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Simulating the Daily Profile of EV Charging Load based on User's Travel Mode

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Abstract—Rapid development of electric vehicles (EVs) has a negative impact on the operating and planning of the power systems, and it is important to accurately simulate the EV charging load when large amount of EV charging demands are connected to the grid. In this paper, an EV charging load simulation method is proposed based on the users' daily travel mode. Different from most of the previous works, this paper adds additional consideration of the charging preference, location type, day type and power consumption rate to improve the simulation accuracy. First, probabilistic distribution models for many defined spatial-temporal variables are established under refined conditions to improve the modelling accuracy, and the models include Burr Type XII, lognormal, generalized extreme, Weibull and Stable distribution, etc. Second, considering additional influential factors, daily profile of EV charging load is simulated based on the established distribution models and Monte Carlo algorithm. To take the public data from the US National Household Travel Survey (NHTS) as example, the proposed method is validated. The results show that the proposed method can provide more realistic daily curve of the charging load with no requirements on the historical charging data. And, the consideration of refined modelling conditions and additional influential factors can improve the accuracy of distribution models and the load simulation.

Keywords—electric vehicle; charging load simulation; travel mode; charging preference; power consumption rate; Monte Carlo

I. INTRODUCTION

Electric vehicles (EVs) are emerging as cleaner alternatives to the traditional fossil-fueled vehicles. However, the randomness and mutuality of traveling and charging demand of EV car users bring non-negligible impacts on the operation and planning of power system when large amount of EV charging demands are connected to the grid [1], e.g. increasing the gap between of peak load and valley load, affecting the power quality, refurbishing the distribution network, etc. Therefore, it is important to accurately simulate the daily curve and the spatial-temporal distribution of the EV charging load integrated into the power grid.

At present, the simulation of EV charging load can be divided into two categories: one is based on the historical data of EV charging load using various data mining algorithms [2]; the other is simulating and modeling it according to the statistical rules of car travelling mode considering that there is not enough historical EV charging load data currently. A stochastic simulation method was used to generate daily travel schedule and charging profiles for a population of EVs based on the GPS travel data collected in an EV demonstration trial [3]. An individual EV user's mobility model revealed by the data of mobile phone activity was generated, and a method for planning electricity demand of EV charging was proposed by coupling charging profiles with EV mobility in urban area [4]. Historical traffic data and weather data were used to formulate a model for estimating the EV charging demand based on big data technologies [5]. Based on Monte Carlo simulation, theory of trip chain was used to describe the spatial-temporal characteristics of users' travel behavior, and the EV charging demand in various places was obtained [6-9]. State-space model was established to simulate the driving pattern and charging load of EVs [10].

However, the accuracy of charging load simulation is dependent on the accuracy of distribution models of travel variables in most of above methods, which can be further improved by refined modelling under different conditions. In addition, factors affecting the EV charging load are not adequately considered in most of the previous works, e.g. charging preference, power consumption rate, etc.

To solve this problem, this paper presents a simulation method for the daily charging load of EVs based on the daily travel pattern of car users and additional influential factors. Distribution models of several spatial-temporal variables are established according to different day type and places. Based on the extracted travel mode of users, daily profile of EV charging load is simulated using Monte Carlo simulation method. Additional factors are considered, i.e. charging preference, location type, day type and power consumption rate, in order to improve the simulation accuracy.

The rest of the paper is organized as follow. Section II establishes probabilistic distribution models for defined spatial-temporal variables and refined conditions, e.g. day type and places. Section III presents an EV charging load simulation method based on the users' daily travel model and Monte Carlo algorithm, and also additional factors are considered in this section to improve the simulation accuracy, including charging preference, location type, day type and power consumption rate. Section IV presents the simulation results based on the NHTS survey data. And the conclusions are given in the final section.

II. Modeling the Spatial and Temporal Characteristic of Daily Travel Mode

A. Probability Distribution Fitting of Time Variables

In this paper, probability distributions of three temporal variables (starting time of the first trip in a day, time duration of the car driving and car parking) are fitted to quantify the temporal characteristics of the daily driving trip. Firstly, the starting time of the first trip is fitted. Secondly, time duration of the car driving is classified according to the starting place and trip destination; noted that the probability distributions of different categories are fitted respectively. Finally, time during of the car parking is classified according to the type of parking place, and probability distributions of different categories are fitted respectively.

1) Starting time of the first trip - t_{s1}

Burr Type XII model is used to fit the distribution of starting time of the first travel. The probability density function is show in (1).

$$f(t_{s1} \mid \alpha, C, K) = \frac{\frac{KC}{\alpha}(\frac{t_{s1}}{\alpha})^{C-1}}{(1+(\frac{t_{s1}}{\alpha})^{C})^{K+1}} \tag{1}$$

2) Time duration of the car driving - T_x

Driving time duration is classified into eight categories according to the locations (two types of starting place multiply two types of ending place) and workday/weekend. Eight types of driving time are shown in Tab. I.

Eight types of driving time are separately fitted using lognormal distribution with different fitting parameters.

3) Time during of the car parking - T_P

Parking time limits the length of charging period and charging load, and affects the following destination. For example, if the parking time is short and the charging energy demand is high, the car user will prefer to select the fast charging mode; and, if the parking time and charging time is long, there probably will be more destination options (be able to drive to farther destinations).

According to the types of parking places and workday/weekend, parking time is divided into six categories. Distribution models of six types of parking time are shown in Tab. II.

TABLE I. Eight Types of Driving Time

Trips	Day Type	
	Workday	***Weekend***
H to non-H	Type 1	Type 5
non-H to non-H	Type 2	Type 6
non-H to H	Type 3	Type 7
H to H	Type 4	Type 8

[a] non-H place includes W place and O place.

TABLE II. Probability Distribution of Parking Time

Parking Place	Location Type		
	W	***H***	***O***
Workday	Stable distribution	Burr distribution	Generalized extreme value distribution
Weekend	Normal distribution	Weibull distribution	Burr distribution

B. Conditional Probability Distribution of Driving Distance

In this paper, driving distance d is regarded as obeying the probability distribution under the condition of driving time. According to the same classification way as driving time, driving mileage is also divided into eight categories. Eight types of driving distance in the i-th time window are separately fitted using Normal distribution. The conditional probability density function is shown in (2).

$$P_d(d \mid \Delta t_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{1}{2\sigma_i^2}(d-\mu_i)^2} \tag{2}$$

Where, Δt_i is the i-th time window of driving time; μ_i is the average value of driving distance in the i-th time window; σ_i is the standard deviation of driving distance in the i-th time window.

C. Spatial Transition Probability

Spatial transition probability refers to the probability that a car driving from destination D_m to the next destination D_{m+1} at a certain moment. Assumed that the current destination D_m is only related to the last destination D_{m-1} rather than the more previous destination, the spatial transition probability can be written as follow.

$$P(D_m \to D_{m+1}) = P(D_{m+1} \mid D_m) \tag{3}$$

The spatial transition probability can be converted into $M \times N \times N$ three-dimensional matrix by discretizing the trip starting time at all time intervals. M is the number of discretized time intervals; N is the number of destination types. The spatial transition probability matrix corresponding to a given time interval is a $N \times N$ two-dimensional matrix shown in (4).

$$P_{t_i} = \begin{bmatrix} p_{t_i,D_1,D_1} & \cdots & p_{t_i,D_1,D_N} \\ \vdots & \ddots & \vdots \\ p_{t_i,D_N,D_1} & \cdots & p_{t_i,D_N,D_N} \end{bmatrix} \tag{4}$$

Where, p_{t_i,D_i,D_j} is the probability of driving from the current location D_i to the next destination D_j during the time interval t_i. Obviously, the sum of the probabilities in the same column is 1. The diagonal probabilities are not necessarily 0, indicating some round trips.

III. Charging Load Simulation Based on Monte Carlo Method

EV charging load is affected by many factors. It is the key to improve the simulation accuracy. Based on the established travel mode models in section II, this section presents a new method to simulate the EV charging load with additional consideration on day type, location type, charging behavior and power consumption rate.

A. *Travel Behavior Simulation*

In this paper, Monte Carlo method is used to simulate the travel behaviors of car users. The corresponding probability distributions are taken as model inputs including the discrete spatial transition probability matrix and continuous probability distribution (i.e. starting time of the first travel, driving time, parking time and driving distance). The spatial-temporal variables are sampled sequentially, thereby the user's daily driving trip is obtained.

1) The starting time of the first trip is sampled based on the corresponding distribution under the condition that the starting place of the first trip is home.

2) With the gained starting time, the destination is sampled by the corresponding spatial transition probability under the condition of the known starting time and starting place. For the first trip, the starting place is home.

3) With the gained destination, the driving time is sampled by the corresponding distribution under the condition of the obtained starting place and trip destination. And, according to the starting time of driving and the driving time duration, the ending time of driving is calculated.

4) With the obtained driving time, the driving distance is sampled by the corresponding distribution under the condition of the time window of driving time.

5) The parking time is sampled by the corresponding distribution under the condition of the obtained trip destination. According to the ending time of driving and parking time duration, the driving starting time of next trip is calculated for simulating next trip.

B. *Charging Load Simulation*

In order to analyze the spatial and temporal distribution of the charging load for different charging behaviors, two types of charging behaviors are designed.

1) The first type of charging behavior

EV charging would be started when the (5) is meet. This means that relationship between the remaining power and the power consumption of next trip must be considered.

$$E_{m,end} - w_n d_{m+1} \le 0.2C \tag{5}$$

Where, $E_{m,end}$ is the remaining power (kW • h) when arriving at the *m*-th trip destination; w_n is the power consumption per kilometer (kW·h/km) of the *n*-th car; 0.2*C* is the lower limit of battery power.

2) The second type of charging behavior

EVs will be charged regardless of whether or not (5) is satisfied.

The charging load is calculated by combining the charging assumptions with the sampled spatial-temporal variables. Take a certain trip of a car as example, the power consumption of this trip is obtained through multiplying the driving time by the power consumption rate of this car. The charging mode (charging power) of this trip parking is selected based on the type of parking location. The charging time duration of this trip parking is obtained through dividing the power consumption by the charging power and considering the parking time limit. According to the above method, the charging time duration and charging power of each trip parking in a day are calculated, and the charging demand of this car for 1,440 minutes a day can be obtained. Finally, a daily curve of charging load is obtained through adding the charging demands of 150,000 cars minute by minute.

Simulation process is shown in Fig. 1.

IV. Case Study

A. *Data*

Assumed that the travel mode of EVs is almost the same as those of fuel vehicles in this paper, the travel data of fuel vehicles is used to establish the model of EV travel. Data used in the case study come from the travel data packet in the NHTS survey statistics in 2009. In this data packet, travel information of each trip for each car during a day is recorded, including starting and ending time, driving time, driving distance and parking time. The daily travel data of 150,000 private cars were used to simulate the EV travel.

B. *Probability Distribution of Time Variables*

1) *Starting time of the first trip*

In this part, different distributions are used to fit the starting time of the first trip. See Tab. III for details.

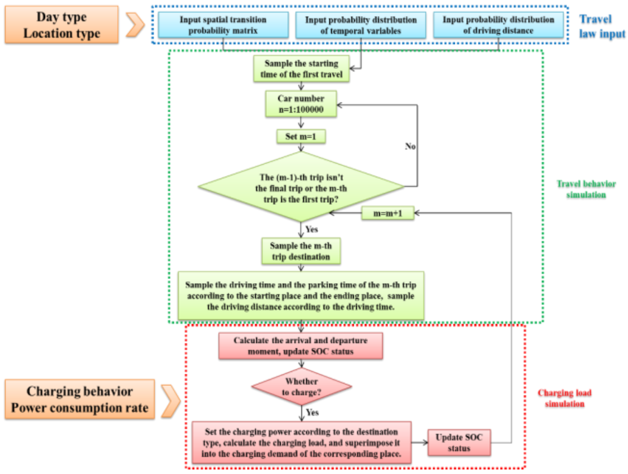


Fig. 1. Process of simulating the charging load

TABLE III. Results of Different Distributions on Workday/Weekend (Starting Time of First Travel)

Parking Time	Distribution	Standard

		R^2	R_a^2
Workday	Burr Type XII distribution	0.9739	0.9725
	Gamma distribution	0.8042	0.7974
	Normal distribution	0.6986	0.6880
Weekend	Burr Type XII distribution	0.9383	0.9342
	Gamma distribution	0.8847	0.8798
	Normal distribution	0.8280	0.8207

b. R^2 is the coefficient of determination, and R_a^2 is the corrected coefficient of determination.

After comparison, it is found that the starting time of the first trip obeys the used Burr Type XII distribution best. And, the coefficient of determination and the corrected coefficient of determination for the used distributions is higher than that for other distributions by over 0.1, for both workday and weekend.

The probability distributions of the starting time of the first trip for different day types are showed in Fig. 2. For workday, the fitting parameters are: α =7.986, C=6.696, K =0.609. For weekend, the fitting parameters are: α =11.46, C =5.79, K =1.24.

As shown in the Fig. 2, the probability distributions of the starting time of the first trip between workday and weekend are different. Distribution on workday is mainly concentrated around 8:00 am, which coincides with the actual working hours in the morning. And, distribution on weekend is mainly concentrated around 10:00 am, which is in line with people's weekend schedule.

2) Driving time duration

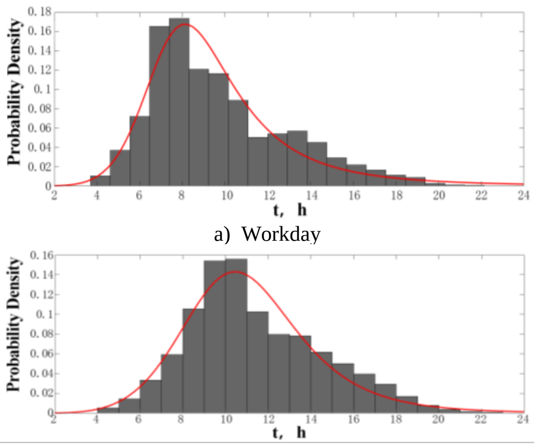
The probability distributions of eight types of driving time are shown in Fig. 3 and Fig. 4 respectively.

For workday, the fitting parameters are:

$$\begin{cases}\mu_{\mathrm{I}}=2.995\\ \sigma_{\mathrm{I}}=0.737\end{cases}\begin{cases}\mu_{\mathrm{II}}=2.816\\ \sigma_{\mathrm{II}}=0.79\end{cases}\begin{cases}\mu_{\mathrm{III}}=3.069\\ \sigma_{\mathrm{III}}=0.749\end{cases}\begin{cases}\mu_{\mathrm{IV}}=3.176\\ \sigma_{\mathrm{IV}}=0.759\end{cases}$$

For weekend, the fitting parameters are:

$$\begin{cases}\mu_{\mathrm{I}}=2.815\\ \sigma_{\mathrm{I}}=0.783\end{cases}\begin{cases}\mu_{\mathrm{II}}=2.701\\ \sigma_{\mathrm{II}}=0.815\end{cases}\begin{cases}\mu_{\mathrm{III}}=2.883\\ \sigma_{\mathrm{III}}=0.782\end{cases}\begin{cases}\mu_{\mathrm{IV}}=3.073\\ \sigma_{\mathrm{IV}}=0.765\end{cases}$$



a) Workday

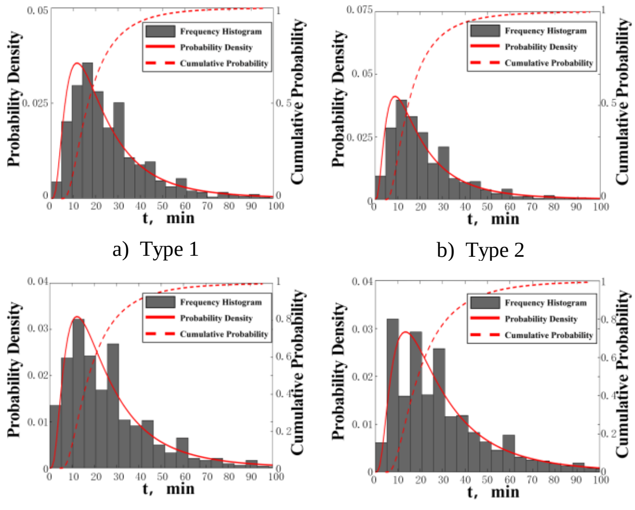
b) Weekend

Fig. 2. Probability distribution of the starting time of the first trip

As shown in Fig. 3 and Fig. 4, the driving time for both workday and weekend can obey the lognormal distribution well. The differences in the distributions of different types of driving time for the same day type are obvious.

3) Parking time

Considering different parking places and different day types, the comparison of the fitting effects of parking time for different distributions is shown in Tab. IV and Tab. V. Especially for the parking time in W place and O place on workday, the coefficient of determination and the corrected coefficient of determination for the used distributions is higher than that for other distributions by over 0.35.



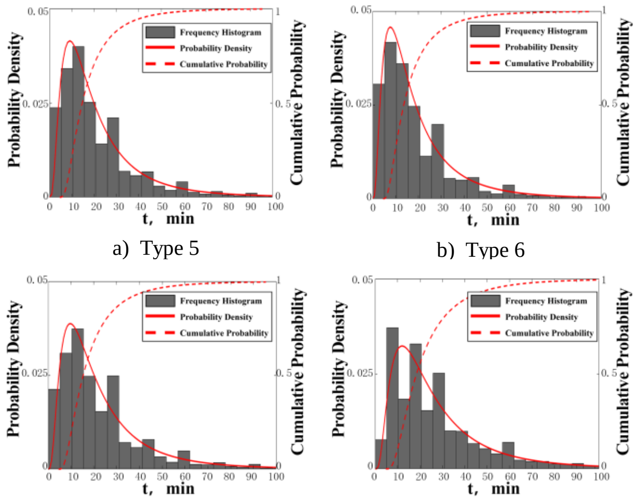
a) Type 1

b) Type 2

c) Type 3

d) Type 4

Fig. 3. Probability distribution of driving time on workday



a) Type 5

b) Type 6

c) Type 7

d) Type 8

Fig. 4. Probability distribution of driving time on weekend

TABLE IV. RESULTS OF DIFFERENT DISTRIBUTIONS ON WORKDAY (PARKING TIME)

Parking Time	Distribution	Standard	
		R^2	R_a^2
W	Normal distribution	0.5543	0.5451
	Generalized extreme value distribution	0.4057	0.3872

Parking Time	Distribution	Standard	
		R^2	R_a^2
	Stable distribution	0.9614	0.9598
O	lognormal distribution	0.5695	0.5660
	Generalized extreme value distribution	0.9243	0.9234
	Weibull distribution	0.3906	0.3856
H	Weibull distribution	0.9477	0.9470
	Gamma distribution	0.9496	0.9489
	Burr Type XII distribution	0.9596	0.9581

TABLE V. RESULTS OF DIFFERENT DISTRIBUTIONS ON WEEKEND (PARKING TIME)

Parking Time	Distribution	Standard	
		R^2	R_a^2
W	Normal distribution	0.6556	0.6370
	Generalized extreme value distribution	0.5773	0.5421
	Stabled distribution	0.6601	0.6212
O	lognormal distribution	0.6561	0.6533
	Generalized extreme value distribution	0.9010	0.8998
	Burr Type XII distribution	0.9175	0.9165
H	Weibull distribution	0.9616	0.9610
	Gamma distribution	0.9586	0.9570
	Burr Type XII distribution	0.9540	0.9521

Distributions of parking time for different places on workday/weekend are shown in Fig. 5 and Fig. 6 respectively.

For W place on workday, the fitting parameters are: α =1.324, β =-0.51, γ =66.379, δ =535.77.

For H place on workday, the fitting parameters are: α =3032.83, C=1.043, K=27.171.

For O place on workday, the fitting parameters are: k=0.765, σ =35.419, μ =63.477.

For W place on weekend, the fitting parameters are: μ =461.059, σ =191.418.

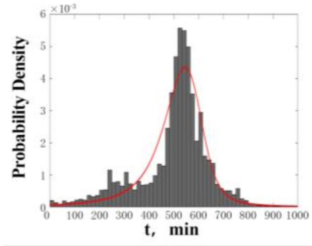
For H place on weekend, the fitting parameters are: a=169.309, b=1.133.

For O place on weekend, the fitting parameters are: α =53.199, C=4.619, K=0.305.

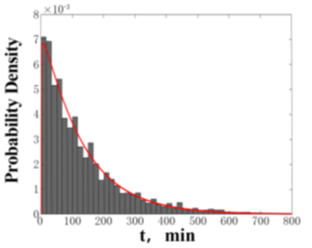
As shown in Fig. 5 and Fig. 6, the distributions are well fitted except for the ones of work place. Due to the hard rules about working hours, parking time at work place is mainly 8 to 10 hours (500 to 600 minutes), and the distribution center is particularly high.

C. Spatial Transition Probability Matrix

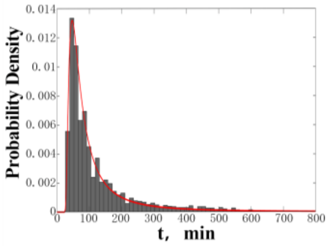
Spatial transition probability matrix for the two typical time periods in workday/weekend is shown in Fig. 7. As shown in the figure, the trip destination is closely related to the traveling time period. And, the spatial transition probabilities for workday and weekend are obviously different during morning rush hours, but are almost the same during evening rush hours.



a) W place

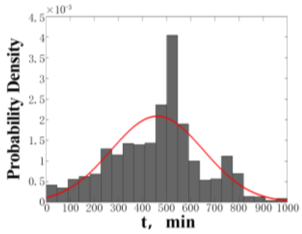


b) H place

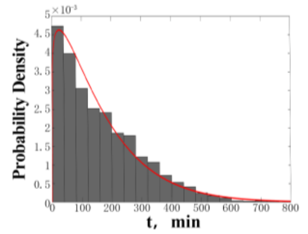


c) O place

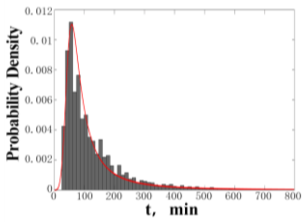
Fig. 5. Probability distribution of parking time on workday



a) W place

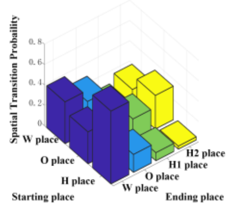


b) H place

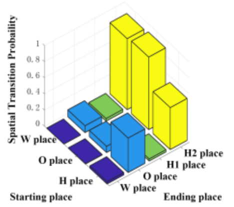


c) O place

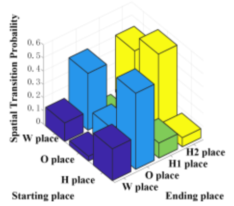
Fig. 6. Probability distribution of parking time on weekend



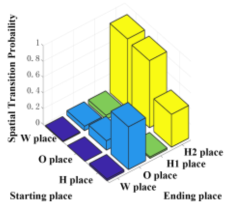
a) 7-8 o'clock on workday



b) 17-18 o'clock on workday



c) 7-8 o'clock on weekend



d) 17-18 o'clock on weekend

Fig. 7. Spatial transition probability

D. *Influencing Factors of Charging Load*

In this paper, power consumption rate (power consumption per kilometer) is used to describe the conditions of electricity consumption. Distributions of charging load at different power consumption rates for the two types of charging behavior are given.

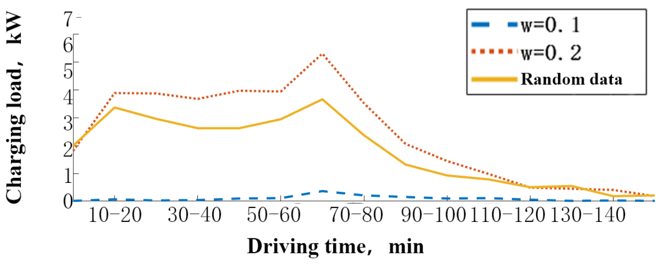
The distributions of charging load at different power consumption rates are showed in Fig. 8. As shown in the figure, for the first type of charging behaviors, power consumption rate has a great impact on charging load distribution. When power consumption rates for different cars are set as the same values, the total charging load of the cars with a bigger power consumption rate will be significantly higher.

For the second type of charging behaviors, the difference of the charging load distributions at different power consumption rates is very small. This is because EVs must be charged after reaching destinations in the second type of charging behaviors, and the charging power is only related to the destination type rather than the power consumption rate, so the load distributions are not much different.

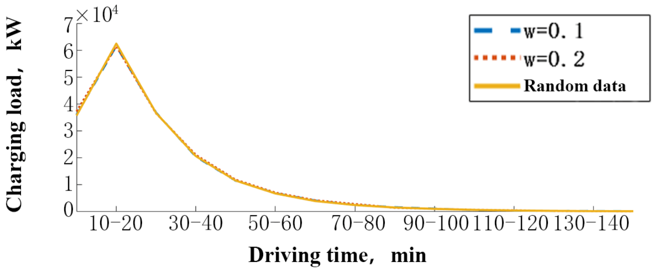
According to the probability distribution of driving time, driving time is mainly between 10-20 minutes. Therefore, for the second type of charging behaviors, the total charging load of EVs with the driving time of 10-20 minutes is the highest. However, for the first type of charging behaviors, a car with a driving time of 10-20 minutes is not necessarily charged, and a car with a longer driving time is more likely to be charged. Therefore, the driving time window with the highest charging load is not 10-20 minutes but 60-70 minutes for the first type of charging behaviors.

V. CONCLUSIONS

In this paper, a charging load simulation method for EVs is proposed based on the car travel mode and Monte Carlo. Different from traditional methods, the proposed method utilizes refined distribution models of various temporal-spatial variables of daily trips and considers more influential factors, i.e. charging preferences, places and day types, etc.



a) The first type of charging behaviors



b) The second type of charging behaviors

Fig. 8. Distribution of charging load with different power consumption rates

The results in the case study show that:

- The probability distribution models of various spatial-temporal variables have high accuracy by considering refined conditions. Determination coefficient and the corrected determination coefficient reach 0.9739 and 0.9725, respectively. The spatial transition probability matrix exhibits noteworthy features for different day types, which conforms to the actual situation and verifies the correctness of the proposed model.
- Trends of daily charging load curves for different types of charging behaviors and different power consumption rates are significantly diverse, indicating the necessity and correctness for consideration of these factors during modeling.

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REFERENCES

[1] HU Zechun, SONG Yonghua, XU Zhiwei. Impacts and Utilization of Electric Vehicles Integration into Power Systems[J]. Proceedings of the CSEE, 2012(4): 1-10.

[2] Majidpour M, Qiu C, Chu P, Pota HR, Gadh R. Forecasting the EV charging load based on customer profile or station measurement[J]. Applied Energy 2016; 163: 134-41.

[3] John Brady, Margaret O'Mahony. Modelling charging profiles of electric vehicles based on real-world electric vehicle charging data[J]. Sustainable Cities and Society, 2016, 34: 203-216.

[4] XU Yanyan, Serdar Çolak1, Emre C. Kara, et al. Planning for electric vehicle needs by coupling charging profiles with urban mobility [J]. Nature Energy, 2018, 3: 484-493.

[5] Mariz B.Arias, Sungwoo Bae. Electric vehicle charging demand forecasting model based on big data technologies[J]. Applied Energy, 2016, 183: 327-339.

[6] WAND Dai, GAO Junyu, LI Pan, et al. Modeling of plug-in electric vehicle travel patterns and charging load based on trip chain generation[J]. Journal of Power Sources, 2017, 359: 468-479.

[7] TANG D, WANG P. Probabilistic modeling of nodal charging demand based on spatial-temporal dynamics of moving electric vehicles[J]. IEEE Transactions on Smart Grid,2016,7(2):627-636.

[8] CHEN Lidan, NIE Yongquan, ZHONG Qing. Electric vehicle charging load forecasting model based on trip chain[J]. Transactions of China Electrotechnical Society, 2015, 30(4): 216-225.

[9] WEN Jianfeng, TAO Shun, XIAO Xiangning. Analysis on charging demand of EV based on stochastic simulation of trip Chain[J]. Power System Technology, 2015, 39(6): 1477-1484.

[10] IVERSEN B, MOLLER J K, MORALES J M. Inhomogeneous Markov models for describing driving patterns[J]. IEEE Transactions on Smart Grid, 2017, 8(2): 581-588.