Slow/Fast Charging Pile Configuration in Multi-areas Based on Time-Space Transfer Characteristics of EV

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Abstract. This paper proposes a charging model to determine the charging load demand of EVs (Electric Vehicles) based on their time-space transfer characteristics in different typical travel days and analyzes the configuration requirements of different charging piles in multi-type urban areas. By dividing travel destinations into five areas types, this paper analyzes the probability characteristics of users' travel purpose, travel time, driving and parking time distribution, and constructs the time-space transfer travel chain of EVs in different typical days. Then, we establish a charging decision model with two charging modes to calculate charging demands and different charging pile requirements of EVs in different functional areas on different typical days by Monte Carlo simulation and SUMO (Simulation of Urban Mobility). The results may provide suggestions for the planning and configuration of charging piles in different functional areas.

Keywords: Time-space characteristics · Charging demand · Charging pile configuration · SUMO · Monte Carlo simulation

1 Introduction

An increasing number of (EVs) will be charged/discharged in EV charging stations in distribution systems [1]. However, the charging behavior of a large number of EVs disorderly connected to the grid will affect the operating state of the power grid. The rising and diversified load demand brings uncertainty and randomness and increases the risk of grid operation [2]. The load patterns of EVs connected to the distribution network significantly impact the power loss in the power system [3]. Thus, in order to charge orderly, EVs need the guidance of appropriate charging strategies. There is a variety of charging modes for charging facilities, due to the difference in charging power between fast and slow charging, under one node of the distribution network, different numbers of charging pile types will affect the maximum charging power connected to the grid and affect its stability and efficiency. Therefore, to guide the orderly charging of EV requires a reasonable configuration of charging facilities in different functional areas of the city.

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Current researches on charging facilities are mostly focused on macroscopic charging station capacity fixation or site selection optimization [4]. Reference [5] plan the location of charging stations according to the overall EV charging needs of the city. Reference [6] considers the impacts of traffic, proposes a novel graph-based approach for the analysis of EV networks with charging stations. Reference [7] establishes the model for the location and capacity of charging stations to minimize costs by dividing the types of areas according to charging requirements. Then, some researchers have narrowed the scope of the research and turned to analyze the number of charging piles. By analyzing the overall charging demand of EVs. Reference [8, 9] establish an charging pile construction model with the minimum cost and calculate the number of charging piles in different regions. Reference [10] considers not only currently connected EVs but also the EVs will be connected to the charging station to study the charging strategy for charging station. In the above researches, few are specifically designed for the different configuration requirements of fast/slow-charging piles in different areas. Meanwhile, most studies on charging facilities take less account of the randomness and flexibility of EV travel [11], which affects the accuracy of the planning and configuration of charging piles.

Based on the travel chain theory, this paper proposes a charging load demand and charging pile configuration analysis method. According to the travel data of car users in NHTS2017 [12], we use Monte Carlo simulation sampling for SUMO to simulate the temporal and spatial travel chain of EVs in different functional areas on different typical days. This paper considers two different charging modes and designs a charging option decision model based on the charging status of parked EVs in each parking area. Through sample analysis, the article generates charging demand curves and the configuration requirements of different charging pile modes in each area on different typical days. In the end, this paper makes suggestions for the planning of charging pile modes in different functional areas.

The remainder of this paper is organized as follows. In Sect. 2, the characteristics of the travel chain are explained in detail. The charging and charging pile demand simulation model is presented in Sect. 3. An example study on a real-urban area is carried out in Sect. 4. Finally, Sect. 5 concludes this paper.

2 Travel Chain Simulation Method

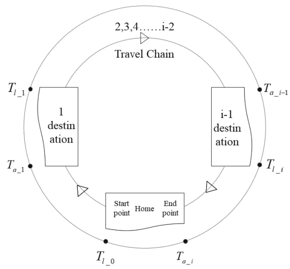

Fig. 1. Travel chain

Through the probability of each travel feature of EVs, this article uses the Monte Carlo method to extract the characteristic of each travel event and generates the travel chain using SUMO. Considering there is no difference between the travel law of EV users and the traditional fuel vehicle users except for the operation mode, we assume the travel of EVs has travel characteristics similar to those of traditional fuel vehicles.

In this paper, the time-space chain of vehicles is set to start and end at home, the travel events of EVs in a day are connected in series according to the travel time sequence and destination, as Fig. 1. Noted that Experience and NHTS2017 data show the travel patterns of vehicle users are affected by whether they are working. Therefore, we distinguish two independent typical days to characterize the travel patterns of users: workdays and weekends respectively.

This paper takes T_{l-0} and t_{p_i} in different areas as the input of the probability distribution. When some feature quantities are known, the remaining quantity can be calculated [13, 14]:

$$T_{a\_i} = T_{l\_i-1} + t_{d(i-1\_i)} \tag{1}$$

$$T_{l\_i} = T_{a\_i} + t_{p\_i} = T_{l\_i-1} + t_{d(i-1\_i)} + t_{p\_i} \tag{2}$$

The simulation process is as follows:

Step1: Determine the current typical day;
Step2: According to the probability distribution of the T_{l-0}, extract T_{l-0} and initialize the vehicle SOC;
Step3: The travel purpose is extracted according to $p_{i\leftarrow i-1}$ and $d_{(i-1,i)}$. Based on the current travel destination type and departure timeT_{l-i-1}, Determine the destination type from the space transition probability corresponding to the time. From the departure place and the extracted destination, determine the mileage of the two locations according to the probability distribution; allocate the regional destination of this type that is closest to this mileage;
Step4: Simulate travel, the travel time is obtained by SUMO;
Step5: Extract the park time according to the probability distribution of park time under the extracted type of area;
Step6: Update the current vehicle arrival time, departure time, and SOC status;
Step7: Return to step 3 and end the loop.

3 Charging Pile Demand Model

This article only studies the charging demand of EVs in different areas during a day trip [5], does not consider the EVs charge at Home after the end of all travel events in a day. This article uses the destination charging method.

3.1 Charging Demand Simulation

It is assumed that the SOC condition of the EV for the first trip in a day is 100% SOC. The Starting SOC Status of the Vehicle Starting the ith Trip (Except for the first trip).

$$SOC_{l\_i-1} = SOC_{a\_i-1} + \frac{Pt_{p\_i-1}}{W_e} \tag{3}$$

$$P = \begin{cases} P_{slow}, \text{slow charge} \\ P_{fast}, \text{fast charge} \end{cases} \tag{4}$$

SOC_{a_i-1} represents the SOC when the vehicle arrives at the destination in $i-1^{th}$ trip; $t_{charge(i-1)}$ indicates the charging time at destination $i-1$, if do not charging at destination $i-1$, $t_{charge(i-1)} = 0$;

The SOC when vehicle arrives at destination in i^{th} trip is:

$$SOC_{a\_i} = SOC_{l\_i-1} - t_{d(i-1\_i)} \times \text{power consumption/km} \tag{5}$$

The remaining SOC Status of The Vehicle after Arriving at the Destination in ith Trip. After the vehicle reaches the destination in i^{th} trip, determine the relationship between SOCremaining and SOCmin:

If $SOC_{a\_i} > SOC_{min}$, then the user does not choose to charge at destination i:

$$SOC_{l\_i} = SOC_{a\_i} \tag{6}$$

If $SOC_{a\_i} \le SOC_{min}$, then the user chooses to charge at destination i.

Then consider the relationship between the length of time the vehicle is parked in the destination and the length of fast and slow charging: The accuracy of charging time selection in destination i is 1 min, $t_{charge(i)} = 0, 1, 2 \ldots\ldots 1440$. Based on the high-cost performance of slow charging:

Firstly, consider whether the EV can be fully charged through the slow charging pile during the parking time. The calculation formula of the slow charging time is:

$$\frac{SOC_{\max} - SOC_{a\_i}}{\frac{P_{slow}}{W_e}} = t_{\text{charge-}need} \tag{7}$$

If $t_{charge\text{-}need} \le t_{p\_i}$, then the vehicle can be fully charged to SOCmax, so the user decides to use slow charging pile:

$$SOC_{l\_i} = SOC_{\max} \tag{8}$$

$$t_{\text{charge(i)}} = t_{\text{charge-}need} \tag{9}$$

If $t_{charge\text{-}need} > t_{p\_i}$, the vehicle cannot be fully charged to SOC_{max}, so the user decides to use a fast charging pile:

$$\frac{SOC_{\max} - SOC_{a\_i}}{\frac{P_{fast}}{W_e}} = t'_{ch\arg e-need} \tag{10}$$

$$\begin{cases} \begin{cases} SOC_{l\_i} = SOC_{\max} \\ t_{ch\arg e(i)} = t'_{ch\arg e-need} \end{cases}, t'_{ch\arg e-need} \le t_{p\_i} \\ \begin{cases} SOC_{l\_i} = SOC_{a\_i} + \frac{P_{fast} t_{p\_i}}{W_e} \\ t_{ch\arg e(i)} = t_{p\_i} \end{cases}, otherwise \end{cases} \tag{11}$$

3.2 Charging Pile Demand Simulation

Using the travel chain to simulate the actual charging decisions of EVs through Monte Carlo and SUMO, after obtaining the curve of the charging demand in each type of area over time, the total number of charging piles required in each area is further calculated and counted, as well as the ratio of fast and slow charging piles.

4 Example Analysis of Charging Pile Demand Figures

4.1 Travel Chain Characteristics

This section uses the travel chain model according to Sect. 2, and obtain the probability distribution of the characteristic of travel chain based on NHTS2017. Apply the charging pile demand decision model in Sect. 3, extract the charging demand curve and the configuration requirements of charging piles using Monte Carlo and SUMO. The article uses Nanjing City (subdivided into 33 regions) as sand table (Fig. 2).

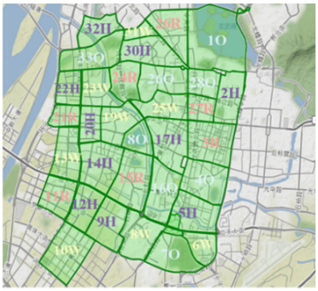

Fig. 2. Simulation map.

Based on the survey of traditional residents' travel, this article divides residents' daily trips into four categories according to the purpose of travel: Home (H), Work (W), Relaxation (R), and Others (R). The vehicle will travel for different purposes in different functional areas, and the charging behavior may occur in any parking area. In addition, the average daily travel chain length of private cars is 3.37 according to NHTS2017. Therefore, this article considers the travel chain structure with a maximum of 4 travel events. The parameters are set as follows: battery capacity 30 kW $\times$ h, slow charging power 3 kW, fast-charging power 30 kW, 1000 vehicles.

Time Characteristic Analysis

Starting Time of the First Drive. The departure place of the first trip in a day is Home. According to [15], the distribution is considered to obey the gamma distribution, and the probability density is:

$$f(T_{l\_0}) = \frac{58.908^{9.881}}{\Gamma(9.881)} T_{l\_0}^{9.881-1} e^{-58.908 T_{l\_0}} \tag{12}$$

There is a certain difference between the first travel time on workdays and weekends. The former are mostly concentrated at 7:00–8:00, while most people in the latter choose to travel between 9:00–10:00.

Park Time. This article does not consider traffic congestion and short-term parking. Users can only charge after arriving at the travel destination, and their parking time affects the length of charging time [4]. The article discretizes the park time data into 96-time sections in one day to reduce the complexity of the charging model, each time section represents 15 min, 1440 min in total. Figure 3, which shows the distribution of park time in H on different typical days.

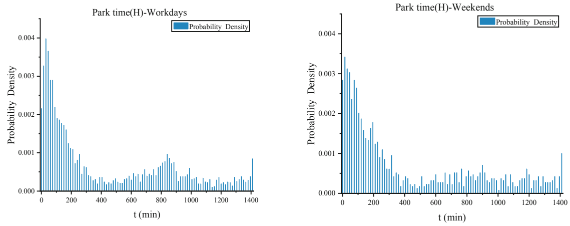

Fig. 3. Park time.

Driving Time. This article does not extract the probability of driving time, but uses SUMO to select real city routes, generate the travel time of the travel event.

Spatial Feature Quantity

Probability Distribution of Mileage. The paper discretizes the mileage with accuracy on a scale of 0.1 km. The probability distribution of mileage can get six types of distribution according to the difference of departure and destination. Figure 4 shows the distribution of mileage from H to R and W.

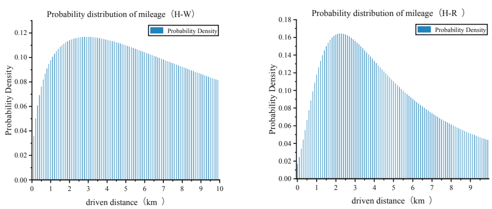

Fig. 4. Mileage probability distribution.

Spatial Transition Probability. According to Markov theory, the Markov Chain can be recorded as the state transition probability and be expressed as conditional probability:

$$P(E_{i-1} \to E_i) = P(E_i | T_{l\_i-1}, E_{i-1}) = p_{i \leftarrow i-1} \tag{13}$$

Discretize the spatial transition probability, generate a three-dimensional matrix M × U × U. M is the number of time intervals, total 96 time-sections, U is the number of travel destination, the section at any time interval is a U × U matrix, as follows:

$$P_{T_k} = (p_{ij}) = \left\{ \begin{matrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{matrix} \right\} \tag{14}$$

$$\sum\nolimits_{j=1}^{U} p_{ij} = 1 \tag{15}$$

Figure 5 shows the transition probability of travel destinations at different start areas in 18:00 on different typical days.

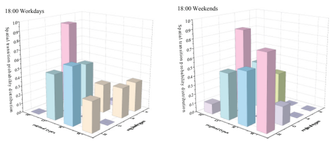

Fig. 5. Spatial transfer probability.

4.2 Charging Load Curve Analysis

The dynamic change curves of EV charging demand in 33 regions in one day are obtained by simulating. After analysis, obtain the daily variation curve of the total charging load for four different functional areas, shown in Table 1 and Fig. 6.

Table 1. Charging load summary

	Statistics	H	W	R	O	total
Workdays	Load	147.5	13952	11279	2161	27539
	Proportion	0.5%	50.7%	41%	7.8%	100%
Weekend	Load	187.3	8460.4	18784.3	924	28356
	Proportion	0.7%	30%	66%	3.3%	100%

On a typical workday, the total charging load of the work area (W) is the largest, accounting for 50% of the total load of the day, and it reaches the peak at 8:00–9:00 in the morning; the total charging load of the Relaxation area (R) is also relatively large. The peak is reached at 10:00 in the morning; the charging load of other districts (O) and residential areas (H) only accounts for 10% of the total electricity load, and the demand for charging is small. Therefore, during the working day, the charging demand in the work area is the largest, followed by the Relaxation.

On a typical weekend day, the total charging load in the Relaxation area (R) is the largest, accounting for 60% of the total charging load. The load increases from 10:00 to the peak and continues until 15:00 in the afternoon; the remaining three types of areas only account for the charging load 40% of the total load, of which the working area (W) accounts for 30%, and other districts (O) and residential areas (H) only account for 4%. On weekends, the R has more EVs parked and results in the greatest charging demand.

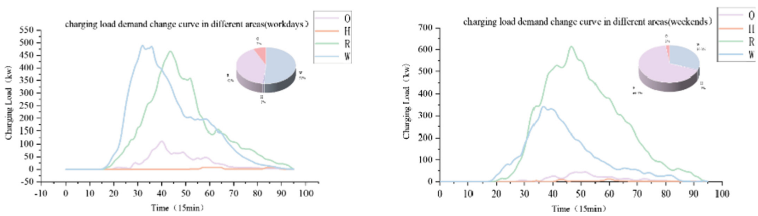

Fig. 6. Charging load demand change curve in different regions.

4.3 Analysis of Charging Pile Configuration Requirements

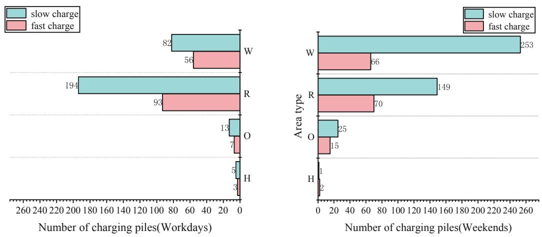

Fig. 7. Number of charging points.

According to the charging decision model in Sect. 3, the demand for slow and fast charging piles of EVs can be obtained when charging, as shown Fig. 7.

For workdays, the demand for charging piles in the work area (W) is greatest, and the demand for slow charging piles in the work area is almost four times that of fast charging. The demand for charging piles is consistent with the charging requirements analyzed in the previous section, and the park time of EVs in the work area is mostly long-term parking due to work, so the demand for slow charging piles is greater. There is also a certain demand of charging piles in Relaxation area (R), and the demand for slow charging piles is twice the number of fast charging piles. However, in other districts (O), charging demand is relatively small during workdays, lead to the small demand for slow and fast charging piles, with a ratio of 3:5. During the day, most users will leave residential areas (H), so the charging load demand in H is small, and the demand for the two types of charging piles is consistent.

For weekends, because users often choose Relaxation area (R) to travel, the demand for charging piles is the largest, and the demand for slow-charging piles is three times that of fast-charging. The charging demand for work area (W) on weekends has decreased, so the demand for charging piles has been reduced. Since the park time in the W on weekends is smaller than that on workdays, so the demand for slow and fast charging piles becomes similar. The demand for charging piles in other districts (O) and residential areas(H) is relatively small, and the ratio of the two types of charging piles is also close to 1:1.

4.4 Suggestions for Charging Pile Mode Configuration

Based on the above analysis, it can be seen that on different typical days, the total demand of charging piles and the proportion of slow/fast charging piles requirements will vary in each functional area, shown in Table 2. Based on the data, the paper provides suggestions for the planning and configuration of slow/fast charging piles in different areas:

(1) For Relaxation area (R), the charging demand is overall higher, and on two typical days: the slow/fast charging ratio is 2.08 and 2.12 respectively, so R should consider building more slow-charging charging piles.
(2) For Work area (W), the charging demand is obviously prominent on workdays, and there is a certain charging demand on weekends. The slow/fast charging ratio is 3.83 and 1.46 on workdays and weekends. Since the charging demand in W on workdays is obviously greater than on weekends, more slow-charging piles should be built mainly considering the needs in the workdays;
(3) For Other districts (O), since the charging demand is small, the installation of charging piles can be reduced. In addition, the slow/fast charging ratios on different typical days are relatively close. Therefore, fast/slow charging piles can be distributed proportionally
(4) For Residential areas (H), the charging demand is very small, but there is also a demand for fast-charging during the day. Therefore, in addition to a large number of slow-charging piles, they should also be equipped with a certain number of fast-charging piles that can meet the urgent needs of users.

Table 2. The proportion of slow /fast charging piles in different areas

	Charging modes	H	W	R	O
Workdays	Slow /fast charge ratio	0.5	3.83	2.12	1.67
	Total number	3	319	219	40
	Proportion	0.5%	55%	37.6%	6.9%
Weekends	Slow /fast charge ratio	1.67	1.46	2.08	1.85
	Total number	8	138	287	20
	Proportion	1.7%	30.4%	62%	5.9%

5 Conclusion

The demand analysis for the configuration of different charging modes is a significant research direction. This paper analyzes the travel chains of EVs on different typical days based on NHTS2017, and obtain the ratio of the demand for slow charging and fast charging in different types of areas.

By analyzing and comparing the simulation data, the article provides suggestions for the configuration of different charging piles modes in different areas: The Relaxation area (R) and Work area (W) require relatively large number of charging piles, and require a larger number of fast-charging configurations. In the meanwhile, Other districts (O) and Residential areas (H) need a fewer number of charging piles, the requirements for different charging pile modes are close. By more reasonable charging pile ratio configuration, it can improve the efficiency of grid operation, contributes to helping the distribution network to effectively dispatch renewable energy, provides an analytical basis for China to promote the participation of electric vehicle charging network in system regulation in the process of moving towards carbon neutrality [16].

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References

1. Bagheri, M., Marzband, M., Al Sumaiti, A., et al: Cost-benefit analysis for multiple agents considering an electric vehicle charging/discharging strategy and grid integration. In: 2020 IEEE 20th Mediterranean Electrotechnical Conference, Palermo, Italy, pp. 19–24 (2020)
2. Ge, Y., Chen, J., Zhu, Y., et al.: Power generation planning considering generalized demand-side resources of Jiangsu province in the 14th five-year plan period power. Power Demand Side Manag. **23**(2), 4–9 (2021). (in Chinese)
3. Chukwu, U.: The impact of load patterns on power loss: a case of V2G in the distribution network. In: 2020 Clemson University Power Systems Conference (PSC), Clemson, SC, USA, pp. 1–4 (2020)
4. Zhao, S., Zhou, J., Li, Z., Zhang, S.: EV charging demand analysis based on trip chain theory. Electric Power Autom. Equip. **37**(8), 105–112 (2017). (in Chinese)
5. Li, L.: Location and Capacity Determination of Taian Electric Vehicle Fast Charging Station Based on Improved Firefly Algorithm. ShanDong University (2020). (in Chinese)
6. Parastvand, H., Bass, O., Chapman, A.: A graph automorphic approach for placement and sizing of charging stations in EV network considering traffic. IEEE Trans. Smart Grid **11**(5), 4190–4200 (2020)
7. Luo, L.: Research on the Optimal Allocation of Distributed Generation and Electric Vehicle Charging Stations under Interactive Environment. Southeast University (2019). (in Chinese)
8. Ren, Y., Shi, L., Zhang, Q., et al.: Optimal distribution and scale of charging stations for electric vehicles. Autom. Electr. Power Syst. **35**(14), 53–57 (2011). (in Chinese)
9. Wen, Y., Hu, Z.: Coordinated charging strategy for electric vehicle charging station based on demand prediction. In: 4th IEEE Conference on Energy Internet and Energy System Integration, Wuhan, China, pp. 659–664 (2020)

10. Jia, L., Hu, Z., Song, Y.: An integrated planning of electric vehicle charging facilities for urban area considering different types of charging demands. Power Syst. Technol. **40**(9), 2579–2587 (2016). (in Chinese)
11. Yue, L.: Study on Charging Strategy and Charging Station Planning of EV Based on Spatial-Temporal Characteristics. University of Science and Technology of China (2019). (in Chinese)
12. U.S. Department of Transportation, Federal Highway Administration. 2017 National Household Travel Survey. http://nhts.ornl.gov. Accessed 29 Aug 2021
13. Liang, H., Lee, Z., Li, G.: A calculation model of charge and discharge capacity of electric vehicle cluster based on trip chain. IEEE Access **8**, 142026–142042 (2020)
14. Wen, J., Tao, S., Xiao, X., et al.: Analysis on charging demand of EV based on stochastic simulation of trip chain. Power Syst. Technol. **39**(6), 1477–1484 (2015). (in Chinese)
15. Wang, D., Guan, X., Wu, J., et al: Analysis of multi-location PEV charging behaviors based on trip chain generation. In: 2014 IEEE International Conference on Automation Science and Engineering (CASE), Taipei, China, pp. 151–156 (2014)
16. Hu, Q., et al.: Analysis on rotating power outage in California, USA in 2020 and its enlightenment to power grid of China. Autom. Electr. Power Syst. **44**(24), 11–18 (2020). (in Chinese)