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Based on the Influence Analysis of Monte Carlo Method on the Random Battery Swap Behavior of Electric Vehicles

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Abstract:

As number of electric vehicles continues to increase, the switching behaviour of electric vehicles is highly stochastic and will have an impact on daily loads. In this article, we use Pearson correlation coefficients to conduct correlation analysis for different switching characteristics, and obtain that the switching waiting time and SOC are important factors affecting the switching behaviour of electric vehicles. The demand model of EV stochastic switching behaviour based on Monte Carlo method was also established to simulate the impact of EV stochastic switching behaviour on daily load under different penetration rates. The results of the simulation analysis show that the stochastic switching behaviour of EVs can have an impact on the daily load, especially in high penetration scenarios, where the volatility of the load increases significantly.

Keywords: pearson correlation coefficient, electric vehicle switching, Monte Carlo method, daily load profile.

INTRODUCTION

As the number of electric vehicles increases, the coordinated relationship between electric vehicles and power grid becomes more and more important. At the same time, the stochastic charging and switching behaviour of electric vehicles not only changes the spatial and temporal distribution characteristics of the traditional electricity demand, but also brings certain impacts on the load of the power grid to a certain extent. Therefore, an intensive study of the influencing factors of stochastic power exchange behaviour of electric vehicles and its functioning mechanism is of great significance for alleviating load pressure, optimizing operation efficiency, and promoting the construction of a new type of social collaboration system based on the power exchange mode. According to various researchs, the power exchange mode has received widespread attention due to its efficient and convenient characteristics, and the electric vehicles adopting the power exchange mode are mainly concentrated in the field of public transport such as network car and bus, for example, NIO, Aulton and other related enterprises have actively put into the use of the power exchange station in a city of Jilin Province, basically adopting all kinds of network cars and buses, which provides a convenient power exchange service for the public sector electric vehicles. Therefore, this paper is mainly focused on the data from 17th July 2022 to 30th May 2023 of the net cars that were exchanged at seven power exchange stations in a city in Jilin Province, to analyse the impact on the characteristics of EV exchange behaviour and the impact on the daily load of the exchange stations under different penetration rates of EVs.

The literature[1] uses Monte Carlo simulation to analyse the impact of EV charging on distribution network losses in two islands at 25% and 50% penetration. The literature[2] EV charging loads are characterised by high spatio-temporal randomness compared to conventional loads, and the results show that EVs bring more uncertainty to the distribution network operation. The literature[3] has developed a statistical model for the power demand of electric vehicles by using the results of a survey of household vehicles conducted by the U.S. Department of Transportation and counting the distance travelled by the vehicles in a day. The literature[4] also considered a variety of uses of vehicles in the analysis, and the different uses of vehicles each possible driving rules, charging time, charging mode selection were determined, based on which Monte Carlo simulation was used to extract the starting charging state, starting charging time of each vehicle, and the load curve was obtained through simulation. The literature[5] measured and analysed the time of day when vehicle users leave their homes and return home, and developed a conditional probability based prediction model to analyse the charging load of vehicles.

As most of the EVs are disordered when performing charging and switching behaviours[6] , the huge disordered switching behaviours of EVs during peak load hours will substantially increase the load on the grid, increasing the peak-to-valley difference of the power system and intensifying the operational pressure on the distribution network. And the orderly power exchange of electric vehicles refers to the use of practical and effective economic or technical means to guide and control the charging of electric vehicles under the premise of meeting the charging demand of electric vehicles, shaving the peak and filling the valley of the power grid load curve, so that the variance of the load curve is small, and ensure the coordinated and interactive development of electric vehicles and the power grid. Therefore, the analysis of the behavioural characteristics of electric vehicle switching is important for the achievement of the 'dual carbon' goals of carbon peaking by 2030 and carbon neutrality by 2060, as well as for the development of electric vehicle switching processes.

Since congestion in the transport network increases with the growth in the number of electric vehicles[7], the safe operation of the grid is significantly affected due to the stochastic switching behaviour of electric vehicles which can easily result in consequences such as line blockage [8], voltage drop, and overloading of the grid. To conduct the analysis of decision factors for EV power exchange is not only a premise for the widespread promotion of EV power exchange mode [9], but also the key to the unified dispatch of power grid [10], the operation of power market[11] , the convenience of users' travelling and the ensuring of the safe, economic and efficient operation of the system. Therefore it is of great value to analyse the decision-making factors for EV switching points, the characteristics of EV switching behaviours, and to explore the electric vehicle regulation potential[12]. Therefore, through the analysis of electric vehicle switching behaviour, and a large number of studies have shown that the analysis of decision-making factors for electric vehicle switching behaviour plays an extremely important role.

THEORETICAL BACKGROUND

Since for the electric vehicle switching behaviour, stochasticity is an important feature, and how to model the stochastic switching behaviour is an important research in this paper. This paper takes seven power exchange stations within a city in Jilin Province as the study area, focuses on the analysis of the characteristics of power exchange behaviour of network vehicles in the region, and uses more than 690,000 pieces of power exchange data provided by the operation backend of the power exchange stations to study the key factors affecting the power exchange behaviour. These characteristic variables include, switching off battery soc, switching off battery mileage, switching on battery SOC, switching on battery mileage, vehicle inbound time, vehicle outbound time, and switching in progress time.

In the process of modelling and analysing the switching behaviour of electric vehicles, this paper classifies the data features according to their degree of influence on the switching behaviour into: key influences and non-key influences.

Monte Carlo method is a numerical computation method based on probabilistic statistical theory, which can effectively solve a variety of practical problems in complex systems through random sampling and simulation. The basic principle is to use a large number of random samples to approximate the mathematical expectation or distributional properties of the target system, and to derive an approximate solution to the problem by counting the performance of these samples. Compared with traditional analytical methods, Monte Carlo methods are particularly suitable for solving high-dimensional complex problems, non-linear system analysis, and scenarios with high uncertainty, and are characterised by computational flexibility and wide applicability.

The Monte Carlo method has a widely range of specific applications and can therefore be used to achieve an analysis of the switching behaviour of electric vehicles.

Through a large amount of data information to construct a stochastic model matching the actual power exchange process, and simulate the randomness characteristics of power exchange behaviours under different penetration rates, so as to achieve the analysis of the impact of stochastic power exchange behaviours of electric vehicles on power exchange stations under different penetration rates.

The quantitative analysis of different factors, such as distance, waiting time, affecting the choice behaviour of power exchange stations is carried out by using Monte Carlo method. The average impact of each factor on the probability of switching station selection is assessed through simulation. At the same time, an applied model is constructed to analyse the behaviour of switching station selection, and analyse the impact of the switching behaviour of electric vehicles on switching stations under different penetration rates.

In this paper, we quantify the impact of each characteristic variable by comprehensively analysing the characteristic variables of electric vehicle switching and modelling the probability density distribution of different characteristics. The Monte Carlo method is combined to simulate the switching behaviour of electric vehicles at different penetration rates and to analyse its impact on the switching station.

USER BEHAVIOURAL CHARACTERISTICS

This section focuses on the pre-processing of the experimental data, and the data preprocessing process consists of two parts: firstly, the treatment of anomalous data, and secondly, the normalisation of the data. Table 1 shows the data of an electric vehicle switched in the experimental area. The intensive analysis of this data can lay a solid foundation for subsequent feature extraction and model construction.

Table 1. Data on the exchange of electricity for an electric vehicle

Name of the site	Change the battery soc.	Mileage on replacement batteries	Change the battery SOC	Mileage on a new battery	Vehicle Approach Time	Vehicle Departure Time	Power changeover start time	Power changeover end time
1	22.60	32462	96.9	4230	2022/7/17 17:40:58	2022/7/17 17:43:42	2022/7/17 17:42:43	2022/7/17 17:43:18
1	36.70	4434	97	26517	2022/7/18 18:10:21	2022/7/18 18:12:11	2022/7/18 18:11:07	2022/7/18 18:11:43
2	33.80	26729	97	18219	2022/7/19 3:48:55	2022/7/19 3:55:23	2022/7/19 3:53:35	2022/7/19 3:54:16
3	45.00	18394	96.9	34191	2022/7/19 11:39:02	2022/7/19 11:41:44	2022/7/19 11:40:38	2022/7/19 11:41:17
1	34.30	34388	96.9	3540	2022/7/19 18:32:29	2022/7/19 18:34:29	2022/7/19 18:33:28	2022/7/19 18:34:03
1	48.80	3715	97	45823	2022/7/20 5:40:41	2022/7/20 5:46:24	2022/7/20 5:45:27	2022/7/20 5:46:03
1	24.80	46024	96.9	35339	2022/7/20 14:45:39	2022/7/20 14:48:32	2022/7/20 14:47:32	2022/7/20 14:48:08
2	21.30	35605	96.9	24675	2022/7/21 2:56:21	2022/7/21 3:02:09	2022/7/21 3:00:09	2022/7/21 3:00:50
3	42.60	24863	96.9	36050	2022/7/21 10:12:47	2022/7/21 10:14:59	2022/7/21 10:13:56	2022/7/21 10:14:35
1	46.60	36221	96.9	4439	2022/7/21 16:57:04	2022/7/21 17:02:00	2022/7/21 16:59:01	2022/7/21 17:01:30
2	22.90	4709	97	6278	2022/7/22 3:27:24	2022/7/22 3:31:28	2022/7/22 3:30:10	2022/7/22 3:30:51
1	28.80	6499	96.9	19958	2022/7/22 11:17:58	2022/7/22 11:21:05	2022/7/22 11:20:06	2022/7/22 11:20:41
1	75.50	2117	96.9	7806	2022/7/22 18:26:56	2022/7/22 18:29:16	2022/7/22 18:28:15	2022/7/22 18:28:51

The travelling distance of an electric vehicle is the main factor influencing the switching behaviour. The travelling distance directly determines how much electricity an electric vehicle consumes, which in turn affects the demand for switching. As the mileage of an electric vehicle increases, the battery power gradually decreases and needs to be swapped after reaching a certain level. Therefore, the travel distance not only reflects the driving conditions of EVs, but is also closely related to the switching behaviour of EVs. The distance travelled by different EVs determines the difference in battery consumption, which in turn affects the switching behaviour of EVs.

Since the time for each electric vehicle to change electricity is basically 1 to 2 minutes when electric vehicles are exchanged, the main influencing factors that will affect the electric vehicle owners to choose the exchange station when they are exchanging electricity also need to consider not only the time of exchanging electricity, but also the queuing and waiting time, which is an important influencing factor in the act of exchanging electricity. Therefore, in order to more accurately analyse the switching behaviour of electric vehicles, it is essential to study the distributional characteristics of queuing waiting time and its impact on the choice of switching station.

$$t_d = t_c - t_e \tag{1}$$

t_d is the switching waiting time for electric vehicles, t_c is the total time that an electric vehicle is in and out of the switching station, t_e is the time at which the electric vehicle undergoes a power changeover. Figure 1 shows the distribution of the average waiting time required for an electric vehicle to be switched at different switching stations.

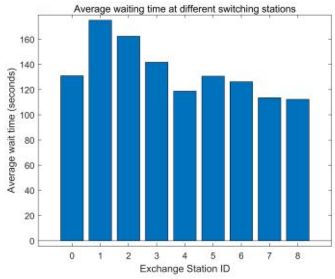

Figure 1. The average waiting time at different switching stations

Also, the daily mileage of an electric vehicle is one of the important factors influencing the switching behaviour. Daily mileage determines battery consumption, which in turn affects the demand for electric vehicle swapping. Therefore, the daily driving range of electric vehicles is closely related to the switching behaviour.

In this paper, in order to effectively analyse the daily mileage of electric vehicles, probability density curves are used to describe their distributional characteristics. By performing statistical analysis on the driving data of a large number of electric vehicles, the probability distribution of daily mileage can be obtained in Figure 2 , and the analysis yields that the daily mileage of most electric vehicles is concentrated in 200km.

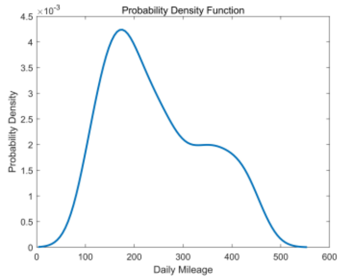

Figure 3. Daily electric vehicle mileage

The level of the SOC value affects whether or not the electric vehicle can continue to be driven and determines whether or not an immediate power change is required. The travelling behaviour of EVs can be studied by the remaining battery power of EVs to see whether the current EVs need to undergo a power changeover, and the distribution pattern of the battery power of EVs when undergoing a power changeover can be obtained by statistically modelling the SOC data of a large number of EVs when undergoing a power switch. Figure 4 shows the probability density distribution of the remaining power of EVs, from which it can be seen that the SOC is basically in the range of 40%-50% when more EVs are exchanging power.

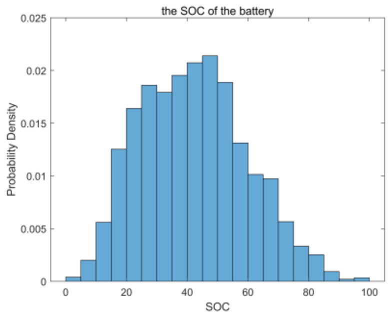

Figure 5. Electric vehicle battery remaining charge

The Pearson correlation coefficient, also known as the product-difference correlation coefficient, is a statistical indicator that expresses the degree and direction of linear correlation between two variables[13]. Ability to analyse correlations between different characteristics by quantifying the strength of linear relationships between variables. The values of Pearson correlation coefficient range from -1 to +1, a value of +1 indicates a perfect positive correlation, a value of -1 indicates a perfect negative correlation, and a value of 0 indicates no linear relationship at all.

Pearson correlation coefficient is widely used to analyse the linear dependence between the variables in the data[14]. It is in multivariate analysis that the Pearson correlation coefficient can identify which features have a strong linear relationship, so in this paper, the Pearson correlation coefficient is selected for the analysis of different influencing factors, and the relationship between the factors is analysed by calculating the Pearson correlation coefficient between different variables, battery SOC, distance travelled, and switching waiting time.

The Pearson correlation coefficient was calculated as (2):

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2} \tag{2}$$

Where X_i and Y_i are the i observation in the sample dataset, $\bar{X}$ and$\bar{Y}$ are the sample means of variables X and Y, respectively, and n is the sample size. The numerator in the formula is the covariance, while the denominator is the product of the standard deviations of the two variables, indicating the standardised covariance.

This study is an analysis of the impact and characteristics of stochastic switching behaviour of electric vehicles based on the data provided by the operation back office of certain switching stations within a city in Jilin Province.

Firstly, the data are processed and the correlation between different features is analysed using Pearson correlation coefficient to obtain the correlation coefficients between pairs of features and to reveal the key factors affecting the switching behaviour of electric vehicles. And through the correlation matrix heat map Figure 6 , it is demonstrated that the maximum mileage and the time of power change are negatively correlated, and the maximum mileage is positively correlated with the SOC, indicating that vehicles with longer mileage usually consume more power.

It is demonstrated that the switching waiting time and the SOC of the swapped battery are key factors in the switching behaviour of electric vehicles[15].

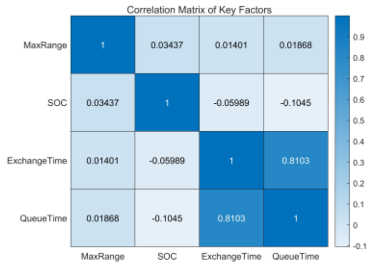

Figure 7. Thermograms associated with different features

Therefore, the switching waiting time and the SOC of the swapped-out battery are all key factors influencing the behaviour of EVs in performing switching. The Pearson correlation coefficient analysis reveals the intrinsic connection between some key factors in the behaviour of electric vehicle switching, through the analysis of these factors, we can better understand the stochastic nature of electric vehicles in the process of switching, and better achieve the study of the impact of electric vehicles on the switching station.

Impact of Different Penetration Rates on the Exchange Station

In this paper electric vehicle switching behaviour is simulated using Monte Carlo method[16], which can be used to simulate and predict the probability and behavioural patterns of switching station selection[17]. The analysis of the switching behaviour can be achieved by simulating the effect of different variables on the switching through random sampling. Figure 5 shows the flowchart of the implementation of the Monte Carlo method.

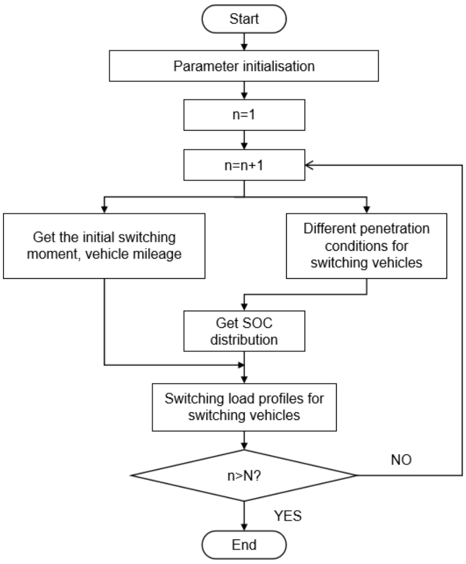

Figure 8. Flowchart of the Monte Carlo method

The Monte Carlo method can be used to analyse the daily load variation and distribution under different EV penetration rates by simulating the stochastic simulation of switching demand[18]. The daily load model of power exchange is established by considering the moment of power exchange, daily driving mileage and power exchange of electric vehicles. Daily load variations for different EV penetration rates are obtained through multiple simulations.

The daily load curve is a curve that describes the change of load over time within a day[19]. By analysing the power demand in 24 hours a day, it reflects the law of load change over time in a period of time, and by analysing the daily load curve of power exchange in a day, it realises the analysis of the impact of power exchange behaviours of different penetration rates on the power exchange station with the change of power exchange time. The accuracy of the daily load profile prediction will directly affect the economic efficiency of the power system operation[20].

$$E=\frac{D}{\eta} \tag{3}$$

E is the energy from the grid during charging, D is the daily mileage and η is the vehicle energy consumption of the EV.

By combining the switching behaviour of electric vehicles with the Monte Carlo method, the load fluctuations under different penetration rates and switching behaviours are simulated to achieve an accurate prediction of the daily load profile. Figure 6 shows the load curves at different permeability.

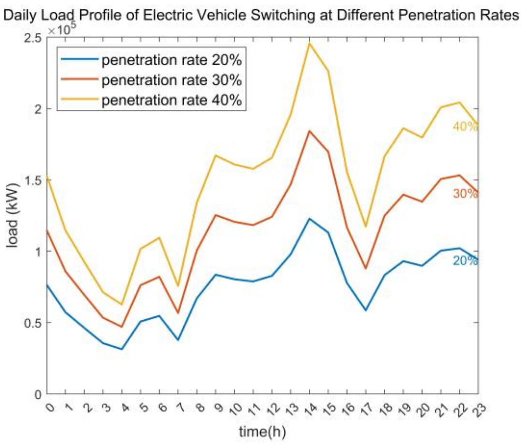

Figure 9. Daily loading curves at different permeabilities

Therefore, the Monte Carlo method was used to analyse the behaviour of EV switching in combination with the different penetration rates of EVs during the four seasons, with peak switching loads concentrated around 00:00 and 14:00, and with the same number of samples, while the daily load profile increased with the growth of EV penetration.

Therefore, it can be obtained that the increase in the penetration rate of electric vehicles will lead to high peak loads in the grid system when they are switched to the grid, which will have an impact on the safe and stable operation of the grid and the switching station.

SUMMARY

In this paper, first of all, we analyse the influencing factors of electric vehicle switching behaviour, simulate the switching behaviour of electric vehicles based on a large amount of data, and study the effect of its influence. Firstly, the characteristics related to electric vehicle switching behaviour were analysed and the correlation between the influencing factors was assessed using the Pearson correlation coefficient method. Results show that the switching waiting time as well as the SOC value of the swapped battery are the key factors influencing the switching behaviour of electric vehicles. Secondly, the stochastic nature of EV switching behaviour is further revealed by modelling and analysing the probability density function of each characteristic variable. Finally, the Monte Carlo method was used to model the switching behaviour of EVs at different penetration rates, and to analyse the impact of EV switching behaviour on the daily load changes of the power system at different penetration rates. It shows that the stochastic nature of EV switching behaviour can lead to changes in the daily load profile, and as EV penetration increases, it can place higher demands on the load of the grid. Therefore, future researches need to fully consider the stochastic nature of EV switching behaviour and the impact of varying penetration loads.

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