centralized method, uses only available power as measured at the distribution transformer and allots equal shares to all connected vehicles. The second, a distributed method, uses local voltage measurements to determine whether the present network load is low (in which case the vehicle can be charged) or high (in which case the vehicle should not be charged). We compare both of these methods to uncontrolled charging.
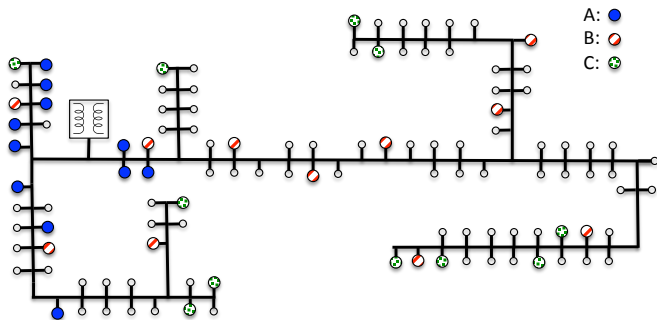
Figure 1: Network model of a real neighbourhood in northern Melbourne containing 112 houses.

II. SIMULATOR

A. Simulator Loop

Our simulations were conducted using our in-house POSSIM Simulator [9], which provides an interface to MATLAB SimPowerSystems for load flow calculations. Simulations are conducted in 5-minute intervals, with the following steps undertaken at each interval:

1. Simulate vehicle movement: update vehicle positions (home or away) using travel survey data (Section II C), and update battery state-of-charge based on vehicle behavior (decrease if driving, increase if charging).

2. Generate household loads: according to household demand profiles (Section II D), generate a demand for each household.

3. Determine charge rates: using one of the algorithms described in Section III, determine what the rate of charge for each connected vehicle should be.

4. Run load flow: apply household and vehicle loads, run load flow simulation, log all relevant current and voltage measurements.

B. Grid Model and Load Flow

Since electric vehicle uptake is projected to be much greater in urban than in rural settings [8], we chose a typical suburban network in northern Melbourne containing 112 houses as a case study. An LV grid model was developed in MATLAB SimPowerSystems. Phases and neutral are modeled individually, as are piecewise sections of the LV backbone and service lines. All houses are connected single-phase; an electric vehicle associated with a given house is connected in parallel on the same phase as the house. Voltages and currents are measured for each phase, and individual household voltages are measured at each house. Houses are 25m apart on average, having a service line of 15m on average. A diagram of our network is presented in Fig. 1.

C. Electric Vehicle Demand

We use private vehicle travel data obtained from the Victoria Department of Transport's extensive travel survey of 2009. Reducing the dataset to those records having distances less than 160km (our assumed EV range), we are left with 3907 individual 24-hour travel records for the district that our neighbourhood is located in. For each vehicle and each day in
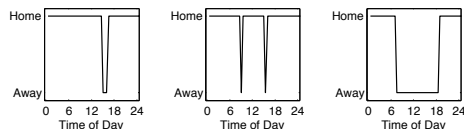

Figure 2: Typical vehicle travel profiles

our simulations, one of these real travel records is chosen at random to determine distances driven (battery discharge) and timing of potential charging (when the vehicle is at home). Fig. 2. Presents some typical driving profiles. We assume that the vehicles in our simulation behave similar to the Nissan Leaf, i.e. a driving range of ~160km and a battery capacity of 24kWh. At a 230V, 15A outlet, the Leaf draws up to 3.45kW.

D. Household Demand

Demand data obtained from the local distribution transformer of our neighbourhood was used to create 24 household demand profiles: one each for weekdays and weekends, for each month of the year. We consider it important to simulate loads individually since there is typically much fluctuation in each household's demand across a day, and since individual loads can have a significant influence on factors such as voltage drop. To introduce randomness into individual household loads, we assign each house a "demand profile", according to a normal distribution (since some houses will be heavier users than others), and we further introduce randomness at each simulation interval for each household using a Weibull distribution (to prevent negative demand). Doing this we achieve demand profiles having high rates of fluctuation, the average of which is still closely in line with the demand profile obtained from real data. Fig. 3 presents some typical individual household load profiles (thin lines), their average (thick line), and real data obtained from the distribution transformer (thick dotted line).
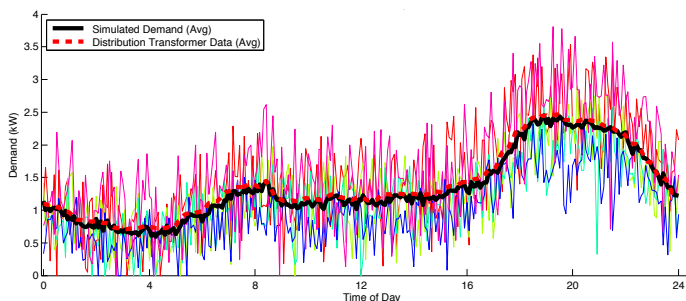

Figure 3: Household demand profiles

E. Battery model

We model EV batteries on a cell-by-cell level using a dynamic state-of-charge dependent open-circuit-voltage, based on values obtained from a real EV battery cell. We further take into account static internal resistance of the battery. Charging then follows a constant-power, constant-voltage (CP-CV) process, with charging power and voltage limits of 3.45kW and 4.2V, respectively. An additional loss factor of 10% is applied between charging power and battery input power to take into account energy loss in converters, the cooling system and monitoring/control systems.

III. CHARGING ALGORITHMS

We compare three charging algorithms as follows:

A. Uncontrolled

In the uncontrolled algorithm, vehicles start charging as soon as they return home, and charge at their maximum rate (3.45kW) until their battery state-of-charge reaches 100%.

B. Equal Share (Centralised)

Our centralized algorithm, which we call "Equal Share", is designed with distribution transformer limitations in mind. It makes the following assumptions: (1) Vehicles can charge at variable rates, (2) these rates can be chosen centrally by the charging aggregator, and (3) the aggregator has access to real-time demand data at the distribution transformer. The charge rates are then chosen as follows: first, the total available charging capacity, as measured at the distribution transformer, is determined (transformer capacity minus household demand). Second, the number of vehicles requiring charge is determined. Third, each of these vehicles is allotted an equal share of available charging capacity. For example, given a transformer having capacity 200kW, existing base load demand of 150kW, and 50 connected vehicles, each vehicle would be assigned a charge rate of 1kW.

C. Voltage Adaptive (Distributed)

Our "Voltage Adaptive" (distributed) algorithm is partly inspired by IBM India's distributed load control "n-Plug" [10], which uses local voltage and frequency measurements to avoid peak load periods when making load scheduling decisions. In our charging method, each residential charger makes its own decision at each simulation interval on whether to schedule the associated EV. The decision is made according to a probability based on two factors:

State-of-charge (SOC): vehicles having a lower SOC should have a higher chance of charging than vehicles with a higher SOC. Let X_i represent the point of connection of individual vehicles, each having state of charge $S(X_i)$. The SOC-based probability $C(X_i)$ of the vehicle at connection point X_i charging is given by:

$$C(X_i) = \begin{cases} 1, & \text{if } S(X_i) < 20 \\ \frac{100 - S(X_i)}{80}, & \text{otherwise} \end{cases}$$

Voltage at connection: voltage as measured at a vehicle's point of connection is helpful in determining whether the local network is experiencing a high load. During peak periods, higher current through the feeder will result in greater losses along the line, and lower voltages. At lowest ("valley") load levels, each house j has a voltage V_j^{high}; we use this for calibration, and to introduce fairness into probability calculations. Let the voltage during a given simulation interval at point of connection X_i be $V(X_i)$. The probability $L(X_i)$ of the vehicle at connection point X_i charging due to local voltage measurement is given by:

$$L(X_i) = \begin{cases} 1, & \text{if } V(X_i) > V_i^{high} \\ 0, & \text{if } V(X_i) < V_{min} \\ \frac{V(X_i) - V_{min}}{V_i^{high} - V_{min}}, & \text{otherwise} \end{cases}$$

where V_{min} is the minimum voltage threshold allowed. We used V_{min} = 218V in our simulations, since our local distribution code limits drops to 216V.

We combine these two factors to determine a single probability $P(X_i)$ that the vehicle connected at point X_i will charge in the next interval:

$$P(X_i) = \begin{cases} 0, & \text{if } L(X_i) = 0 \\ \frac{C(X_i) + L(X_i)}{2}, & \text{otherwise} \end{cases}$$

The reasoning behind this is as follows: if the local voltage measurement is already below the allowed threshold V_{min}, then the load should definitely not be scheduled. If it is above the threshold, then SOC and present network load should contribute equally to the probability of the load being scheduled. If $Random(0,1) < P(X_i)$, then the charger schedules its load, and vehicle V_i charges to completion.
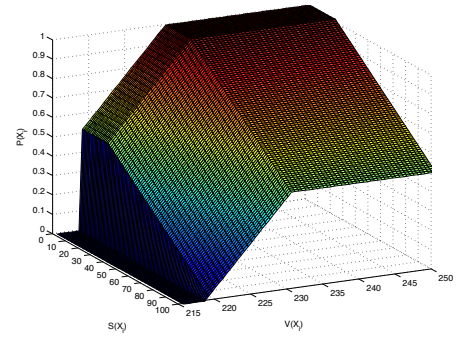

Figure 4: Probability surface for distributed charging algorithm.

Fig. 4 shows the values for $P(X_i)$, given voltages (x-axis) and vehicle SOC (y-axis). For example, if voltage is high and vehicle SOC low, then the probability of charging will be very high. If vehicle SOC is at 50%, and there is a medium load on the network, then the probability of charging is only about 70%. Finally, if the vehicle SOC is high, and the present demand on the grid is high (i.e., low voltage), then the chance of the vehicle charging is very low.

An important consideration when using a probability-based scheduler is the simulation interval size. For example, using the probability surface of Fig. 4 and assuming SOC of 90% and voltage of 220V, the probability of charging would only be 14.6%. However, over the course of half an hour, sampling in 5-minute intervals, there are 6 repeated trials. This raises the percentage of the load being scheduled at some point in this half-hour period to 1 - (1-0.146)⁶ = 61.2%, in other words quite high. Thus it is important to scale the probability for the sample period down so that it corresponds to the desired probability of scheduling a load within a longer period of time. This can be done using the following formula:

$$P_{int} = 1 - (1 - P_{full})^{\frac{T_{int}}{T_{full}}}$$

where P_{int} and T_{int} are the probability and time of the sampling period, and P_{full} and T_{full} are the probability and time of the desired scheduling period.

IV. RESULTS

The position in the network at which vehicles are added has a significant influence on system reliability. To examine this in more detail, we chose to run each charging algorithm, at electric vehicle penetrations of 0, 5, 10, … , 40%, for each of three different vehicle assignments. The vehicle assignments are as follows:

A: Most vehicles are located close to the transformer.

B: Vehicles are spread fairly evenly throughout the network.

C: Most vehicles are located far away from the transformer, at the far ends of the network.

Fig. 1 shows these assignments for EV penetrations of 10%: full blue circles correspond to assignment A; dashed red circles correspond to assignment B; spotted green circles correspond to assignment C.

Each run involved a simulation of the network for 36 hours, from noon on one day until midnight of the next. The first 12 hours were used to initialize battery states of charge to realistic values; the final 24 hours were used to analyze impact of charging algorithms on the network over the course of a full day. All runs used demand profiles typical of a weekday in July, the month of highest demand in Melbourne.

We classified runs as "failures" if any of the following criteria were met:

1. Voltage at any household falling outside of distribution code requirements (at least 216 V)

2. Phase currents exceeding the ratings of our modeled backbone cable (480 A)

3. The transformer being loaded at greater than 150% of its nominal capacity (i.e. greater than 300kW)

4. The transformer being loaded at greater than 100% of its nominal capacity (200kW) for 12 consecutive hours

5. Voltage unbalance exceeding distribution code requirements (2%)

6. Power factor on any phase dropping below distribution code requirements (0.8)

Table 1 presents a complete summary of all runs. Green checkmarks indicate successful runs; red crosses indicate failures. Subscripts indicate which of the criteria above were the reasons for failure. Interestingly, no runs failed due to voltage unbalance or low power factor.

Further results from some individual runs are presented in Figs. 5-7. Figs. 5a, 5b, 5c present demand data, individual household voltages, and battery states of charge, respectively, for the uncontrolled algorithm applied to the run involving an EV penetration of 40% and vehicle assignment C. Figs. 6 and 7 present the same data for the equivalent runs for the Equal Share and Voltage Adaptive charging algorithms, respectively.

Clearly, location of electric vehicles has a significant impact. Using vehicle assignment A, uncontrolled charging is sustainable at penetrations up to 20%, whereas vehicle assignment C does not even allow 5%.

Charging Algorithm	Vehicle Assignment	Electric Vehicle Penetration, %								
		0	5	10	15	20	25	30	35	40
Uncontrolled	A	✓	✓	✓	✓	✓	✗₁₂	✗₁₂₃	✗₁₂₃	✗₁₂₃₄
	B	✓	✓	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃₄
	C	✓	✗₁	✗₁₂	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃	✗₁₂₃₄	✗₁₂₃
Equal Share (Centralized)	A	✓	✓	✓	✓	✓	✓	✓	✓	✗₁
	B	✓	✓	✓	✓	✓	✓	✓	✗₁	✗₁
	C	✓	✓	✗₁	✗₁	✓	✓	✗₁	✗₁	✓
Voltage Adaptive (Distributed)	A	✓	✓	✓	✓	✓	✓	✗₁₂	✗₃	✗₂
	B	✓	✓	✓	✓	✗₂	✓	✗₁₂₃	✗₁₂₃	✗₂₃
	C	✓	✓	✓	✗₂	✗₂	✗₁₂	✗₁₂₃	✗₁₂₃	✗₂₃

Table 1: Full summary of all runs

Uncontrolled charging adds to peak demand at the worst possible time, and fails early as a result. Both the Equal Share and Voltage Adaptive algorithms outperform uncontrolled charging, with the Equal Share algorithm having success at penetrations as high as 40%. The Equal Share algorithm never leads to transformer or cable overload, in line with its original design motivation. The Voltage Adaptive algorithm does not fail due to voltage drop until 25% EV penetration, also in line with its original motivation.

It must be noted that there is a tradeoff involved with these performances: the Equal Share and Voltage Adaptive algorithms are slower to charge the batteries (as Figs. 5c, 6c, and 7c show). Using the Equal Share algorithm no charge is provided at all until peak demand period is well and truly over, and even then the charge rates can be low; using the Voltage Adaptive method, vehicles must sometimes wait a long time (several hours in some cases) until charging is initiated. However, all vehicles reach an SOC of 100% overnight in all cases.

## V. CONCLUSION AND FUTURE WORK

Both centralized and distributed methods can offer significant advantages over uncontrolled charging. In our network, our distributed method allowed for approximately 3-4 times as many vehicles to be connected without network failure; our centralized method allowed for approximately 3-6 times as many vehicles to be connected. The location of vehicles in the network has a significant influence; when vehicles are connected near the ends of the network, there is a significantly increased risk of voltage drop.

Other distribution networks may suffer from these problems in a different order and at different thresholds, since the criteria for failure are highly dependent on the topology and size of the network. Nevertheless, these results contribute to the growing body of results that if electric vehicles reach higher levels of penetration, then either significant network upgrades, or smart controlled charging algorithms (or both) will be essential to maintain system reliability.
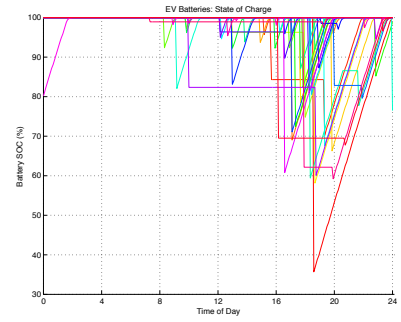
These experiments have provided some insight into the boundaries of what can be achieved with improved charging methods; our next efforts will be dedicated to finding a charging solution that is optimal, while still taking all of the specific grid constraints into account.
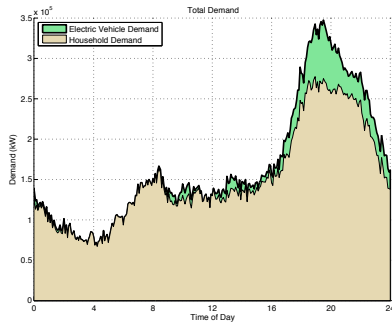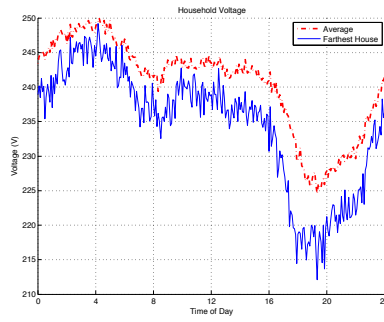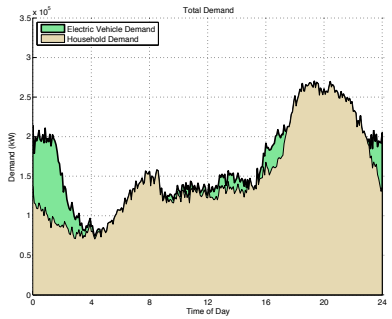
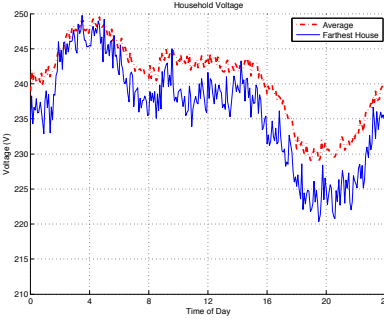a. Household and vehicle demand   b. Individual household voltage   c. Batteries' states of charge
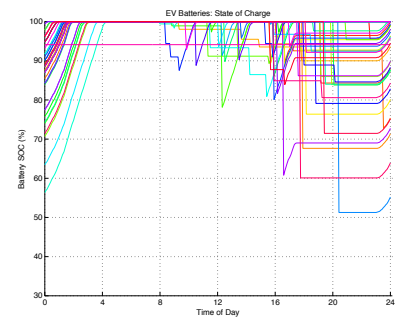
Figure 5: Results for an individual run of uncontrolled charging, 40% EV penetration, vehicle assignment C.

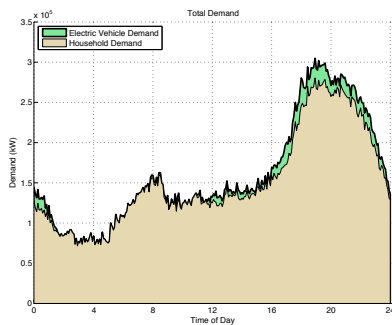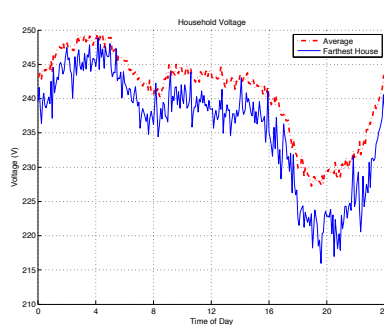a. Household and vehicle demand   b. Individual household voltage   c. Batteries' states of charge
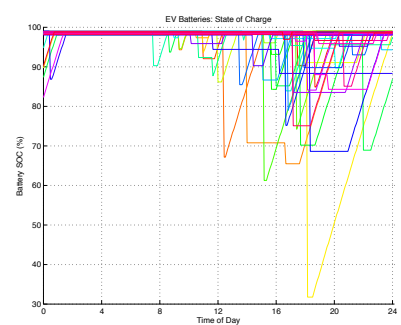
Figure 6: Results for an individual run of Equal Share (centralized) charging, 40% EV penetration, vehicle assignment C.

a. Household and vehicle demand   b. Individual household voltage   c. Batteries' states of charge

Figure 7: Results for an individual run of Voltage Adaptive (distributed) charging, 40% EV penetration, vehicle assignment C.

REFERENCES

[1] Better Place. Online: http://www.betterplace.com Accessed Nov. 2012.

[2] M. Masoum, P. Moses, and S. Hajforoosh, "Distribution transformer stress in smart grid with coordinated charging of Plug-In Electric Vehicles," in *Proc. IEEE Power and Energy Society Conference on Innovative Smart Grid Technologies (ISGT)*, Jan. 2012.

[3] R. Carter, A. Cruden, A. Roscoe, D. Densley, and T. Nicklin, "Impacts of harmonic distortion from charging electric vehicles on low voltage networks," in *Electric Vehicle Symposium 26*, May 2012.

[4] J. Lopes, F. Soares, and P. Almeida, "Integration of electric vehicles in the electric power system," *Proc. of the IEEE*, vol. 99, no. 1, pp. 168-183, Jan. 2011.

[5] P. Richardson, D. Flynn, and A. Keane, "Impact assessment of varying penetrations of electric vehicles on low voltage distribution systems," in *Proc. IEEE Power and Energy Society General Meeting,* Jul. 2010

[6] K. Clement-Nyns, E. Haesen, and J. Driesen. "The impact of charging plug-in hybrid electric vehicles on a residential distribution grid," *IEEE Trans. Power Delivery*, vol. 25, pp. 371-380, Feb. 2010.

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

[8] P. Paevere, A. Higgins, Z. Ren, G. Grozev, M. Horn, C. McNamara, Y. B. Khoo, and T. Elgindy, "Spatial modelling of electric vehicle charging demand and impacts on peak household electrical load in Victoria, Australia," CSIRO Research Publications Repository online: https://publications.csiro.au/, Accessed Aug 2012.

[9] POSSIM: POwer Systems SIMulator, Online: http://www.possim.org, Accessed Sep 2012.

[10] T. Ganu, D. P. Seetharam, V. Arya, R. Kunnath, J. Hazra, S. A. Husain, L. C. De Silva, and S. Kalyanaraman, "nPlug: a smart plug for alleviating peak loads," in *Proc. of the 3rd International Conference on Future Energy Systems*, May 2012.