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Learning EV Integration Impact on a Low Voltage Distribution Grid

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***Abstract*—Electric vehicles (EVs) are transforming the modern transportation and energy systems. However, due to increasing battery and charger capacities with long charging times, adverse effects on distribution grid are expected with mass penetration of EVs. In this paper, we investigate and evaluate the voltage impact of EV integration into a 37-bus IEEE distribution grid model to extract the signature of power system congestion information. The statistical distribution of voltage at local nodes are obtained with respect to node distance to substation and different EV integration rates. It is observed that both EV integration and node distance affect the observed voltage means and deviations at the local node significantly. The obtained results show that each local node can infer the congestion in the distribution grid by only observing its own voltage levels. This will open new possibilities for local control mechanisms that will enable fair power sharing among EVs irrespective of their physical location.**

I. Introduction

Electric vehicles (EVs) are finally moving towards mass adoption with increased efforts from manufacturers such as Tesla and Volvo. However, electric utility grid is still not ready for EV transition. The mass penetration of EVs into the utility grid will result in detrimental effects due to coincidence between peak loading and EV charging [1]. The integration of EVs into the distribution system with an uncoordinated fashion at high market rates increases peak loading on line/transformer, energy losses, voltage deviations, and the need for network reinforcements [2]–[6]. The possible impacts of this integration on a residential distribution grid, which are mostly related to voltage drops and deviations, and power losses, are studied in [7].

There are many control methods proposed in the literature to address EV-grid integration related problems. Most of the solutions require information exchange of each EV with a central location to optimize the operation of the EV with respect to a certain variable such as cost, efficiency, renewable energy tracking, etc. [6], [8], [9]. These approaches require centralized server and do not fully address the fairness among users. In [7], authors analyzed the voltage profiles of the grid nodes under different degrees of EV penetration for uncoordinated and coordinated charging cases. Their coordinated charging tries to achieve optimal charging by minimizing the power losses. However, this requires deployment of smart metering devices and ability to send charging signals to individual vehicles. Voltage drop violation and the overloading of the grid constitute two important constraint for a charging control method. In [10], authors proposed a charging optimization technique considering these system constraints. They also showed the relationship between the congestion level and voltage of the grid nodes. This work also relies on cyber-physical structures that carry information between vehicles and a charging service provider.

Alternative studies, which use local measurements in a decentralized manner, propose a voltage-based feedback controller for EV charging with a *predetermined* voltage reference value for all nodes [11]. Similar procedure is also used for photovoltaic (PV) solar integration in the distribution grid where critical voltage levels are assumed to be fixed among various nodes in the system [12]. A distributed solution using local voltage levels is discussed in [13], where using voltage thresholds that are obtained from historical voltage data is suggested. In [14], an improved decentralized algorithm is proposed, where voltage threshold values are calculated by power flow analysis. Although each of these techniques perform voltage control, they lack in considering the very specific local information at each node, which is dependent on the grid congestion and location of the node in the grid. Using only average voltage values that are estimated after days of measurement will suffer from lack of flexibility for precise control and capturing important location and time signatures.

Decentralized operation of an EV charging algorithm relies on the measured and preset threshold voltage values. This makes it very important to understand the effects of any system parameter on the voltage values. In a recent study, we presented a detailed analysis regarding the relationships between distance vs. voltage and power in a simplified distribution grid model [15]. Using the results of this analysis, we proposed a method that ensures fairness for a charging algorithm for this simplified model. In this follow-up study, we demonstrate a more realistic method to learn the operating voltage range of EV on-board charger rather than utilizing simplified assumptions. We used statistical Monte-Carlo (MC) simulations of the stochastic charging and residential loading events. The effects of parameters like node distance to substation and EV penetration ratio to the resulting statistical voltage distribution at local nodes are analyzed. The results provide invaluable information to *learn* the status of the distribution system, and they can be used to develop control algorithms of grid connected EV and PV power electronic systems.

The organization of the paper is as follows. Section 2 of the study presents the system components used in the developed model. Section 3 explains the developed case studies and simulation results. A discussion of the obtained results is provided in Section 4. Finally, Section 5 presents the conclusions and planned future work.

II. Problem Description and System Modeling

Since the distribution grid is an electric circuit, its states can be estimated or at least observed through its electrical variables such as end-node voltages. Given the fact that the grid voltage tends to drop as the system is loaded, we can infer that the event of voltage drop can be interpreted as a sign of congestion in the system. Also, the degree of the congestion can be estimated depending on the amount of drop [16]. This relationship is similar to the working principle of TCP/IP, which is the underlying protocol of the today's Internet. It uses the amount of time that it takes data packages to get to their destination. With this time information, it estimates the level of congestion and adjusts the download rates accordingly.

In the case of distribution grid, congestion refers to the loading level of the grid. A main question to consider is whether the measured voltage at any node of the grid reflects the amount of congestion at the time of measurement. Voltage drops may occur due to various reasons at any time, and the time it takes to recover also changes. Therefore, a statistical methodology is needed to extract the information of whether the nearby distribution grid is congested via an end-node measurements. Assuming distribution grid power demand doesn't change significantly from day to day, the statistics of the measured voltage records should also show a stable behavior on daily basis. This means that the mean value of the voltage should follow a certain distribution during a day signifying an uncontested situation. The amount of dispersion of the distribution around its mean value over a day time will vary depending on congestion level of the grid. As an example, the typical power consumption of a residential house tends to rise to peak value in the evening hours causing drops in voltage levels. Such insignificant power consumption of a single house doesn't make much difference in voltage levels but cumulative loading actions of many houses (as in the case of EV charging) might have severe impact on the grid and will be noticed by observing the voltage [7].

This chapter presents a realistic distribution simulation. The goal is to adjust the dynamic loading of the grid at different levels through EV charging and observe its effect on the measured node voltages through statistical analysis. System modeling is done using MATLAB and Simulink. Each of the sub-components of the system model are described below.

A. EV Load Modeling

EVs arrive at and depart from a residential charging station according to a Gaussian distribution with mean and standard deviation of (17h30,1h00) and (07h47, 0h23), respectively. The model generates state of charge (SOC) values for each EV at the time of grid connection based on a Gaussian daily trip distribution with mean and standard deviation of (40.0 mi, 5.0 mi). Each EV is assumed to have a 60 kWh battery pack with an on-board charger of 7 kW corresponding to around 30 A AC rms current for a rated voltage of 240 V. EVs are assumed to employ constant DC charging current to charge their batteries.

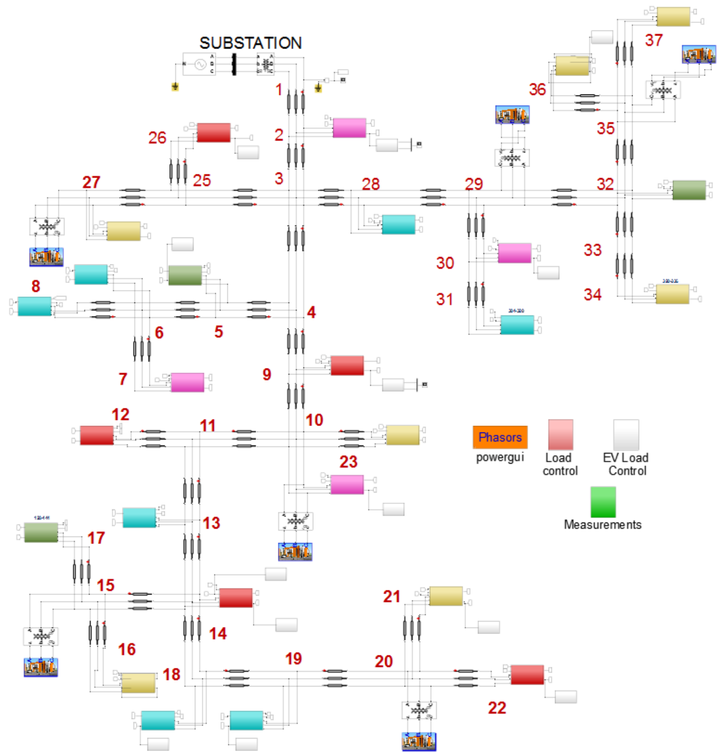


Figure 1: MATLAB Simulink phasor model used for the analysis of the IEEE 37-Bus test system.

B. Distribution Grid Modeling

The primary distribution grid used in this study is based on the IEEE 37-Bus test system, which is an unbalanced grid that operates at a nominal voltage of 4.8 kV [17]. The primary network implemented for this study in MATLAB is shown in Fig. 1. Each colored box in Fig. 1 represents a neighborhood that is connected to a primary feeder bus. There are a total of 26 neighborhoods in the grid powered from different phases to ensure more balanced operation.

Each neighborhood is modeled as a secondary network shown in Fig 2. The secondary network is developed following a similar procedure described in [17]. It contains four inner nodes and at each node a pole-mounted transformer of 25 kVA is located. Each transformer steps-down the primary feeder voltage of 4.8 kV to a secondary voltage level of 120/240V and supplies four residential houses. In total, there are 416 residential and six commercial customers in the model. The overall distribution grid operates slightly under 2MW at peak hours without any charging event.

C. Residential and Commercial Load Modeling

A random consumption data generator has been designed for residential homes. This generator uses 16 days of residential

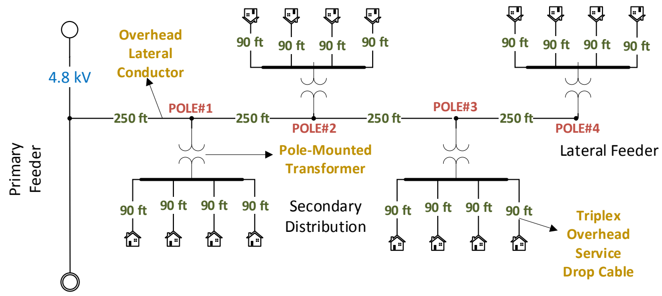


Figure 2: Secondary distribution network structure implemented in the MATLAB model.

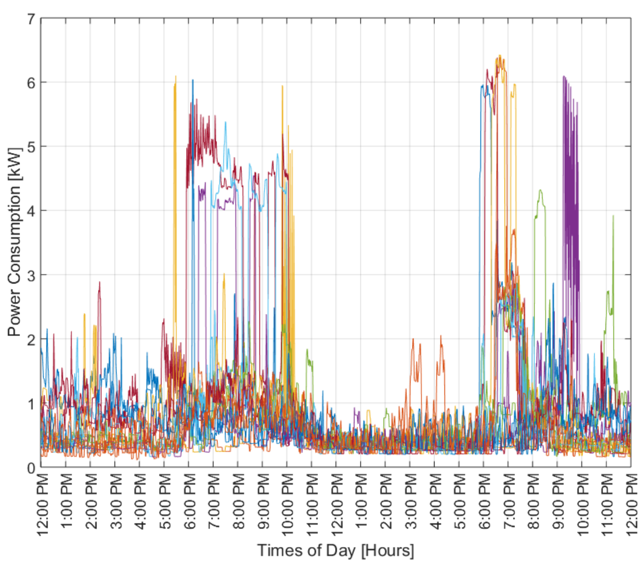


Figure 3: 16 days (shown in different colors) of power consumption data of a household.

power consumption data given in Fig. 3. The household consumption data was obtained using publicly available data from E-gauge [18]. This data is used to create a statistical distribution of the load model for one-minute resolution under the assumption that the data is normally distributed. The generated power consumption probability distribution function (PDF) is then used to populate a load profile in one-minute resolution for each house in the grid model. Each house is assumed to operate at 0.9 power factor lagging at all times.

The commercial loads are located at Bus-10, 15, 20, 27, 29, 35 and each draws a peak power of 130kW. The commercial loading profile is downloaded from public Open-EI data repository for a mid-size office building.

III. Simulation Study

A. Simulation Set-up

Understanding the impact of the loading in the distribution grid on the local voltages can be a key to a fully autonomous control methodology. For this purpose, we performed MC simulations where we tested *two scenarios* with different levels of loading.

For each scenario, we take voltage measurements at five houses located in different neighborhoods. These neighborhoods are chosen such that their distances to the substation increases from 1 to 5, i.e. 1 being closest to the substation and 5 being the farthest ranging from 1 km to 2.4 km. First house is located under neighborhood node 26^{th} (1.05 km) in Fig. 1, second house is at 9^{th} (1.44 km), third is at 10^{th} (1.50 km), fourth is at 14^{th} (1.87 km), and finally fifth is located at node 22^{th} (2.43 km).

In each scenario, the EV penetration is tested at %0, %20, and %40 levels. The difference between *two scenarios* is that in the first scenario the measured houses do not have any EV charging event whereas in the second scenario EV charging event occurs at the measured houses. A simulation time interval of 4pm-8pm is chosen since majority of EV arrivals occur in this time frame. In each MC simulation, residential loads are independently produced from their inferred load distribution levels, and EV arrival and departure times are randomly determined from their respective distributions. A total of independent 30 MC simulations are conducted to extract important statistical signatures.

B. Results

The MC simulations generate 30 daily operations for five different houses in the grid under two different scenarios. The results are shown as box plots to highlight the statistical features of all the MC simulations.

Figures 4–6 show the box plots of the measured voltages of each house for a 15 minute duration (chosen between 6:00pm - 6:15pm) under the two scenarios. Under the first scenario, where the tested houses do not have an EV, the effect of EV penetration in the rest of the grid can be observed specifically on the tested houses. It can be seen from Fig. 4 that when EV penetration is %0 in the grid, the mean of the observed voltages decreases gradually for the houses depending on the distance of the house from the substation. It can also be observed that the deviation of voltages for each house is comparably very small and similar to each other although it gets worse when the distance is further away from the transformer. This result shows that the main factor effecting the local voltage distribution is the distance of the house to the substation when there is no EV penetration in the system. However, the relationship is very complex due to the radial structure of the system [15]. Also, the variance of the voltages are similar although houses are in different neighborhoods.

When the EV penetration is increased to %20, and %40 in the grid, even though the tested houses do not have any EV connected, the observed mean voltages drop and the voltage deviations increase for each house as shown in Fig. 5. Although a general trend of mean decrease and deviation increase can be observed, the effect of changing EV penetration on each house is different. If the tested houses have also plug-in EVs (scenario 2), then the observed voltage deviations considerably

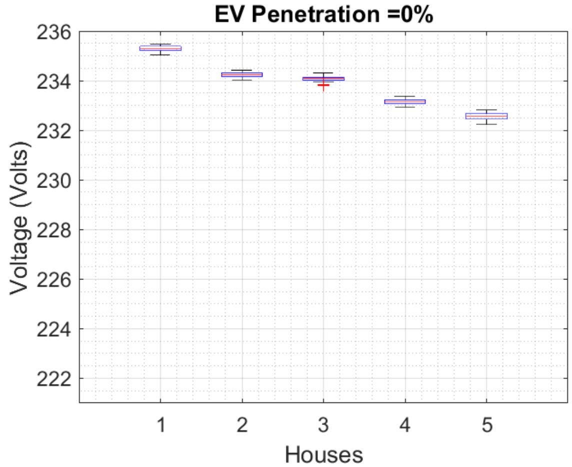
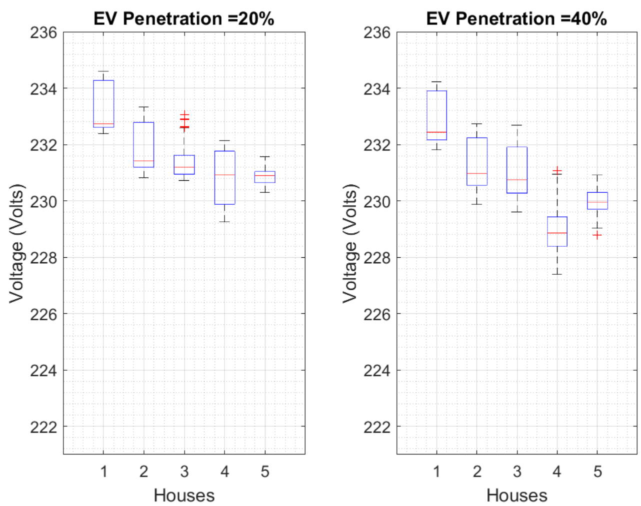


Figure 4: Voltage profile of 5 houses with 0% EV penetration both valid for scenario-1 and 2.

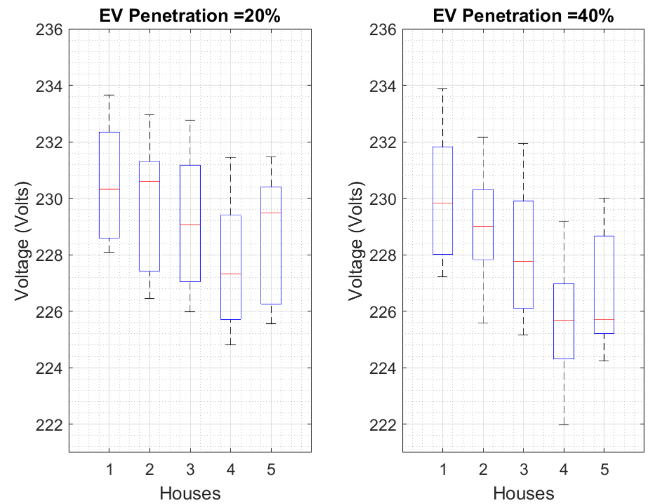


(a) (b)

Figure 5: Voltage profile of 5 houses with (a) 20% and (b) 40% EV penetration for scenario-1.

increase and mean values decrease compared to scenario 1 as shown in Fig. 6.

For a closer look at the voltage profile of a particular node in scenario 2 over the total simulation time interval, House-3 is chosen as an example. Figs. 7– 9 show the voltage plots of all the 30 MC simulations of this house in scenario 2 throughout four hours of simulation time for 0%, 20%, and 40% EV penetrations, respectively. As can be seen, voltage deviations are much higher in 20% and 40% cases compared to 0% case. The voltage deviations differ not only with different EV penetrations but also with time due to change in grid loading. As a result, each 15-min slot distribution statistics need to be observed and recorded for a dynamic and effective voltage-based control structure as examplified in Figs 4–6.



(a) (b)

Figure 6: Voltage profile of 5 houses with (a) 20% and (b) 40% EV penetration for scenario-2.

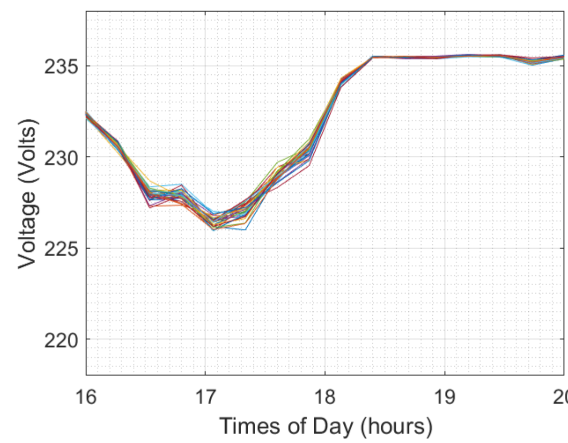


Figure 7: Voltage profile of house-3 at 0% EV penetration (All 30 MC simulations together - scenario 2).

IV. Analysis and Discussion

The obtained results indicate several important points. First, the mean voltage levels and observed voltage deviations at each house is very much dependent on both the distance of house from the substation, the radial topology of the distribution grid, and the EV penetration level. This conclusion shows that any globally set voltage control levels would not be optimal, and the voltage control levels for each house should be determined or learned independently for a fair capacity distribution. Secondly, each house has the capability of observing its own voltage levels and hence voltage distributions. This produces a local observation of the grid congestion at each house. Also, the mean and deviation levels summarize the expected levels of voltage including the combined effect of whole grid and the specific house. This is very hard to analytically deduct and can only be formulated

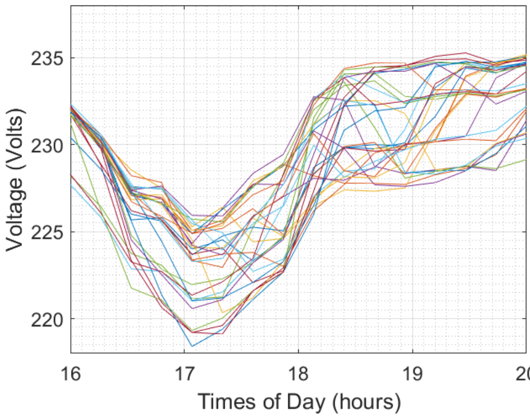


Figure 8: Voltage profile of house-3 at 20% EV penetration (All 30 MC simulations together - scenario 2).

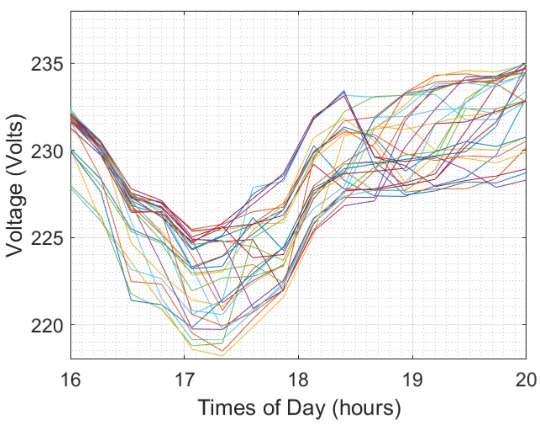


Figure 9: Voltage profile of house-3 at 40% EV penetration (All 30 MC simulations together - scenario 2).

under very strict assumptions as shown in another study [15]. Therefore, local information learning has the potential to be used for a local voltage control mechanism that can be used for EV integration as well as PV interconnection to the distribution grid as a very cost-effective and practical method. While a similar effort has been recently done utilizing local frequency measurements for location estimation in the distribution grid [19], we believe voltage measurements have a good potential to extract information of grid congestion.

V. Conclusions and Future Work

Voltage vs. distance relationship in a distribution network is highly non-linear due to different node currents, line distances, and complex distribution grid topology. Learning the nominal operating voltage levels in each node connected to distribution network provides invaluable information about the status of the grid, distance of the node to the substation, and thereby the type of control for EV charging that can be used at that node for a fair and sustainable EV grid integration. In this paper, the voltage impact of EV integration is studied to extract the local voltage distributions, which were observed to be important signatures of power system congestion.

The obtained results show that each local observed voltage distributions carry information about the congestion and EV penetration levels of the distribution network. Future work will include developing novel distributed and learning based voltage control techniques using the methods described in this paper.

References

[1] F. Erden, M. C. Kisacikoglu, and O. H. Gurec, “Examination of EV-grid integration using real driving and transformer loading data,” in *9th International Conference on Electrical and Electronics Engineering*, Nov. 2015.

[2] L. P. Fernandez, T. G. S. Roman, R. Cossent, C. M. Domingo, and P. Frias, “Assessment of the impact of plug-in electric vehicles on distribution networks,” *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 206–213, Feb 2011.

[3] S. Shafiee, M. Fotuhi-Firuzabad, and M. Rastegar, “Investigating the impacts of plug-in hybrid electric vehicles on power distribution systems,” *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1351–1360, Sept 2013.

[4] E. Veldman and R. A. Verzijlbergh, “Distribution grid impacts of smart electric vehicle charging from different perspectives,” *IEEE Trans. Smart Grid*, vol. 6, no. 1, pp. 333–342, 2015.

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

[6] N. Leemput, F. Geth, J. V. Roy, A. Delnooz, J. BÃŒscher, and J. Driesen, “Impact of electric vehicle on-board single-phase charging strategies on a flemish residential grid,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1815–1822, July 2014.

[7] K. Clement-Nyns, E. Haesen, and J. Driesen, “The impact of charging plug-in hybrid electric vehicles on a residential distribution grid,” *IEEE Transactions on Power Systems*, vol. 25, no. 1, pp. 371–380, Feb 2010.

[8] G. Binetti, A. Davoudi, D. Naso, B. Turchiano, and F. L. Lewis, “Scalable real-time electric vehicles charging with discrete charging rates,” *IEEE Trans. Smart Grid*, vol. 6, no. 5, pp. 2211–2220, Sept 2015.

[9] T. Wu, Q. Yang, Z. Bao, and W. Yan, “Coordinated energy dispatching in microgrid with wind power generation and plug-in electric vehicles,” *IEEE Trans. Smart Grid*, vol. 4, no. 3, pp. 1453–1463, Sept 2013.

[10] O. Sundstrom and C. Binding, “Flexible charging optimization for electric vehicles considering distribution grid constraints,” *IEEE Transactions on Smart Grid*, vol. 3, no. 1, pp. 26–37, March 2012.

[11] A. T. Al-Awami, E. Sortomme, G. M. A. Akhtar, and S. Faddel, “A voltage-based controller for an electric-vehicle charger,” *IEEE Trans. Veh. Technol.*, vol. 65, no. 6, pp. 4185–4196, 2016.

[12] A. R. Malekpour and A. Pahwa, “A dynamic operational scheme for residential pv smart inverters,” *IEEE Trans. Smart Grid*, vol. 8, no. 5, pp. 2258–2267, Sept 2017.

[13] I. Mareels, T. Alpcan, M. Brazil, J. de Hoog, and D. a. Thomas, “A distributed electric vehicle charging management algorithm using only local measurements,” *IEEE Innovative Smart Grid Tech. Conf. (ISGT)*, pp. 1–5, 2014.

[14] M. J. Zangs, P. B. E. Adams, T. Yunusov, W. Holderbaum, and B. A. Potter, “Distributed energy storage control for dynamic load impact mitigation,” *Energies*, vol. 9, no. 8, 2016.

[15] E. Ucer, M. C. Kisacikoglu, and M. Yuksel, “Analysis of an internet-inspired EV charging network in a distribution grid,” in *IEEE PES Transmission and Distribution. Conf. Expo.*, accepted, 2018, Available:http://mck.people.ua.edu/uploads/8/7/7/8/87787552/ucer_t_d_paper.pdf.

[16] N. O’Connell, Q. Wu, J. Østergaard, A. Nielsen, S. Cha, and Y. Ding, “Day-ahead tariffs for the alleviation of distribution grid congestion from electric vehicles,” vol. 92, p. 106–114, 11 2012.

[17] A. R. Malekpour and A. Pahwa, “Radial test feeder including primary and secondary distribution network,” in *North American Power Symp.*, Oct 2015, pp. 1–9.

[18] Energy monitoring systems for residential and commercial applications. http://www.egauge.net/. [Online; accessed 31-Jan-2018].

[19] W. Yao, J. Zhao, M. J. Till, S. You, Y. Liu, Y. Cui, and Y. Liu, “Source location identification of distribution-level electric network frequency signals at multiple geographic scales,” *IEEE Access*, vol. 5, pp. 11 166–11 175, 2017.