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Analysis of Multi-location PEV Charging Behaviors Based on Trip Chain Generation

Dai Wang, Xiaohong Guan, *Fellow, IEEE,* Jiang Wu, *Member, IEEE*, and Junyu Gao

***Abstract*—In this paper, we focus on analyzing multi-location charging behaviors of plug-in electric vehicles (PEVs) under the Time-of-Use (TOU) pricing scheme. Trip chain model incorporating the information on start time, end time, driving distance, start location and end location of each trip is used to depict the sequence of daily driving missions. Statistical distributions of travel patterns are fitted from a real-world driving dataset. Then a method is developed to generate the complete trip chain of each individual PEV. Simulation results show that due to the TOU price, people prefer the overnight charging at home, although workplace charging can support PEVs with smaller battery capacities and long-distance commute trips. Furthermore, with a large enough battery capacity, charging at workplaces will not be necessary if vehicle-to-grid (V2G) technology is not considered. Although high charging power accelerates PEV's charging processes during price-valley periods, it imposes higher requirements on the charging facilities and distribution grid.**

***Index Terms*—multi-location charging, PEV, charging load, trip chain, travel pattern**

I. Introduction

PEV is considered to be a relief from the growing pressure caused by oil dependency, environment pollution and greenhouse gas emissions. It is predicted that between 6% and 30% of vehicles in use will be PEVs by the year 2030 [1]. These PEVs will rely on the energy from the electricity grid, which suggests the uncertainty and variability in electricity demand. Recently, substantial studies have been carried out to evaluate the possible impact on power system due to PEV charging load. It is presented that many problems, such as power congestion [2], peak load increase [3], power losses [4] and voltage decrease [5], can arise from uncontrolled PEV charging. In [6], authors concluded that the major impact is on medium and low voltage distribution systems. The lack of accurate information about the charging demand can hinder optimized integration of PEVs into electrical grid and lead to excess infrastructure [7]. Therefore, it is necessary to evaluate the impact and impose some restrictions on the charging to alleviate impacts of PEVs on the distribution system.

Charging load profile is the key to predict and evaluate PEVs' impact on the grid. It is directly determined by the PEV owner's driving behavior and travel patterns including departure time, arrival time, driving distance and parking locations [8]. In [9], 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. In [6], the author used more than 44 million GPS data from 76 representative vehicles to build a stochastic model of daily travel distance and arrival/departure time. However, these studies do not involve detailed information of start time, end time, start location and end location of each trip, which is required for a more accurate analysis of multi-location charging behavior.

Furthermore, early publications often assumed that PEVs can be plugged into grid only at home [10-11]. There is only one departure and one arrival event per day. Only between the present departure time and last arrival time is PEV charging available. However, in a low voltage distribution grid, work places are also frequently parking locations. In [8] and [12], authors investigated the parking events at work places and found that people parked longest at work places with a mean value of more than 8 hours. It provides such a lucent opportunity for more flexible PEV charging strategies, which support a smaller battery capacity for daily commute, other than charging only overnight.

In this paper, we investigate the impact of multi-location charging, which has not been studied in previous papers. PEVs can be connected to the grid both at home and work places. Statistical distributions of daily travel patterns are modeled from the 2009 National Household Travel Survey (NHTS) real-world data [13]. Based on the statistical results on daily travel patterns, a method is proposed to generate trip chains, which contains the detailed information of the start time, end time, start location, end location, and driving distance of each trip. With such information, the multi-location minimum-cost charging behavior of each PEV owner is formulated as a linear programming problem. In summary, the contributions of this paper are as follows:

1) A fundamental study on PEV travel patterns is conducted based on the real-world dataset. Statistical distributions of several key factors are modeled and a method is developed to generate daily trip chains.

2) The multi-location charging load is analyzed. The results are instructive for the design and instruction of charging infrastructure.

The rest of the paper is organized as follows: In Section Ⅱ, real-world data are used to model daily travel patterns. We propose a method to generate trip chains in Section Ⅲ. The minimum-cost charging behavior is also depicted in this

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D. Wang, X. Guan, J. Wu and J. Gao are with the Ministry of Education Key Lab for Intelligent Networks and Network Security (MOE KLINNS), School of Electronic and Information Engineering, Xi'an Jiaotong University, Xi'an, China. (Email: {daiwang, xhguan, jwu, jygao}@sei.xjtu.edu.cn)

X. Guan is also with the Center for Intelligent and Networked Systems (CFINS), Department of Automation, TNLIST, Tsinghua University, Beijing, China.

section. Simulation results are shown in Section Ⅳ. Finally, conclusions are drawn in Section Ⅴ.

II. Daily Travel Patterns

Daily travel patterns cover the information about the parking location, parking duration, driving distance of each trip, etc. The PEV battery must be charged with enough energy for vehicle usage. Parking location determines whether it is available for PEVs to plug in. Parking duration decides the maximum charging period at this location. The amount of energy demand depends on the driving distance of each trip. Under the assumption that the energy consumption is in proportional to the driving distance [14], the energy consumption of PEVs can be easily calculated. So travel pattern models will provide basic information to accurately analyze the charging demand and evaluate the impact of charging load. In this section, the trip chain model is used to describe the sequence of PEV's daily driving activities. Several distributions of travel pattern factors are derived from the NHTS dataset.

A. Real-world Driving Data

The NHTS dataset contains millions of data on both long-distance and local travel by the American public. The joint survey gathers trip-related data such as mode of transportation, duration, distance and purpose of trip. It also gathers demographic, geographic, and economic data for analysis purposes. The parking locations are classified into three categories: Home (H), Work Place (W) and Others (O). PEVs travel between either two of these places, as in Fig. 1.

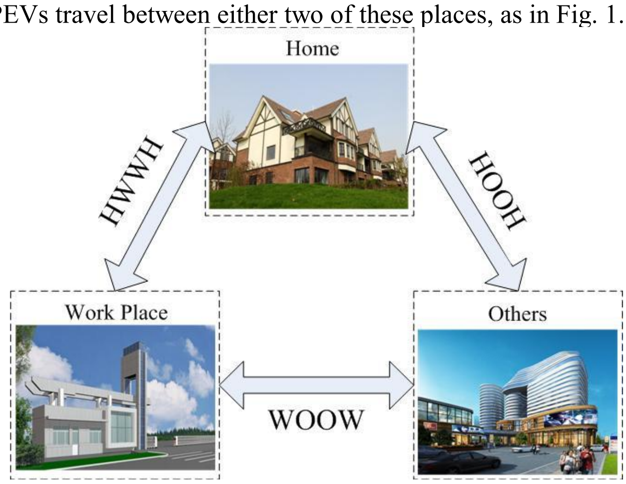

Figure 1. Travel modes of PEVs

There are three travel modes: Home to Others or Others to Home (HOOH), Workplace to Others or Others to Workplace (WOOW) and Home to Workplace or Workplace to Home (HWWH). The change of parking location is modeled as a stochastic process $\{X(t); t \in \tau\}$ where τ is the time interval, for discrete time $\tau = \{0,1,\ldots,T\}$. $\mathbf{S}=\{\mathrm{H, W, O}\}$ is the state space of *X(t)*. The transition probability is defined as:

$$p_{y,z}(t,t') = P\{X(t') = z \mid X(t) = y\} \quad (y,z \in S) \tag{1}$$

where *y* is the start location at time *t* and *z* is the end location at time *t'*.

Since the NHTS dataset contains the detailed parking events both at home and at work places, it allows us to analyze the impact of multi-location charging load. From Fig. 2, it can be seen that besides parking overnight at home, people park the longest at work places, and the mean duration is 8 hours. This result indicates that if charging events could be possible at the work places, PEVs for the daily commute would be possible with a significantly smaller battery than in the case of charging only overnight. In this paper, we consider that work place is also available for PEVs to plug in.

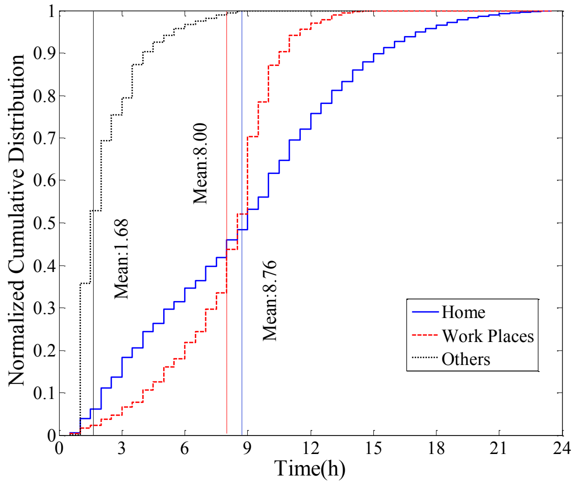

Figure 2. Parking duration at different locations.

B. Notion of Trip Chain

In this paper, the trip chain is used to describe a sequence of trips that begins at home, involves one or more visits, and ends at home. It includes all information which determines available charging periods and energy demand for each PEV. The trip chain of each individual PEV is defined as:

$$\begin{aligned}(\mathbf{T}^s,\mathbf{T}^e,\mathbf{d}\ ,\mathbf{L}^s,\mathbf{L}^e) = (&T_1^s,T_2^s,\ldots,T_n^s;T_1^e,T_2^e,\ldots,T_n^e;\\ &d_1,d_2,\ldots,d_n;L_1^s,L_2^s,\ldots,L_n^s;L_1^e,L_2^e,\ldots L_n^e)\end{aligned} \tag{2}$$

$$s.t. \quad L_{j+1}^s = L_j^e \tag{3}$$

Where T_j^s = Start time of the *j*th trip;

T_j^e = End time of the *j*th trip;

d_j = Distance of the *j*th trip;

L_j^s = Start location of the *j*th trip;

L_j^e = End location of the *j*th trip;

n = Number of trips involved in PEV's trip chain;

Equation (3) represents that the end location of last trip is the start location of the next trip. This trip chain definition is introduced purely because of the presentational simplicity it offers, and the modeling framework is in principle applicable with a multi-location charging analysis which requires the parking location and duration.

A PEV's travel patterns vary from day to day. It is viewed in this study that this variation is random, and each possible pattern occurs with a certain probability. The approach taken in this study is to establish these probabilities from the NHTS dataset and generate $(\mathbf{T}^s,\mathbf{T}^e,\mathbf{d}\ ,\mathbf{L}^s,\mathbf{L}^e)$ by simulation. Now, consider the following identity:

$$
\begin{aligned}
&\Pr[\mathbf{T}^{s},\mathbf{T}^{e},\mathbf{d}\ ,\mathbf{L}^{s},\mathbf{L}^{e}\,] \\
&=\Pr[T_1^s,T_2^s,\ldots,T_n^s;T_1^e,T_2^e,\ldots,T_n^e;d_1\,,d_2,\ldots,d_n; \\
&\quad L_1^s,L_2^s,\ldots,L_n^s;L_1^e,L_2^e,\ldots L_n^e] \\
&=\Pr[T_n^s,T_n^e,d_n,L_n^s,L_n^e\,|T_1^s,T_2^s,\ldots,T_{n-1}^s;T_1^e,T_2^e,\ldots,T_{n-1}^e; \\
&\qquad d_1\,,d_2,\ldots,d_{n-1};L_1^s,L_2^s,\ldots,L_{n-1}^s;L_1^e,L_2^e,\ldots L_{n-1}^e] \\
&\times\Pr[T_{n-1}^s,T_{n-1}^e,d_{n-1},L_{n-1}^s,L_{n-1}^e\,|T_1^s,T_2^s,\ldots,T_{n-2}^s;T_1^e,T_2^e,\ldots,T_{n-2}^e; \\
&\qquad d_1\,,d_2,\ldots,d_{n-2};L_1^s,L_2^s,\ldots,L_{n-2}^s;L_1^e,L_2^e,\ldots L_{n-2}^e] \\
&\times\cdots\times\Pr[T_1^s,T_1^e,d_1\,,L_1^s,L_1^e]
\end{aligned}
\tag{4}
$$

Namely, the simultaneous probability associated with $(\mathbf{T}^{s},\mathbf{T}^{e},\mathbf{d}\ ,\mathbf{L}^{s},\mathbf{L}^{e})$ can be expressed as a product of a series of conditional probabilities,

$$
\begin{aligned}
&\Pr[T_j^s,T_j^e,d_j,L_j^s,L_j^e\,|T_1^s,T_2^s,\ldots,T_{j-1}^s;T_1^e,T_2^e,\ldots,T_{j-1}^e; \\
&d_1\,,d_2,\ldots,d_{j-1};L_1^s,L_2^s,\ldots,L_{j-1}^s;L_1^e,L_2^e,\ldots L_{j-1}^e], \\
&\quad j=1,2,\ldots,n.
\end{aligned}
\tag{5}
$$

In this conditional probability, the attributes of the next trip are dependent on the past history (start time, $T_1^s,T_2^s,\ldots,T_{j-1}^s$; end time, $T_1^e,T_2^e,\ldots,T_{j-1}^e$; trip distance, $d_1\,,d_2,\ldots,d_{j-1}$; start location, $L_1^s,L_2^s,\ldots,L_{j-1}^s$; and end location, $L_1^e,L_2^e,\ldots L_{j-1}^e$).

C. Statistical Distributions of Several Key Factors

To generate PEVs' trip chains, distributions of travel patterns should be derived from the NHTS dataset. Since trip chains begin at home, we firstly need to obtain the distribution of the initial departure time from home. In our previous work [15], it is shown that the departure time distribution can be fitted in the form of chi-square distribution.

$$
P_{DEP}(t_{depn,i})=\frac{t_{depn,i}^{(\upsilon-2)/2}e^{-t_{depn,i}/2}}{2^{\upsilon/2}\Gamma(\upsilon/2)}
\tag{6}
$$

where $t_{depn,i}$ is the normalized departure time at the ith departure time window and defined as $t_{dep,i}/\Delta$, and Δ is the discretized window size. υ is determined to minimize the root-mean-square error of the response variable by applying sequential quadratic programming. The NHTS real-world data also verify the distribution, as shown in Fig. 3.

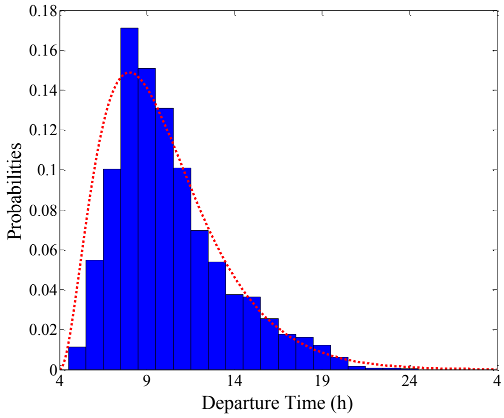

Figure 3. Distribution of the initial departure time.

Then we study the distribution of trip duration. Distributions in three travel modes are shown in Fig. 4. It can be seen that the time distribution of trip between home and work place is more uniform with the biggest mean value of 31.08min and the smallest variance of 16.80min. Due to the high uncertainty of start points and destinations of the other two modes (because "Others" contains various locations such as school, shopping mall, church, and etc.), their standard deviations are higher than that of HWWH mode. Most trips of these two modes are with short distance, which usually take 5~30min and range smaller than those of HWWH mode.

From a common sense, the trip distance is closely related to the trip duration. Long distance trips usually take long trip time. This correlation can be quantified by the β value defined as $Cov(y,x)/Var(x)$, where $Cov(y,x)$ is the covariance between random variables y and x, and $Var(x)$ is the variance of random variable x. The value for β ranges from -1 to 1, and if two variables are not correlated at all, i.e., completely independent each other, the value of β is zero. The β values of the three travel modes are calculated and shown in Table I.

TABLE I. VALUES OF β IN THREE TRAVEL MODES .

Travel Modes	HOOH	WOOW	HWWH
β	0.817	0.760	0.871

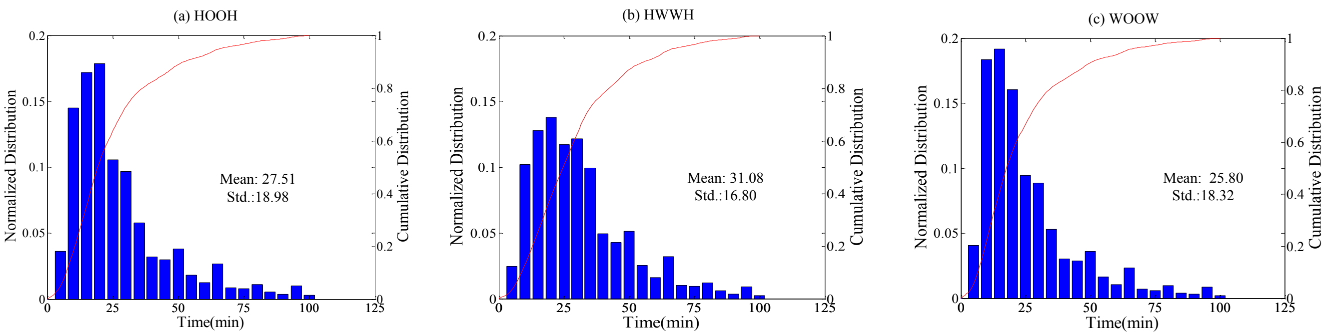

Figure 4. Distribution of trip duration in different travel modes.

Therefore, trip distance and trip duration are strongly and positively correlated. The trip distance distribution at a concerning travel time is expressed as a conditional probability. The conceptual illustration of the trip duration and trip distance distribution is shown in Fig.5. The trip distance distribution at the ith trip duration window is expressed as the Gaussian distribution.

$$P_{Dis,Dur}(d \mid \Delta t_i) = \frac{1}{\sqrt{2\pi\sigma_i^2}} e^{-\frac{(d-\mu_i)^2}{2\sigma_i^2}} \quad (7)$$

where Δt_i is the ith trip duration window, μ_i is the mean of the trip distance at the ith trip duration window, and σ_i is the standard deviation of the trip distance at the ith trip duration window.

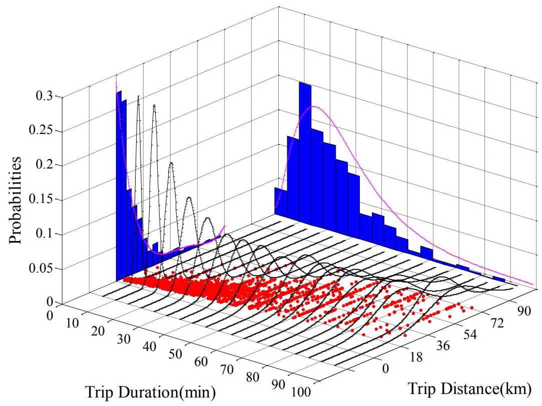

Figure 5. The illustration of the trip duration and trip distance distribution.

III. Trip Chain Generation and Minimum-cost Charging Formulation

Based on the trip chain model and distributions of key factors obtained in Section II, daily driving missions can be reproduced with a relatively small number of cases. After we obtain the descriptive information of trip chains, including start time, end time, trip distance, start and end location, the multi-location charging behavior can be simulated and the impact can be evaluated. In this section, a simulation method is developed to generate the trip chain of each PEV. Then the minimum-cost charging behavior is formulated as a linear programming model.

A. Trip Chain Generation

To perform a simulation, the transition probability described in (1) is required. However, it is not convenient to obtain these probabilities from the dataset through sampling. Instead, we define the *transition direction probability* as:

$$p_{yz}(t) = \sum_{\Delta t=0}^{T-t} \mathrm{P}\{X(t+\Delta t) = z \mid X(t) = y\} \quad (y, z \in S) \quad (8)$$

where Δt is the trip duration. The PEV will leave location y for location z at time t if $y \neq z$, while the PEV will stay at the same location if y=z. After the transition direction is determined, the trip duration will be generated according to the distribution of the specific travel mode. Then the trip distance will be generated according to the conditional distribution (7).

For each PEV, the flow chart of trip chain generation is presented in Fig. 6. We firstly sample the initial departure time according to (6). Then the transition direction will be determined by the transition direction probability. We can then indicate whether the PEV stays at the same location or moves to other locations. If $y \neq z$, it indicates the PEV will take a trip to other locations and the trip number will be updated. Then we generate the trip duration and trip distance according to the distribution presented in Section II-C. The trip duration will be added to the start time to calculate the end time of the trip. If $y = z$, it indicates that the PEV will stay at the same place during next period. We continue to determine the transition direction next time. With this process, we can obtain the detailed information about the trip chain, including start time, end time, trip distance, start and end locations.

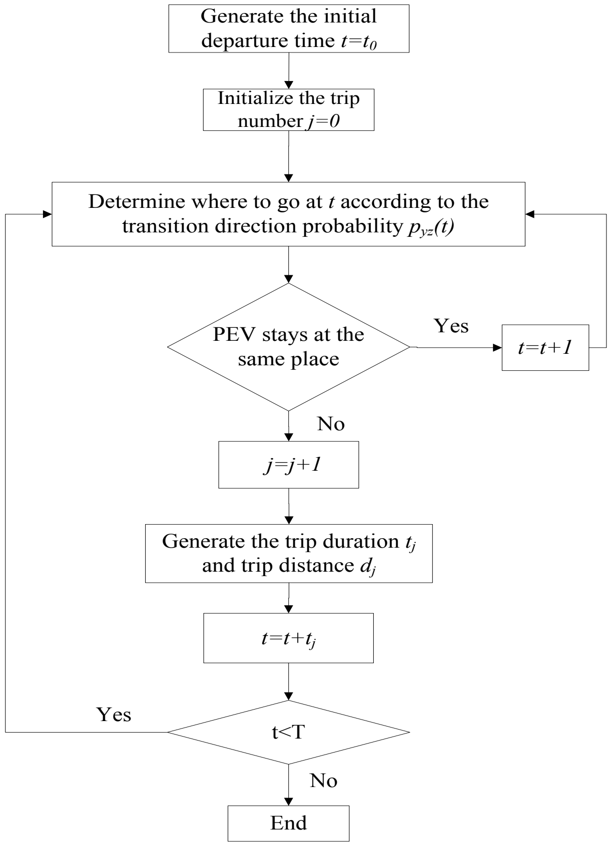

Figure 6. Flow chart of trip chain generation.

B. Minimum-cost Charging Formulation

With the assumption that PEV owners are rational, they would like to charge their PEVs during lower price periods. To analyze the impact of multi-location charging, we formulate PEV owners' charging behavior as a linear program problem, which aims to achieve the minimum charging cost under TOU price. For each PEV,

$$\min_{u_h} \quad C = \sum_{h=1}^{H} p\Delta l \cdot \lambda_h u_h \quad (9)$$

$$s.t. \quad S_{h+1} = S_h + u_h p \quad h \in [h_k^a, h_k^d], \quad k \in [1, 2, \cdots, K] \quad (10)$$

$$S_{h_k^d} - E_k = S_{h_{k+1}^a} \quad (11)$$

$$E_k = \sum_{m=1}^{M_k} d_k^m / \kappa \quad k \in [1, 2, \cdots, K] \tag{12}$$

$$\tau \cdot S_{\max} < S_t < S_{\max} \tag{13}$$

$$u_h = \begin{cases} 0 \; or \; 1 & if \; h \in [h_k^a, h_k^d] \\ 0 & else \end{cases} \tag{14}$$

where C is the total charging cost; H is the number of time slots in the planning horizon of the problem; p is the constant charging power; Δl is the length of a time slot; λ_h is electricity price at time slot h. We define S_h as the amount of battery storage for the PEV at h. K is the total number of parking events at available charging locations; h_k^a and h_k^d are the arrival time and departure time respectively for kth parking event at the available charging location; E_k is the energy consumption by the vehicle between two parking events for charging; M_k is the number of trips between kth and $k+1$th parking events at home or work places; d_k^m is the distance of mth trip between kth and $k+1$th parking events. Electric drive efficiency is κ km/kWh. $S_{\max}$ is the capacity of battery. τ is the lower bound of the battery storage to avoid over discharge. u_h is the binary decision variable indicating whether PEV is charging during time slot h.

The objective (9) is to achieve the lowest charging cost. Constraint (10) and (11) update the battery storage during charging periods and travel periods, respectively. Constraint (12) defines the energy consumption between two charging events. Constraint (13) restricts the battery storage to stay between its upper and lower bounds. Constraint (14) ensures that PEVs can be charged only between arrival time and departure time at available charging locations.

It should be noted the optimization model is used to describe PEV owner's charging behavior and analyze the impact of multi-location charging, rather than providing a charging strategy to guide people's charging behavior.

IV. CASE STUDY

In this section, trip chains of 100 PEVs are generated by simulation. The initial energy of these vehicles is uniformly distributed between 10% and 50% of the battery capacity. We examine the PEV charging during a day (24h) starting from 0:00 to 24:00. It is assumed that all PEVs have the same specifications as "Nissan Leaf" [14], whose battery capacity is 24kWh and electric drive efficiency is 6.7 km/kWh. To avoid excessive discharge of the battery, the state of charge (SOC) is required to be always beyond 10%. The charging power for all PEVs is set to 3kW.

A. Charging Load Profile

Because of the constant charging power, the charging load is proportional to the number of vehicles plugged into the grid. Thus, the charging load is expressed by the percentage of vehicles which are charged. Figure 7 shows the charging load profiles of two charging patterns including uncontrolled charging, minimum-cost charging. Uncontrolled charging means that the PEV is immediately connected to the grid to charge as soon as arriving home or work places. The charging process will not finish until when either the battery is full or the PEV must leave. For uncontrolled charging, although the load is less fluctuant and the peak is lower, the cost increased by 361%, compared with the minimum-cost charging behavior.

For the minimum-cost charging, the PEV owner charges the battery during lower price periods, as described in Section III-B. It can be seen that PEV owners adjust their charging behavior, responding to the TOU price. The load reaches a high peak at 23:00, because almost all PEVs are at home and the price comes to the valley from this moment. Besides, from 8:00 to 19:00, people are reluctant to charge their batteries since the price is relatively high during this period. Thus, there are only a few charging activities at work places.

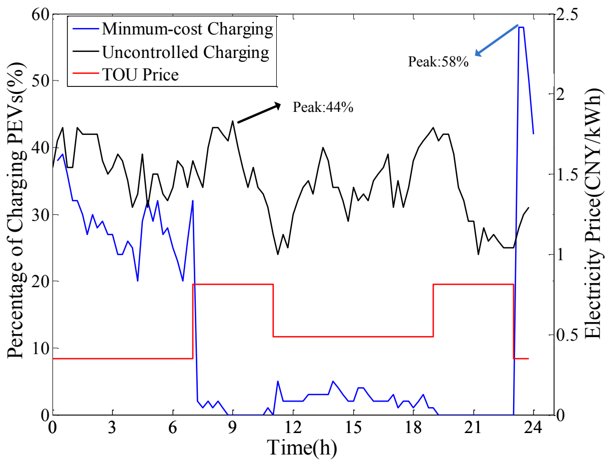

Figure 7. Charging load of two charging patterns.

We examine trip chains of those PEVs which are charged at work places. The common feature is that the commute distance of these PEVs is usually more than 83km. Overnight charging cannot guarantee them to complete the daily driving missions. They have to gain a supplementary amount of energy at work places, even when the price goes much higher.

B. Influence of Battery Capacity and Charging Power

For PEVs, two factors have great influences on the charging behavior. They are battery capacity and charging power. With a higher charging power, PEVs can be charged more quickly during the price-valley time. With a larger battery capacity, PEVs can store more energy and the charging behavior can be more flexible.

Charging load profiles with different battery capacities are shown in Fig 8. It can be seen that the charging load during price-valley period decreases with the growth of battery capacity, while the charging load during other periods increases. Since the electricity price is lowest from 23:00-7:00, PEVs try to obtain enough energy for the daily driving missions. However, for some PEVs with long distance trips, they have to charge at work places, when the battery capacity is not large enough and charging overnight at home cannot satisfy the energy demand of the whole trip chain. We find that when the battery capacity is larger than 32 kWh, charging during price-valley time can guarantee enough energy and no charging activities happen at work places. This implies that without introducing vehicle-to-grid (V2G) technology, massive construction of charging facilities at work places would be not necessary from a pure economic perspective when the battery capacity is large enough.

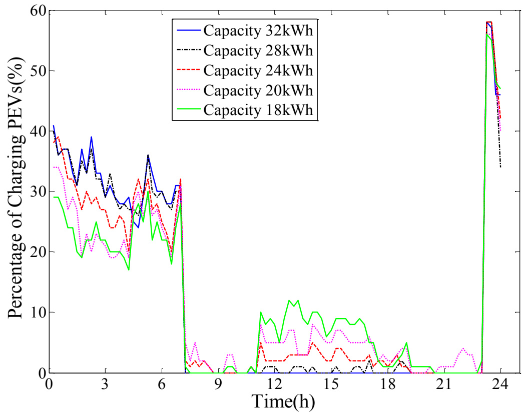

Figure 8. Charging load profiles with different battery capacities.

The influence of charging power is shown in Fig. 9. It can be seen that the load peak increases in proportion to the charging power. More charging activities occur at work places when the charging power is lower, since PEVs cannot gain enough energy through overnight charging before leaving home. We also find that even though a higher charging power can make the battery completely charged within a shorter period, there are still some PEVs which need to be charged at work places. All of these vehicles have long distance trips. Overnight charging during price-valley periods has completely charged the battery full, but it still cannot meet the energy demand for the whole trip chain. Besides, it should be noted that the high charging power imposes a great requirement on the charging facilities and distribution grid, since it may cause a high peak load which may be hazardous for the distribution grid.

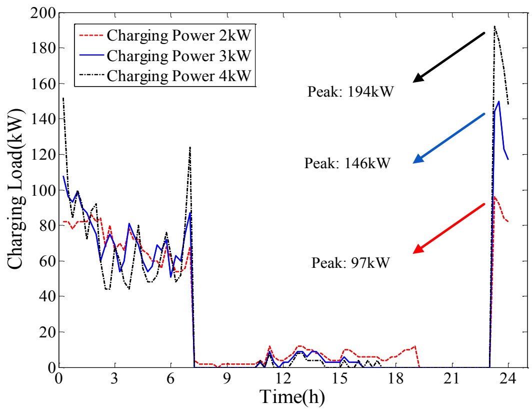

Figure 9. Charging load profiles with different charging power.

V. Conclusions

In this paper, we study multi-location charging behaviors of PEVs. Several statistical distributions of travel patterns are derived from the NHTS dataset. To describe the sequence of daily travel activities, we present the trip chain model incorporating the detailed information of each trip, namely start time, end time, trip distance, start location and end location. Then we perform a simulation to generate trip chains. Finally a minimum-cost charging formulation is presented to describe the multi-location charging behavior. Conclusions are drawn as follows:

(1) People prefer to charge at home after 23:00 due to the lower electricity price. Only a few charging activities happen at work places when certain PEVs have long distance trips and they need supplementary energy at work places.

(2) When the battery capacity is larger than 32kWh, rare charging activity occurs at work places. This implies if the battery capacity is large enough and V2G technology is not considered, work place charging would not contribute to PEV owner's economic interests.

(3) Charging power also has a great influence on people's charging behavior. High charging power can accelerate the charging process during the price-valley periods, but it may impose a higher requirement on the charging facilities and distribution grid.

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