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Daily electric vehicle charging load profiles considering demographics of vehicle users

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HIGHLIGHTS

- Typical electric vehicle charging load is simulated considering user demographics.
- New probabilistic travel models are established for each user type.
- Charging preference, power consumption rate, day type and locations are included.
- Typical charging load profiles vary with different types of users.

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ABSTRACT

Travel pattern of an electric vehicle (EV) user and the accuracy of their probability distribution models are the key factors affecting the simulation and prediction of EV charging load. Most of the existing works utilized the travel data for all kinds of populations and ignored the influence of people social attributes on their travel pattern, which deteriorates the accuracy of the charging load model. This paper demonstrates that the daily EV charging load profiles vary with different demographic and social attributes by presenting a refined EV charging load simulation method considering people's demographics and social characteristics, e.g. gender, age, education level. First, to improve the fitting accuracy of people travel pattern, new probabilistic models of many defined spatial–temporal variables are established under refined conditions (i.e. location, day type, etc.). Second, additional factors (i.e. charging preference, power consumption rate, etc.) are included to simulate the daily profile of EV charging load based on the refined probabilistic models and Monte Carlo algorithm. Data from the US National Household Travel Survey are used to validate the proposed method. The results show that the user's demographic and social attributes have a considerable effect on the magnitude and peak time of the EV charging load profile, particularly for workdays and workplace. The proposed probabilistic models can improve the accuracy of the data fitting and the charging load simulation.

1. Introduction

Due to urban environmental pollution and the global energy crisis, many governments have set ambitious goals for the development of electric vehicles (EVs) [1], resulting in rapid growth for EVs worldwide [2]. France and UK have announced to stop sales of petrol and diesel automobiles by 2040. Denmark has proposed a ban on the sale of diesel and petrol vehicles from 2030 and hybrid from 2035. However, many studies have shown that a large number of EVs will require a considerable amount of charging electricity [3,4] and significantly increase the peak load and randomness on the demand side [5], which increase the expenditures on the capacity expansion and operational pressure of the distribution networks [6,7]. To alleviate the above issues, it is of importance to simulate and predict the EV charging load reliably.

Most existing works established the simulation and prediction model based on various data mining algorithms and primarily three kinds of datasets. (1) Historical charging records collected from public charging infrastructure [8-13] and private charging outlets [14-16], in the forms of power in kW, energy in kWh and the state of charge (SOC), etc. (2) Traffic and trip trajectory data, e.g. traffic volume and

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Nomenclature

Abbreviation

EV	Electric vehicle
SOC	State of charge
GIS	Geographic Information System
CCTV	Closed Circuit Television
NHTS	U.S. National Household Travel Survey
GEV	Generalized Extreme Value distribution
tLS	t Location-Scale distribution
H	Region type – Home
H1	Region type – Home-1: to return home for a short stay in the middle of a day
H2	Region type – Home-2: to return home and finalize the daily trip
W	Region type – Work place
O	Region type – Other place
non-H	Regions other than Home, including W region and O region

Indices and sets

t	Index of times
i	Index of samples
m	Index of destination

Constants

a, C, K	Parameters of probability density function of Burr Type XII
μ_i, σ_i	Parameters of probability density function of Normal distribution
α, β, γ, δ	Parameters of probability density function of Stable distribution
k, σ, μ	Parameters of probability density function of GEV distribution
a, b	Parameters of probability density function of Weibull distribution
M	Number of discretized time intervals in the spatial transition probability
N	Number of destination types
w_n	Energy consumption per kilometer (kW·h/km) of the n-th car
C	Battery capacity (kW·h)

Variables

x_t^*	Charging load at the time t after normalization
x_t	Original charging load at time t
x_{tmin}	Minimum value of the charging load time series
x_{tmax}	Maximum values of the charging load time series
R^2	Coefficient of determination
R_a^2	Corrected coefficient of determination
y_i	The i-th sample of the data set y to be fitted (n samples in total)
$\bar{y}$	Mean of all samples
$\hat{y}_i$	Fitted value of y_i
t_{s1}	Starting time of the first trip
T_x	Time duration of the car driving
Tp	Time duration of the car parking
D	Driving distance
Δt_i	The i-th time window of driving time
D_m	The m-the destination
$p_{ti,Di,Dj}$	Probability of driving from the current location to the next destination during the time interval
$E_{m,end}$	Remaining energy (kW·h) in the EV battery when arriving at the m-th trip destination

congestion index [17], traffic network data [18-20], GIS data [18], CCTV data [19]. Weather data [21,22] were also used to simulate their impacts on the driving distance and cycles [23], vehicle driving dynamics [24], and therefore to improve the accuracy of the subsequent EV charging load simulation and forecasting [25]. (3) Car travel records from the U.S. National Household Travel Survey (NHTS) [26-28] and GPS data [29,30], including driving time, duration, distance, and destinations. Currently, this method has been becoming the mainstream category because of the reliability and easier availability of such data. Many previous works of this method focused on developing probabilistic models of vehicle driving patterns and utilized various stochastic algorithms to simulate the driving and charging events at different locations and times, e.g. Monte Carlo [31-34], Markov chain [35], kernel density estimation [36], state-space model [37]. The EV charging load can be predicted if the forecast of EV travel behaviour is available [26].

However, the reliability of this method is restricted by the representativeness and accuracy of the probabilistic distribution models. Existing research shows that people of different ages, incomes, and educational background have different working and living patterns [38,39], which leads to different travel mode and energy consumptions. For instance, an individual's occupation will significantly affect the departure time of the daily trip and their parking time [3] as well as the peak load of the daily load profile [40]. Few studies have been refining the impacts of demographics on the travel pattern, which brings hidden errors to the charging load simulation.

To fill the research gap, this paper presents a simulation method for the daily EV charging load based on the travel pattern and demographics of car user. Probabilistic models of several spatial–temporal variables are established according to different day type and locations to improve model accuracy. With the consideration of different charging preference and power consumption rate, the daily profile of EV charging load is simulated using Monte Carlo method. In the end, typical EV load profiles for various user groups (e.g. male, female, highly educated and low educated population, etc.) are provided and compared. The results show that the user's demographic and social attributes have a considerable effect on the magnitude and peak time of the EV charging load profile.

The rest of the paper is organized as follow. Section II demonstrates the travel pattern of different populations, which is the foundation of this work. Section III proposes the overall framework of the charging load profile simulation considering user classification. Section IV defines the variables of spatial–temporal travel characteristics and presents their refined modelling methods to improve the fitting accuracy. Section V and VI develops the model for simulating the travel behaviour and EV charging load considering the charging preference and power consumption rate, etc. Section VII uses the NHTS survey data to validate the proposed method and provides various typical load profiles for different user groups. And the conclusions are given in the final section.

2. Travel characteristics of different demographic groups

Different people have different working and living modes and therefore have different travel characteristics. And, this will significantly affect the spatial–temporal distribution of the charging load. In most previous studies, diverse populations shared the same travelling probabilistic models, which led to errors in charging load simulation. In this section, the travel data for different user groups are analyzed in terms of both time and space dimensions to understand the travel patterns of different populations better. The demographic attributes considered and their classifications are shown in Table 1.

The departure time of the first trip, the end time of the daily trip, and the daily travelling distance are selected to compare the daily travel behaviour of different EV user groups. The U.S. NHTS dataset is taken as an example [41], as shown in Fig. 1-Fig. 3. In general, the daily travel of different groups has their characteristics; thereby, it is necessary to consider the differences between various populations in the modelling of travel pattern.

It can be seen from Fig. 1 the departure time of the first trip for young and middle-aged people is concentrated at around 7:00 am during the workday, which is consistent with the commuting time of students and office workers. The departure time for the elderly is generally later and more flexible, ranging from 7:00 am to 11:00 am, which is also in line with the lifestyle of retired older adults. A similar rule applies to the end time of daily travel. Young adults tend to arrive home from 16:00 to 18:00, while the arrival time of the elderly is widely distributed from 11:00 am to 18:00. As shown in Fig. (c), the elderly have shorter daily travelling distance, which can be attributed to the physical and psychological condition of the elderly.

Fig. 2 shows that the time for the relatively low-level educated people going to and getting off work is more dispersed compared to that for the other people; moreover, more people leave for work at noon or during midnight as well as get off work at very early daytime or during midnight than the higher-educated people. This might be because people with lower education levels usually perform unstable jobs. Fig. 3 shows that the males' attendance time is generally earlier than that of females and their daily driving distance is also longer.

3. Charging load profile simulation considering Users' demographics

As demonstrated above, EV users with different demographic characteristics show distinct travel modes, which affects the profile shape and magnitude of the charging load. To improve the representativeness of the travelling models and therefore the accuracy of the charging load simulation, the charging load model should be established for various user categories according to their demographics (e.g. gender, education background, age). This section clarifys the overall framework of the methodology to simulate the EV charging load profile for different vehicle user categories.

Taking one demographic attribute (gender) as an example, the method of modelling the typical charging load curves for male/female users is described. Fig. 4 shows the main process as well as the input and output at each stage. The typical curves of the other user groups can be derived by analogizing the following steps.

1). Filter the travel data according to the demographics of each user, e.g. male/female.
2). Taking the filtered data as input, establish the probabilistic models of all defined spatial–temporal travelling variables (i.e. starting time of the first travel, driving time, parking time and driving distance) for male/female users. The modelling method of the probabilistic travelling models was explained in Section IV, and the detailed probabilistic models used for different variables and user categories are shown in Table 2.
3). Taking the above probabilistic models as input, use the methods presented in Section V and VI to simulate the travel behavior as well as the energy consumption and charging events during the daily trip with additional consideration on day type, location type, charging preference and the rate of battery energy consumption. Then, a given number of samples (charging load curves) are generated for male/female users. Note that the number of generated samples can be changed according to the number of EV users and demographics in the simulated area.
4). Average and normalize the curves of male/female users to eliminate the effects of abnormal loads, the simulation number, and the unit of load on typical curves. The min–max normalization is adopted as shown in (1)

$$x_t^* = \frac{x_t - x_{t\min}}{x_{t\max} - x_{t\min}} \tag{1}$$

where x_t^* is the charging load at the time t after normalization; x_t is the original charging load at time t; $x_{t\min}$. and $x_{t\max}$ are the minimum and maximum values of the charging load time series, respectively. To facilitate the curve comparison, the minimum and maximum values are taken as the same. Modelling Method of Travel Characteristics

4. Modelling method of travel characteristics

The user's travel characteristics are an essential input for simulating the EV charging load. Different driving behaviours have a profound impact on the location and duration of a charging event. For example, an increase in driving time duration will lead to an increase in EV energy consumption and longer charging time; driving to different destinations will change the spatial distribution of the charging load. Therefore, accurate modelling of travel features is a crucial part of the entire charging load simulation process. This section proposes a generally adaptive modelling method for the probabilistic models of travelling time–space variables, laying a foundation for the subsequent development of EV charging load models for different user groups.

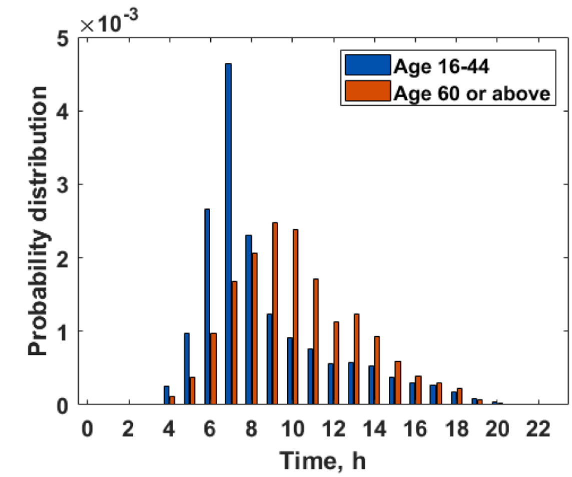
In this paper, the accuracies of the probabilistic distribution models of all travel variables are improved by using various algorithms, including Burr Type XII, Lognormal, Stable, Normal, Generalized Extreme Value (GEV), Weibull, Exponential, Gamma, Birnbaum-Saunders, Inverse Gaussian, Loglogistic, Logistic, Nakagami, Rician, and t Location-Scale (tLS) distribution. The above algorithms can cover a wide range of distribution shapes and satisfy the diversity of distribution patterns in various defined travel variables. For example, the Normal curve is bell-shaped, low at both tails, high in the middle, and left–right symmetrical. The Logistic distribution has a longer tail and a higher kurtosis than the normal distribution. The Inverse Gaussian, the Lognormal and the Nakagami distribution are used to model right-skewed, non-negative data. The Stable distribution and the t Location-Scale distribution are suitable for modelling heavy tails (more prone to outliers). The Exponential distribution is a particular case of the gamma distribution, and it is useful in modelling events that occur randomly over time. The Burr distribution includes many commonly used distributions such as gamma, lognormal, loglogistic, bell-shaped, and J-shaped beta distributions (but not U-shaped).

The selected distribution models are used to fit a given variable respectively, and the model which performs best is determined as the adopted one. The evaluation indexes of the model accuracy are the coefficient of determination R^2 and the corrected coefficient of determination R_a^2 as shown in (2–3).

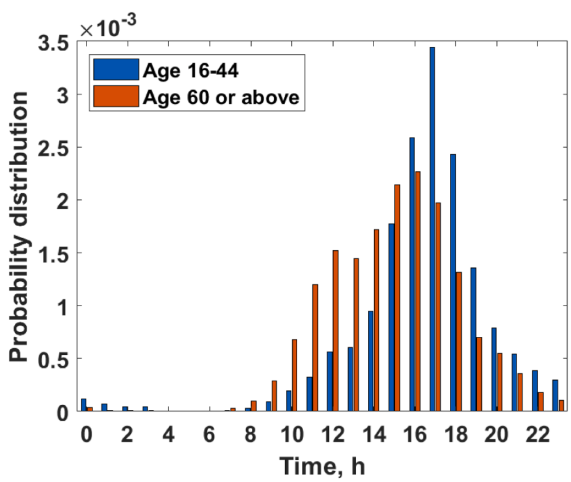
$$R^2 = \frac{\sum_{i=1}^{n} (\hat{y}_i - \bar{y})^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2} \tag{2}$$

Table 1
Demographic Groups.

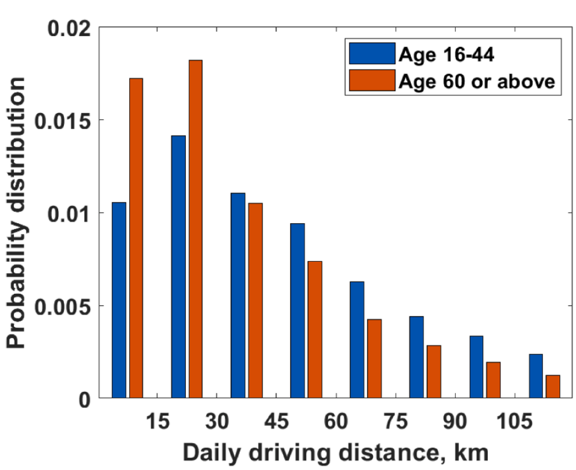
Demographics	Categories
Gender	Male
	Female
Age	16–44
	45–59
	≥60
Education level	Bachelor below
	Bachelor or above



(a) The departure time of the first trip



(b) The end time of the daily travel

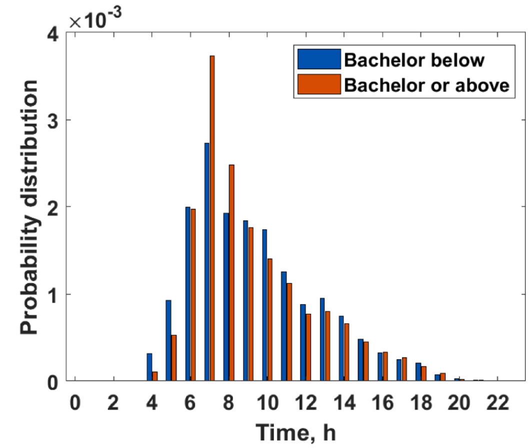


(c) Daily driving distance

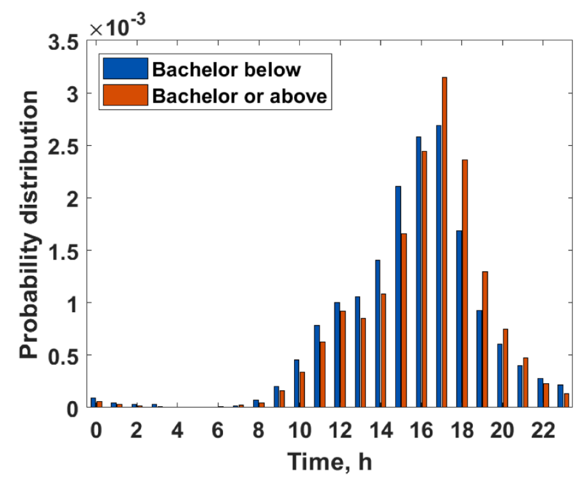
Fig. 1. Daily travel patterns of different age groups (workday).

$$R_a^2 = 1 - (1 - R^2) \times \frac{n-1}{n-p-1} \tag{3}$$

where y_i is the i-th sample of the data set y to be fitted (n samples in total); $\bar{y}$ is the mean of all samples; $\hat{y}_i$ is the fitted value of y_i; p is the



(a) The departure time of the first trip



(b) The end time of the daily travel

Fig. 2. Daily travel pattern of people with different educational backgrounds (workday).

number of parameters in the probability distribution model used.

A. Probability Distribution Fitting of Time Variables

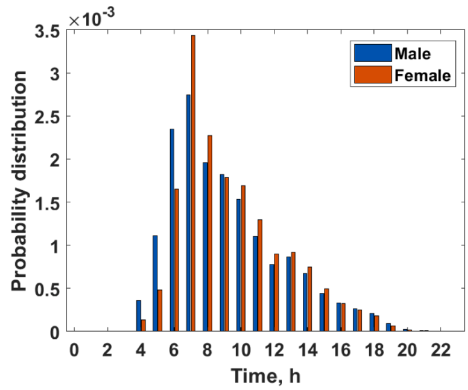
In this paper, probability distributions of three temporal variables (starting time of the first trip in a day, the time duration of the car driving and car parking) are fitted to quantify the temporal characteristics of the daily driving trip. Firstly, the starting time of the first trip is fitted.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

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

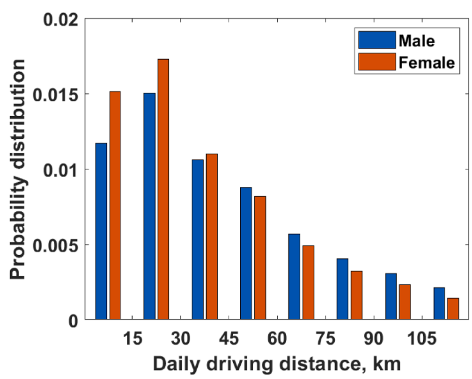
Burr Type XII model is used to fit the distribution of the starting time of the first travel. The probability density function is shown in (4).

$$f(t_{s1}|\alpha, C, K) = \frac{\frac{KC}{\alpha}(\frac{t_{s1}}{\alpha})^{C-1}}{(1 + (\frac{t_{s1}}{\alpha})^C)^{K+1}} \tag{4}$$

2). Time duration of the car driving - T_x



(a) Departure time of the first trip



(b) Daily driving distance

Fig. 3. Daily travel patterns of different gender groups (workday).

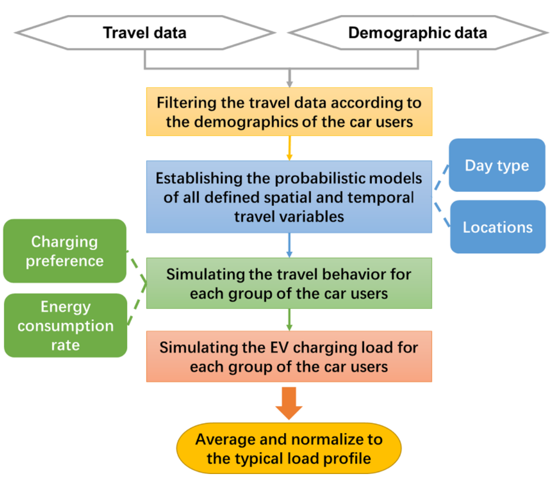


Fig. 4. The modelling procedure of typical charging load profile for a given user group.

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 Table 3. Eight types of driving time are separately fitted using the lognormal distribution with different fitting parameters.

3). Time duration of the car parking - *Tp*

Parking time limits the length of the 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 extended, there probably will be more destination options because of being 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 kinds of parking time are shown in Table 4.

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 (5).

$$P_d(d|\Delta t_i) = \frac{1}{\sqrt{2\pi}\sigma_i} e^{-\frac{1}{2\sigma_i^2}(d-\mu_i)^2} \tag{5}$$

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 likelihood that a car is driving from destination D_m to the next destination D_{m+1} at a specific time slot. Assumed that the current destination D_m is only related to the last destination D_{m-1} regardless of other previous destination, the spatial transition probability can be written as (6).

$$P(D_m \to D_{m+1}) = P(D_{m+1}|D_m) \tag{6}$$

The spatial transition probability can be converted into a $M \times N \times N$ 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 (7).

$$P_{t_i} = \begin{bmatrix} p_{t_i,D_1,D_1} & \cdots & p_{t_i,D_1,D_N} \\ \vdots & \ddots & \vdots \\ p_{t_i,D_N,D_1} & \cdots & p_{t_i,D_N,D_N} \end{bmatrix} \tag{7}$$

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

5. Travel behaviour simulation

In this paper, Monte Carlo method is used to simulate the travel behaviours of car users [42]. The corresponding probabilistic models for a given population are taken as model inputs including the discrete spatial transition probability matrix and probability distribution of all defined spatial–temporal travelling variables. All the variables are sampled sequentially, thereby the daily driving trip of each user can be 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.
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. According to the starting time of

Table 2
Probabilistic Models for Different Genders (Workday).

Gender	Spatial-temporal variables						
	Start Time	Driving Time	Parking Time	Driving Distance			Trip Destination
				Trip Type	Driving Time (min)	Distribution	
Male	GEV	GEV (H-nonH)	tLS (W)	H-nonH	0–15	Gamma	Transition probability matrix for male
					15–30	GEV	
					30–45	Rician	
					45 above	Weibull	
		Stable (nonH-nonH)	GEV (O)	nonH-nonH	0–15	tLS	
					15–30	Stable	
					30–45	GEV	
					45 above	Nakagami	
		Burr (nonH-H)	Gamma (H)	nonH-H	0–15	GEV	
					15–30	GEV	
					30–45	Weibull	
					45 above	Nakagami	
		Lognormal (H-H)		H-H	0–15	Stable	
					15–30	GEV	
					30–45	GEV	
					45 above	GEV	
Female	Burr	Burr (H-nonH)	Stable (W)	H-nonH	0–15	Gamma	Transition probability matrix for female
					15–30	GEV	
					30–45	GEV	
					45 above	GEV	
		Burr (nonH-nonH)	GEV (O)	nonH-nonH	0–15	Nakagami	
					15–30	GEV	
					30–45	Rician	
					45 above	GEV	
		Burr (nonH-H)	Gamma (H)	nonH-H	0–15	Gamma	
					15–30	GEV	
					30–45	GEV	
					45 above	Rician	
		Stable (H-H)		H-H	0–15	Gamma	
					15–30	Stable	
					30–45	Stable	
					45 above	GEV	

Table 3
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 4
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

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 duration of driving.

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 duration, the starting time of the next trip is calculated for simulating next trip.

6. Charging preference and charging load simulation

Based on the simulated travelling behaviours of each users, the charging load profiles can be simulated [42]. To improve the load simulation accuracy, the charging preference is considered during the load simulation. Two types of charging behaviours are designed.

1). A conservative charging preference

EV charging would be started when the is met. This means that EV users will charge their cars when the remaining energy in the EV batteries is unable to support the energy consumption of the next trip.

$$E_{m,end} - w_n d_{m+1} \leqslant 0.2C \tag{8}$$

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

2). A positive charging preference

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

The charging load is calculated by combining the charging assumptions with the sampled travel process. Take a specific trip of a vehicle as an example, the simulation process is illustrated below and shown in Fig. 5.

1) The energy consumption of this trip is calculated by multiplying the

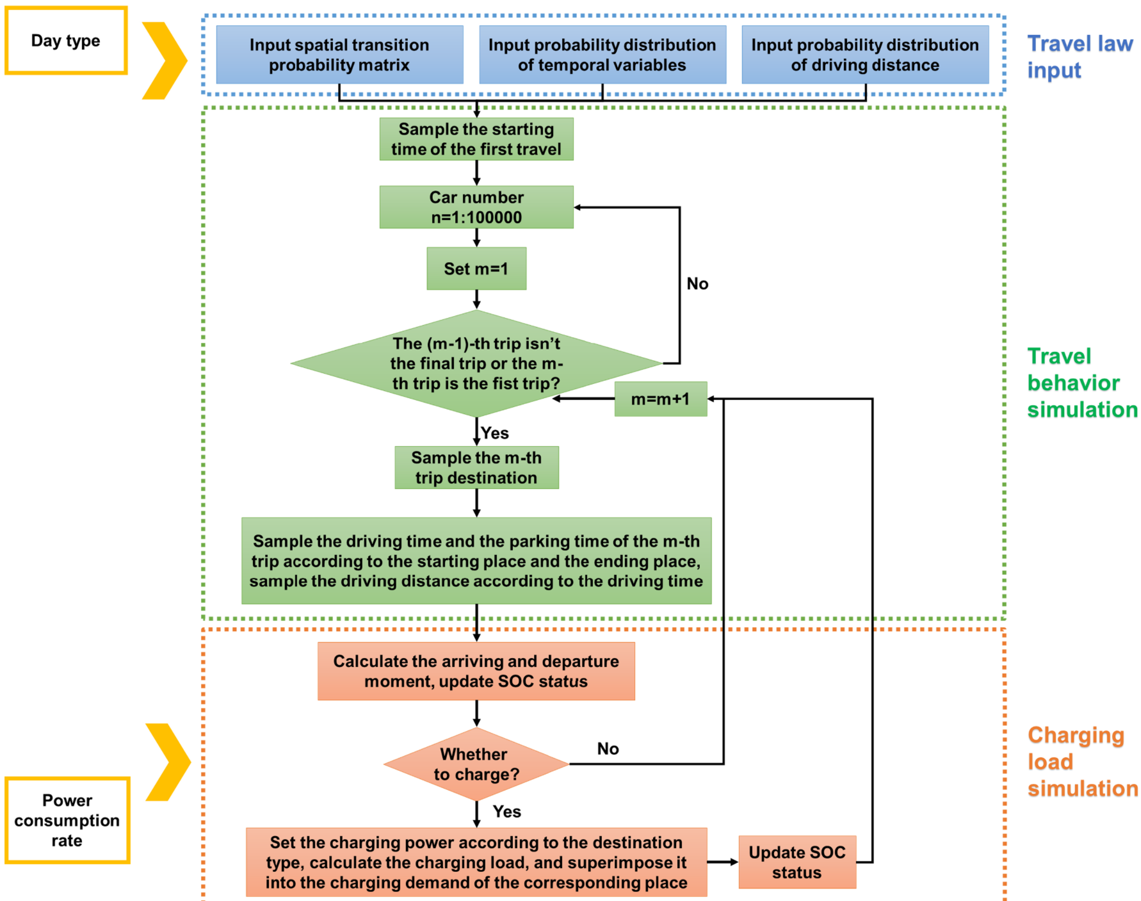


Fig. 5. Process of simulating the charging load.

driving distance by the power consumption rate of this car.

2) The SOC of the EV battery is updated when the vehicle stops driving.
3) The charging preference and the subsequent journey of the EV driver determines whether the car will be charged once it is parked at this simulation iteration or waits until the remaining electricity cannot supply the next trip.
4) If charged, the charging power can be determined according to the type of parking location.
5) The charging time duration of this parking event is calculated by dividing the energy consumption by the charging power and also constrained by the parking time limit.
6) The SOC of the EV battery is updated again when the car leaves the parking place.
7) Repeat the step 1 to 6, the charging time duration and charging power of each parking event in a day for one vehicle are calculated. The time series of charging load of this vehicle in each parking place can be obtained.
8) Repeat the step 1 to 7, the daily load profiles of a given number of EVs in different places can be simulated. The regional charging load profile can be calculated by aggregating the profiles for all the vehicles..

7. Case study

A. Data discription and model assumption

This paper assumes that the travel mode of EV users is the same as that of fuel vehicle users. Data used in the case study come from the travel data packet in the U.S. NHTS in 2009 [41]. 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. It also includes the demographic information of the respondents (e.g. gender, age, education, occupation, income, etc.), which is the basis for distinguishing each type of user. According to the statistics of the data, it is assumed that each car user can make up to three trips a day.

In this paper, some parameters are assumed in the simulation, which is not always accurate in reality. The energy consumption rates and capacity of each EV are randomly selected from a specific range according to current battery technology. The charging power and the number of EVs in a region are assumed to be constant. However, these parameters can be modified easily if real-world data are available. The specific values of the parameters in the case are set as follows.

1). 100,000 EVs are simulated.
2). the energy consumption rate of each EV is randomly set to 0.1 ~ 0.25 kW·h/km, the capacity of each EV battery is randomly chosen from 40 ~ 50 kW·h, and the initial SOC is 0.8C.
3). considering the battery degradation due to over-charging or over-discharging, the upper and lower limits of SOC are set to 0.2 and 0.8, respectively.
4). the charging power in the W, O, H1 region is 8 kW, while in H2 region is 4 kW [43].

B. Probability Distribution of Time Variables

1). Starting time of the first trip

To fit the starting time of the first trip, three distribution models are proposed and compared. Table 5. shows the used distribution models

Table 5
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

[a] R^2 is the coefficient of determination, and R_a^2 is the corrected coefficient of determination.

and their performances. It is found that the Burr Type XII distribution works the best. And, the coefficient of determination and the corrected coefficient of determination for the Burr Type XII distribution is higher than that for other distributions by over 10%, for both workday and weekend.

The probability distributions of the starting time of the first trip for different day types are showed in Fig. 6. For workday, the fitting parameters are: $\alpha = 7.986$, C = 6.696, K = 0.609. For weekend, the fitting parameters are: $\alpha = 11.46$, C = 5.79, K = 1.24. As shown in the Fig. 6, the probability distributions of the starting time of the first trip between workday and weekend are different. Distribution on workday is mainly around 8:00 am, which coincides with the real-world situation. And, the 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. 7 and Fig. 8 respectively. It is observed that the driving time for both workday and weekend obey the lognormal distribution well. The differences in the distributions of different types of driving time for the same day type are obvious. The fitting parameters for workday and weekend are shown in (9) and (10), respectively.

$$\begin{cases}\mu_{\mathrm{I}} = 2.995\\ \sigma_{\mathrm{I}} = 0.737\end{cases}\begin{cases}\mu_{\mathrm{II}} = 2.816\\ \sigma_{\mathrm{II}} = 0.79\end{cases}\begin{cases}\mu_{\mathrm{III}} = 3.069\\ \sigma_{\mathrm{III}} = 0.749\end{cases}\begin{cases}\mu_{\mathrm{IV}} = 3.176\\ \sigma_{\mathrm{IV}} = 0.759\end{cases} \tag{9}$$

$$\begin{cases}\mu_{\mathrm{I}} = 2.815\\ \sigma_{\mathrm{I}} = 0.783\end{cases}\begin{cases}\mu_{\mathrm{II}} = 2.701\\ \sigma_{\mathrm{II}} = 0.815\end{cases}\begin{cases}\mu_{\mathrm{III}} = 2.883\\ \sigma_{\mathrm{III}} = 0.782\end{cases}\begin{cases}\mu_{\mathrm{IV}} = 3.073\\ \sigma_{\mathrm{IV}} = 0.765\end{cases} \tag{10}$$

3). Parking time

Considering different parking places and different day types, the performance of different distribution models for parking time is shown in Table 6. and Table 7. Nearly all the distibutions achieved above 0.9 fitting accuracy. The best fit appears to the distribution of W place and O place on workday, whose coefficient of determination and the corrected coefficient of determination are higher than that of the other benchmarks by over 0.35. Distributions of parking time for different places on workday/weekend are shown in Fig. 9 and Fig. 10 respectively. It is suggested that the distributions are well fitted except for the ones of the workplace.

For W place on workday, the fitting parameters are $\alpha = 1.324$, β = -0.51, $\gamma = 66.379$, $\delta = 535.77$.

For H place on workday, the fitting parameters are $\alpha = 3032.83$, $C = 1.043$, $K = 27.171$.

For O place on workday, the fitting parameters are $k = 0.765$, $\sigma = 35.419$, $\mu = 63.477$.

For W place on weekend, the fitting parameters are $\mu = 461.059$, $\sigma = 191.418$.

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

For O place on weekend, the fitting parameters are $\alpha = 53.199$, $C = 4.619$, $K = 0.305$.

C. Spatial Transition Probability Matrix

Spatial transition probability matrixes for the two randomly selected time periods on workday/weekend are shown in Fig. 11. As shown in the figure, the trip destination is closely related to the travelling time period. And, the spatial transition probabilities for workday and weekend are different during morning rush hours but are almost the same during evening rush hours.

D. Impacts of Charging Preference on Charging Load

In this section, the distributions of charging load at different energy consumption rates (energy consumption per kilometer) for the two types of charging preference are shown in Fig. 12. To clarify the sensitivity of energy consumption rate and charging preference on the charging load, the charging load needed for the trip driving from H2 to W are demonstrated as an example. Taking the point (10–20, 6) on the curve as an example, it means that for EV users whose commuting duration is 10 to 20 min, their demand for charging in this trip reaches 6×10^4 kW.

As shown in the figure, for the conservative charging preference, energy consumption rate has a significant impact on the charging load distribution. Meanwhile, for the positive charging preference, the energy consumption rate has very limited impacts on the charging load, and the demand for charging is much higher than the conservative charging. This might be because EVs would be charged once arriving at the destinations, and the driving distance of each trip and the destination type would have larger impacts on the charging load demands than the energy consumption rate.

Note that, according to the probability distribution of driving time, driving time is mainly between 10 and 20 min. Therefore, for the second type of charging preference, the charging load of EVs with the driving time of 10–20 min is significantly higher than the rest driving time. However, for the first type of charging preference, the driving time duration with the highest charging load is not 10–20 min but 60–70 min. More importantly, the charging load for the driving time of 10–20 min is reduced, which is good to the grid, because a car with a

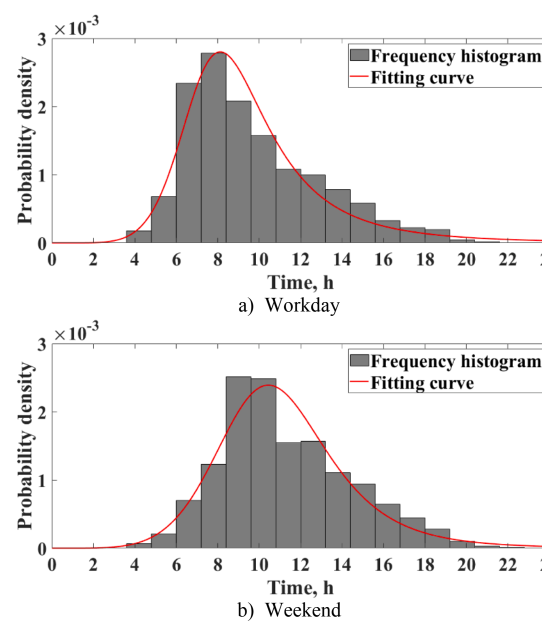


Fig. 6. Probability distribution of the starting time of the first trip.

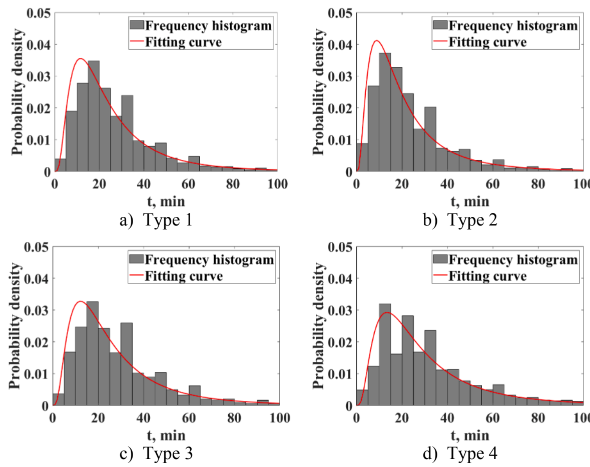


Fig. 7. Probability distribution of driving time on workday.

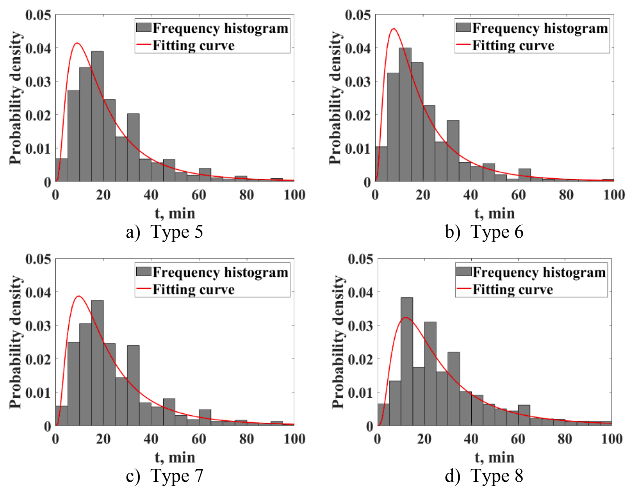


Fig. 8. The probability distribution of driving time on the weekend.

Table 6
Results of Different Distributions of Parking Time on Workday.

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

driving time of 10–20 min is not necessarily to be charged.

E. Daily Charging Load Profiles for different user groups

The above results show that the proposed simulation method is able to simulate the probabilistic models and charging load accurately. Based on the above results, this section attempts to provide the daily charging load profiles for different user groups.

Fig. 13 to Fig. 15 are typical charging load profiles for different age groups, gender groups, and education groups. The results show that the typical profiles of different user populations have large differences under certain conditions (e.g. workday, office areas), which proves the necessity of considering population classification in this paper. Fig. 13 to Fig. 15 can be found in Appendix.

Table 7
Results of Different Distributions of Parking Time on Weekend.

Parking Time	Distribution	Standard	
		R^2	R_a^2
W	Normal distribution	0.6556	0.6370
	Generalized extreme value distribution	0.5773	0.5421
	Stable 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

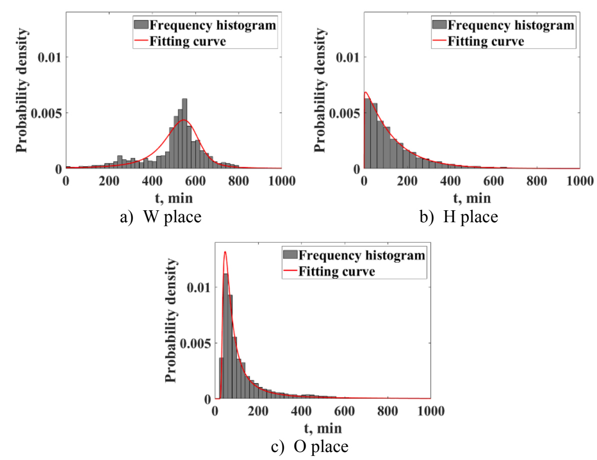


Fig. 9. The probability distribution of parking time on workday.

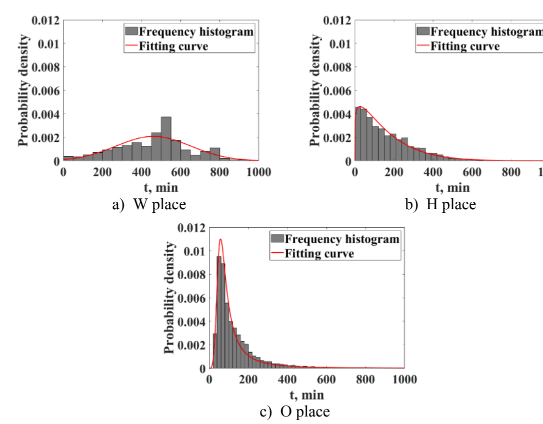


Fig. 10. The probability distribution of parking time on weekend.

As can be seen from Fig. 13, the age of the EV users has a significant impact on the shape, peak and peak time of the load profile, especially on weekdays and office areas. This is caused by the difference of working and living patterns of various age groups.

1). On weekdays and H1 region, the load profile of elderly people shows a single sharp peak, and the peak appears at noon – 12:00. This might because the elderly people have more time staying at home during the daytime. The load profiles of users of other ages show double peaks at around 10:00–11:00 and 16:00. This might because the young people go home for lunch break and dinner and

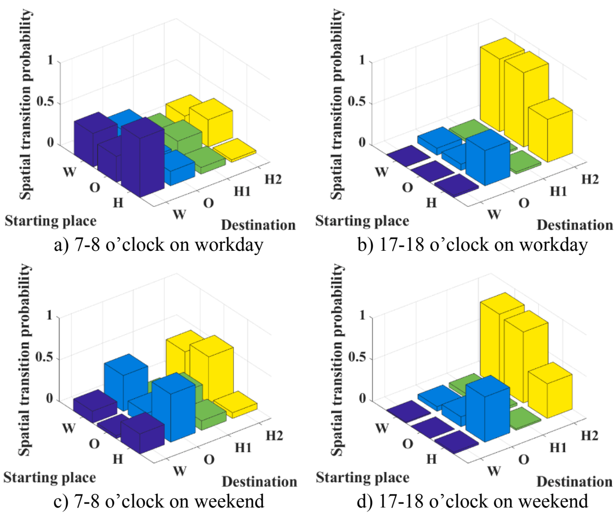


Fig. 11. Spatial transition probability.

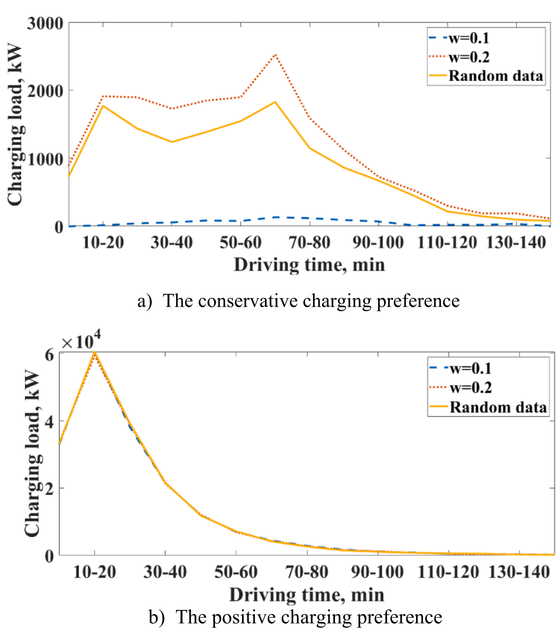


Fig. 12. Distribution of charging load with different energy consumption rates.

then leave for work or play. Their peaks are lower than that of older users, with a maximum difference of 41%.

2). On weekdays and in the H2 region, the peak of load profile of the elderly users is advanced by 16%, while the peak value is reduced by 10%. This coincides with the lifestyle of the elderly people, who tends to return home earlier than the others. In addition, load profile of older adults have lower peak because they normally return home at flexible times, resulting in random time of charging.

3). In the W region, the higher the age of the users is, the lower the charging demand they require. In particular, the daily total charging load of elderly users is extremely lower than that of the younger users by up to 77%. This might because the older users are less active and drive less, which is related to factors concerning physical strength and mentality.

Fig. 14 shows that the shapes of the charging load profile for males and females are similar. However, the charging demand of males is higher than that of females, and the difference is even larger on the weekend, reaching 46% in the H1 region. Due to physical differences, male users are more tolerance to long-distance driving and more likely to travelling out on the weekends.

Fig. 15 shows that the difference in education levels are mainly reflected in the load profiles for the commuting regions (i.e. H2 and W region), while the differences in magnitude and shape of the profiles in other regions are very small. In the H2 region, the evening rush hours for the high-educated people are later than the low-educated people, which are 20:00 and 16:00, respectively. In the W area, the charging demand of the highly educated population is significantly higher than that of the low educated population (up to 32%), and has a much clear morning peak. It might be for the reasons that, highly educated people are generally more willing to work hard, and low educated people always have more irregular working hours.

8. Conclusions

In this paper, an EV charging load simulation method is proposed based on users' demographics, refined probabilistic distribution models of temporal-spacial travel mode and other additional factors, including charging preference and energy consumption rate. Different from traditional methods, the proposed method utilizes refined probabilistic models with consideration of day type and location as well as the users' demographics to improve the simulation accuracy. Based on the improved method, the typical daily profiles for various user groups are provided. The results in the case study validate the proposed model and compare the load profiles of various categories of EV users.

- The demographics of EV users have a significant effect on the magnitude and peak time of the daily charging load, particularly for workdays and workplace.
- The accuracy of the probability distribution models of various spatial–temporal variables is improved by considering additional refined conditions. The fitting performance evaluation index reach up to 0.9739 and 0.9725.
- The daily charging load profiles for different types of charging preferences and different energy consumption rates are significantly diverse, indicating the necessity for considering these factors during charging load modeling.

Future works are worthy of exploring in several aspects:

1). Different demographics have a unique way of adapting EV uses, e.g. the tolerance to low SOC and the preference for vehicle type, which is not considered in this work. Taking these factors into account will further improve the accuracy of simulating the daily charging load profile.

2). Based on the typical load profiles, the actual population demographics and their weights in a given region, long-term regional EV charging load prediction can be made to help the planning of a large share EV system, for example, to guide the charging pricing, charging infrastructure planning, and load shifting.

CRediT authorship contribution statement

Jing Zhang: Methodology, Software, Validation, Data curation, Writing - original draft. **Jie Yan:** Conceptualization, Writing - review & editing. **Yongqian Liu:** Supervision. **Haoran Zhang:** Visualization. **Guoliang Lv:** Investigation.

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Appendix

(See Figs. 13-15)

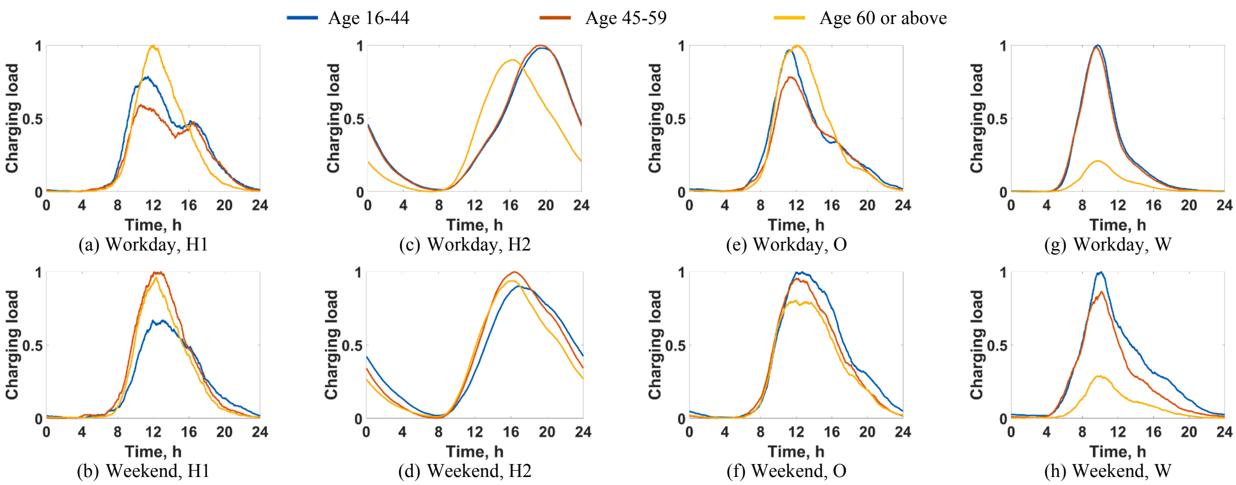

Fig. 13. Typical daily curves for users with different ages.

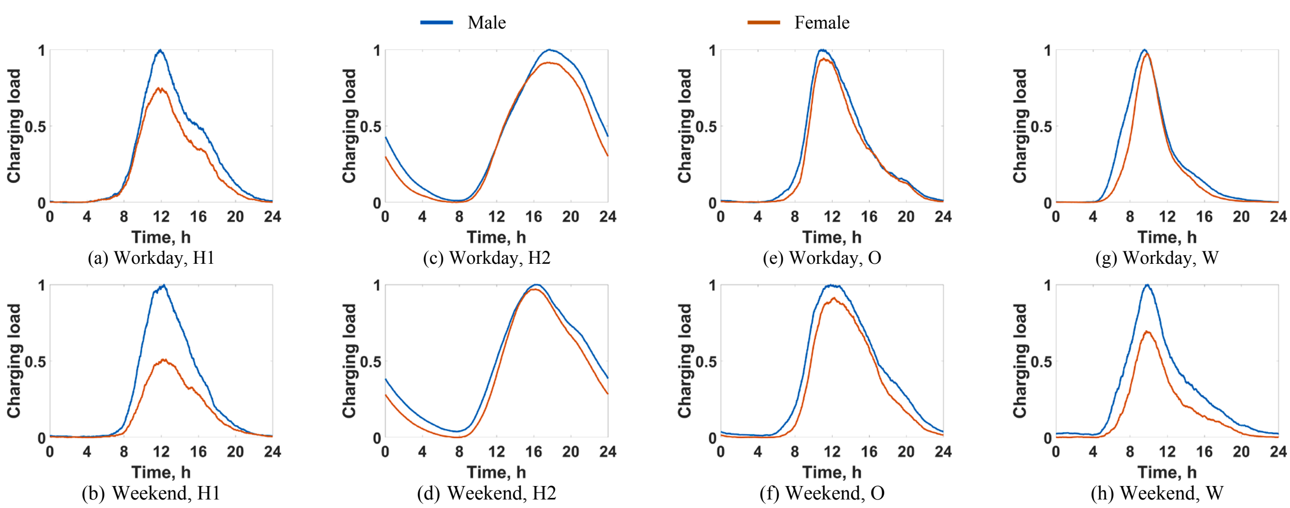

Fig. 14. Typical daily curves for users with different genders.

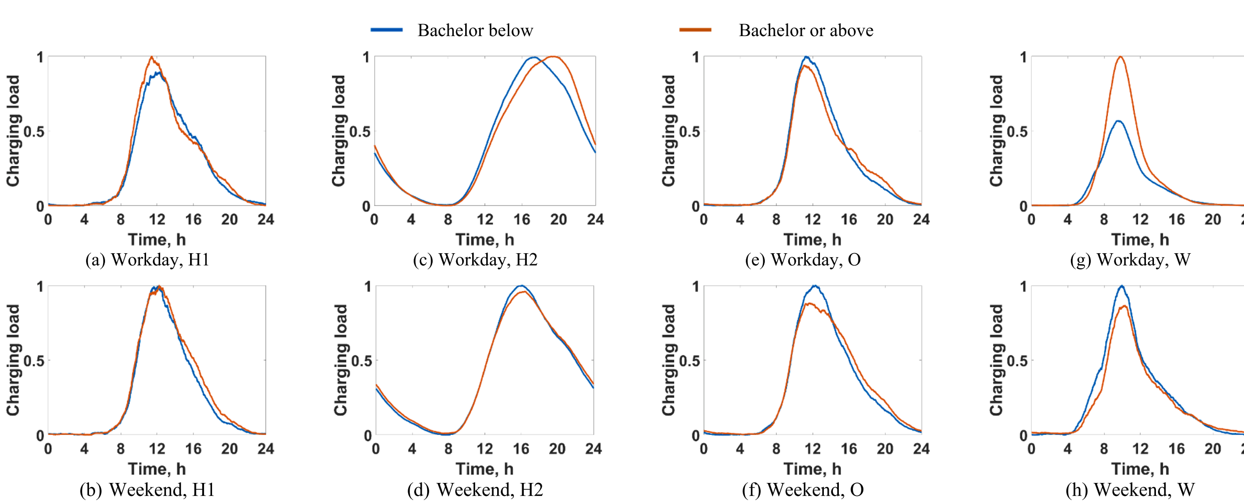

Fig. 15. Typical daily curves for users with different education levels.

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