Spatiotemporal Distribution Model of Charging Demand for Electric Vehicle Charging Stations Based on Markov Chain

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Abstract. Considering the diversity of travel habits of users, spatiotemporal distribution model of charging load for highly random electric vehicles (EV) based on Markov chain, is proposed. According to the residents' travel habits of the 2017 National Household Travel Survey (NHTS) in the United States, the destinations are divided into homes, work places, and other locations. Based on Markov Chain and Monte Carlo method, a highly random and complex process chain with unlimited processes is constructed. The distribution of start times and end times in one-day journey is fitted by the parameterless distribution with normal distribution as the kernel. The distribution of travel time, travel distance and dwell time is fitted by lognormal distribution. Then, a spatiotemporal distribution model of one-day vehicle travel is established. Considering the influence of EVs, the dual-input fuzzy algorithm of travel time and travel distance is used to calculate the power consumption of the trip. According to the crowd's travel anxiety and different travel needs, different charging frequencies and different charging power levels are used for vehicle charging behavior. Finally, the Monte Carlo method is used to calculate and analyse the charging load of EVs in different classification scenarios, such as household income, home address, weekdays and weekends. The one-day electric vehicle load distribution model was successfully established in three locations. The results show that the load of electric vehicle charging stations is not only affected by factors such as holidays, but also by the composition of the urban population.

1. Introduction
Electric vehicles are a clean energy vehicle, which has become a hot spot in the development of the domestic and foreign auto industry in recent years. However, due to the uncertainty and differences of electric vehicle users' needs and behaviors, the future large-scale electric vehicle charging load has uncertain characteristics in time and space, such as randomness, intermittent, and volatility[1,2], challenging the safe operation and scheduling of existing power grids. The establishment of load prediction model for electric vehicle charging station (EVCS) has become an urgent problem to be solved. It can provide the theoretical basis for the establishment and operation of future electric vehicle charging stations and adjustment of grid control strategy.

Ref.[3] analyzes the charging methods, geographical location and driving characteristics of battery replacement stations, residential charging stations and Charging station in public places, and proposes a probabilistic load model. However, the fixed charging time, charging time and power consumption are not consistent with the actual multiple trips and charging times of the users. Ref.[4] proposed the concept of whole trajectory space and quantified the driving, stopping and charging of EVs. However, in the description of the trip chain, 2 or 3 fixed trips couldn't describe more driving one day travel and
reflect the randomness of travel. In [5] a statistical model of charging load for EVCS is established based on the travel chain of electric vehicle users. Monte Carlo simulation method is used to obtain the calculation method of power demand, and one or two simple journey chains are obtained by linear correlation analysis. In [6,7], a Markov chain model was used to describe three decision-making behaviors of an EV during a day of travel: driving, charging, and stopping. However, the behavior of stopping is determined by the transition state. Actually EV usually stop for every travel. The dwell time is random.

Ref.[8] combined different types of EVs and parking characteristics. The parking generation rate model was used to predict parking demand, and a charging demand calculation method was established based on the parking demand spatiotemporal distribution model. Ref.[9] considers the charging characteristics of the battery, and derives the probability distribution of the initial state of charge from the probability density function of the driving distance. In [10], the kernel density function was used to replace the deterministic probability distribution function to fit the driving law of EVs. The probability distribution function was used to generate random numbers with coupling characteristics to describe the vehicle behavior. But this method ignores intermediate processes. This will cause the model to fail to accurately describe the actual charging behavior. Ref.[11] proposed a multi-day once-charge model for a large electric vehicle charging load model. Based on the number of charging times, the population is clustered. But changes in the crowd will lead to reduced accuracy of the driving trip.

In [12], based on the queuing theory and traffic flow theory, the load of the charging station on the expressway was analyzed. The arrival time of the electric vehicle was assumed to follow the Poisson distribution, and the load model of the highway charging station was established. In [13], considering the type of EV, the number of charging times and the charging time, a load model of the charging station was established based on queuing theory. In [14], under the assumption that the charging station service is known, combining the charging demand and traffic demand, the spatiotemporal distribution model of EV's charging demand is obtained by using Agent-Cellular Automata during the dynamic change process. In [15], the location of the charging station, charging time, peak time, previous charging records and changes in electricity prices were considered, and a cluster load prediction model was established based on the Agent mechanism. In [16], a BP neural network was used to calculate the number of exchanges for electric buses, and a model for predicting the exchange load of electric buses was established based on Monte Carlo algorithm. Due to the law of bus exchange, the model has a poor prediction effect on the replacement or charging of highly random private cars. In [17], through the pre-processing of historical data, based on the real-time regression of the number of charging stations and charging time, the load prediction models of charging stations in various places were obtained by the regression method. In [18], based on the historical load statistics of EVCS, the electric vehicle charging parameter model with uncertain number of vehicles was estimated. When the number of vehicles is fixed, the load curve can be fitted and predicted, but it is difficult to maintain a high degree of consistency between the driving law of EV and the model, so it cannot be well adapted.

This article fully considers randomness of EV behavior, variable charging power and charging times. Based on the travel requirements and people's anxiety about the remaining power, the spatiotemporal distribution model of charging demand for EVCS is established. In section 2, according to the trippub and tour17 data sets of the 2017 National Household Travel Survey (NHTS) in the United States[19], the distribution of start and end times in one-day journey is fitted by the parameterless distribution with normal distribution as the kernel. The distribution of travel time, travel distance and dwell time is fitted by lognormal distribution. In section 3, based on the Markov chain, a one-day driving chain of EVs with completely random behavior is formed by the transfer matrix. In section 4, the fuzzy algorithm is used to process the travel time and travel distance in each trip to calculate the power consumption of the trip. The vehicle determines different charging frequencies and charging power charging behaviors as needed. In section 5, the Monte Carlo method is used to establish a spatiotemporal distribution model of EVCS to forecast and analyze the charging load in
different classification scenarios, including household income, home address, weekdays and weekends. Finally, section 6 concludes the work reported in this paper.

2. Statistical Model of EVs Behavior Data

According to the trippub data and the tour17 data set of 2017 NHTS, EVs can travel between three destinations, including home, work, and other locations. The tour of a driver from one place to another is called a trip, and the sum of all the trips made by a driver within one day is called a journey. According to the family ID number, driver ID number and travel information records of the travel data set, the start time of journey, the end time of journey, the travel time, the travel distance and dwell time between adjacent trips can be known for each trip on the journey.

2.1. Statistical distribution

Due to the complicated distribution extraction in the modeling process, in order to simplify the statistical distribution, the parameterless distribution with the normal distribution as the kernel is used. This distribution is defined by smoothing functions and bandwidth values. The probability density function is shown in Equation (1), where $f_h(x)$ is the probability density function, where $n$ is the sample size, $K(\cdot)$ is the kernel smoothing function, and $h$ is the bandwidth.

$$f_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x-x_i}{h}\right); \quad -\infty < x < \infty$$  \hspace{1cm} (1)

According to the statistics of the 2017 NHTS survey, a lognormal distribution is used. The probability density function is shown in formula (2), where $\mu$ is the mean of the variable $x$ logarithm, and $\sigma$ is the standard deviation of the variable $x$ logarithm.

$$f(x \mid \mu, \sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{-\frac{-(\ln x - \mu)^2}{2\sigma^2}} \quad x > 0$$  \hspace{1cm} (2)

2.2. Fit effect test

The Kolmogorow-Smirnov test (K-S) is based on cumulative distribution function, which is used to test whether an empirical distribution conforms to a certain theoretical distribution or to compare whether two empirical distributions are significantly different. In order to test the fitting effect, the K-S test method was used.

3. Markov chain

3.1. Travel Chain

According to the driving direction of each trip in tour17, it can be divided into home(H), work(W), and other locations(O). Assuming home is the starting point of day journey, there are no restrictions on the number of trips in the process. The directions and the number of trips are completely random.

The day's journey starts from home, you can go from H to H\O\W, complete a trip, pause for a certain period of time, continue the journey, repeat the transfer process until n journeys are completed, and finally go home. The end flag is determined by the randomly drawn end time of the journey and the end-of-travel rule. The whole process are shown in Figure 1.

The end-of-travel rule: Set the threshold range value $a$ and the travel end time $T_e$ of a day, the end time of a trip $t_e$. If $t_e \in (T_e-2a, T_e+a)$ and the travel end location is home, the journey is successful and the journey of the day ends. If $t_e \in (T_e-2a, T_e+a)$ and the end of the trip is not home, the journey is modified, re-extract last trip and the last trip is set to return home to complete the journey of the day. If $t_e > (T_e+a)$, the journey fails, delete this This journey and re-journey. If $t_e < (T_e-2a)$, the journey is not completed, continue to travel.
3.2. Transition probability matrix for vehicle travel direction

Markov stochastic process is a random process without aftereffects. For the system, there is a transition probability from one state to another, and the next state can be calculated based on the current state. The original state before the transition has nothing to do with the Markov process. The sequence of states in the entire Markov random process is called a Markov chain. Recording the current state as $A_i$ and the next state as $A_j$, the conditional probability is

$$P( A_i \rightarrow A_j ) = P(A_j | A_i) = P_{ij}$$

(3)

If the location where the vehicle is located is regarded as a state, according to Markov theory, it can be estimated based on the current state that the location of the vehicle at the next moment. Considering the actual situation of human activity, there is no constant 24-hour day transition probability. For example, the transition probability of returning home in the evening must be higher than others. Therefore, the transition matrix should also have the time attribute of the current state. The transition probability from state $A_i$ to state $A_j$ at time $t$ is recorded as $P_{ij,t}$, then the transition probability matrix at time $t$ is

$$P_t = \begin{pmatrix}
    P_{11,t} & \cdots & P_{1n,t} \\
    \vdots & \ddots & \vdots \\
    P_{n1,t} & \cdots & P_{nn,t}
\end{pmatrix}$$

(4)

At time $t$, when the vehicle is in state $A_i$, it may turn to any state $A_j$ ($j \in \{1, n\}$) at the next time. Time $t$ can be any time of day, so the above transition matrix should satisfy

$$
\begin{aligned}
0 \leq P_{ij,t} & \leq 1, i, j = 1, 2, 3...n \\
\sum_{j=1}^{n} P_{ij,t} &= 1 \\
0 & \leq t \leq 24
\end{aligned}
$$

(5)

For home, work, and other locations in the data set, $n$ is 3, which corresponds to states $A_1$, $A_2$ and $A_3$ in turn. The vehicle at time $t$ is transferred from one location to another location, the probability matrix is

$$
\begin{pmatrix}
    t & H & W & O \\
H & \begin{pmatrix} P_{11,t} & P_{12,t} & P_{13,t} \end{pmatrix} \\
W & \begin{pmatrix} P_{21,t} & P_{22,t} & P_{23,t} \end{pmatrix} \\
O & \begin{pmatrix} P_{31,t} & P_{32,t} & P_{33,t} \end{pmatrix}
\end{pmatrix}
$$

(6)
In the formula (6), \( P_{ij,t} \) is determined by the travel frequency in the data of local travel survey.

4. Calculation of Electric Vehicle Charging Load

4.1. Fuzzy calculation of power consumption

The charging load of EVs is related to the power consumed per mile, and some literatures assume that it to be a fixed value, which will cause some errors in the prediction. According to the processed data, each trip has the characteristics of its mileage and driving time. Considering the charging behavior of EVs based on mileage and time in the market today, the following assumptions are made on power consumption. (1) The power consumption of a hundred kilometers is affected by the mileage and travel time of each trip. And the maximum input value of the system is a value whose cumulative probability of the corresponding statistical distribution is 0.995. (2) Because the influencing factors have the normal distribution characteristics, the membership function shape is set to Gauss. (3) Considering speed limit and congestion, the abnormal weight is 0.3 when formulating rules. (4) The output is the corrected specific gravity \( \lambda(\lambda \in (0,2)) \) for power consumption of one hundred kilometers.

The fuzzy calculation surface is shown in Figure 2, where the output PC is corrected specific gravity \( \lambda \), and the inputs S and T are the driving mileage and driving time, respectively. The power consumption of the 100-mile trip can be obtained through the results of fuzzy calculations (i.e. \( W^* = \lambda W \), where \( W \) is the average power consumption of vehicles in the standard state for 100 kilometers, and \( W^* \) is the average power consumption of vehicles in this section for 100 kilometers).

Fig.2 Fuzzy view results of Power consumption per hundred kilometers

4.2. Vehicle Charge Calculation

People's charging activity depends on the state of EVs and the next trip. It should not use a fixed charging mode or charging frequency. Therefore, the charging assumption is: (1) Two charging SOC thresholds: PT1 and PT2. PT1 is the safety margin, which is set to 0.3 according to the next trip and people's anxiety threshold, and fast charging is used for charging. PT2 is the threshold for slow charging when the vehicle is parked for a long time, set to 0.6. (2) Two constant power charging power levels: fast charging power \( P_f = 30 \text{kW/h} \) and slow charging power \( P_s = 7 \text{kW/h} \).

\[
\begin{aligned}
\text{SOC}_{\text{tx}} &= \text{SOC}_i - \text{SOC}_{\text{tn}} \\
\text{SOC}_{\text{tn}} &< \text{PT1} \\
P &= (\text{PT1} + \text{SOC}_{\text{tn}} - \text{SOC}_i) \times C \\
\text{t}_s &= \frac{P}{P_f}
\end{aligned}
\]

Formula (7) is used to judge the use of the fast charging mode and the calculation of the charge capacity. \( \text{SOC}_{\text{tx}} \) is the SOC of EV after completing the next trip, \( \text{SOC}_i \) is the SOC of EV after the last trip, and \( \text{SOC}_{\text{tn}} \) is the amount of SOC consumed by the vehicle on the next trip. \( P \) is the amount of power required to be charged. \( C \) is the battery capacity of EVs. \( P_f \) is the power of fast charging mode and \( t_s \) is the dwell time required for charging, so that the charging process of the location of EVs and its charging load in time are recorded.
\begin{equation}
\begin{aligned}
\text{SOC}_i < \text{PT2} \\
T_i \geq TD
\end{aligned}
\end{equation}

When the above formula (8) is satisfied, it is a chargeable charging stage, \( T_s \) is the dwell time between two trips, and \( TD \) is the time threshold for judging the charge. The EVs are charged with slow charging power \( P_t \). This process and its charging load in time are recorded.

4.3. Charge load model

The Monte Carlo method comes down to three main steps: construct or describe the probability process, implement sampling from a known probability distribution, and establish various estimators. Through discretizing a vehicle's one-day driving into a Markov stochastic process, the vehicle's destination transfer matrix can be obtained by statistics, and the vehicle's travel Chain during the journey can be achieved. The charging load is modeled based on the charging assumptions.

![Flow-chart for load forecast of EVCS](image)

The simulation assumes that all \( n \) cars start from home, and the initial SOC_0 is uniformly distributed. The start time \( T_0 \), end time \( T_e \), travel time \( t_i \), dwell time \( T_d \) and travel distance \( S_i \) are independent of each other (This is, \( i \) represents the number of vehicles \( i \), \( j \) represents the \( j \)-th trip of journey). And the travel process satisfies the Markov stochastic process assumption. According to the driving direction based on transition matrix, travel chain was obtained and its power consumption is recorded by fuzzy calculation. The load distribution is cumulatively superimposed by time and place. When all the \( n \) number of cars have been drawn, return and complete the N Monte Carlo repeat extraction. The charging load modeling process is shown in Figure 3.
5. Case study results

According to the 923573 trips of the trippub data set and 678459 trips of the tour17 data set in 2017 NHTS, the Trippub dataset tends to the characteristics and purpose of the traveler, and the tour17 dataset tends to the time and distance attributes of journey. Because two data sets are generated from the same survey, only the information features they present have different tendencies, so they can be used in conjunction with analysis and have more accurate behavioral characteristics.

The number of vehicles in the study is \( n = 1000 \). The vehicle battery capacity is \( C = 25.6 \text{kW.h} \). The average power consumption per 100 km traveled in the standard state is \( W = 20 \text{kW/100km} \). The two charging SOC thresholds are \( PT1 = 0.3 \) and \( PT2 = 0.6 \). The initial SOC \( 0 \) follows a uniform distribution \( U(0.9,1) \), and the boundary value of the end-of-travel rule is \( a = 0.5 \text{h} \). The three locations H/O/W represent residence\-other locations\-working area.

5.1. Classification of household income

In order to simplify the eleven levels of household income in the statistical data collection, they are divided into three groups: Group 1(G1) of households earn less than $25,000, group 2(G2) of households earn between $25,000 and $100,000 and group 3(G3) of households earns more than $100,000. The start time, end time, travel time, travel distance, and dwell time of the journey are shown in Figure 4. The charging load results under the family income classification conditions are shown in Figure 5.

It can be seen from 10 am to 20:00 pm in residential areas that the higher the household income of group is, the greater the charging load of group is. Peak charging loads of Groups 2 and 3 are 60 kW and 100 kW higher than those of Group 1, respectively. It can be seen from 20:00 pm to 10 am the next day in residential areas that the lower the household income of group is, the greater the charging load of group is. Trough charging loads of Groups 2 and 3 are 50 kW and 90 kW lower than those of Group 1, respectively. The charging load trends in other areas and work areas are similar to those in residential areas, with two transition points of 10am and 20 pm. From 10 o'clock to 20 o'clock, the higher the household income of group is, the greater the charging load of group is. From 20:00 pm to 10 am the next day, the lower the household income of group is, the greater the charging load of group
is. However, the overall charging load in other areas showed a "bell shape". The charging load in the work area showed two peaks, which occurred at 6 o'clock and 14 o'clock, respectively.

5.2. Workday/Weekend Classification

According to the standard classification of Monday to Friday as workdays and Saturday to Sunday as weekends, the start time, end time, travel time, travel distance, and dwell time of the journey are shown in Figure 6. The charging load results under the date type classification conditions are shown in Figure 7.

The charging load on weekends and workdays intersects around 18:00 in the residential areas. The charging load on workdays from 10:00 to 18:00 is greater than that on weekends. The peak area on weekends lasts longer and the charging load on weekends after 18:00 is greater than that on workdays in the residential areas. In other areas, the peak time of the workdays is much earlier than that on weekends, the duration is long and the charging load is large. When the load decreases on workdays, the heavy charging load on the weekends remains for a period of time. In the working area, the shift point is at 10 a.m. and 20 pm. From 10 am to 20 pm, the charging load on workdays is higher than that on the weekends, and from 20 pm to 10 am the next day, the load demand on the weekends is higher than the workdays. In general, the charging load on the workdays is relatively high and the charging load on the weekends is delayed, which is consistent with the weekend's entertainment behavior.

5.3. Urban/Rural Classification

The classification is whether the home address is urban or rural. The classification is mainly based on the URBRUR flag in the original data set. The start time, end time, travel time, travel distance, and dwell time of the journey are shown in Figure 8. The charging load results under the address classification conditions are shown in Figure 9.
In terms of the charging load in the residential area, the charging load required by the village is generally higher than that of the town. The reason is that the driving distance is generally larger than that of the town. The two trends are similar, but the peak area of the rural group is earlier and lasts longer. In other areas and work areas, the change trend of rural groups and urban groups is similar, but between 10 am and 20 pm, the urban group trends in other areas are relatively smooth and the rural group load changes are relatively rugged. In the work areas the charging load of the rural group varies relatively randomly. In general, the load of rural groups is relatively high, and its peak area is relatively early and lasting relatively long. This mainly reflects the characteristics of distance properties around the city or village, and also shows that the charging load of a city is not only determined by itself, but also bear the difference and pressure brought by the surrounding area.

5.4. Overall comparison
Comparing the charging load amounts combined by equal weights under each classification condition with the load amount obtained when not classified, as shown in Figure 10.

It can be seen from Figure 10 that all H/O/W positions have the same trend under any conditions. However, these curves obviously do not completely coincide. This may be because the corresponding weights under various conditions may be uneven or there may be a coupling relationship.
6. Conclusion
This article considers the diversity and differences in electric vehicle travel habits. Based on the analysis of multiple data sets in the 2017 NHTS, the random behavior of EVs throughout the day is fully described using Markov chains. Considering the influence of driving time and driving distance on power consumption, the real-time charging demand is determined according to the remaining SOC of the vehicle battery. And the spatiotemporal distribution of charging demand for private electric vehicles under different conditions is obtained.

According to the classification analysis of household income, different income conditions correspond to different types of work activities, and this factor has different effects on the charging load of different groups. According to the classification analysis of weekdays / weekends, different types of dates correspond to different activities and activity times, and these have different effects on charging load, which is consistent with weekend rest and entertainment behavior. According to urban and rural classification analysis, this mainly reflects the distance characteristics between the city and the surrounding countryside. Because the geographical location of different residences has a different impact on the distance of daily activities and traffic attributes, these have some impact on charging load. This shows that the charging load of EVCS in a city is not only determined by itself, but also bears the load difference and pressure brought by the surrounding area. The spatiotemporal distribution model of charging demand for EVCS can obtain the charging load demand of EVCS in the city by analysing the structure of the urban population and surrounding villages. The model can be applied to the construction of EVCS, such as location selection, capacity setting or daily planning.

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