INL/CON-17-43890-Revision-0

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August 2018

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Prepared for the
U.S. Department of Energy
Office of Energy Efficiency and Renewable Energy
Under DOE Idaho Operations Office
Contract DE-AC07-05ID14517

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Abstract—**Residential electric vehicle charging load profile is indispensable to achieve reliable control strategies for mitigating negative effects on power distribution system due to emerging electrified transportation. This paper introduces a data-driven framework of charging load profile generation for residential plug-in electric vehicles. Real world historical residential charging behavior data is utilized to construct empirical charging decision making model by using machine learning algorithm. A multiple channels method with kernel density estimation is proposed to construct probability density functions for estimating charging duration based on parking duration. A generation algorithm considering parking time and travel demand dependency is introduced to generate residential charging behaviors. This framework is extensible to generate various charging load profiles and simulate varied residential charging scenarios under different number of households and charging rates. This will be crucial for designing and validating residential charging control strategies.**

I. Introduction

Increasing electric vehicle (EV) usage for accelerating transportation electrification has crucial impacts on greenhouse gas emissions and energy dependency. In order to improve the adoption of electric vehicles, tremendous work is being performed to electrify powertrain systems and the transportation system [1]. Lots of research works on charging station placement, e.g. [2], [3], etc. to make EVs get charged easily. Meanwhile, much research has been performed to design energy management strategy in order to optimize the energy usage of electric vehicles and redude their range anxiety, e.g. [4]–[7]. Recently more than 700,000 plug-in vehicles are on road in US since 2010 market introduction [8]. To meet charging demand from EVs, charging stations are installed at both residential and commercial locations. However, the increasing number of residential EV chargers is likely to increase the effects on electricity generation adequacy, transformer aging, and distribution system power quality, etc. as discussed in [9].

Several mitigation schemes proposed in the literature, including indirect control using Time-Of-Use (TOU) rates [10]–[13] and direct control using smart charging algorithms [14]–[24], etc. However, if, while designing the TOU schedule, the total demand and load profile of the EV load is not taken into consideration, the effects of EV charging under a TOU schedule might get worse [10]–[13]. The power system could be utilized more efficiently if the EV charging rate and charging start time are controlled to optimize a desired grid objective [25], [26]. Therefore, an informative EV load profile (including the available charging time interval, the required energy, etc.) is fundamental to achieve a good performance in control scheme. Much research used random distributions to simulate the residential EV charging load profile [27]–[29]. But this doesn't work to validate the performance of control strategies in realistic application. To our best knowledge, there is no residential charging load profile that is derived from realistic data or informative enough to be used for system level control strategies.

This paper aims to develop a scalable and flexible framework that can generate informative residential EV charging load profiles by taking advantage of a historical charging behavior data set. Data-driven models can be constructed from large scale historical data to describe the underlying realistic charging behaviors. Based on these data-driven models, the residential EV charging load profile can be generated with regard to different number of households and charging rates. The generated charging load profile for a single household illustrates the residential parking and charging behavior, including arrival and departure time, arrival SOC and departure SOC requirement for each home parking. The charging load profile can provide comprehensive information to design residential charging strategy for flattening the overall load shape profile, minimizing the charging cost, or minimizing power losses, etc.

II. Methodology

A. Data Set for Modeling

Idaho National Laboratory partnered with ECOtality, Nissan, General Motors, and other city, regional and state governments, electric utilities, other organizations and members of the general public, to deploy over 12,000 AC Level 2 charging units and over 100 DC fast chargers in 20 metropolitan areas. Approximately 8,300 Nissan LEAF, Chevrolet Volts, and Smart ForTwo Electric Drive vehicles were enrolled in the project. The data collection phase of The EV Project ran from January 1, 2011, through December 31, 2013 and captured almost 125 million miles of driving and 4 million charging events. The detailed information of this project and data set can be found in [30].

Different areas usually have different residential charging load patterns. The proposed data-driven generation framework in this paper will be suitable for different areas. Charging load profiles in different areas for both weekdays and weekends can be derived by using historical data and the proposed framework. Historical data in a specific area is needed to construct the required data-driven models. In this paper, a subset of historical data of Nissan Leaf in San Francisco

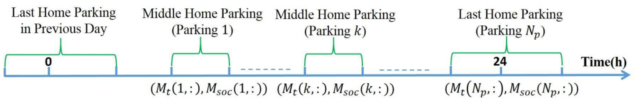

Fig. 1. A diagram for daily residential parking behavior

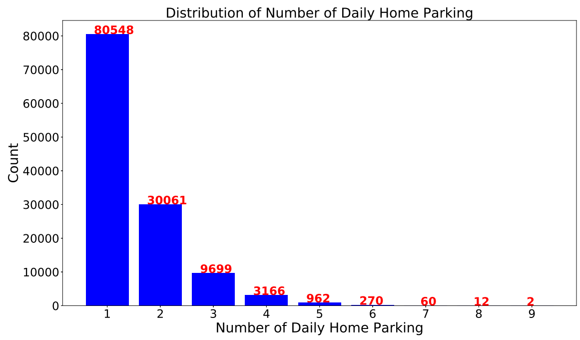

Fig. 2. A histogram for number of daily home parking in San Francisco between 2012 and 2013

during weekdays will be utilized to demonstrate the data-driven generation framework for residential charging load profiles.

B. EV Residential Parking Model

The daily residential parking behavior of an EV can be modeled as $P_h = (N_p, M_t, M_{SOC})$. In this model, N_p is the number of home parking for each vehicle within a day, $M_t \in R^{N_p \times 2}$ is a matrix for parking time information, including the arrival time (parking start time) and departure time (parking end time) in each column, respectively. $M_{SOC} \in Z^{N_P \times 2}$ is a matrix for parking SOC information, including the arrival SOC (parking start SOC, SOC_a) and departure SOC (parking end SOC, SOC_d) in each column, respectively. According to SOC change/increase (the difference between arrival SOC and departure SOC in each row of M_{SOC}), we can know whether the EV performs charging action during a home parking. All these information is illustrated in Figure 1. Based on the parking time and SOC information, the following data-driven decision making models are constructed for residential charging load profile generation.

Figure 2 is an example to illustrate the distribution of number of home parking for historical data in San Francisco. It shows that lots of daily residential parking behavior only has one time of parking at home. However, there are still many daily residential parking activities that have more than one home parking actions within one day. Most of residential parking behaviors include no more than five parking events.

C. Residential Charging Decision Making

Residential charging decision making model is used to describe whether a charging action occurs during a parking action. Based on the knowledge from historical real world data, this paper assumes that the residential charging decision of a home parking action is determined by the home parking duration (T_{pd}) and the arrival SOC (SOC_a). For each parking action, parking duration is obtained by using the arrival time and departure time. Therefore, we have the following model to determine whether a charging action is necessary.

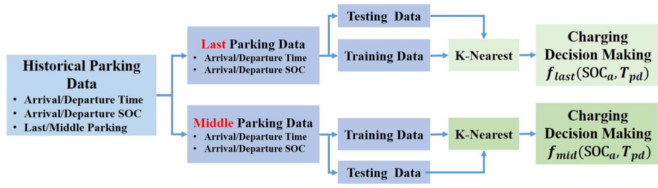

Fig. 3. Data-driven modeling process for charging decision making

$$\text{charging decision} = f(SOC_a, T_{pd}) = \begin{cases} 1, & \text{if charged} \\ 0, & \text{if not charged} \end{cases} \tag{1}$$

Due to different charging behaviors between the daily middle short-time parking and last long-time parking, the charging decision making for a home parking behavior has been modeled separately for these two cases: $f_{last}(SOC_a, T_{pd})$ for last home parking and $f_{mid}(SOC_a, T_{pd})$ for middle home parking. They have similar model formulation only with different parameters, which are obtained from different parts of historical data. The K-nearest machine learning algorithm is utilized to construct these two charging decision making models by feeding the corresponding historical data. Figure 3 illustrates the detailed procedure on how to build these two models. When new parking behavior data is obtained, we can utilize these two models to decide whether a charging action is necessary. If a charging action is needed, the following charging duration model will help to decide how much the charging time will be and the energy will be charged.

D. Charging Duration Model

The actual charging duration (T_c) within each parking duration when a charging action occurs is necessary to know or predict how much energy will be charged or energy demand. Assume that the charging action in the last home parking can always achieve a full battery state because of its long parking duration. Therefore, we only has to utilize data-driven method to create a prediction model for charging duration of middle parking behavior.

Figure 4 illustrates real world data distribution between SOC increase and parking duration at each parking with charging action from historical data. By using the historical data and providing the realistic average charging rate (3.74kW for 2012 Nissan Leaf) and battery capacity (20kWh for 2012 Nissan Leaf), we can calculate the charging duration according to SOC increase and then find the potential relationship with parking duration. Figure 4 demonstrates large uncertainties of SOC increase by giving specific parking duration. This means that realistic charging duration can have randomness with regard to parking duration. Furthermore, the uncertainty becomes larger when parking duration increases. In order to handle these situations, we design a multiple channels

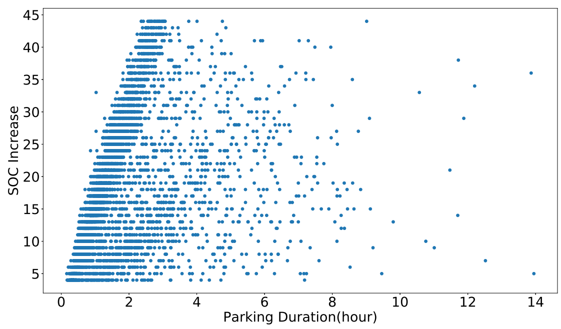

Fig. 4. Distribution of SOC increase in percentage with regard to parking duration for Nissan Leaf in San Francisco

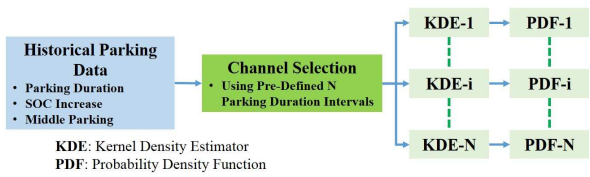

Fig. 5. Multiple channels method for charging duration prediction

method as shown in Figure 5 to produce the probability density function for each given parking duration interval. The size of these intervals is not necessary to be equal to each other. Generally we can utilize small size of interval for small parking duration. Assuming to use N parking duration intervals, we can obtain N different probability density functions for charging duration prediction. By using these obtained probability density functions, we can generate the corresponding charging duration values. This is powerful to simulate the realistic patterns between parking and charging duration when a large size of samples are needed.

E. Overall Generation Framework for Residential Charging Load Profile

The purpose of this paper is to generate electric vehicle residential charging load profiles under different charging rates. Historical data is used to construct data driven models, e.g. charging decision making models and charging duration model. In order to obtain charging load profile by giving a charging rate and number of households, the charging decision making models and charging duration model are used to establish the entire generation procedure as shown in Figure 6.

The input information of the overall generation process includes the historical data, the new charging rate and the required number of households. The original parking behavior in historical data $\{P_h\}$ is kept the same. We need to recalculate the potential charging load or energy demand from residential EVs at each parking under a newly given charging rate. By using the charging decision making models ($f_{last}(SOC_a, T_{pd})$, $f_{mid}(SOC_a, T_{pd})$) and charging duration model ($D_{ct}(T_{pd})$), we can utilize the proposed Algorithm 1 to generate a new data set ($\{P_h^{new}\}$) which can describe the new charging load

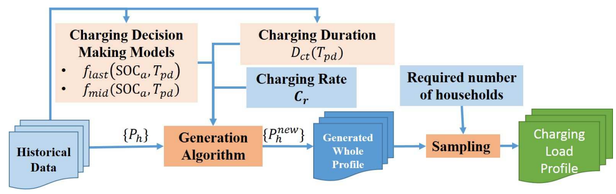

Fig. 6. Overall generation framework for residential EV charging load profile

under charging rate C_r. In Algorithm 1, it works for one daily sample in historical data to generate a new daily sample in new data set. Therefore, each sample in historical data has to be transformed by this algorithm so that we can obtain the entire new profile $\{P_h^{new}\}$. After the generated whole profile is obtained, we can sample this profile with replacement according to the required number of households to get the needed residential charging load profile.

Algorithm 1: Generation Algorithm

Input: P_h, $f_{last}(SOC_a, T_{pd})$, $f_{mid}(SOC_a, T_{pd})$, $D_{ct}(T_{pd})$, C_r

Output: $P_h^{new} = (N_p, M_t^{new}, M_{soc}^{new})$

Initialization: $i = 1$, Calculate the SOC difference between two consecutive parking to get $\{\text{Diff}(k, k+1), k = 1, ..., N_p - 1\}$, where $\text{Diff}(k, k+1) = M_{SOC}(k, 2) - M_{SOC}(k+1, 1)$

while $i < N_p$ **do**
- $SOC_a = M_{SOC}(i, 1)$, $T_{pd} = M_t(i, 2) - M_t(i, 1)$
- $y = f_{mid}(SOC_a, T_{pd})$
- **if** y==*1* **then**
  - T_c = sample($D_{ct}(T_{pd})$)
  - SOC_d = min(100, $SOC_a + 100 C_r T_c$/capacity)
  - $M_{soc}^{new}(i, 1) = SOC_a$, $M_{soc}^{new}(i, 2) = SOC_d$
- **else**
  - $M_{soc}^{new}(i, 1) = SOC_a$, $M_{soc}^{new}(i, 2) = SOC_a$
- $M_t^{new}(i, :) = M_t(i, :)$
- $M_{soc}(i+1, 1) = M_{soc}^{new}(i, 2) - \text{Diff}(i, i+1)$
- $i = i + 1$

while $i == N_p$ **do**
- $SOC_a = M_{SOC}(N_p, 1)$, $T_{pd} = M_t(N_p, 2) - M_t(N_p, 1)$
- $y = f_{last}(SOC_a, T_{pd})$
- **if** y==*1* **then**
  - SOC_d = min(100, $SOC_a + 100 C_r T_c$/capacity)
  - $M_{soc}^{new}(N_p, 1) = SOC_a$, $M_{soc}^{new}(N_p, 2) = SOC_d$
- **else**
  - $M_{soc}^{new}(N_p, 1) = SOC_a$, $M_{soc}^{new}(N_p, 2) = SOC_a$

III. Results

In order to demonstrate the functionality of the proposed generation framework for residential charging load profiles, we illustrate the results by utilizing a subset data of 2012 Nissan Leaf in San Francisco in EV Project. As shown in

Figure 2, the residential parking behavior within one day can have several parking actions. In the proposed generation process, we do not change the parking time information but generate new charging demand (SOC increase) in each parking action according to new charging rates. Figure 2 illustrates that there are at most nine residential parking actions within one day. Most of the samples only have three residential parking actions. Therefore, the following results only demonstrate the results for data samples with one, two and three residential parking actions within one day.

Results compare the statistical analysis under three different cases: actual case is for the original historical data; 3.74kW case is for the newly generated profile by using charging rate of 3.74kW; 6.48kW case is for the newly generated profile by using charging rate of 6.48kW. Each figure from Figure 7 to Figure 12 includes both the percentage of charging actions during parking and SOC increase distribution of charging actions. Percentage of charging actions during parking describes the percentage of parking actions in which charging actions take place. SOC increase distribution of charging actions describes the overall distribution of SOC increase for all charging actions. This is a distribution to show the energy demand from residential charging.

Figure 8, 10 and 11 illustrate the statistic analysis results of middle parking for charging load profiles with two and three parking actions within one day. Very little difference exists in the results for percentage of charging actions during parking. This is determined by the charging decision making model $f_{mid}(SOC_a, T_{pd})$. This similar percentage means the charging decision making model is stable under different charging rates. Distributions of SOC increase demonstrate the different patterns under different charging rates. Generally, distributions of case 3.74kW are close to those from actual historical data. This is because that the average actual charging rate is close to 3.74kW. Case 6.48kW has larger percentages on high SOC increase values. This generally follows the realistic mechanism that, with the same available charging duration, more energy will be charged by using a higher charging rate. These results show a good capability for our proposed framework to generate reasonable residential charging load profiles under different charging rates.

Figure 7, 9 and 12 illustrate statistic analysis results of last parking actions for charging load profiles with one, two, three parking actions within one day, respectively. In each result, the percentage of charging actions during parking are almost the same. This shows that charging decision model $f_{last}(SOC_a, T_{pd})$ works well. But we still can see the light difference between investigated cases under different charging rates. If the daily residential parking behavior has more than one parking actions, the percentage of charging actions for the last parking has got a slightly decrease when the charging rate increases. This is because that more energy can be charged during middle parking due to a higher charging rate. This illustrates our proposed framework can capture realistic time dependence along different parking actions when charging rate is changed. The SOC increase distributions are almost the same under different charging rates. The slightly difference in Figure 9 and 12 is caused by more charged energy in previous middle parking actions due to higher charging rates.

Fig. 7. Statistic results of last parking actions for residential charging load profile with only one parking action within one day

Fig. 8. Statistic results of middle parking actions for residential charging load profile with two parking actions within one day

IV. Conclusion

This paper introduces a data-driven framework to generate residential EV charging load profiles. To our best knowledge, this is the first work to construct realistic residential charging load profiles based on real-world collected data. The established data-driven models for charging decision making and charging duration make the framework extensible for different scales of scenarios, i.e. different number of households and charging rates. This is durable for future application with large-scale deployment of EVs. Detailed experiments and comparisons show the capability and validate the functionality of the proposed framework. This work will be important and fundamental for developing system-level residential charging strategies with benefit of realistic EV charging load profile.

Fig. 9. Statistic results of last parking actions for residential charging load profile with two parking actions within one day

Fig. 10. Statistic results of first middle parking actions for residential charging load profile with three parking actions within one day

Fig. 11. Statistic results of second middle parking actions for residential charging load profile with three parking actions within one day

Fig. 12. Statistic results of last parking actions for residential charging load profile with three parking actions within one day

ACKNOWLEDGMENT

This work is performed for the U.S. Department of Energy under Idaho National Laboratory contract number DE-AC07-05ID14517. Funding is provided by the U.S. DOE Office of Energy Efficiency and Renewable Energy's Vehicle Technologies Office.

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