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Individualized Smart Charging to Mitigate the Growing Electrical Peak Demand from EVs as Home Appliances

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Abstract — **In this paper we analyze the upcoming trends in electric vehicle (EV) to grid integration. We identify various challenges and opportunities that EVs present to the users and Utilities. Then, we present two progressively intelligent solutions for autonomous, cost efficient and sustainable charging of EVs to address the major problems due to EV charging at the individual, residence and grid levels. Our simulation study shows that the proposed smart charging solutions can effectively mitigate the potentially overwhelming peak demand challenge due to the synchronized charging activities. Therefore, leading to a win-win proposition for both the user and the Grid and accommodating seamless integration of EVs as appliances into the Smart World.**

Keywords—Electric Vehicles, Electrical Grid, Electrical Peak Demand, Smart Charging, Smart World.

I. Introduction

Exponential advances in computer science, vehicle electronics [1] and battery technology [2] have propelled the recent advances in EV manufacturing, adoption and operation, providing new opportunities for sustainable and smart mobility. Thus, the EVs are expected to play a pivotal role in the creation of clean and smart transportation [3]. However, the rise in EV sales and consequent energy demand shift from fossil fuels to electricity adds significant strain on the existing power grid, distribution network and residential electric infrastructures.

First, let us look at the Grid level peak demand and supply balance challenge. Fig. 1 shows the California Net Demand Curve of March 30, 2018. We notice a sharp ramp in power demand of about 9,871 MW between 5 pm and 8 pm, the period when most of the working population return home and switch on home – appliances [4]. As EVs become the new "appliances on wheels" they are expected to cause additional demands to the grid at the same peak period. For instance, there are approximately 14.5 million automobiles registered in California in 2016 [5]. Although there are about 300,000 registered EVs in California today [6], the state has set a goal of adopting 1.5 million EVs on road by 2025 [6], i.e. an increase of 1.2 million additional EVs and approximately 10% of all automobiles. To calculate the EV-caused electric peak demand, we assume these EVs return home and start charging at around 6 pm, at 7 kW. As shown in Fig. 1, the extra load amounts to 8,400 MW on top of the increased demand from other home appliances, causing a total of approximately 18,000 MW ramp or over 100% increase in demand in 3 hours, a growing electric peak demand on the Peaker power plants. As EVs reach 50% of all automobiles, i.e., 7 million, the ramp will reach 350% for the peak demand hours, a potentially prohibitive electric peak demand on the Peaker power plants.

Next, at the residence level, if EVs are used as the primary means of household transport, significant upgrades must be made to the local distribution transformer and home power circuits to accommodate EVs as home appliances. Statistically, an average American Family owns 2.28 vehicles [7], assuming 2 electric vehicles per family are charging at the same time, the total power consumed from the local distribution, due to Level-2 EV charging, at any given time is 14 kW [8]. If the average home power circuit is 24 kW the EV load contribution is over 50%, leaving little room for usage of other heavy

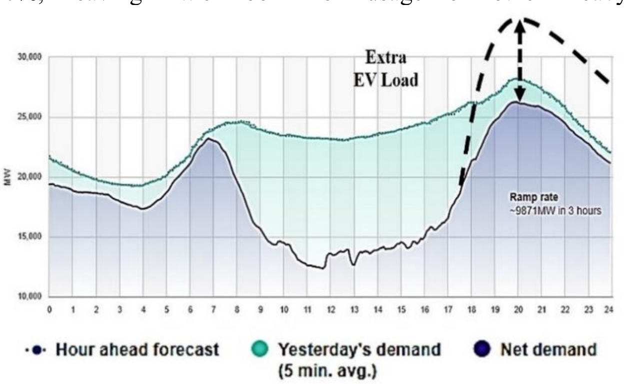

Fig. 1. California Net Demand (i.e., Total Demand minus Renewable Energy Sources) on March 30, 2018 (Courtesy: California ISO))

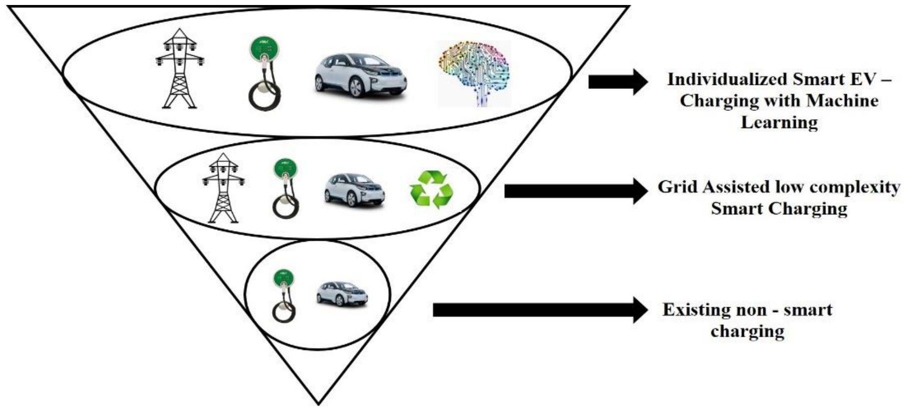

Fig. 2. AI-based autonomous smart charging assistant

wattage appliances like air conditioning at the same time. Existing smart charging solutions focus on delaying the EV charging to off-peak hours. Unfortunately, the current distribution transformers are designed to cool down during the off-peak hours [9]. Such off-peak EV charging will reduce the cool – off time, potentially degrading the normal operations of transformers.

Finally, at an individual EV level, unnecessary frequent charging increases the number of charging cycles, and potentially leads to faster degradation of battery capacity [10]. The introduction of ultra – fast charging, may also contribute to the reduced battery life time and/or capacity [11]. On the other hand, the failure of the user to remember to charge the EV may result in a depleted EV battery, rendering it unfit for the following trip. Hence, there is a need for automatic charging decision-making to mitigate the human limitations and errors.

Therefore, it is important to address these inevitable challenges and use them as an opportunity to create economically viable and sustainable solutions. As a result, we view the EV-Grid charging problem from the perspectives of the major participants and the scale of adoption in the sustainable mobility ecosystem: (1) Electric Grid or Utilities: Problem of uniform distribution of Net load; (2) EV owner or User: To create economic value and improve user experience; and, (3) Original Equipment Manufacturer (OEM): To improve battery life and create a viable business model. These views help us improve the quality and resilience of our smart charging solutions.

II. OBJECTIVE

Many research studies have tried to address the challenge of additional EV charging demand on the grid. The most common approaches are: 1) Vehicle to Grid (V2G) based, [12–14], 2) Demand–Response (DR) based, proposed in [15–17]. The common aim of these approaches is to reduce the EV induced peak on the net demand by either incentivizing the EV users to voluntarily give up charging of EVs using DR scheme and/or resupplying electric energy to the grid using V2G. These solutions force EV users to rely on off – peak charging. With increased integration of EVs, this leads to: 1) EV-induced Demand peaks during off – peak times; 2) Reduced cool–off time for distribution transformers. Moreover, off–peak slow charging during late night may be useful for Personal Electric Vehicles (PEVs) but may hinder time – bound transportation services like emergency vehicles or public transportation.

In this paper, to address the challenges imposed on power grid by EVs, as discussed in Section I, and to improve on the earlier research, we present a series of progressively intelligent smart EV charging solutions, as illustrated in Fig. 2. The proposed EV– Grid collaborative smart charging solution utilizes the predicted electricity demand, renewable energy supply and pricing data from the grid and combines this information with the learnt usage and charging pattern of the individual EV to distribute the EV load more uniformly throughout the day and week. This distribution of the net load helps mitigate the demand peaks and prevents the need for creation of peak power plants, thereby creating economic value for the utilities[18].

Since the solution enables EV self – charging based on the learnt usage patterns, it serves as an AI-based autonomous smart charging assistant and relieves the user from the burden of charging decision. Further, the learnt usage pattern enables a customized charging session according to the driving characteristics of each individual and thereby prevents unnecessary overcharging. The resultant decrease in charging cycles prolongs battery life [19] and also helps spread the charging activities collectively over a larger time span, e.g., a week.

Moreover, the proposed smart charging solution can be used to create new business models involving integration of Home energy management systems with EV charging, creating new markets for energy products and business models for automotive manufacturers, e.g., as evident by the Tesla – Solar City merger [20].

In this paper we present the smart charging solution in the following structure. Firstly, in the methodology section we discuss the progressive improvements in our design of the smart charging system and algorithm. Then a comprehensive evaluation is made and results are discussed. Finally, we conclude the paper with recommendations on future improvements to the proposed solutions.

III. METHODOLOGY

In this section we discuss the methodology and proposed system architecture of the grid-assisted EV smart charging algorithm. The proposed solution has these progressively intelligent features: 1) To shift the EV charging to off – peak time. 2) To integrate renewable energy stored in the batteries of Home Energy Management systems. 3) To identify and integrate individual user's EV usage and charging need into the solution through machine learning algorithms like logistic regression.

Data Source: All information pertaining to the predicted and actual load is inferred from the actual demand and supply data provided by California ISO [21].

The modern day electric grid is smart, i.e., it utilizes supervisory control and data acquisition (SCADA) system [22], a large scale networked-sensory system, to analyze the electricity consumption accurately in real-time in order to adjust the power generation to balance the electricity demand and supply. Further, the utilities operating the grid also employ sophisticated big data analytics to predict the future usage and energy availability to improve demand response. The grid stores the energy demand and the renewable energy availability data in the cloud. Hence our first objective is to harness this existing information of the grid to enable smart charging at low complexity through a distributed computing approach.

Thus, our proposed "Joint EV-Grid collaborative approach to smart charging" starts by leveraging this grid-provided high-fidelity demand-supply information and creating a charging plan with user preferences. Fig. 3 illustrates the workflow of our Joint EV–Grid Smart Charging solution. Electronic Control Unit (ECU), an embedded system in the EV, can be used to host the smart charging algorithm. After suitable authentication and authorization steps, the EV can access the predicted price and availability of renewable energy information from the Charging station. Here, the charging station acts as a local access point for Price and Renewable energy information from the utilities.

This information-based power transfer system is implemented based on communication protocols like the ISO 15118. The communication stack can be implemented on an ECU in the EV called Electric Vehicle Charging Controller (EVCC) and its counterpart in the charging station called Supply Equipment Charging Controller (SECC). The "Price preference" and "Renewable Preference" from the user are inputs to the smart charging algorithm through the Human Machine Interface (HMI) in the vehicle. In our prototype system we have used a Desktop PC connected to a server that hosts the smart charging dashboard for visualization.

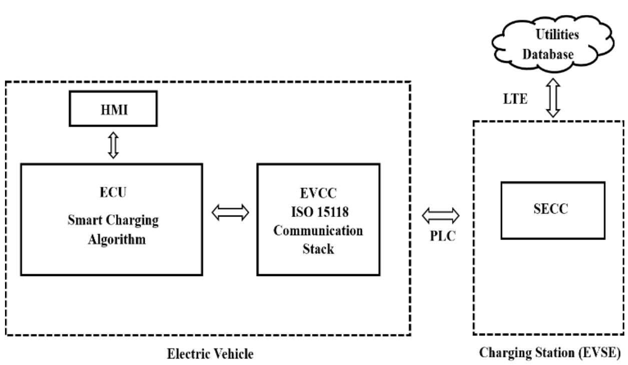

Fig. 3. Overview of the Joint EV – Grid Smart Charging Workflow

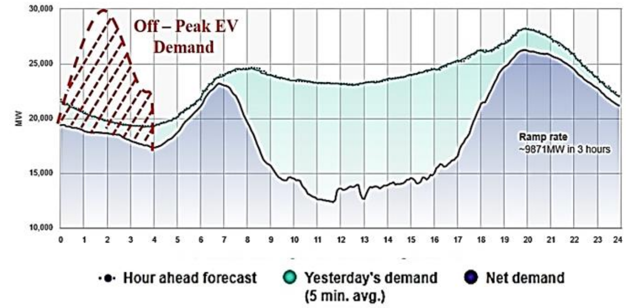

Fig. 4. Artificial Peak Demand due to EV Charging in off-peak hours

Unfortunately, on closer observation, we notice that: as the pricing and renewable energy availability information is the same to all EVs, if all users choose the price-optimized charging preference after returning home at 6 pm, the corresponding EVs would start charging at 12 am, i.e., the time of minimal cost of charging, resulting in an artificial peak starting at 12 am, see Fig.4. Hence, there is a need for a more robust smart charging decision for uniform distribution of net load.

We believe this can be better achieved by identifying and integrating individual user's EV usage and charging need into the solution through machine learning algorithms. This leads to our refined joint EV-Grid optimization algorithm. As a result, the improved algorithm learns the EV usage characteristics of each individual and creates a unique charging plan tuned to their usage profile.

Human decision making is limited by its inability to analyze multi–dimensional big data and unearth hidden patterns. Machine Learning, when combined with big data, enables machines to learn the intricate relationships in multi – dimensional data, to extract complex patterns and use these insights for reliable and time - bound decision-making, thereby leading to the development of "Autonomous agents". EV

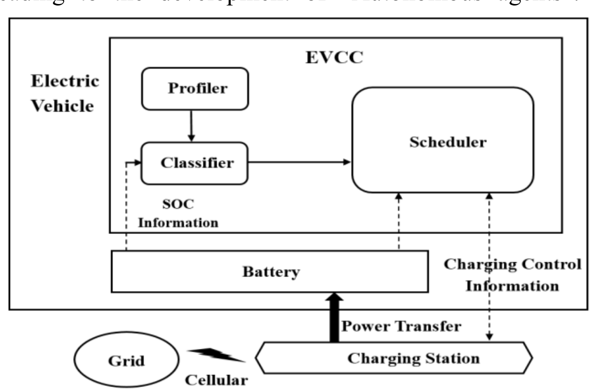

Fig. 5. Autonomous Smart Charging Implementation in EVCC

charging is no different and we believe that autonomy can be integrated into this process. Fig. 5 represents the enlarged view of the ECU hosting the smart charging algorithm in Fig. 3. It shows the implementation of integrating the individual user's EV usage and charging need into a more intelligent Joint EV – Grid smart charging application. The autonomous charging solution mainly consists of: 1) Profiler, 2) Classifier, and 3) Scheduler.

The profiler is preloaded with charging/driving profiles based on the 1) Frequency of charging (Plugin frequency), 2) Distance travelled each day, 3) Duration of plugin, 4) Battery consumption per trip. Our initial profiles include:

- Category 1: (Home-Maker) High Frequency of round trips and less battery consumption per trip. Example: Typical Homemaker and the elderly.
- Category 2: (Regular Commuter) Here, we target class of users with low round trip frequency and battery usage, for example: office-commuters and students. They exhibit relatively lesser number of charger plugins.
- Category 3: (Delivery Person) This category represents the heavy users like long distance commuters, Mail – delivery, public transportation etc.

These initial profiles could be further adapted to better fit each EV's usage pattern with enhanced autonomous capability.

The Classifier learns the different user profiles from the profiler. Based on the EV usage/charging data it classifies the present user of the EV into one of these categories. We have used logistic regression algorithm as the classifier.

The scheduler prepares a charging plan, based on the classifier output and negotiates a power transfer schedule with the charging station.

Together the Profiler, Classifier and Scheduler allow the EV to self–charge, by learning the driving/charging characteristics of the EV user. Further, by creating these profiles we ensure that the charging load can be distributed throughout the day and week to maximally mitigate the EV-caused peak demand.

IV. Experiment Designs and Results

The progressively intelligent smart charging solutions have been designed and implemented taking into consideration the various grid and user specific needs. In this section we systematically evaluate these solutions by unearthing the results obtained at various stages of development. These results are used to evaluate:

1) Accuracy and robustness: The optimality of scheduling plan resulted from using the hour-ahead and day-ahead price prediction and renewables availability from the grid as it helps in preparing a charging plan in advance. This may also help in providing the scheduled EV charging information to the grid at any given point of time to supplement the current SCADA for earlier provisioning of Peaker generation.

2) Load Management: The effectiveness to distribute EV charging more uniformly to reduce peak.

3) Cost Effectiveness: Economic benefits of smart charging.

Table 1. Smart Charging Results

Time of Charge	**18:00 – 05:00**	**06:00 – 17:00**
Battery Energy before charging (kWh)	0	0
Transferred Energy (kWh)	30	30
Cost (cents) / Saving **Non-smart, full- rate at 7kW**	384.83/ (as reference)	116.41/ (70%)
Cost (cents) / Saving **Non-smart, half-rate at 3 kW**	322.08/ (16%)	85.95/ (78%)
Cost (cents) / Saving **Smart Charging with real-time actual info**	175.68/ (54%)	84.14/ (78%)
Cost (cents) / Saving **Smart Charging with hour-ahead Prediction**	175.68/ (54%)	84.14/ (78%)
Cost (cents) / Saving **Smart Charging with day-ahead Prediction**	175.60/ (54%)	84.14/ (78%)

A. Robust Grid-Assisted Low-Complexity Smart Charging

Firstly, we make the following assumptions: 1) Total EV battery capacity: 30kWh; 2) Full charging rate: 7kW for a 240V level 2 charging station; 3) Half charging rate: 3kW for a 240V level 2 charging station (assuming a charging station of variable output power); 4) We ignore the power loss due to resistance, capacitance and inductance of the intermediate circuitry between the charging station and the EV; and, 5) A dynamic electricity price model that varies proportionally to the corresponding total demand at Grid-level.

Let us consider the Joint EV-Grid based smart charging system. The test cases are broadly classified based on the energy mix that constitutes the supply:

1) EV Charging solely based on Energy Pricing information from Grid.

2) EV Charging considering Renewable Energy integration due to Home Energy Management System and Power Grid at scale.

To present a comprehensive evaluation of the economic benefits of smart charging with the integration of renewable energy we present the following charging strategies for each of the main cases: 1) Non-smart charging at full-rate, 2) Reduced-rate non-smart charging at half-rate, 3) Smart charging algorithm with perfect grid load/cost information, 4) Smart charging algorithm with grid-provided predicted load/cost information (day-ahead or hour- ahead prediction). The results are presented in Table 1, and Fig. 6 & 7.

B. Individualized Smart Charging with EV Usage and Charging Profiling through Machine Learning

Next, we integrate machine learning algorithms like logistic regression to learn automatically the charging profiles of the individual EV without explicit user input.

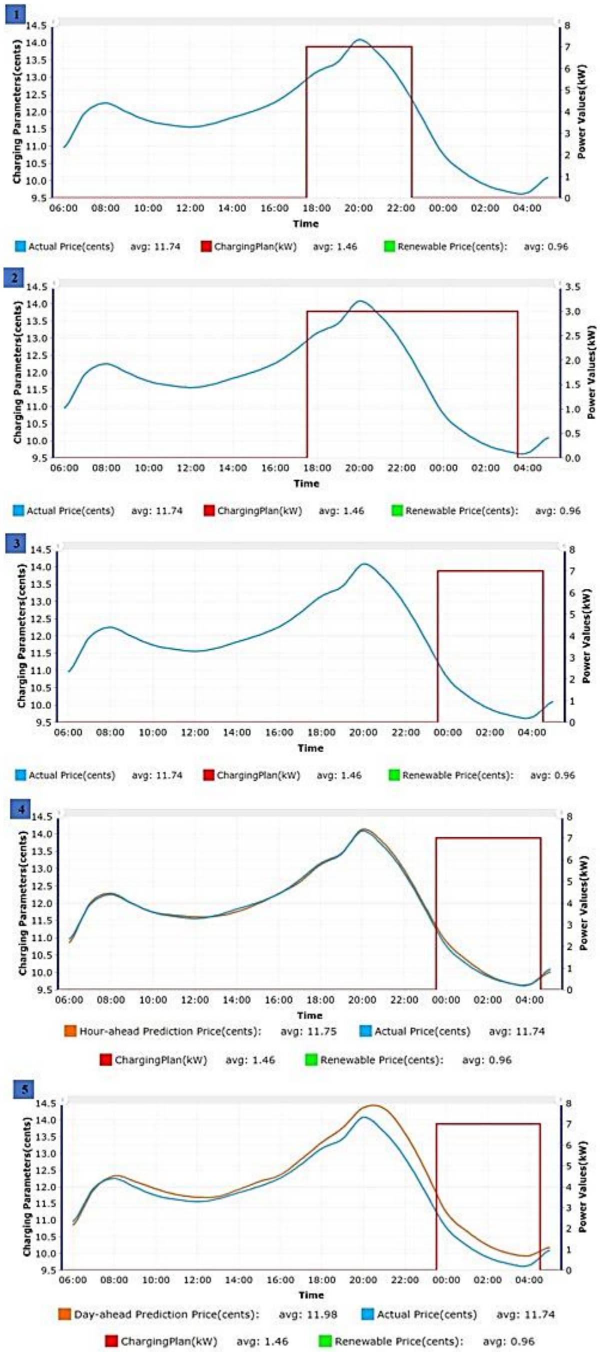

Fig. 6. Smart Charging based only on Grid-Provided Price Information.

1) Non – Smart Charging at Full – Rate

2) Non – Smart Charging at Half – Rate

3) Smart Charging with Real-Time Actual Load/Price information

4) Smart Charging with Hour-Ahead Predicted Load/Price information

5) Smart Charging with Day-Ahead Predicted Load/Price information

Here our primary focus is augmenting the previous solution by exploring the diversity of EV usage patterns to maximize the opportunities to spread the charging activities across the day and week. We have developed an intelligent charging prototype to enable the following features:

1) Autonomous decision-making for charging;

2) Individualized EV charging decision based jointly on user profiles and grid information;

This refined smart charging solution helps:

1) *Mitigate the EV-induced artificial Peak in the otherwise off-peak hours at the Grid- and Residence-level;*
2) *Reduce unnecessary charging cycles to improve battery life at the EV-level.*

The results for the Individualized Smart Charging with EV Usage and Charging Profiling are presented in Fig. 8.

V. DISCUSSION

The results obtained provide an unequivocal evidence that our Smart charging system addresses the core challenges of EV- Grid energy balance.

Table 1 summarizes the results for the Grid-assisted smart charging solution. Let us consider the results for charging period from 6 pm (i.e., 18:00) to 5:00 am as both the highest and the lowest cost of charging are present within this interval. We also assume the Power Grid is the only source of electrical energy (i.e., no residential renewable energy generation). This is an ideal time – span to illustrate the benefits of smart charging over regular charging. Further, it is the time when most the EV driving population charge their vehicles. The cost of charging at full-rate 7 kW without smart charging (Fig. 6.1) is 384.83 cents. When we lower the charging rate to half-rate at 3 kW, the cost drops to 322.08 (Fig. 6.2). Although it takes twice as long to charge the battery, slower half-rate charging is able to spread the load into the off-peak hours to lower the cost, achieving 16% monetary saving.

Furthermore, by using our Grid-assisted smart charging, the cost can be reduced to 175.68 cents, less than half the cost of non-smart full-rate charging (Fig. 6.3). Clearly smart – charging leads to significant economic benefits.

Then, we assess the robustness of our solution when using predicted information made available by the grid instead of the actual information which may not be available in real-time. As shown in Fig. 6.4 & 6.5, smart charging with hour-ahead predicted tariff and day-ahead predicted tariff, respectively, achieves similar outcome as when using the actual tariff for charging decision-making. A clear proof that grid-provided predictions are as good as the actual tariff for the purpose of supporting smart charging decision-making. Moreover, it shows that our solution is robust to make decisions based on predicted day-ahead charging data that facilitates earlier planning of charging schedule. Such schedule information could be then relayed to the grid operator to improve the demand-response performance by accurately provisioning the electricity generation ahead of time.

Fig. 7 demonstrates the results for another charging time-period: between 06:00 and 17:00, where renewable energy is integrated into the power grid from solar farms and/or home energy storage and management systems. Particularly, this time-span helps illustrate the use of smart-charging algorithm to maximize the integration of renewable energy resource for EV charging. As shown in Table 1, smart charging the EV during the day between 06:00 – 17:00 helps the EV user to save 91.54 cents than charging during the time-period of peak demand, i.e., 18:00 to 05:00. Compared to non-smart full-rate charging at evening peak-hours, the saving adds to a total of 268.42 cents per full-charge, approximately 78% saving. Clearly, there is a significant advantage of charging EV at the day-time when renewable energy is available.

Finally, Fig. 8 shows the use of our Individualized Smart Charging with EV Usage and Charging Profiling to explore the optimal charging schedule tailored to the user's need without burdening the user with the potentially complicated decision-making task. The graphical representation of the charging plan from our intelligent scheduler for the 3 charging profiles, namely Category 1 (Home-maker), Category 2 (Regular

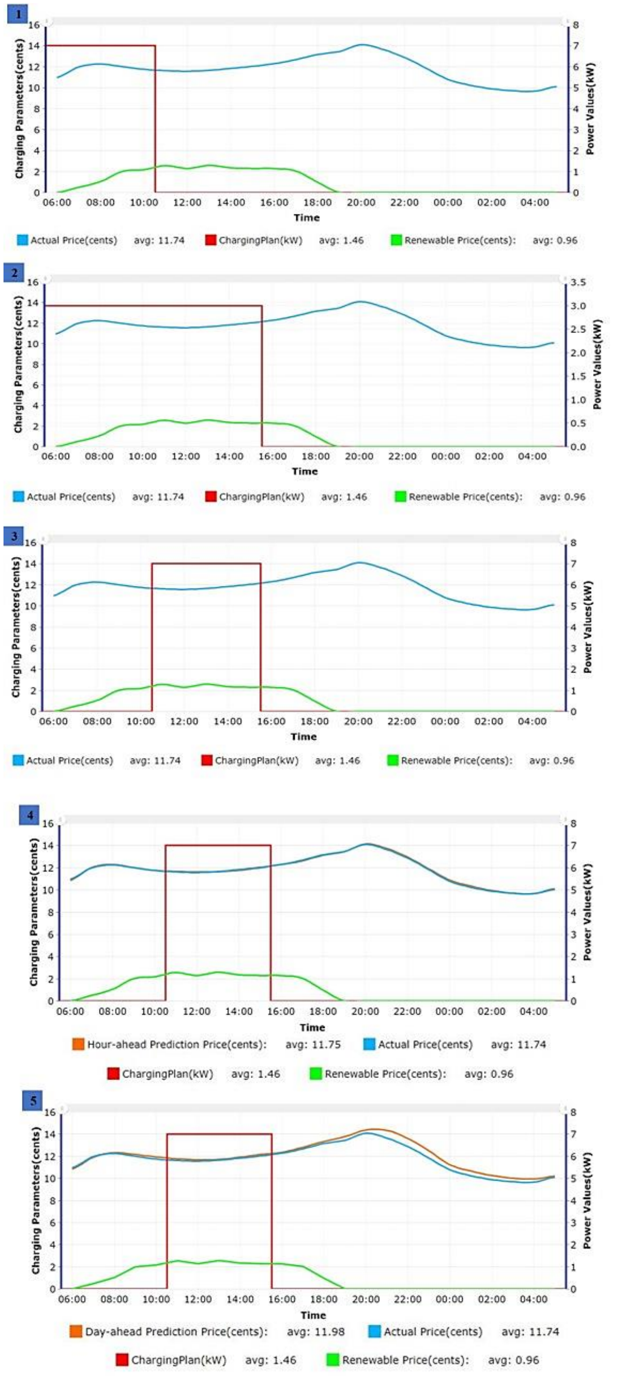

Fig. 7. Smart – Charging with Grid-Provided Price and Renewable Energy Information.

1) Non – Smart Charging at Full – Rate

2) Non – Smart Charging at Half – Rate

3) Smart Charging with Real-Time Actual Load/Price information

4) Smart Charging with Hour-Ahead Predicted Load/Price information

5) Smart Charging with Day-Ahead Predicted Load/ Price information

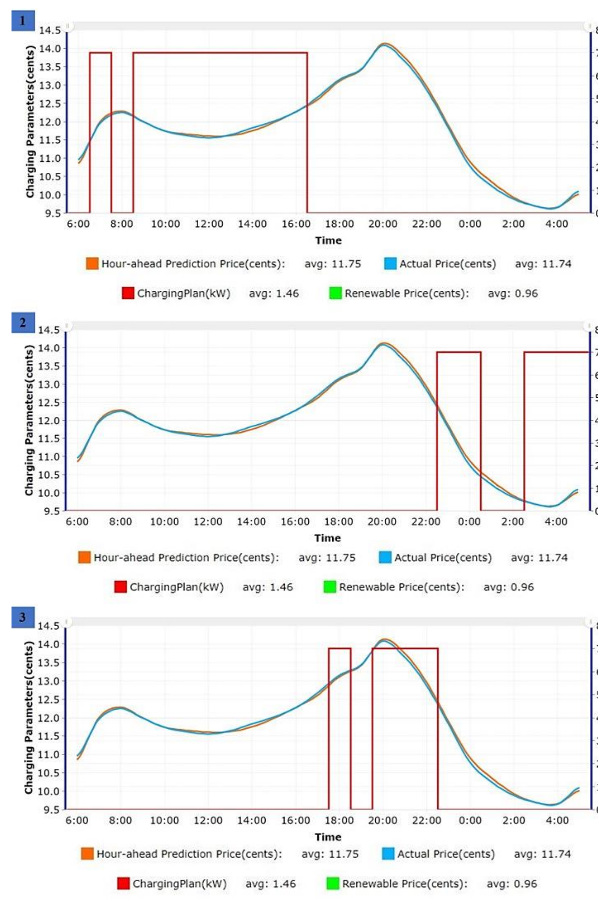

Fig. 8. Autonomous Smart Charging Results.

1) Category 1: Home -Maker profile

2) Category 2: Regular Commuter profile

3) Category 3: Delivery Person profile

Commuter), and Category 3 (Delivery person). For a home – maker's EV, the charging may take place during the day with maximum availability of solar energy, the primary source of renewable energy. This profile may include multiple trips in the morning and evening (e.g., grocery shopping, trip for children's after-school activities etc.). Consequently, to harness the renewable energy, the scheduler proposes the charging plan as shown in Fig. 8.1 to maximize the EV charging in the day-time when the EV is at home. Fig. 8.2 gives a graphical representation of charging schedule created for Category 2 (Regular Commuter). For this profile, the charging does not have to be frequent or daily, as the number of miles driven daily is less. So, the scheduler proposes a charging plan when the EV battery charge goes below a certain threshold in order to spread the load across the week. The charging of this profile takes place mainly at late night or early morning, where the load is minimal, and the risk of electricity outage before EV is fully-charged may not cause problem for the short-distance commute. Figure 8.3 shows the charging schedule for a Category 3 EV user. The charging must be frequent, irrespective of the load/cost curve, as it represents heavy user base of the driving population. So, the charging must be started as soon as the vehicle gets back home irrespective of the threshold and demand/cost.

Conclusion

In this paper, we examine the opportunities and challenges to accommodate EVs as home appliances at 3 different scales: the grid-, residence-, and EV-level. We envision the smart charging solutions as a synchronizing mechanism between the higher rate of EV penetration and a relatively slower expansion rate of the grid. This synchronization mechanism: 1) Creates economic value for consumers; 2) Improves user-convenience; 3) Helps utilities in demand-response management; and, 4) Leads to autonomous charging mechanism that blends into autonomous mobility. We have developed prototypes that integrate progressively intelligent charging capabilities to support this upcoming trend and provide direct evidences for using Individualized Smart Charging to mitigate the growing electrical peak demand from EVs without burdening the user with the complicated decision-making.

We would like to acknowledge that the proposed smart charging solutions are prototypes with data modelled around typical cases. We believe that a combination of big data and deep learning utilizing data sets like calendar information, social media and health records can be used to create richer and more accurate profiles to personalize charging.

The proposed smart charging solutions can be improved for main stream adoption. The bi-directional communication between the EV and the grid could potentially result in increasing risk of security threats like malicious cyber-attacks. There is a high probability for hackers to create pseudo demand peaks in the grid infrastructure, by increasing false demand response (DR) event requests. Consequently, we need a secure monitoring system that understands the messages transmitted between the EV-Charging Station-Utility communication system and predict security threats in advance and neutralize them.

References

[1] T. Seba, Clean Disruption of Energy and Transportation: How Silicon Valley Will Make Oil, Nuclear, Natural Gas, Coal, Electric Utilities and Conventional Cars Obsolete by 2030, First Beta. United States of America: Tony Seba; Beta edition (May 20, 2014).

[2] "Five emerging battery technologies for electric vehicles | Brookings Institution," Brookings, 30-Nov-2001.

[3] "Fueling a Clean Transportation Future (2016)," Union of Concerned Scientists. [Online]. Available: https://www.ucsusa.org/clean-vehicles/clean-fuels/transportation-fuels-future. [Accessed: 06-Apr-2018].

[4] J. S. John, "The California Duck Curve Is Real, and Bigger Than Expected," 03-Nov-2016. [Online]. Available: https://www.greentechmedia.com/articles/read/the-california-duck-curve-is-real-and-bigger-than-expected. [Accessed: 30-Mar-2018].

[5] "Number of registered automobiles in California 2016 | Statistic," Statista.[Online].Available:https://www.statista.com/statistics/196024/number-of-registered-automobiles-in-california/. [Accessed: 06-Apr-2018].

[6] J. Allen, T. Lopez, S. Ransom, P. Cazel, and N. Crisostomo, "Zero-Emission Vehicles and Infrastructure," California, Jul. 2017.

[7] M. Noor, "Many Families Limiting Themselves to a Single Car," The New York Times, 27-Jul-2008.

[8] "Level Up Your EV Charging Knowledge," ChargePoint. [Online]. Available: https://www.chargepoint.com/blog/level-your-ev-charging-knowledge/. [Accessed: 30-Mar-2018].

[9] C. Farmer, P. Hines, J. Dowds, and S. Blumsack, "Modeling the impact of increasing PHEV loads on the distribution infrastructure," in System Sciences (HICSS), 2010 43rd Hawaii International Conference on, 2010, pp. 1–10.

[10] "Battery Lifetime: How Long Can Electric Vehicle Batteries Last?" CleanTechnica. [Online]. Available: https://cleantechnica.com/2016/05/31/battery-lifetime-long-can-electric-vehicle-batteries-last/. [Accessed: 02-May-2017].

[11] "Ultra-fast Charging – Battery University." [Online]. Available: http://batteryuniversity.com/learn/article/ultra_fast_charging. [Accessed: 30-Mar-2018].

[12] Z. Wang and S. Wang, "Grid Power Peak Shaving and Valley Filling Using Vehicle-to-Grid Systems," IEEE Trans. Power Deliv., vol. 28, no. 3, pp. 1822–1829, Jul. 2013.

[13] K. Mahmud, S. Morsalin, M. J. Hossain, and G. E. Town, "Domestic peak-load management including vehicle-to-grid and battery storage unit using an artificial neural network," in 2017 IEEE International Conference on Industrial Technology (ICIT), 2017, pp. 586–591.

[14] G. Lacey, G. Putrus, and E. Bentley, "Smart EV charging schedules: supporting the grid and protecting battery life," IET Electr. Syst. Transp., vol. 7, no. 1, pp. 84–91, 2017.

[15] S. Shao, M. Pipattanasomporn, and S. Rahman, "Grid Integration of Electric Vehicles and Demand Response with Customer Choice," IEEE Trans. Smart Grid, vol. 3, no. 1, pp. 543–550, Mar. 2012.

[16] V. S. K. M. Balijepalli, V. Pradhan, S. A. Khaparde, and R. M. Shereef, "Review of demand response under smart grid paradigm," in ISGT2011-India, 2011, pp. 236–243.

[17] L. Zhao and V. Aravinthan, "Strategies of residential peak shaving with integration of demand response and V2H," in 2013 IEEE PES Asia-Pacific Power and Energy Engineering Conference (APPEEC), 2013, pp. 1–5.

[18] D. C. Wagman, "Energy Storage Projects to Replace Three Natural Gas Power Plants in California," IEEE Spectrum: Technology, Engineering, and Science News, 17-Jul-2018. [Online]. Available: https://spectrum.ieee.org/energywise/energy/renewables/energy-storage-projects-to-replace-three-natural-gas-power-plants-in-california. [Accessed: 24-Jul-2018].

[19] G. Lacey, G. Putrus, and E. Bentley, "Smart EV charging schedules: supporting the grid and protecting battery life," presented at the IEEE Vehicle Power and Propulsion Conference (VPPC 2015), 8, 2016.

[20] D. Muoio, “Elon Musk has a brilliant plan to change your roof,” Business Insider. [Online]. Available: http://www.businessinsider.com/why-tesla-solarcity-merger-makes-sense-2016-11. [Accessed: 02-Apr-2018].
[21] “California ISO - Todays Outlook.” [Online]. Available: http://www.caiso.com/outlook/outlook.html. [Accessed: 02-May-2017].
[22] M. Regula, A. Otcenasova, M. Roch, R. Bodnar, and M. Repak, “SCADA system with power quality monitoring in Smart Grid model,” in 2016 IEEE 16th International Conference on Environment and Electrical Engineering (EEEIC), 2016, pp. 1–5.