Analysis on Charging Demand of Shared Vehicle Based on Spatiotemporal Characteristic Variable Data Mining

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Abstract. The wide application of shared vehicles in the future will bring about tremendous importance to the power grid and planning of charging facilities. At present, there are flaws in the prediction methods for shared vehicles charging demand. Based on data mining of national household travel survey (NHTS), this paper constructs a two-dimensional dynamic traffic behaviour model supported by spatiotemporal feature variables. Then, in order to explore the characteristics of continuous charging and centralized charging of shared vehicles, two charging scenarios are set to construct a charging behaviour model. Finally, the Monte Carlo method is used to simulate the shared vehicle traffic charging behaviour, and get the result of the shared vehicle charging demand at different times and regions. The impact of the load on the grid is analyzed in the same time. The results show that the interactive spatial-temporal characteristic variables can reasonably describe the characteristics of time-space two-dimensional uncertain changes in shared vehicles and the method can make a scientific prediction of the shared vehicle charging demand.

1. Introduction
With the intensification of environmental problems and the improvement of technical level, electric vehicles have become more and more popular in daily life, becoming a green and convenient means of transportation. In order to alleviate urban traffic congestion, sharing vehicles as an emerging means of transportation will become the main force of public transportation in the future. The shared car mainly uses electricity as an energy source, and the large-scale popularization in the future will make the smart grid and smart transportation closely linked and interact with each other[1]. Considering the social behaviour of car traffic and the physical behaviour of sharing car charging, charging load forecasting for shared cars is a key hub for connecting smart grids and smart transportation.

In recent years, many scholars have conducted a lot of research on electric vehicle load forecasting [2-10]. In [11-12] based on the initial charging time and vehicle mileage model, combined with the SOC and other influencing factors model, analyzed the charging load of different models. In [13] established a mathematical probability model of two independent random variables, namely initial charging time and daily driving mileage, and then derived the charging probability at each moment to calculate the charging load. In [14-15], the fuzzy inference method is used to simulate the user billing process and calculate the charging probability and charging load of electric vehicles in different regions. In [16], the parking characteristic model of the electric vehicle in different regions is generated according to the parking generation rate, and the spatially distributed charging load is obtained. The above literature only constructs multiple time or space one-dimensional simple variables of electric vehicles, and builds a load forecasting model based on this. This type of load forecasting
method only statically predicted loads in time or spatial dimensions and lacked the ability to fully describe the temporal and spatial dynamics of an electric vehicle. In [17-18] considered the time and space changes of electric vehicles, established a line model, and used this Monte Carlo simulation method to calculate the charging load of electric vehicles. In this type of method, the travel chain has a relatively fixed time space setting, and the private car with a relatively single traffic orientation has a good prediction effect, but there are considerable defects in the shared car with multiple and disordered traffic characteristics. Unlike private electric vehicles, shared cars as public transport, there is no relatively fixed driving route and time, driving characteristics and charging characteristics are more random and scattered. Traffic travel can occur at any time and place, and the time it takes will affect the choice of the user's destination, and the space will also influence the choice of user time. At present, the research on the prediction method of shared vehicle charging load is not deep enough. The simple space-time variation model does not conform to its traffic behaviour characteristics. It is necessary to construct a two-dimensional dynamic traffic behaviour model of time and space interaction, and then build a charging behaviour model, and based on this, the charging load is predicted. The traffic behaviour of shared cars is related to people's travel behaviours. It has sociological characteristics. To describe them scientifically, big data analysis methods can be adopted to convert sociological information into mathematical information. This paper uses the data from the US National Household Travel Survey (NHTS) [19] published by the US Department of Transportation in 2017 as a database for studying the behaviour of shared car traffic. Firstly, the key mathematical model of the shared vehicle driving characteristics is obtained through data analysis. Secondly, the relationship between each mathematical index model is constructed, a complete automobile traffic behaviour model is established, and then the charging behaviour model of the vehicle is established according to the electrical theory. Monte Carlo simulation method, the traffic behaviour and charging behaviour of each car is extracted to simulate the charging process. In order to explore the characteristics of the two charging modes of shared car continuous charging and centralized charging, this paper sets two different charging situations, and discusses two periods of large traffic behaviour differences on working days and rest days, four categories. The shared vehicle charging load situation in different regions, and the impact of the shared vehicle's charging load on the typical load of the grid in summer and winter.

2. Traffic behaviour characteristic variable analysis

The traffic behaviour of a car is characterized by a change in spatial position on a certain sequential time scale. To fully describe the traffic behaviour, two characteristic variables of time and space are needed. The time and space of shared car changes randomly and disorderly. There is no relatively fixed route and time point. Data analysis should be carried out on a large amount of traffic data. Traffic behavioural variables of continuous time and space feature variables should be used to model traffic behaviour of shared cars. The time feature quantity is a variable that describes the change rule of the user's travel time, including the starting travel time, the travel time, the parking time, and the like. Through the above several time feature quantities, the user's day time chain can be obtained. Assuming the initial travel time of the first travel, the travel time of the i-th travel, and the parking time of the i-th travel, the time and the i+1th travel of the i-th travel to the destination can be obtained. The starting travel time of the i-th travel can be obtained.

\[ t_{ui} = t_{si} + t_{ti} \]  

(2.1)

\[ t_{ui+1} = t_{ui} + t_{ti} + t_{di} \]  

(2.2)

The spatial feature quantity is a variable that describes the spatial variation of the user's travel, including the destination type and mileage. According to the actual functional area of the city, it can be divided into several areas, denoted by Di. The transition between spatial feature quantities is determined by the probability of spatial transition at that moment. The mileage of the i-th trip is
indicated by $d_l$. Through the changes of the above two spatial feature quantities, the traffic behaviour characteristics of the user can be obtained.

When the user travels in a traffic, since the user behaviour characteristics change with different time and different locations, the time feature quantity and the spatial feature quantity are interactively affected. For example, in the different regions, the first starting travel time and the parking time will be different, and the user's destination selection will be different at different times. Therefore, the time chain and the space chain are not independent of each other, and the interaction characteristics must be fully considered and comprehensively studied.

3. Data analysis of temporal and spatial characteristic variables

The traffic behaviour of shared car users is very random, the time variables and spatial variables are scattered. To abstract the mathematical model from it, we need to analyze the massive random data to get a relatively accurate logical model. Now we use the big data analysis method to convert sociological information to mathematical information to study the user's traffic behaviour. At present, there is a lack of statistics on electric vehicle traffic information, so the use of fuel vehicle travel data instead of electric vehicle data is used for research. The data used in this paper is derived from the NHTS[19].

3.1. Travel destination

The car has a large number of travel destinations and analyzes the data in the NHTS2017.

|                        | Living Area | Working Area | Commercial Area | Recreation Area | Other |
|------------------------|-------------|--------------|-----------------|-----------------|-------|
| Working day            | 37.9        | 15.1         | 24.7            | 14.9            | 7.4   |
| Weekend day            | 40.1        | 5.7          | 30.8            | 18.1            | 5.3   |

As can be seen from the above table 1, the destination of shared car travel can be classified into living area, working area, commercial area, recreation area ($D_1$-$D_4$), and the destinations of working days and weekend days are more obvious. In particular, since the shared car has the property of public transportation, its first travel origin is different from that of the private car, and it can be any area of $D_1$-$D_4$.

3.2. Spatial transition probability matrix

When the user starts the journey at a certain starting point at a certain time, the destination that arrives may be any area of $D_1$-$D_4$, and the transition probabilities of different destinations are different. The space transfer in this time period can be described by a matrix $P_k$ of $k*4*4$ discretized according to a certain time period $t_k$. The $i$-th row of the matrix $P_k$ represents the departure point $D_i$, and the $j$-th column represents the arrival place $D_j$. $k$ is the number of time intervals after discretization, and $P_k$ is the space transition probability matrix in the $k$ period. In this paper, one day is divided into two time periods according to 2 hours, and $k=12$ time periods are obtained. According to the data analysis result, the space transfer matrix of 12 working days and one day of rest day can be obtained. For example, $P_{4\text{day}}$ and $P_{4\text{end}}$ are spatial probability transfer matrices for 6-8o'clock working days and weekend days.

$$P_{4\text{day}} = \begin{bmatrix}
0.056 & 0.734 & 0.132 & 0.078 \\
0.225 & 0.572 & 0.139 & 0.064 \\
0.229 & 0.532 & 0.189 & 0.05 \\
0.491 & 0.262 & 0.11 & 0.137
\end{bmatrix}$$

$$P_{4\text{end}} = \begin{bmatrix}
0.125 & 0.242 & 0.286 & 0.347 \\
0.492 & 0.291 & 0.148 & 0.069 \\
0.436 & 0.13 & 0.295 & 0.139 \\
0.463 & 0.06 & 0.184 & 0.293
\end{bmatrix}$$

3.3. First travel time
The first travel location of the shared car can be arbitrarily selected in $D_1-D_4$. From the data analysis results, the probability distribution of working days and rest days can be obtained. According to the data fitting result, the first travel time conforms to the multi-dimensional normal distribution.

$$f(t_{a1}) = \sum_{n=1}^{n} a_n * N(\mu_n, \sigma_n^2)$$  \hspace{1cm} (3.1)

$\sum_{n=1}^{n} a_n = 1$, $N(\mu_n, \sigma_n^2)$ is standard normal distribution function.

![Figure 1. Distribution for the first travel time on working day and weekend day](image)

The data of the first travel time is analyzed through working days and rest days, and the probability density is shown in Figure 1. Data fitting was performed using a multidimensional Gaussian distribution. The error of each fitting order is shown in Table 2.

**Table 2. Gaussian fitting error**

| Order | SSE   | R-square | RMSE  |
|-------|-------|----------|-------|
| Working day |       |          |       |
| 1     | 0.0099| 0.9235   | 0.0101|
| 2     | 0.0028| 0.9779   | 0.0055|
| 3     | 0.0028| 0.9781   | 0.0056|
|       | 0.0118| 0.9119   | 0.0111|
| Weekend day |      |          |       |
| 2     | 0.0023| 0.9801   | 0.0078|
| 3     | 0.0013| 0.9905   | 0.0037|

SSE, R-square, and RMSE are evaluation indicators of the Gaussian fitting effect, which represent the sum of squared residuals, correlation and root mean square error, respectively. The smaller the SSE and RMSE, the larger the R-square, the more accurate the fit. The results in Table 2 show that the 2nd and 3rd order Gaussian fitting effects of the first travel time on the working day are better than the 1st order, and the 2nd and 3rd order Gaussian fitting effects are equivalent. The 2nd order Gaussian distribution can be selected for the first travel time of the simplified analysis workday. The 3rd order Gaussian fitting effect on the rest day is better than the 1st and 2nd order, so the 3rd order Gaussian distribution is selected for the first travel time on the rest day. The result is showed in table 3 below.
Table 3. First travel time probability density parameter

|                | \(a_1/\mu_1(h)/\sigma_1(h)\) | \(a_2/\mu_2(h)/\sigma_2(h)\) | \(a_3/\mu_3(h)/\sigma_3(h)\) |
|----------------|--------------------------------|--------------------------------|--------------------------------|
| Working day    | 0.34/7.46/0.77                 | 0.66/9.20/2.75                 |                                |
| Weekend day    | 0.05/9.9/0.67                  | 0.51/9.17/1.70                 | 0.44/12.59/3.78                |

3.4. Travel time

The duration of the shared car is related to the type of starting point. The data is fitted according to the starting and ending points, and the driving duration is in accordance with the lognormal distribution.

\[
f(t) = \frac{1}{t \sqrt{2\pi} \sigma} \exp \left\{ -\frac{\ln(t) - \mu_0^2}{2\sigma^2} \right\}
\]

(3.2)

\(t\) is the driving time, \(\mu, \sigma\) is the expected and standard deviation of the corresponding starting point. The value of \(\mu, \sigma\) working day and rest day is shown in the matrix below, the \(i\)-th row represents the departure point \(D_i\), and the \(j\)-th column represents the arrival place \(D_j\).

\[
\begin{align*}
\mathbf{m}_{\text{day}} &= \begin{bmatrix}
2.8 & 2.89 & 2.51 & 2.61 \\
2.97 & 2.83 & 2.48 & 2.67 \\
2.58 & 2.34 & 2.2 & 2.5 \\
2.59 & 2.42 & 2.4 & 2.5 \\
2.81 & 2.83 & 2.52 & 2.69 \\
2.91 & 2.87 & 2.49 & 2.69 \\
2.6 & 2.42 & 2.23 & 2.59 \\
2.66 & 2.74 & 2.51 & 2.7
\end{bmatrix}
\end{align*}
\]

\[
\begin{align*}
\mathbf{s}_{\text{day}} &= \begin{bmatrix}
1.13 & 0.81 & 0.8 & 0.93 \\
0.84 & 0.99 & 0.86 & 0.95 \\
0.8 & 0.85 & 0.95 & 0.99 \\
0.92 & 0.94 & 0.88 & 1 \\
1.09 & 0.85 & 0.8 & 0.91 \\
0.86 & 1.05 & 0.85 & 0.94 \\
0.82 & 0.94 & 0.98 & 1 \\
0.95 & 0.98 & 0.88 & 1.1
\end{bmatrix}
\end{align*}
\]

\[
\begin{align*}
\mathbf{m}_{\text{end}} &= \begin{bmatrix}
2.8 & 2.89 & 2.51 & 2.61 \\
2.97 & 2.83 & 2.48 & 2.67 \\
2.58 & 2.34 & 2.2 & 2.5 \\
2.59 & 2.42 & 2.4 & 2.5 \\
2.81 & 2.83 & 2.52 & 2.69 \\
2.91 & 2.87 & 2.49 & 2.69 \\
2.6 & 2.42 & 2.23 & 2.59 \\
2.66 & 2.74 & 2.51 & 2.7
\end{bmatrix}
\end{align*}
\]

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1.13 & 0.81 & 0.8 & 0.93 \\
0.84 & 0.99 & 0.86 & 0.95 \\
0.8 & 0.85 & 0.95 & 0.99 \\
0.92 & 0.94 & 0.88 & 1 \\
1.09 & 0.85 & 0.8 & 0.91 \\
0.86 & 1.05 & 0.85 & 0.94 \\
0.82 & 0.94 & 0.98 & 1 \\
0.95 & 0.98 & 0.88 & 1.1
\end{bmatrix}
\end{align*}
\]

Figure 2. Distribution for the travel time

Figure 2 is a probability distribution curve of the driving time \(D_1-D_2\) on the working day \(D_1-D_3\).

3.5. Mileage
When a car is driving in a city, it can basically be regarded as running at a constant speed. Therefore, the driving mileage $d$ can be approximated as:

$$d = v(t_r) \times t_r \tag{3.3}$$

$v(t_r)$ is the average speed, and the constant speed driving process is regarded as a constant. It is known from the central limit theorem and the law of large numbers that $d$ satisfies the normal distribution, and its expectation and standard deviation $\mu_d(t_r), \sigma_d(t_r)$ should be The length of the segment is related to $t_r$. As can be seen from the foregoing, $t_r$ is mainly concentrated within 200 min. Now $t_r$ is divided into a window for 20 minutes for data analysis, and the values of $\mu_d$ and $\sigma_d$ in each time window are obtained. The result is showed in table 4 below.

### Table 4. Mileage logarithm distribution parameters

| $[t_i, t_{i+1})$/min | $\mu_d$/km | $\sigma_d$/km |
|----------------------|-------------|-------------|
| (0,20)               | 2.90        | 3.71        |
| (20,40)              | 11.60       | 8.22        |
| (40,60)              | 21.99       | 18.33       |
| (60,80)              | 40.07       | 57.58       |
| (80,100)             | 58.11       | 86.1        |
| (100,120)            | 85.133      | 139.878     |
| (120,140)            | 109.92      | 152.61      |
| (140,160)            | 146.134     | 239.085     |
| (160,180)            | 176.081     | 222.59      |
| (180,200)            | 217.066     | 325.363     |

3.6. Parking time

Different areas represent different behaviours of users, and the length of parking in each of the four types of cars varies from one trip to another. According to the classification of parking places, the data can be fitted to obtain a log-normal distribution that satisfies the parking time. In particular, the length of parking for the last trip of the car is determined by the end of the trip and the first travel time of the next day. The result is showed in table 5 below.

### Table 5. Parking time logarithm distribution parameters

|               | $D1$ | $D2$ | $D3$ | $D4$ |
|---------------|------|------|------|------|
| Working day   | $\mu_d$/min | 4.34 | 6.2  | 3.12 | 3.7  |
|               | $\sigma_d$/min | 1.18 | 1.15 | 1    | 1.39 |
| Weekend day   | $\mu_d$/min | 4.49 | 5.17 | 3.29 | 4.1  |
|               | $\sigma_d$/min | 1.16 | 1.36 | 1.01 | 1.37 |

4. Charging behaviour analysis

4.1. Charging situation setting

The current operating mode of the shared car is generally taken by the owner of the car, it is parked at the parking place for charging. This method can ensure that the car has sufficient power and does not affect the next stage of driving, but the charging frequency is frequent, and the charging device and the battery are depleted. In addition, another mode can be adopted: if the battery is lower than the lower limit after use, we can set a lower limit value for the shared car, and charge. Otherwise it will not be charged. This article will set these two charging scenarios for load forecasting.
Case 1 (continuous charging): The car is charged after each end of the journey, and the charging duration must not exceed the parking time.

Case 2 (centralized charging): After each end of the car, the remaining amount of electricity is judged according to formula (3.4) to determine whether to charge. This article does not consider the situation that the remaining battery power is not enough to support the next trip without charging. In this case, the car is considered to be temporarily recharged.

\[
(E \times SOC_i - d_i \times k) \leq 0.4E
\]  
(3.4)

\(E\) is the car battery capacity, kW·h; \(d_i\) is the mileage of the \(i\)-th trip, km; \(k\) is the power consumption per kilometer of the car, kW·h/km.

In both cases, when the \(i\)-th trip reaches the destination \(D_{(i+1)}\) charging, the formula (3.5) is satisfied to select slow charging, otherwise the fast charging is selected.

\[
(E \times SOC_i - d_i \times k + P_s \times t_c) \geq 0.2E
\]  
(3.5)

\(P_s\) is the slow charging power, kW; \(t_c\) is the charging duration, h. After charging is completed, the SOC of the \((i+1)\)-th pass is:

\[
SOC_{i+1} = \frac{E \times SOC_i - d_i \times k + P \times t_c}{E \times h}
\]  
(3.6)

\(\eta\) is the charging efficiency and is taken as 0.9. \(P\) is slow charging or fast charging power, kW.

4.2. Charging process simulation

Take the parameter setting of the “Beiqi ec200” electric vehicle and the charging power of Shenzhen charging facility, which are the main models invested by several major shared car operators in Shenzhen.

1) Electric vehicle battery capacity \(E=20\)kW·h
2) Electricity consumption per kilometer of electric vehicles \(k=0.15\)kW·h/km
3) Fast charging power \(P_f=60\)kW
4) Slow charging power \(P_s=7\)kW
5) If the end of the car journey exceeds 24 am, the trip is the last trip

The Monte Carlo method is a thought method that uses massive random data to simulate precise logic, a computational idea that uses mass to obtain quality. The figure 3 showed the Monte Carlo method is used to simulate the shared car traffic behaviour and charging behaviour, and the charging demand is calculated.
5. Load forecasting results and grid load analysis

In the future, shared cars will become more and more popular in major cities. This paper considers that there are sufficient charging facilities, sets the number of shared cars in Shenzhen to 300,000, and simulates traffic behaviour and charging behaviour. Then, the charging load in 2 charging situation of 4 areas on working day and weekend day is calculated.
Figure 4 shows the load curves for two charging situations on weekdays and weekend days. The load of situation 1 continued to increase from about 6 o'clock to about 21 o'clock, while the load of situation 2 was mainly concentrated at 2 o'clock in the morning, and then began to decline. Since the situation 1 charge during parking, the number of charging is consistent with the frequency of sharing the car, and the higher the travel frequency, the greater the load. The situation 2 charge when the electricity is low, so the number of charging is relatively small. And in the city, it is generally a short trip, the car generally concentrates charging when the battery is at the end of the morning, and the other time is less charged. The charging load of situation 1 is expressed as “small, numerous, and scattered”, and situation 2 is expressed as “large, less, and concentrated”. Therefore, the charging is concentrated in the early hours of the night, and the load in case 2 is much larger than that in case 1. In the daytime, the load is much smaller than the situation. The load change of continuous charging is relatively stable, the peak-to-valley difference is small, the concentrated charging load changes relatively sharply, and the peak-to-valley difference is large.

Figure 5. Situation 1: four types of regional load curves
It can be seen from the figure 5 and figure 6 that in the case of a weekend day, the living area load is greater than the working day, and the load starts to increase earlier than the working day, indicating that the weekend day is longer at home. In the second case, the load in the living area accounts for more than 90% of the total load, which means that people basically choose to go home and charge when they travel for the last time. In both cases, the load on the workday work area is much greater than the weekend day. The load curve changes in the commercial area and the leisure area are basically the same. In the first situation, the load of the two areas is concentrated from noon to night, reflecting the concentration of people's shopping and leisure behaviour during this period. Operators can consider planning more charging piles in the living area, and formulating flexible charging pricing methods in the commercial districts and leisure areas during the evening hours to encourage users to charge and increase revenue.
As shown in figure 7 and figure 8, a large amount of shared car charging will affect the power grid. Compared with the power grid in summer, the charging load has a greater impact on the power grid in winter. The maximum charging load will increase the grid in winter load by about 17% in the early morning, and the concentration of the grid load will increase the stability of the grid. In case 1, the charging load has less impact on the power grid, and the change law of the charging load has a strong correlation with the grid load law. It can be regarded as the charging load is evenly distributed to the grid load at each moment, so that it is evenly increased. In the second case, the charging load has a large impact on the power grid, and it is concentrated in the early morning hours. However, the large load concentrated in the early morning plays a role of filling the grid load, making the load fluctuation of the entire power grid less throughout the day.

6. Conclusion

(1) In this paper, through the data analysis method, the social information is transformed into mathematical information, and the traffic behaviour characteristic model of the spatial-temporal characteristic variables is constructed. This model is in line with the special driving characteristics of shared cars, and the method of predicting its load is scientific.

(2) There are significant differences in charging loads between the four different areas on weekdays and weekend days. According to this, the grid company can reasonably plan charging piles in various regions, formulate flexible electricity prices, and guide users to orderly charge. Shared car operators can develop charging and billing strategies, provide value-added services, and improve the quality of shared car operations.

(3) In the future, a large number of shared vehicles will have a certain impact on the grid after they are connected to the grid, including the winter grid load. The continuous charging mode has a relatively moderate impact on the grid, which ensures that the vehicle is fully charged, but the equipment with frequent charging and loss is not economically efficient. The centralized charging has a relatively strong impact on the grid, but the centralized charging in the early morning can produce a valley filling effect on the grid, which is beneficial to the grid. The grid operates to maximize charging efficiency and save costs, but users need to plan their trips to avoid low battery.

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