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Modeling of plug-in electric vehicle travel patterns and charging load based on trip chain generation

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HIGHLIGHTS

- Multi-location charging behavior of PEV is modeled.
- Detailed PEV powertrain models are considered.
- MCLP strategy can reduce the charging load peak by 47%.
- Charging during price valley time can meet most of PEVs' travel demand.
- V2G would be profitable if battery replacement cost decreases by 25%.

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ABSTRACT

Modeling PEV travel and charging behavior is the key to estimate the charging demand and further explore the potential of providing grid services. This paper presents a stochastic simulation methodology to generate itineraries and charging load profiles for a population of PEVs based on real-world vehicle driving data. In order to describe the sequence of daily travel activities, we use the trip chain model which contains the detailed information of each trip, namely start time, end time, trip distance, start location and end location. A trip chain generation method is developed based on the Naive Bayes model to generate a large number of trips which are temporally and spatially coupled. We apply the proposed methodology to investigate the multi-location charging loads in three different scenarios. Simulation results show that home charging can meet the energy demand of the majority of PEVs in an average condition. In addition, we calculate the lower bound of charging load peak on the premise of lowest charging cost. The results are instructive for the design and construction of charging facilities to avoid excessive infrastructure.

1. Introduction

Major studies have articulated that transportation electrification is necessary for slowing down the climate change around the world [1]. California's Governor Brown has also released the zero-emissions vehicle (ZEV) mandate, targeting the deployment of 1.5 million ZEVs by 2025, the vast majority of which will be plug-in electric vehicles (PEVs) [2]. Integration of such a large number of PEVs will cause variability and uncertainty to electric power systems. Lack of accurate forecasting on PEVs' energy and power demand will also result in excessive or insufficient infrastructure of charging facilities [3]- [4].

In order to simulate PEV charging load, we need to incorporate both driving patterns and charging patterns. One solution is to use an agent-based simulation toolbox (such as MATSim [5], Aimsun [6], etc.) and combine with some charging strategies to simulate the behavior of PEVs. However, when the number of PEVs is large, computation time will be an obstacle if we directly simulate each PEV's behavior [7].

Compared with this method, using a probabilistic model would significantly relive the computation burden. It also has more predictive power than purely using historical data [8]. In Ref. [9], travel patterns of the PEVs were modeled by three variables: departure time, arrival time and total travel distance. The dependence

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Nomenclature

D_j	Random variable, distance of trip j
G_j	Random variable, type of trip j
L_j^e	Random variable, end location of trip j
L_j^s	Random variable, start location of trip j
N^*	Initial value of the remaining times for arriving home
N_j	Random variable, remaining number of times for arriving home before trip j
T_j^d	Random variable, duration of trip j
T_j^e	Random variable, end time of trip j
T_j^p	Random variable, parking duration after trip j
T_j^s	Random variable, start time of trip j
$\widehat{d}_j$	Generated driving distance of trip j
$\widehat{l}_j^e$	Generated end location of trip j
$\widehat{l}_j^s$	Generated start location of trip j
$\widehat{t}_j^d$	Generated duration of trip j
$\widehat{t}_j^e$	Generated end time of trip j
$\widehat{t}_j^p$	Generated parking duration after trip j
$\widehat{t}_j^s$	Generated start time of trip j
d_j	Realization of random variable D_j
g_j	Realization of random variable G_j
j	Trip index, $j = 1, 2, \ldots, J$
l_j^e	Realization of random variable L_j^e
l_j^s	Realization of random variable L_j^s
n_j	Realization of random variable N_j
t_j^d	Realization of random variable T_j^d
t_j^e	Realization of random variable T_j^e
t_j^p	Realization of random variable T_j^p
t_j^s	Realization of random variable T_j^s

structure between the variables was modeled using a normal copula function. But the authors assumed that all trips started from home and ended at home. In Refs. [10,11], the authors modeled the spatial and temporal distributions of PEV charging load for public charging stations. However, charging loads at home and workplaces, where the average parking time is more than 16 h [12], are not studied. In Ref. [13], the authors proposed a statistical modeling approach to generate daily driving mission sets. The temporal distributions of departure time and arrival time are modeled in the form of chi-square distribution and conditional normal distribution respectively. But the spatial distributions are not discussed in the paper. In Refs. [14–16], the distribution of start charging time was considered as a crucial factor for PEV charging load profiles. Certain distribution (e.g. normal distribution) is used to model PEV plug-in time. However, these studies do not include the information on parking locations and exact time of each trip. The absence of coupled temporal and spatial information will hinder us from accurately analyzing charging load profiles, if PEV can charge at multiple locations.

In order to tackle the above problems which are mainly caused by the incomplete description of travel patterns, we need to consider the detailed information of each trip, including start time, end time, start location, end location and trip distance. One effective tool is the trip chain, which is for describing the features of multiple travel activities of a day [17]. The trip chain model has been widely adopt for analysis of public transport usage [18], travel behavior [19], and trip mode choice [20]. Trip chain modeling is heavily dependent on the travel survey data. Fortunately, the National Household Travel Survey (NHTS) dataset [21], which contains a fairly large number of vehicle driving data, provides us a good opportunity to develop a trip chain generation method. In our previous work [22], a trip chain generation method was presented. But the method could not account for the correlations between different travel patterns. In addition, the impact of charging load on the power grid was not studied. In Ref. [23], trip chain is used to model the spatial randomness of PEV movement. However, the coupled relationship between location and time cannot be captured by the proposed method, and each trip chain is limited to contain either 2 or 3 trips. Most of publications mentioned above assume that the energy consumption of individual PEV is proportional to driving distance. However, the energy consumption is obviously related to some detailed information of the trip like speed, acceleration, terrain, etc. This oversimplification may lead to an inaccurate estimation on PEV charging load.

In this paper, we model the driving and charging behavior of individual PEVs to generate temporal and spatial grid-scale impact predictions. Firstly, we analyze the NHTS dataset to explore the correlations and distributions of different factors. Naive Bayes model is used to capture the stochastic nature of travel behavior and account for the correlations between different travel patterns. Monte Carlo method is applied to generate PEV's daily trip chain, including the information of start time, end time, start location, end location and distance of each trip. We validate the proposed methodology by comparing the simulated data to the real data. In order to get an accurate estimation on the charging load based on trip chains, we use a detailed powertrain model to calculate the energy consumption and then simulate the multi-location charging load with different charging strategies. Three factors (the battery capacity, daily driving distance and the off-peak price duration), which have great influence on the charging load, are analyzed. To be specific, the contributions of this paper are threefold:

1) Multi-location charging behaviors of PEVs are studied using the real-world data. A trip chain generation method is proposed based on the Naive Bayes model, which are effective to process the activity-based transportation data [24] and can capture the stochastic nature of travel behaviors. Temporally and spatially coupled itineraries can be generated by the proposed method.
2) Compared with previous literature [9–16,22,23], the proposed methodology incorporates the detailed powertrain model to estimate the second-by-second energy consumption on trip-specific driving cycles which include the information on speed, acceleration, terrain, etc.
3) The impacts of multi-location charging load in different scenarios are evaluated. The results are instructive for the design and instruction of charging facilities. Meanwhile it provides a reference to set the length of off-peak time to avoid new peaks caused by PEV charging.

The rest of the paper is organized as follows: The trip chain model is introduced in Section 2. In Section 3, we present a Naive Bayes based simulation method to generate PEV itineraries for a whole day. Then the method is validated in Section 4. Charging load simulations are shown in Section 5. Finally, conclusions are drawn in Section 6.