IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received March 26, 2018, accepted May 2, 2018, date of publication May 14, 2018, date of current version May 25, 2018.

Digital Object Identifier 10.1109/ACCESS.2018.2835825

An Analysis of the Charging Characteristics of Electric Vehicles Based on Measured Data and Its Application

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This work was supported by the Major State Research Development Program of China under Grant 2016YFB0101800.

ABSTRACT The accurate modeling of the charging characteristics of electric vehicles (EVs) is the basis for the load forecasting, infrastructure planning, and orderly charging management. While, research based on the measured charging data of EVs is seldom carried out, and the concrete modeling of the correlations of various parameters is a gap in the knowledge. Aiming at this, we carried out an investigation based on operational data, from August 2016 to August 2017, of an EV charging service company in Nanjing, China. The time-energy characteristics of EV charging behavior can be described using the probability distributions and correlations of three charging parameters, i.e., charging start time, charging duration, and charged capacity. In this paper, we fitted the probability densities of these charging parameters using the kernel estimation method and verified the correlations of time parameters of the charging behavior. Multiple copula functions were used to model the correlation between the time and energy parameters of different types of charging behaviors. On this basis, we also carried out stochastic simulation for the load curve of disordered charging and analyzed the potential of the EV charging load participating in the orderly management and its coordination with the output of power generation using renewable energy.

INDEX TERMS Electric vehicle, charging load, kernel density estimation, correlation, copula function.

I. INTRODUCTION

The transportation sector consumes more than a half of the oil resources in the world and at the same time generates huge amounts of greenhouse gases [1]. Transportation electrification is an important way to reduce the dependence of human society on fossil energy. If electric vehicles (EVs) driven by clean, high-efficient electric energy with extensive sources are popularized, the transportation sector can get reduce its dependence on non-renewable energy resources and aim for zero emissions on the customer side [2].

For this reason, various countries across the world are actively prompting the development of EVs. In addition to implementing a set of economic subsidy policies for the production and marketing of EVs, governments of many countries also put the formulation of the timeline for prohibiting sales of oil-fueled vehicles on their agenda [3], [4]. It is foreseeable that an era of growth of EV numbers will be ushered in.

The development of EVs will bring about a profound effect on the planning and operation of the power system [5], [6]. To cope with the load growth resulting from the large-scale EV charging, it is bound to expand the capacity of the power system. The uncertain spatial and temporal distribution of the disordered charging load of EVs will probably lead to an increasingly large difference between the peak and valley loads on power grid and waste of investment in power distribution equipment. In addition, it makes the optimal control of power grid more difficult and reduces the safety and economic efficiency of the operation of the power grid. While, EVs, as mobile energy storage, if their charging behavior can be well-managed using a proper strategy and advanced means of communication, it will present a broad application prospect in peak load shifting, auxiliary service for power systems, and cooperative consumption of new energy sources [7], [8].

To achieve the integrative development of EVs and smart grid and give full play to the potential of EVs as mobile energy storage, the charging characteristics of EVs need to be modeled accurately for load forecasting, charging equipment planning, and design of orderly charging strategies.

Estimating the probability distributions of EV charging characteristic parameters including charging start time and state of charge of batteries according to statistical data of oil-fuelled vehicles and then simulating large-scale EV charging through stochastic simulation is a commonly used method for analyzing charging characteristics of EVs. By using statistical data about private cars, the temporal distribution of EV charging loads was analyzed in previous studies [9], [10]. Based on the analysis of the parking demand characteristics in different districts of some cities, other workers [11] simulated the spatial and temporal distribution characteristics of the large-scale EV charging behavior. Different modes of traffic situations were obtained by analyzing the historical traffic and meteorological data and the charging behavior of EVs was classified by using the decision tree algorithm [12]. A predictive model for EV charging behavior was proposed [13], [14] based on the trip chain. By using the model, one can simulate the travel behavior of users after constructing trip chains according to different purposes of vehicle travel and then calculate the charging demands in different regions.

While analyzing the charging behavior of EVs using the data of oil-fuelled vehicles, it is necessary to make a series of assumptions as the driving characteristic parameters are transformed to charging characteristic parameters. For example, it must be assumed that the batteries of EVs are full of electricity at the beginning of driving on each day [9], that the charging demand is only related to daily mileage [15], and that only several types of EVs run in the research area [16]. However, these assumptions probably limit the modeling results to specific scenarios. It is worth noting that some researchers believe that the charging characteristic parameters of EVs are independent of each other [11]–[14], and the assumption has been accepted by numerous studies. While in the research, we provide evidence to the effect that the application of the assumption leads to biased calculation results.

Presently, there are also some studies based on the measured charging data of EVs. A temporal distribution model of loads at a single charging station was established in [17] using the historical data of a charging station in Taiwan. In the literature [18], the forecasting method for EV load was studied using the machine learning method based on the EV charging data at the University of California, Los Angeles (USA); however, the data used in the above research were derived from single sources and therefore are unable to reflect the difference in the charging behavior of EVs in different regions.

The EV charging data used in the research came from an EV charging service company in Nanjing, China. The company has built charging stations in various districts of the city including the residential, working, and commercial districts, as shown in Figure 1. Therefore, the data were derived from wide sources and thereby are able to embody the charging characteristics of EVs.

Although others [15], [19] also considered the correlations of charging characteristic parameters of EVs, they fail to reveal the full complexity and changeable correlations of different charging characteristic parameters of EVs due to the lack of support from measured data and the simple correlation models established. In the research, we modeled the probability distributions and the correlations of charging characteristic parameters of EVs based on the measured charging data. The remainder of the paper is arranged as follows: Section 2 introduces the data acquisition and processing methods; Section 3 carries out kernel estimation for the probability density functions of various parameters and verifies the correlation between two parameters: the charging start time and the charging duration; Section 4 classifies the EV charging behavior in accordance with the temporal characteristics; Section 5 modeled the correlations of EV charging parameters using the copula functions; Finally, we use the charging characteristics of EVs to conduct the load forecasting and the evaluation of orderly charging potential, and analyze the temporal distribution of EV charging loads and the coordination with the output of power generation using renewable energies.

FIGURE 1. Distribution of charging stations of the EV charging service company, Nanjing.

II. DATA ACQUISITION AND PROCESSING

The data used in the research were derived from the platform of an EV charging service company in Nanjing, China.

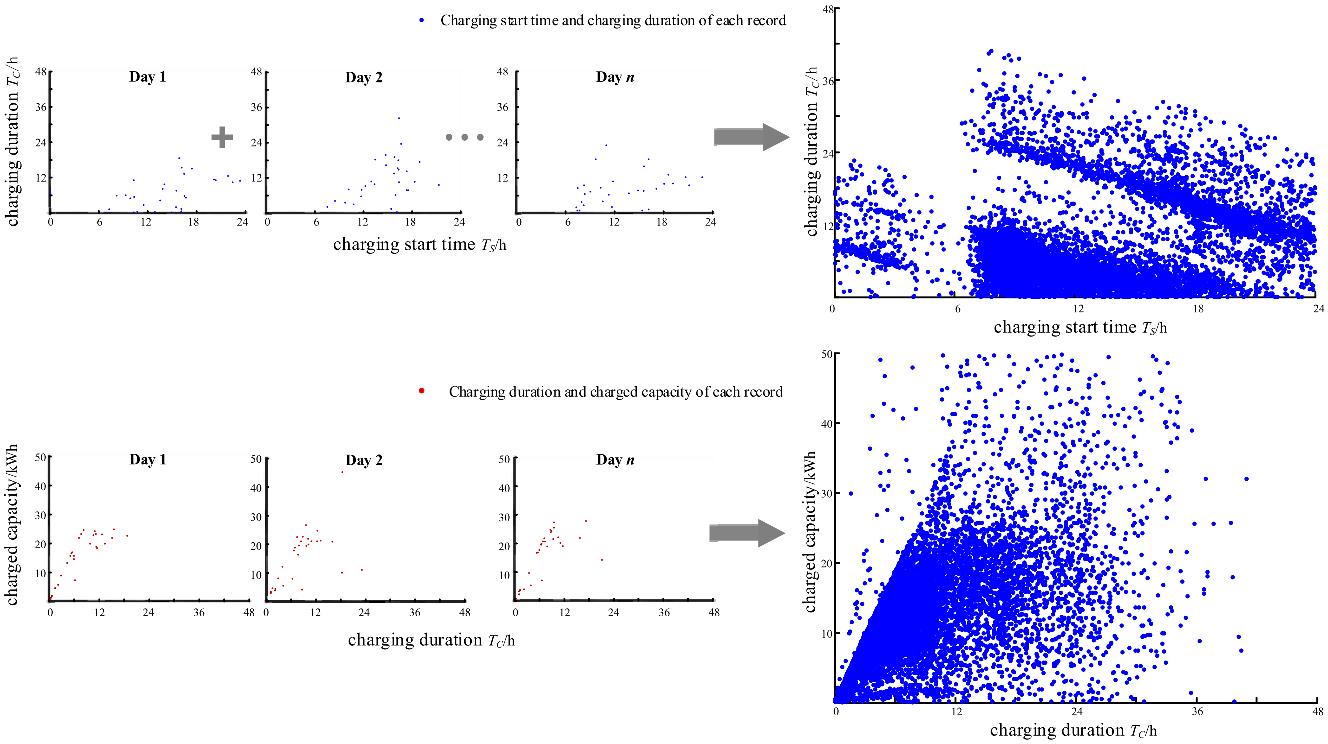

FIGURE 2. Planar scatter plot for the distribution of raw data and the formation thereof.

The company has built many charging stations in different districts to mainly provide service for EVs. By using the intelligent charging piles at their stations, users can realize self-service charging and payment [20].

After charging EVs using the equipment at the platform, users will leave a record containing various charging information in the background. At present, more than 10,000 charging records from August 2016 to August 2017 are stored in the platform. To analyze the EV charging characteristics, we extracted four groups of data from these charging records, i.e. charging start time T_S, charging duration T_C, charging end time T_E, and charged capacity E_C. In the data extraction, those outliers with the charged capacity E_C of zero were removed. As a single charging station had a small dataset size in a single day and the data were highly random, we clustered all of the valid charging data in the research period to ascertain the regularity of the EV charging behavior and analyze the overall distribution and the correlations of various charging data. The distribution and formation process of the raw data are shown in Figure 2.

Before proceeding any further, the following concepts need to be explained:

① Owing to the construction of charging piles precedes the development of EVs, when EVs are charged at the platform, their charging behavior does not change due to the busyness of the charging equipment. Therefore, the EVs show their charging characteristics in natural state.

② The charging service company does not conduct orderly management for the EV charging behavior at the platform. The EVs are charged immediately after being parked and disconnected with charging piles after finishing charging before leaving the charging stations. As the parking and charging time parameters of EVs are consistent, we took the charging start time T_S as the start time of parking and the charging end time T_E is the end time of parking. It is worth noting that the charging duration T_C refers to the time period for which EVs are connected to the power grid via charging piles, instead of the duration during which electricity is unidirectional transmitted to the EVs. T_S, T_C, and T_E have the following relationship:

$$T_E = T_S + T_C \tag{1}$$

③ No personal information including user names in each charging recorded is involved in the data extraction and analysis and no individual charging behavior is traced, which averts the possibility of infringing the privacy of users [18].

III. TEMPORAL CHARACTERISTICS OF EV CHARGING BASED ON KERNEL DENSITY ESTIMATION

The temporal characteristics of EV charging are determined by three parameters: charging start time T_S, charging duration T_C, and charging end time T_E. According to the data obtained in Section 2, we conducted kernel estimation for the probability density functions of the three parameters at first and verified the correlation between charging start time and charging duration using relevant conclusions from probability theory.

A. KERNEL DENSITY ESTIMATION

While using the parameter estimation method to carry out probability density fitting, the form of the probability density function must be assumed. If the probability density function used is not consistent with the actual conditions, the results are likely to be erroneous. Driven by data, the non-parameter estimation method does not need to assume subjectively the form of the probability density function for data to be fitted. At present, many non-parametric estimation methods, including the kernel density estimation, have been developed and gradually applied to various topics in economics and medical science [21]. In the section, we adopted the kernel density estimation method to fit the probability density functions of the start time, duration, and end time of EV charging.

Suppose that $X_1, X_2, \ldots, X_n$ are n samples observed; $K(\cdot)$ is a given Borel measurable function on R; $h_n > 0$ is a constant related to n, and when n is infinite, h_n tends to zero.

$$\hat{f}_K(x) = \frac{1}{nh_n}\sum_{i=1}^{n} K(\frac{X_i - x}{h_n}) \tag{2}$$

The above formula is the kernel density estimation of $f(x)$, $K(\cdot)$ is a kernel function and h_n represents the window width.

To guarantee the reasonability of the estimation, the unimodal probability density function with zero as the center is generally used as $K(\cdot)$. When $K(\cdot)$ satisfies the smoothness condition, $\hat{f}_K(x)$ as the function of x also has the same smoothness. The commonly used kernel functions include uniform, Gaussian, and Epanechnikov kernels. In this research, the Gaussian kernel was employed as the kernel function of the probability density estimation [22], as expressed in Formula (3).

$$K(u) = \frac{1}{\sqrt{2\pi}}\exp(-u^2/2) \tag{3}$$

Suppose that T_{Si}, T_{Ci}, and T_{Ei} ($i = 1, 2, \ldots$, n) represent the charging start time, charging duration, and charging end time of each record, then the kernel estimation for the probability density of the charging start time is

$$\hat{f}_{KS}(T_S) = \frac{1}{\sqrt{2\pi}nh_{Sn}}\sum_{i=1}^{n}\exp\left(-\left(\frac{T_{Si}-T_S}{h_{Sn}}\right)^2\right) \tag{4}$$

The kernel estimation for the probability density of the charging duration can be expressed as

$$\hat{f}_{KC}(T_C) = \frac{1}{\sqrt{2\pi}nh_{Cn}}\sum_{i=1}^{n}\exp\left(-\left(\frac{T_{Ci}-T_C}{h_{Cn}}\right)^2\right) \tag{5}$$

The kernel estimation for the probability density of the charging end time is

$$\hat{f}_{KE}(T_E) = \frac{1}{\sqrt{2\pi}nh_{En}}\sum_{i=1}^{n}\exp\left(-\left(\frac{T_{Ei}-T_E}{h_{En}}\right)^2\right) \tag{6}$$

In Formulae (4) to (6), h_{Sn}, h_{Cn}, and h_{En} are the window widths of the kernel density estimation for the charging start time charging duration, and charging end time, respectively.

B. SELECTION OF WINDOW WIDTH

The selection of window width h_n has a significant effect on kernel estimation. If h_n is too small, the increasing randomness makes the distribution estimation of the temporal characteristic parameters of the EV charging behavior adopt an irregular shape; while if h_n is too large, its detailed characteristics cannot be reflected.

The least squares cross-validation is an adaptive window width selection method [23]. According to the kernel density estimation $\hat{f}_K(x)$ in Formula (2), its integrated squared error (ISE) with the true probability density can be expressed as

$$\begin{aligned}\mathrm{ISE}\left(\hat{f}_K\right) &= \int_{-\infty}^{\infty}\left(\hat{f}_K(x) - f(x)\right)^2 \mathrm{dx}\\ &= \int_{-\infty}^{\infty}\hat{f}_K^2(x)\mathrm{dx} - 2\int_{-\infty}^{\infty}\hat{f}_K(x)f(x)\mathrm{dx}\\ &\quad + \int_{-\infty}^{\infty} f^2(x)\mathrm{dx}\end{aligned} \tag{7}$$

The h_n which makes the ISE minimum is adopted as the optimal window width. The last term in Formula (7) does not depend on $\hat{f}_K(x)$, so the optimization of the window width is equivalent to a minimization problem.

$$R\left(\hat{f}_K\right) = \int_{-\infty}^{\infty}\hat{f}_K^2(x)\mathrm{dx} - 2\int_{-\infty}^{\infty}\hat{f}_K(x)f(x)\mathrm{dx} \tag{8}$$

The least squares cross-validation follows the basic idea of constructing an estimation of $R(\hat{f}_K)$ and obtaining the optimal window width h_n by minimizing the estimation.

In Formula (8), $\int_{-\infty}^{\infty}\hat{f}_K(x)f(x)\mathrm{dx} = \mathrm{E}(\hat{f}_K(x))$, so $n^{-1}\sum_{i=1}^{n}\hat{f}_K^{(-i)}(X_i)$ is an unbiased estimation, in which

$$\hat{f}_K^{(-i)}(X_i) = \frac{1}{(n-1)h_n}\sum_{j\neq i} K\left(\frac{X_j - X_i}{h_n}\right) \tag{9}$$

By calculation

$$\begin{aligned}\frac{1}{n}\sum_{i=1}^{n}\hat{f}_K^{(-i)}(X_i) &= \frac{1}{n(n-1)h_n}\sum_{i=1}^{n}\sum_{j=1}^{n}K\left(\frac{X_i - X_j}{h_n}\right)\\ &\quad - \frac{K(0)}{(n-1)h_n}\end{aligned} \tag{10}$$

The following can be derived:

$$\begin{aligned}&\int_{-\infty}^{\infty}\hat{f}_K^2(x)\mathrm{dx}\\ &= \frac{1}{n^2h_n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}\int_{-\infty}^{\infty}K\left(\frac{X_i - x}{h_n}\right)K\left(\frac{X_j - x}{h_n}\right)\mathrm{dx}\\ &= \frac{1}{n^2h_n}\sum_{i=1}^{n}\sum_{j=1}^{n}\int_{-\infty}^{\infty}K\left(\frac{X_i - X_j}{h_n} + t\right)K(t)\,\mathrm{d}t\\ &@\frac{1}{n^2h_n}\sum_{i=1}^{n}\sum_{j=1}^{n}K^*\left(\frac{X_i - X_j}{h_n}\right)\end{aligned} \tag{11}$$

Where $K^*(u) = \int_{-\infty}^{\infty}K(u+t)K(t)\,\mathrm{d}t$.

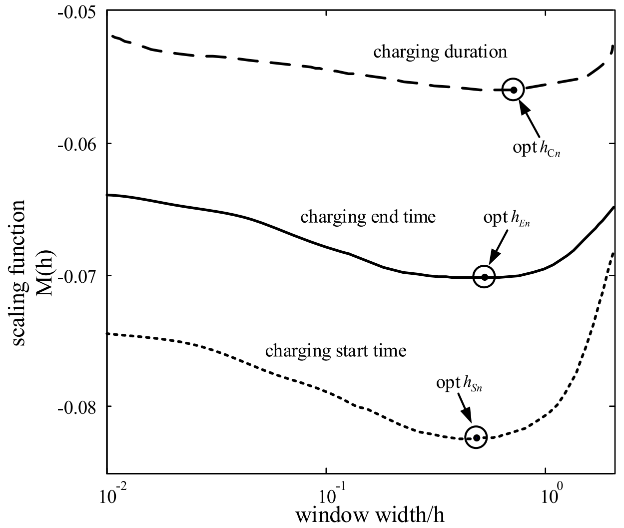

FIGURE 3. Change of the scaling functions with the window widths.

When n is large, it can be used to replace n-1 in Formula (10) and substituted into Formula (8) together with Formula (11). In this way, a scaling function equivalent to Formula (8) can be obtained:

$$M(h_n) = \frac{1}{n^2 h_n} \sum_{i=1}^{n} \sum_{j=1}^{n} K_1\left(\frac{X_i - X_j}{h_n}\right) + \frac{2K(0)}{nh_n} \qquad (12)$$

Where $K_1(u) = K^*(u) - 2K(u)$.

When the Gaussian kernel function is taken as $K(\cdot)$, the following can be obtained by using integration by substitution:

$$K^*(u) = \frac{1}{2\sqrt{\pi}} \exp\left(-\frac{u^2}{4}\right) \qquad (13)$$

Then, the optimal bandwidth obtained through verification using the least squares method is

$$h_{\text{opt}} = \arg\min_{h>0} M(h) \qquad (14)$$

It is verified [24] that, under the conditions that the density function and its one-dimensional marginal density are bounded, the bandwidth selected using Formula (14) is asymptotically optimal.

C. VERIFICATION OF THE CORRELATION BETWEEN THE CHARGING START TIME AND THE CHARGING DURATION

The results of kernel density estimation for the time parameters of EV charging behavior based on the measured data are shown in Figure 4. In previous research on the modeling of the EV charging behavior [11]–[14], it was assumed that the charging time parameters are independent of each other and the correlations between these parameters are not taken into account in load forecasting. Based on the kernel density estimation for the probability distributions of time parameters, the section proves the existence of the correlations of the time parameters of EV charging behavior using the relevant conclusions from probability theory.

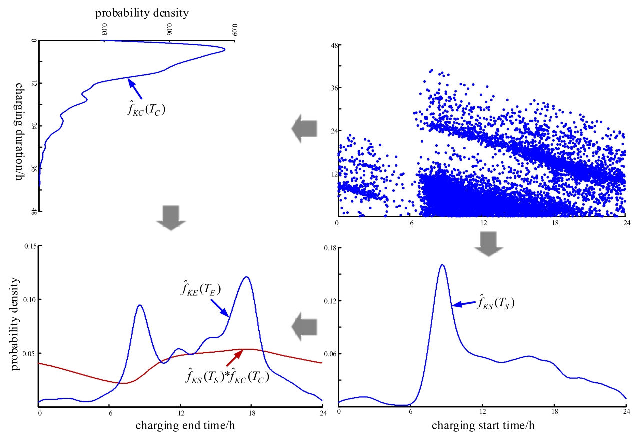

FIGURE 4. Kernel density estimations of the time parameters of EV charging behavior.

When the random variable Z represents the sum of the independent random variables X and Y, then

$$f_Z(z) = \int_{-\infty}^{+\infty} f_X(x) f_Y(z-x)\,\mathrm{d}x \qquad (15)$$

That is, when two random variables are independent, the probability density function of the sum of the two variables can be obtained by the convolutions of each of the probability density functions [25].

Suppose that the charging start time T_S and the charging duration T_C are independent, the probability density function of the charging end time can be expressed as follows according to Formulae (1) and (15):

$$f_E = f_S * f_C \qquad (16)$$

The probability density function of the charging end time can be calculated using the results of kernel density estimations for the charging start time and the charging duration, as shown in Figure 4. It is found that, the calculation result based on the assumption that the time parameters are independent of each other differs from the probability density function of the charging end time. The calculation using Formula (17) shows a relative error between the two results of up to 55.59%.

$$\varepsilon_r = \int_{-\infty}^{+\infty} \left| \frac{\hat{f}_{KS}(t_S) * \hat{f}_{KC}(t_C) - \hat{f}_{KE}(t_E)}{\hat{f}_{KE}(t_E)} \right| \mathrm{d}t_E \qquad (17)$$

The above analysis shows that under the assumption that the charging start time and the charging duration are independent to each other, large deviation appears in the calculation results. For this reason, it should not simply consider that the time parameters are independent in the research on the EV charging behavior. The following sections further analyze the concrete forms of the different correlations of the parameters and accurately model the charging behavior of EVs.

IV. CLASSIFICATION OF EV CHARGING BEHAVIOUR BASED ON TEMPORAL CHARACTERISTICS

The planar scatter plot for the distributions of charging start time and the charging duration in Figure 2 shows that the EV charging behaviors are clustered on the plane with T_S and T_C as the coordinates. It can also be seen, from Section 3, that the two parameters T_S and T_C are correlated. To analyze the charging characteristics of EVs, the EV charging behavior is classified according to the two parameters T_S and T_C using the following procedure:

① If the charging start time T_S of a charging record is less than six, let $T_S^{\mathrm{NEW}} = T_S + 24$ and other parameters remain unchanged. It is considered that the charging before dawn is the continuation of the charging in the day before, so the charging start time is shifted backwards by 24h when it is quantitatively analyzed with the charging behavior in that day.

② The charging behavior when the sum of the charging start time T_S and the charging duration T_C is less than 24 is classified as one type. As this type of charging behavior is ended on the same day starting the charging, it is called intra-day EV charging.

③ Another type of charging behavior is when the sum of the charging start time T_S and the charging duration T_C is greater than 24. This type of charging behavior is not ended on the day starting the charging but lasts into the next day, so it is called inter-day EV charging.

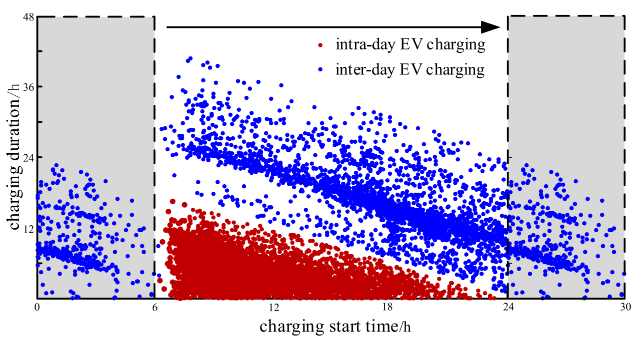

FIGURE 5. Classification results: EV charging behavior based on the temporal characteristics.

The classification results are displayed in Figure 5. To further explain the reasonableness of the above classification of EV charging behavior, we calculated the coefficient of correlation between the charging start time T_S and the charging duration T_C.

Pearson correlation coefficient and Kendall rank correlation coefficient both reflect the statistics of the correlation of variables. The former is an index for measuring the linear correlation of variables while the latter is able to effectively measure the non-linear relationship of variables [26]. Given a set of data $\{(x_{1i}, x_{2i}), i = 1, 2, \ldots, N\}$ of a random vector $X = (X_1, X_2)$, the Pearson correlation coefficient ρ and Kendall rank correlation coefficient τ of variables X_1 and X_2 can be calculated using Formulae (18) and (19), respectively.

$$\rho = \frac{\sum_{i=1}^{N}(x_{1i}-\bar{x}_1)(x_{2i}-\bar{x}_2)}{\sqrt{\sum_{i=1}^{N}(x_{1i}-\bar{x}_1)^2}\sqrt{\sum_{i=1}^{N}(x_{2i}-\bar{x}_2)^2}} \tag{18}$$

$$\tau = \binom{N}{2}^{-1}\sum_{i<j}\mathrm{sign}[(x_{1i}-x_{1j})(x_{2i}-x_{2j})] \tag{19}$$

TABLE 1. Correlation coefficients between the charging start time and charging duration.

	Pearson correlation coefficient ρ	Kendall rank correlation coefficient τ
No classification	0.1655	0.0512
Intra-day EV charging	-0.4783	-0.3320
Inter-day EV charging	-0.7640	-0.6002

The closer the absolute values of ρ and τ are to 1, the stronger the correlation between variables. As shown in Table 1, the coefficients of correlation between T_S and T_C are both close to 0 when the EV charging behavior is not classified. However, after the classification, the correlation of the two parameters can be apparently shown through the coefficients of correlation. It can be seen from Figure 5 and Table 1 that after backward-shift of the charging behavior before dawn, the charging start time and the charging duration of the inter-day charging exhibit a favorable linear correlation.

Although it has been proved in Section 3 that the time parameters of charging behavior are not independent to each other, the correlation of the parameters cannot be described using statistics if the charging behavior is not classified. The classification of charging behavior in the section lays a foundation for modeling the correlation between the parameters.

V. TIME-ENERGY CHARACTERISTICS OF THE MULTI-TYPE CHARGING BEHAVIOUR BASED ON THE COPULA FUNCTION

The charging characteristics of EVs can be described using its time and energy parameters. Sections 3 and 4 verify that the time parameters of the charging behavior have correlations and classify the EV charging behavior according to the temporal characteristics, respectively. In the section, we applied the copula method to carry out the modeling of the probability distributions and correlations of various parameters of different types of EV charging behavior.

A. SUPERIORITY OF THE COPULA METHOD IN ANALYSING THE DEPENDENCE STRUCTURE OF CHARGING BEHAVIOUR PARAMETERS

Copula functions link the joint distribution function of variables with their marginal distribution functions and describe the correlations of variables. Proposed by Sklar, they have been widely used for the non-parameter measurement for the correlation of random variables [27].

Sklar's theorem is the theoretical basis of the copula method: for marginal distribution functions $F_1(x_1)$, $F_2(x_2), \ldots, F_N(x_N)$, there exists a copula function C satisfying:

$$F(x_1, x_2, \cdots, x_N) = C(F_1(x_1), F_2(x_2), \cdots, F_N(x_N)) \quad (20)$$

If $F_1(x_1), F_2(x_2), \ldots, F_N(x_N)$ are continuous, the copula function C is uniquely determined and $\mathrm{F}(x_1, x_2, \ldots, x_\mathrm{N})$ is the joint distribution function of the marginal distribution functions $F_1(x_1), F_2(x_2), \ldots, F_N(x_N)$.

Analyzing the dependence structure of variables of EV charging behavior using the copula method confers the following advantages:

① The form of the copula function is not limited by the marginal distribution function, so the copula function and the marginal distribution function can be considered, respectively. While studying the distribution characteristics of the parameters of EV charging, the distribution characteristics of single parameters can be described using the method in Section 3, while the dependence structure of parameters can be expressed using the copula function. Compared with the direction construction of the joint distribution function of these parameters, the copula method is able depict the charging characteristics of EVs in a more subtle manner.

② Copula functions have various forms and their structures can be symmetric or asymmetric. They can illustrate the upper-tail dependence, lower-tail dependence, or various dependences for the mixture of the two. The various forms of copula functions allow convenient description of the complicated, changeable correlation between EV charging behavior parameters.

③ The copula function can be used for the stochastic simulation of the distribution of multi-variant models, and provide a basis for the practical application of the charging characteristics of EVs in load forecasting, orderly charging, and cooperative consumption of new energy sources.

B. SELECTION OF THE FORMS AND PARAMETERS OF THE COPULA FUNCTIONS

In Section 4, the EV charging behavior is divided into two types: intra- and inter-day charging. The parameters of each type of the charging behavior show two typical correlations: the first is the correlation between time parameters. According to Section 3, the charging start time T_S and charging duration T_C have prominent coupling characteristics. The second is the correlation between the time and energy parameters. The charged capacity E_C is limited by the charging duration T_C, so they also present certain correlation. In accordance with the two groups of correlations of the three parameters, the time-energy characteristics of the EV charging can be fully described.

Four typical copula functions are used to model the correlation between the time and energy parameters of different types of charging behaviors. The parameters of some copula functions can be directly solved according to the coefficient of correlation, while some need to be calculated using methods such as maximum likelihood estimation [28].

In the maximum likelihood estimation based on nonparametric kernel density estimation, the marginal distribution density of each variable is replaced with the distribution function solved using the nonparametric kernel estimation.

$$\hat{F}(x) = \int_{-\infty}^{x} \hat{f}_K(t)\mathrm{d}t \quad (21)$$

The value of each variable $\hat{f}_K(t)$ can be calculated using the method proposed in Section 3, the value of the log-likelihood function can be expressed as

$$L(\omega) = \sum_{i=1}^{N} \ln c(\hat{F}_x(x_i), \hat{F}_y(y_i); \omega) \quad (22)$$

Where, ω is the parameter to be estimated, c represents the copula probability density function expected to be selected, and $\hat{F}_x(x_i)$ and $\hat{F}_y(y_i)$ are the values of the probability distribution functions of variables x and y at the i th observation data point. Then, the estimated value of ω is:

$$\hat{\omega} = \arg\max L(\omega) \quad (23)$$

The following section introduces the potential copula functions and the selection method for their parameters:

① Gaussian Copula function

Under two-dimensional condition, the distribution function and the density function of Gaussian copula can be separately expressed by Formulae (24) and (25):

$$C(u, v; \theta) = \Phi_\theta(\Phi^{-1}(u), \Phi^{-1}(v)) \quad (24)$$

$$c(u, v; \theta) = \frac{1}{\sqrt{1-\theta^2}} \times \exp\left\{-\frac{\zeta_1^2\theta^2 - 2\theta\zeta_1\zeta_2 + \zeta_2^2\theta^2}{2\left(1-\theta^2\right)}\right\} \quad (25)$$

Where, θ is a parameter characterizing the correlation of variables; $u = F(x)$ and $v = G(y)$ are the marginal cumulative distribution functions of variables x and y, respectively; Φ_θ is a two-dimensional standard normal distribution function with the correlation of coefficient being θ; and Φ^{-1} is the inverse function of the one-dimensional standard normal distribution function. $\zeta_1 = \Phi^{-1}(u)$ and $\zeta_2 = \Phi^{-1}(v)$ are standard normal distribution variables.

The correlation parameter θ of the Gaussian copula can be calculated using the Kendall rank correlation coefficient τ, and the two obey the following relationship:

$$\theta = \sin\left(\frac{\pi\tau}{2}\right) \quad (26)$$

The two-dimensional Gaussian copula function has a symmetric structure and is insensitive to the change of the variables at the tail, so it is suitable for the characterization of the relationship of two-dimensional random variables with symmetric and asymptotically independent tails.

② The t copula function

Under two-dimensional condition, the distribution function and density function of the t Copula function can be expressed using Formulae (27) and (28) [28]:

$$C(u, v; \theta, k) = T_{\theta,k}(T_k^{-1}(u), T_k^{-1}(v)) \quad (27)$$

$$c(u, v; \theta, k) = \frac{t_{\theta,k}(T_k^{-1}(u), T_k^{-1}(v))}{t_k(T_k^{-1}(u))t_k(T_k^{-1}(v))} \quad (28)$$

Where, θ is a parameter for characterizing the correlation of variables and its value is also calculated using Formula (26); k represents the number of degrees of freedom of the t distribution and its value can be determined using the maximum likelihood estimation after determining the value of θ; $T_{\theta,k}$ represents a two-dimensional t distribution function with the correlation coefficient and the degree of freedom being θ and k, respectively; and T_k^{-1} denotes the inverse function of an one-dimensional t distribution function with the number of degrees of freedom being k.

The two-dimensional t copula function has a symmetric structure and thick tails, so it is applicable to depicting the relationship between two-dimensional random variables with symmetric, correlated tails.

③ Gumbel copula function

The basic form of the two-dimensional Gumbel copula is

$$C(u, v) = \exp\{-[(-\ln u)^{\alpha} + (-\ln v)^{\alpha}]^{\frac{1}{\alpha}}\} \quad (29)$$

It has a complicated form of the probability density function, as expressed by Formula (30).

$$\begin{aligned} c\,(u, v) = {} & \frac{(\ln u \ln v)^{\alpha-1}}{uv} \times \exp\{-[(-\ln u)^{\alpha} + (-\ln v)^{\alpha}]^{\frac{1}{\alpha}}\} \\ & \times[(-\ln u)^{\alpha} + (-\ln v)^{\alpha}]^{\frac{1}{\alpha}-2} \\ & \times\{[(-\ln u)^{\alpha} + (-\ln v)^{\alpha}]^{\frac{1}{\alpha}} + \alpha - 1\} \end{aligned} \quad (30)$$

For the parameter $\alpha \in [1, +\infty)$, its value can be solved using Formula (31) [29].

$$\alpha = \frac{1}{1-\tau} \quad (31)$$

The Gumbel copula function has an asymmetric structure and thick upper tail. It is suitable for depicting the relationship between variables with strong upper-tail dependence and lower-tail asymptotical independence.

④ Clayton copula function

The basic form of the two-dimensional Clayton copula function is

$$C(u, v) = (u^{-\alpha} + v^{-\alpha} - 1)^{-\frac{1}{\alpha}} \quad (32)$$

$$c(u, v) = (uv)^{-\alpha-1}(\alpha + 1)(u^{-\alpha} + v^{-\alpha} - 1)^{-\frac{1}{\alpha}-2} \quad (33)$$

The parameter $\alpha \in (0, +\infty)$ can be determined using the maximum likelihood method and its log-likelihood function can be deduced using Formulae (22) and (33) (see Appendix).

Showing an asymmetric structure, the Clayton copula function has a thick lower tail. It is suitable for the characterization of the relationship between variables with strong lower-tail dependence and upper-tail asymptotic independence.

For a pair of the variables to be studied, the Akaike information criterion (AIC) based on likelihood function can be used to select the copula model that most suitable for describing their correlation after determining the parameters for modeling their correlation using different copula functions according to the aforementioned method. When the marginal distribution function of the random variables is expressed as the nonparametric kernel density estimation, the AIC criterion function is:

$$\mathrm{AIC}_k = -2\sum_{i=1}^{N} \ln c(\hat{F}_x(x_i), \hat{F}_y(y_i); \theta_k) + 2k \quad (34)$$

Where k represents the number of parameters in the copula function, and the copula model which minimizes AIC_k is most suitable for describing the relationship between the variables to be studied.

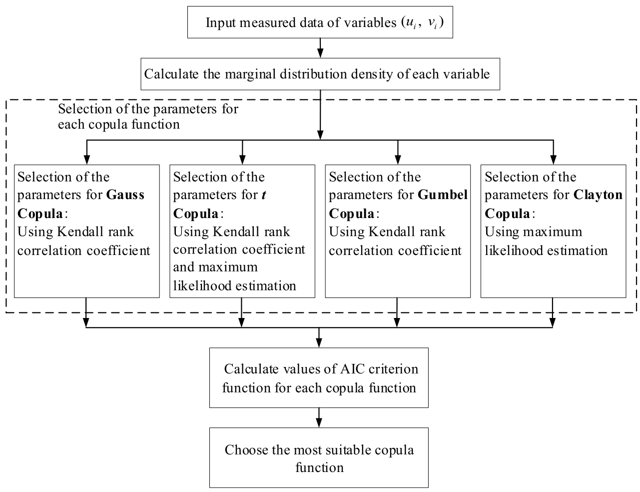

FIGURE 6. Selection of the form and parameters of the copula function.

In summary, the flow chart for selecting the parameters and forms of the copula functions that describe relations of different variables is illustrated in Figure 6.

C. SELECTION AND ANALYSIS OF THE COPULA FUNCTIONS

By using the method described in Section 5.2, we analyzed the correlations of the charging start time T_S, charging duration T_C, and the charged capacity E_C of the intra- and inter-day EV charging. The results are displayed in Table 2 and Figure 7.

Owing to T_S and T_C being negatively correlated, there are no Gumbel and Clayton copula functions for them. For the intra-day EV charging, the AIC of the t copula function of T_S and T_C is -1756.48, which is smaller than that of the Gaussian copula function, so the t copula function with the correlation coefficient and number of degrees of freedom of -0.4982 and $k = 6$ is more suitable for describing the

TABLE 2. Selection of the forms and parameters of copula functions.

	Intra-day EV charging				Inter-day EV charging			
	Charging start time and charging duration T_S - T_C		Charging duration and charged capacity T_C - E_C		Charging start time and charging duration T_S - T_C		Charging duration and charged capacity T_C - E_C	
Copula function	AIC value	Parameter value	AIC	Parameter value	AIC value	Parameter value	AIC value	Parameter value
Gaussian	-1495.49	-0.4982	-4866.35	0.7793	-2852.40	-0.8092	-161.13	0.2210
t	-1756.48	-0.4982, 6	-6096.01	0.7793, 3	-3105.27	-0.8092, 4	-200.42	0.2210, 5
Gumbel	None		-4604.85	2.3194	None		-156.26	1.1653
Clayton			-5905.49	2.0631			-272.61	1.2651

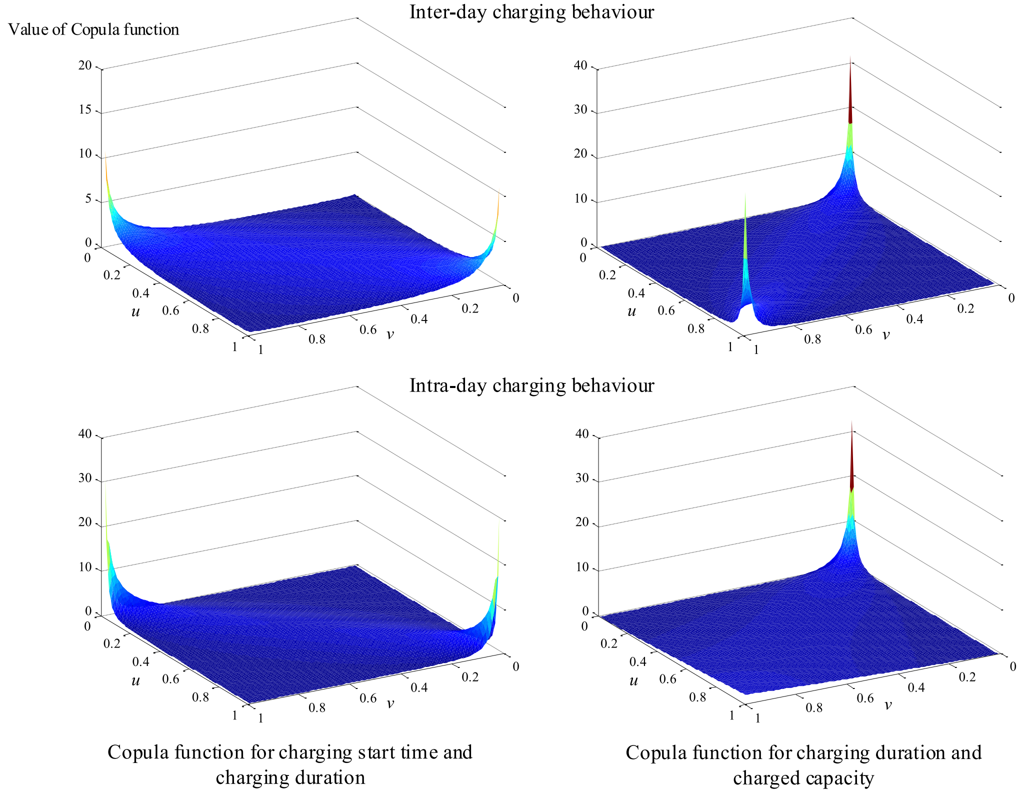

FIGURE 7. Copula functions with different variables.

correlation between the two parameters. Similarly, it is also reasonable to depict the relationship between T_S and T_C of the inter-day EV charging using the t copula function with the correlation coefficient and number of degrees of freedom of -0.8092 and $k = 4$. The t copula function has thick tails, which indicates that T_S and T_C present prominent tail-dependence. Meanwhile, no matter whether for intra- or inter-day EV charging, when the charging starts early in a day, the charging is likely to be sustained for a long time; while if the charging starts later, the charging duration is also likely to be short. We also find that the absolute value of the correlation coefficient in the t copula function of T_S and T_C for inter-day charging is closer to one, with more apparent tail-dependence. This is related to the concentrated end-times of inter-day charging behavior.

The t copula function with the correlation coefficient of 0.7793 and three degrees of freedom also presents superiority in depicting the relation between the charging duration T_C and the charged capacity E_C of the intra-day EV charging. For intra-day EV charging, when the charging duration is short, little quantity of electricity is charged due to the limitation of the duration; while with the increase in the charging duration, an EV has a larger probability of obtaining more energy from the power grid.

As for the inter-day EV charging, it is more reasonable to describe the relationship between the charging duration T_C and the charged capacity E_C using the Clayton copula function with lower-tail dependence and upper-tail asymptotic independence. This is mainly because inter-day EV charging lasts for a longer time. Similarly, when the charging duration is short, the charged capacity E_C is also small due to the aforementioned limitation; however, as the charging duration reaches a certain time, the relationship between E_C and T_C gradually weakens. This suggests that the overlong charging duration does not mean that an EV needs to acquire energy in a way that is positively correlated with T_C, which provides conditions for the orderly management of the charging of EVs.

VI. APPLICATION OF EV CHARGING CHARACTERISTICS

After modeling the EV charging characteristics, different types of the charging behavior can be simulated according to the probability distributions of each parameter and the correlations of various parameters. On this basis, we analyzed the influences of the EV charging load on the power grid and its potential in orderly charging management and cooperative consumption of new energy sources.

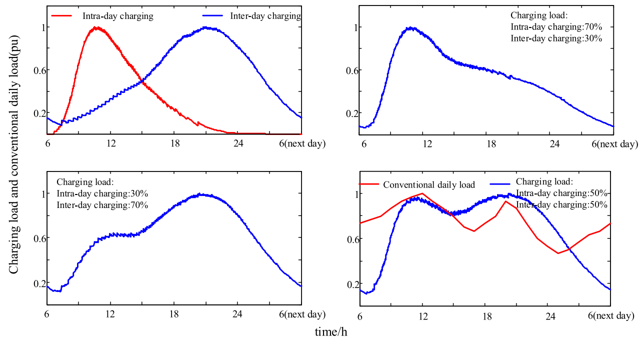

FIGURE 8. Charging load curves of EVs and conventional daily load curves.

A. EV LOAD FORECASTING: INFLUENCE OF DISORDERED CHARGING ON THE POWER GRID

Given the probability distributions for the charging start time T_S, the charging duration T_C, and the charged capacity E_C, the correlations between T_S and T_C as well as between T_C and E_C can be modeled using the copula functions proposed in Section 5. Then, a set of random numbers capable of describing the time-energy characteristics of EV charging can be generated using the following method [30]:

① Three random numbers u, s, and t which are uniformly distributed in the range [0, 1] are generated;

② Assume that $c_u(v) = \frac{\partial C(u,v)}{\partial u}$ is the conditional distribution function of copula function C, and that $c_u^{(-1)}(v)$ is its pseudo-inverse function. In addition, C_{SC} is the copula function between T_S and T_C, and C_{CE} is the copula function between T_C and E_C. Let $v = c_{SC,u}^{(-1)}(s)$ and $w = c_{CE,u}^{(-1)}(t)$, then u, v, and w are the values of the marginal distribution functions of the charging duration T_C, charging start time T_S, and charged capacity E_C, respectively.

③ F_S, F_C and F_E are the marginal probability distribution functions of T_S, T_C and E_C, respectively. Let $t_S = F_S^{(-1)}(v)$, $t_S = F_S^{(-1)}(v)$ and $e_C = F_C^{(-1)}(u)$, then t_S, t_C and e_C are a group of random numbers following the distribution of, and relationships between the charging characteristic parameters.

This method was adopted to conduct the stochastic simulation for the charging behavior of N EVs. The actual power of the charging piles in the platform is in the range of 3 to 5 kW, so it was considered that the EVs were charged with a constant power of 4 kW. According to the charging start time T_S and charged capacity E_C of each EV, the charging load curves are obtained. Then, we attained the overall charging load curve is obtained by superposing the charging load curves of N EVs.

The load curves with different proportions of the intra- and inter-day EV charging were computed (Figure 8). For ease of comparison, the peak load was taken as the reference value to carry out per unit calculations for the load data, through which the following two conclusions were obtained:

① The spatial difference of the EV charging loads can be reflected by the proportions of different charging behaviors. If the intra-day EV charging accounts for a larger proportion, the charging load curve shows apparent characteristics of the working district: users park their EVs for charging before going to work, and then drive their EVs out of the charging stations after work, so the charging load climbs the peak in the time period of 9:00 to12:00 AM. When the inter-day charging accounts for a larger proportion, the peak load occurs in the time period of 20:00 to 22:00 PM. The load is heavy at night, with obvious characteristics of a residential district, and users charge their EVs for a long time after ending their trip on that day. Under conditions that the intra- and inter-day EV charging behaviors account for the same proportion, the charging load curve has two peaks. This is similar to the temporal distribution of EV charging loads in large areas, such as, cities.

② The comparison between the EV charging load curve and the conventional load curve reveals that the peak periods of the two curves are superimposed and the former presents a larger difference between the maximum and minimum loads. When the EV charging load reaches 30% in the power distribution network, its peak load will increase to 1.4 times that of its original value. If the EV charging is not orderly and guided under this condition, more waste of the investment is likely to occur at the fixed facility, thus reducing the economic efficiency of the operation of the power distribution network.

B. ORDERLY CHARGING POTENTIAL AND COORDINATION WITH THE POWER GENERATION NETWORK USING RENEWABLE ENERGY SOURCES

EVs, as mobile energy storage, are expected to play a role in many aspects, including peak load shifting, cooperative consumption of new energies, and provision of an auxiliary service for the power system. In the research, we verified the conditions for the orderly charging management of EVs by using the EV charging model based on the measured data.

The potential of orderly charging of EVs can be evaluated using the ratio R of the charging duration to the time period in which the electric energy is unidirectionally transmitted from the power grid to the EVs. The ratio R is called the charging time flexibility of an EV. The larger the value of R, the smaller the ratio of the time period in which the electric energy is unidirectionally transmitted from the power grid to

TABLE 3. **Charging time flexibility of EVs.**

Range of R	Proportions of EV charging behaviours	
	Intra-day EV charging	Inter-day EV charging
$(3, \infty)$	15.90%	58.63%
(2, 3]	43.66%	34.73%
(1.25, 2]	34.17%	6.15%
(1.25, 2]	34.17%	6.15%

the EVs to the total time in which EVs are connected with the power grid. On that condition, the EVs can be more flexibly charged.

As shown in Table 3, the value of R for intra-day EV charging is usually greater than two, while that for inter-day EV charging is usually greater than three. The result indicates that, the time in which the electricity is transmitted from the power grid to the EVs accounts for only a small proportion of the time in which the EVs are connected to the power grid. Therefore, the temporal distribution of EV charging operations presents favorable flexibility. By taking reasonable incentive and guidance measures, we are able to avoid EV charging during peak hours, reduce the investment in charging facilities, and provide a peak load shifting service for the power grid.

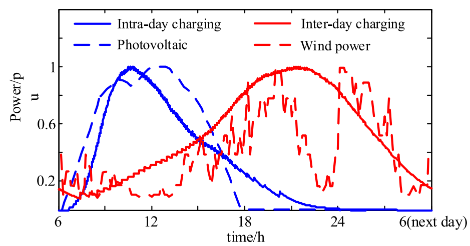

FIGURE 9. **Curves of the EV charging load and the power generation output using renewable energy sources.**

Figure 9 shows the comparison of the EV charging load curves with the typical daily output curves of photovoltaic and wind power generation: the intra-day EV charging load is similar to the typical output curve of a photovoltaic power generation system [31]. The Kendall rank correlation coefficient was 0.79 between the time series of the two curves. The time series of the inter-day EV charging load curve and the typical output curve of the wind power generation [32] presented a Kendall rank correlation coefficient of 0.44. This indicates that different types of EV charging behavior are coordinated with the output of the power generation using renewable energy sources. Therefore, if coordination can be made best by designing a reasonable scheduling policy, EVs can play their part in consuming power generated using renewable energy sources, reducing the configuration capacity of energy storage, and improving the rate of utilization of renewable energy. In this way, EVs can become more environmentally-friendly.

VII. CONCLUSION

We studied actual operational data pertaining to an EV charging service company in Nanjing, China. The following conclusions may be drawn:

① The one-dimensional probability distribution of charging parameters was fitted using the kernel density estimation method. On this basis, we verified that the time parameters of EV charging presented a strong correlation using the convolution formula. If the correlation were ignored, large errors would occur in the calculation.

② EV charging was divided into two types: intra- and inter-day EV charging according to whether the charging ended on the same day on which it started, or not. The results reveal that the correlations between the charging start time T_S, charging duration T_C, and charged capacity E_C cannot be described using statistics if the charging behavior is not classified. In other words, the classification of the charging behavior is the basis for the quantitative modeling of the correlations between the parameters. In addition, the overall difference in EV charging characteristics in different districts can be revealed in accordance with the different proportions of the two charging behaviors.

③ We analyzed the correlations of two groups of parameters, charging start time T_S and charging duration T_C, as well as charging duration T_C and charged capacity E_C based on copula functions and the fitting results of the one-dimensional probability density of the charging parameters. Then, the forms and parameters of the copula functions were selected using the correlation coefficients and the maximum likelihood method. The results demonstrated that the T_S and T_C of intra- and inter-day EV charging behaviors are negatively correlated, accompanying the strong tail-dependence observed. T_C and E_C, for intra-day EV charging, are positively correlated, together with a strong tail-dependence. Inter-day EV charging has a strong lower-tail dependence and is asymptotically independent of the upper tail: this means that the relationship between charged capacity E_C and charging duration T_C weakens when T_C is large.

④ EV charging characteristics can be described in accordance with the probability distributions and the correlations of the charging start time T_S, charging duration T_C, and charged capacity E_C. One could also carry out extensive research on the load forecasting of EV charging and the optimization of the charging schedule. Through stochastic simulation, we simulated the load curve under conditions of disordered charging and verified the potential benefits of, and ability to, charge EVs in an ordered manner. Meanwhile, we also analyzed the potential of EVs in the orderly management of charging and its coordination with the output of a power generation network using renewable energy sources.

APPENDIX

Log-likelihood functions of each copula function

Gaussian Copula

$$L(\theta) = T \times \ln \frac{1}{\sqrt{1-\theta^2}} - \frac{\theta^2 \sum_{i=1}^{T} \left(\zeta_{1i}^2 + \zeta_{2i}^2\right) - 2\theta \sum_{i=1}^{T} \zeta_{1i}\zeta_{2i}}{2\left(1-\theta^2\right)}$$

t Copula

$$L(k) = \sum_{i=1}^{T} t_{\theta,k}(T_k^{-1}(u_i), T_k^{-1}(v_i)) - \sum_{i=1}^{T} t_k(T_k^{-1}(u_i)) - \sum_{i=1}^{T} t_k(T_k^{-1}(v_i))$$

Gumbel Copula

$$\begin{aligned} L(\alpha) = &\sum_{i=1}^{T} ((\alpha - 1)\ln(\ln u_i \ln v_i) - \ln u_i - \ln v_i) \\ &- \sum_{i=1}^{T} [(-\ln u_i)^{\alpha} + (-\ln v_i)^{\alpha}]^{\frac{1}{\alpha}} \\ &+ (\frac{1}{\alpha} - 2) \sum_{i=1}^{T} [(-\ln u_i)^{\alpha} + (-\ln v_i)^{\alpha}] \\ &+ \sum_{i=1}^{T} \{[(-\ln u_i)^{\alpha} + (-\ln v_i)^{\alpha}]^{\frac{1}{\alpha}} + \alpha - 1\} \end{aligned}$$

Clayton Copula

$$L(\alpha) = \alpha \sum_{i=1}^{N} \ln u_i v_i + T\ln(\alpha + 1) - (\frac{1}{\alpha} + 2) \sum_{i=1}^{T} \ln(u_i^{\alpha} + v_i^{\alpha} - u_i^{\alpha} v_i^{\alpha})$$

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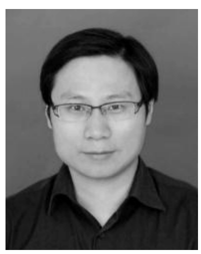

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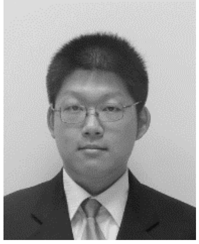

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