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***Abstract*—Short-term load forecasting plays a critical role in power system planning and operation. Along with the electrification of various loads, electricity demands are becoming increasingly hard to predict. Notably, the recent rise in electric vehicles (EVs) has further contributed to this unpredictability. To address this issue, this paper proposes a probabilistic load forecasting strategy utilizing Gaussian process regression, structured in a day-ahead manner. While many works focus on deterministic prediction, probabilistic forecasting offers additional insights into variability and uncertainty, enabling more flexible and reliable operation for power systems. To enhance the accuracy of the load forecasting model, the inputs include features related to EV charging habits as well as commonly used weather information. The load forecasting results are evaluated using various metrics, including conventional ones that assess the accuracy of point forecasts, as well as additional metrics that test the reliability of prediction intervals. The proposed load forecasting method is finally tested on real residential power consumption data and EV charging data sampled from real-world sources. The results prove that the new features can greatly improve the performance of the load forecasting method.**

***Index Terms*—load forecasting, electrical vehicle, Gaussian process regression, probabilistic forecasting.**

I. Introduction

Load forecasting has been a critical topic for power systems. An accurate load forecast might lead to great savings for utilities, while a larger forecasting error can cause a severe increase in operation costs [1]. In particular, short-term load forecasting (usually minutes, hours, or day-ahead) can provide valuable insights to enhance system operations [2]. Typically, load forecasting is conducted at aggregated levels, e.g., a certain area, a given feeder, or under a distribution transformer [3] to predict the electricity demand. It has always been a challenging task due to the complex temporal dependencies and various exogenous factors, like the weather conditions [4].

Conventionally, utilities relied heavily on the expected values obtained from the load forecasting process for decision-making. Thus, various methods have been investigated and studied in pursuit of reducing prediction error. An ensemble forecasting framework is introduced in [5] to improve the prediction accuracy for aggregated loads. But load forecasting, which deals with randomness, is fundamentally a stochastic rather than a deterministic problem[6]. Therefore, it is more reasonable to get the output of a load forecaster in a probabilistic form, e.g., a probability density function or a prediction interval (PI). In the past years, the growing market competition, aging of electrical devices, and high proliferation of distributed energy resources have highlighted the importance of probabilistic load forecasting [3]. As pointed out in [7], some utilities have begun to adopt a probabilistic perspective when considering potential demand levels, and a density forecasting of long-term peak demand is then introduced. A constrained quantile regression averaging method is developed in [8] to combine several probabilistic forecasting models to improve the performance.

Besides, the rapid growth of electrical vehicles (EVs) is eventually altering users' load profiles. Results in [9] indicate that the integration of EVs into distribution networks may not only raise the peak load demand but also shift the timing of the peak. As claimed in [10], the integration of EVs can bring a positive impact on power systems when operated correctly, but meanwhile, EV charging loads may aggravate load-side uncertainties. In order to enhance the power system operation in response to the growing penetration of EVs, some researchers have been concentrating on EV charging load prediction. A hybrid forecasting model for EV's charging behavior is proposed in [11]. A reinforcement learning-based EV charging load forecasting method is introduced in [12]. But [11] and [12] focus on the individual EV level or the charging station level, with their outputs being deterministic. However, due to the high uncertainties caused by EV charging,

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the deterministic predictions are hard to ensure accuracy, thus resulting in an inappropriate operation. Additionally, compared to forecasters for the individual EV or charging station, forecasting at aggregated levels (such as an entire feeder) can be more valuable for power system operators.

To this end, we propose a probabilistic forecasting strategy based on Gaussian Process Regression (GPR) [13] for short-term load forecasting of a distribution feeder integrated with EV charging demands. As a non-parametric method, GPR shows great flexibility to adapt to complex relationships. With the predicted values and the associated uncertainties as the outputs, GPR also provides a measure of confidence of the prediction. To track the pattern of the EV charging load and improve the performance, extra features related to the EV charging are included in the input data. The contributions of the paper can be summarized as:

- A probabilistic forecasting model is adapted for day-ahead load forecasting of a utility feeder with EV charging loads. Compared to deterministic forecasting, the probabilistic model is more in line with the stochastic nature of electricity usage, especially when EV charging is integrated.
- The forecasting results are evaluated using not only deterministic metrics. The obtained PIs are quantitatively evaluated using metrics accounting for both interval lengths and coverage probabilities to demonstrate their reliability.

II. Dataset Description

The load forecasting is based on the real residential load data of a utility feeder in the U.S. and the EV charging load profiles collected from the nearby area. The dataset contains historical load information for 3 years, with a resolution of one hour. Based on the time stamps, corresponding weather information is also collected as the input features for load forecasting.

A. Residential load data

The utility feeder includes more than one hundred residential customers, all equipped with smart meters. By neglecting the losses, we treat the sum of all the customers' loads recorded from the smart meters as the load of the whole feeder. The total load of the feeder at time t can be denoted as $P_R(t)$. Note that no EVs are connected to the utility feeder, which means $P_R(t)$ here is the EV-free load.

B. EV charging load data

Unlike the customer-level smart meters for measuring electrical consumption at the customer-level, the amount of meters that measure the EV charging power alone is often limited. Thus public driving behavior surveys are often used as source information for modeling EV charging loads [14]. But in this work, we incorporate the real EV charging load data in the modeling process. The modeling process is outlined below.

Firstly, a kernel density estimation (KDE) is used for fitting the probability density function of the starting charging time. Assume that $CT_1, CT_2, \ldots, CT_n$ are the samples of the starting charging time (CT). The probability density of CT is:

$$f(CT) = \frac{1}{nV}\sum_{i=1}^{n} K\left(\frac{CT - CT_i}{h}\right) \tag{1}$$

where n is the number of samples, h is the bandwidth, which is the parameter in KDE that controls the smoothing of the resulting density curve. $K(\cdot)$ denotes the kernel function, weighing the contributions of sample points to the estimation of the density at CT. Here, the Gaussian kernel is utilized as the kernel function due to its symmetrical characteristic.

The charging load of EVs is affected by temperature, driving distance, and charging power. In this work, we select Gamma distribution [15] for the battery capacity distribution C_0, as shown in (2), and assume the initial state of charge SOC_0 obeys a normal distribution $SOC_0 \sim N(0.8, 0.12)$, respectively.

$$G(C_0) = \frac{1}{\beta_C^{\alpha_C}\Gamma(\alpha_C)} C_0^{\alpha_C - 1} e^{-\frac{C_0}{\beta_C}} \tag{2}$$

Then, the initial energy of the EV i's battery can be expressed as:

$$E_0^i = C_0^i \times SOC_0^i \tag{3}$$

The influence of environmental factors such as ambient temperature on the energy consumption of EVs during driving is further adopted as a regression model (4) as suggested in [16]:

$$\begin{aligned} e_0 = b + v_1 v + v_2 v^2 + c_e^T P_e + aA \\ + h_e H_e + t_1 T + t_2 T^2 + t_3 T^3 \end{aligned} \tag{4}$$

where e_0 and v denote the energy consumption per kilometer and the average travel speed, respectively. P_e are the vectors representing the percentage of link length with a gradient. A and H_e are the air conditioner and heater usage times per kilometer, respectively. T is the ambient temperature, which can be obtained from the regional weather information. Others are coefficients. Therefore, the remaining battery level of the EV can be obtained:

$$E^i = E_0^i - e_0^i \times l^i \tag{5}$$

where l^i is the traveling distance sampled from the log-normal distribution. It is assumed in this work that users will charge when the remaining battery is below a specific value to deal with range anxiety. The charging power of vehicle i can be randomly sampled from a uniform distribution: $\overline{P}_{char}^i \sim$ U$(4.5, 5.5)$ (kW) [17]. Considering the range anxiety, the charging power of the vehicle i is:

$$P_{char}^i = \begin{cases} \overline{P}_{char}^i(\text{kW}) & \text{if } E^i < a_1^i \times C_0^i \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where a_1^i is the range anxiety coefficient, which is randomly chosen from 0.15 to 0.3.

Vehicle i's charging time duration T_C^i depends on the electricity consumed and the charging power. Considering the continuity of battery use, it can only be charged to 0.8 of its full capacity:

$$T_C^i = \frac{0.8 \times C_0^i - E^i}{\overline{P}_{char}^i} \tag{7}$$

From the starting charging time CT_i, the charging power P_{char}^i and charging time T_C^i, we can get the time-series charging load of EV i, denoted as $P^i(t)$. Then, the total charging load $P_{EV}(t)$ can be calculated by adding the time-series charging load of all the EVs:

$$P_{EV}(t) = \sum_{i=1}^{N^{EV}} P^i(t) \tag{8}$$

III. Methodology

A. Features for Load Forecasting

Based on the available dataset, the following features are used for load forecasting:

- $H_D(t)$: Hour index of the day. $H_D(t) \in \{1, 2, \cdots, 24\}$.
- $D_W(t)$: Day index of the day. $D_W(t) \in \{1, 2, \cdots, 7\}$.
- $D_Y(t)$: Day index of the year. $D_Y(t) \in \{1, 2, \cdots, 365\}$.
- $M_Y(t)$: Month index of the year. $M_Y(t) \in \{1, 2, \cdots, 12\}$.
- $\boldsymbol{T}_H(t)$: Temperature information of the past 24 hours. $\boldsymbol{T}_H(t) = \{T_{t-24}, \cdots, T_{t-2}, T_{t-1}\}$.
- $\boldsymbol{T}(t)$: Temperature at time t. To simulate the potential errors of weather forecasting, Gaussian noise is added.
- $\boldsymbol{P}_H(t)$: Historical load data of the past 24 hours. $\boldsymbol{P}(t) = \{p_{t-24}, \cdots, p_{t-2}, p_{t-1}\}$.
- $C_H(t)$: This feature is related to users' charging preference, representing the charging probability at time t. In practice, this feature can be obtained through questionnaires about users' charging habits or based on historical EV charging information.

B. Gaussian Process Regression

Given the significance of incorporating uncertainty into load forecasting, the GPR technique is utilized for its outstanding capability of measuring uncertainties and excellent flexibility in capturing nonlinearity. The fundamental idea of GPR is to predict dependent variables based on the distances between explanatory variables. Specifically, in our load forecasting task, the explanatory variables $\boldsymbol{X} = [x_1, x_2, ..., x_n]$ include the input features for load forecasting, while the response variables $P(x) = [p(x_1), p(x_2), ..., p(x_n)]$ are the hourly load of the whole feeder. Different from the deterministic models, here $p(x_t), t \in [1, ..., n]$ is not a single value but a random variable, and the function $p(\cdot)$ is drawn from a Gaussian process:

$$p(x) \sim \mathcal{GP}(\mu(x_t), k(x_t, x_t')), \tag{9}$$

where $\mu(x_t)$ reflects the expected value of the load, and $k(x_t, x_t')$ is the covariance function to show the dependence between data points. In this work, the Squared Exponential Kernel function is selected as the covariance function:

$$k(x_t, x_t') = \sigma^2 \exp\left(-\frac{\|x_t - x_t'\|_2^2}{2\lambda^2}\right) \tag{10}$$

The covariance function (10) is utilized to calculate the covariance matrix of the data points in the training set. The hyperparameters of (10) are determined by the training process of GPR. From the training set, a joint Gaussian distribution in n dimensions constructed on the training data points can be written as follows:

$$P(x) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}), \tag{11}$$

where

$$\boldsymbol{\mu} = \begin{bmatrix} \mu(x_1) \\ \vdots \\ \mu(x_n) \end{bmatrix} \tag{12a}$$

$$\boldsymbol{\Sigma} = \begin{bmatrix} K(x_1,x_1) & \cdots & K(x_1,x_n) \\ \vdots & \ddots & \vdots \\ K(x_n,x_1) & \cdots & K(x_n,x_n) \end{bmatrix} \tag{12b}$$

After training, the GPR can predict the load at a certain time t by conditioning the joint Gaussian distribution of the training and test data:

$$\begin{bmatrix} p(x_1) \\ \vdots \\ p(x_n) \\ p(x_t) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \boldsymbol{\mu} \\ \mu_t \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma} & \boldsymbol{\Sigma}_{Nt} \\ \boldsymbol{\Sigma}_{Nt}^T & \boldsymbol{\Sigma}_{tt} \end{bmatrix}\right) \tag{13}$$

where $\mu_t = \mu(p_t)$, $\boldsymbol{\Sigma}_{Nt}$ and $\boldsymbol{\Sigma}_{Nt}^T$ are the training-test set covariance and its transpose. $\boldsymbol{\Sigma}_{tt}$ is the test set covariance. Let $P_x = [p_1, ..., p_n]$ denote the observation of $[p(x_1), ..., p(x_n)]$. From the Bayes' theorem, we have:

$$p(x_t)|P_x \sim \mathcal{N}(\mu(x_t), \sigma(x_t)) \tag{14}$$

where $\mu(x_t)$=$\boldsymbol{\Sigma}_{Nt}^T\boldsymbol{\Sigma}^{-1}P_x$,$\sigma(x_t) = \boldsymbol{\Sigma}_{tt} - \boldsymbol{\Sigma}_{Nt}^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\Sigma}_{Nt}$. The prediction results are probabilistic for the test point t, providing not only the expected value but also a measure of uncertainty.

C. Evaluation Methods

To evaluate the performance of the proposed probabilistic load forecasting, two categories of metrics are used: the first category consists of deterministic metrics, while the second category assesses the reliability and representativeness of the forecasted distributions.

The deterministic metrics include the standard mean absolute percentage error (MAPE), and root mean squared error (RMSE). The definition over the total number of N samples are given as:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|\overline{p}(x_t) - p^*(t)|}{p^*(t)} \times 100\% \tag{15}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\overline{p}(x_t) - p^*(t))^2} \tag{16}$$

where $\overline{p}(x_t)$ denotes the expected value of the forecasting load at time t, while $p^*(t)$ represents the real load value at time t. However, since these commonly used deterministic metrics focus solely on the expected values of the forecasting, they do not adequately evaluate the proposed probabilistic load forecasting.

To this point, quantitative evaluation of prediction intervals [18] are included to test the probabilistic performance. Two important aspects of PIs: the length and coverage probability, are both considered in the quantitative evaluation. It is preferable to get shorter PIs, since too wide PIs might be meaningless and hard to be applied in system operation. To measure the relative lengths of PIs to the actual values, the normalized mean PI length (NMPIL) is introduced:

$$NMPIL = \frac{1}{N}\sum_{t=1}^{N}(\frac{p^U(x_t) - p^L(x_t)}{p^*(t)}) \tag{17}$$

where $p^U(x_t)$ and $p^L(x_t)$, are the upper and lower bounds of the PIs of time t. A larger NMPIL value indicates that the PIs are longer in comparison to the actual values.

Another critical criterion for PIs is the coverage probability, which monitors how frequently the actual data points would lie within the constructed PIs. The PI coverage probability (PICP) can be calculated as:

$$\begin{aligned} PICP &= \frac{1}{N}\sum_{t=1}^{N} c_t \\ c_t &= \begin{cases} 1 & \text{if } p^*(t) \in [p^U(x_t), p^L(x_t)] \\ 0 & \text{otherwise} \end{cases} \end{aligned} \tag{18}$$

Ideally, the PICP should be close to the confidence level on which the PIs are based. For example, if a variable follows the normal distribution with mean value μ, standard deviation σ, the ideal values of PICPs for PIs $[\mu-\sigma, \mu+\sigma]$, $[\mu-2\sigma, \mu+2\sigma]$ and $[\mu-3\sigma, \mu+3\sigma]$ should be 68%, 95% and 99.7%, respectively, as shown in Fig. 1. But in practice, the PICP may not perfectly match with the ideal values due to various factors, e.g. data noise, model under- or over-fitting. Therefore, the difference between the actual PICPs and the ideal values should also be considered when judging the quality of PIs.

Sometimes PI lengths and PICP are interconnected: wider PIs may contain more data points, leading to larger PICP and vice versa. To account for both criteria, a coverage-length-based criterion (CLC) is also introduced in [18]:

$$\begin{aligned} CLC &= \frac{NMPIL}{S(PICP, CP^*, \eta)} \\ S(PICP, CP^*, \eta) &= \frac{1}{1 + e^{-\eta(PICP - CP^*)}} \end{aligned} \tag{19}$$

$S(\cdot)$ is a sigmoidal function and CP* is the ideal value of the coverage probability for the given PI. η is a positive parameter. The further the PICP is below CP*, the more the sigmoidal function's value decreases; meanwhile, the value of CLC will greatly increase. So the smaller value of CLC indicates a better-constructed PI, with short PI length and great coverage probability.

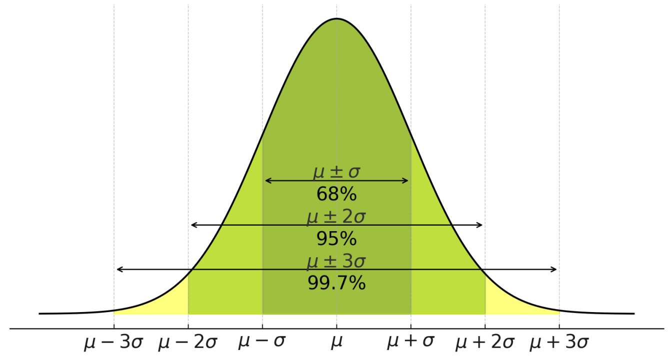

Fig. 1. Normal distribution with mean value μ, standard deviation σ.

IV. Case Study

A. Overview

In this section, the proposed GPR-based probabilistic load forecasting is applied on our dataset to explore its effectiveness. The dataset includes the real load data of the whole utility feeder and the charging load for 30 electric vehicles, sampled from a model based on real EV charging load profiles. The load information of 22 consecutive months is set as the training set, and the following 2 months are used as the testing set. After training and obtaining the joint Gaussian distribution model, the load forecasting process is conducted in day-ahead format, which means $\overline{p}(x_t)$, the expected value of the forecasting load at time t will be added to the input feature to predict $p(x_{t+1})$. This process is iteratively repeated until the forecasting is conducted for every hour of the day. Finally, the results are evaluated from both deterministic and probabilistic perspectives.

B. Results Analysis and Performance Comparisons

The GPR-based load forecasting is performed under three different settings for comparison:

Case 1: In this case, the historical data without EVs is used to forecast the EV-free loads of the utility feeder. All the time indices $H_D(t), D_W(t), D_Y(t)$ and $M_Y(t)$, historical load data $\boldsymbol{P}(t)$, and the weather-related features $T(t)$ and $T_H(t)$ are included in the input features $\boldsymbol{X}$. Note that the historical load data includes only the residential loads, which means $\boldsymbol{P}(t) = \{P_R(t-24), \cdots, P_R(t-2), P_R(t-1)\}$. The corresponding output is the EV-free residential load of the feeder at time t, which means $p(x_t) = P_R(t)$.

Case 2: In this case, we use the historical data with EVs to forecast the loads of the utility feeder including EV charging loads. With the same input features with Case 1, the output load data is replaced by the sum of the residential loads and the EV charging loads. Then we have $\boldsymbol{P}(t) = \{P_R(t-24) + P_{EV}(t-24), \cdots, P_R(t-2)+P_{EV}(t-2), P_R(t-1)+P_{EV}(t-1)\}$, and $p(x_t) = P_R(t)+P_{EV}(t)$. No extra feature is included in the input feature set $\boldsymbol{X}$.

Case 3: On the basis of Case 2, the user's charging habit feature $C_H(t)$ is included in the input feature set $\boldsymbol{X}$. The

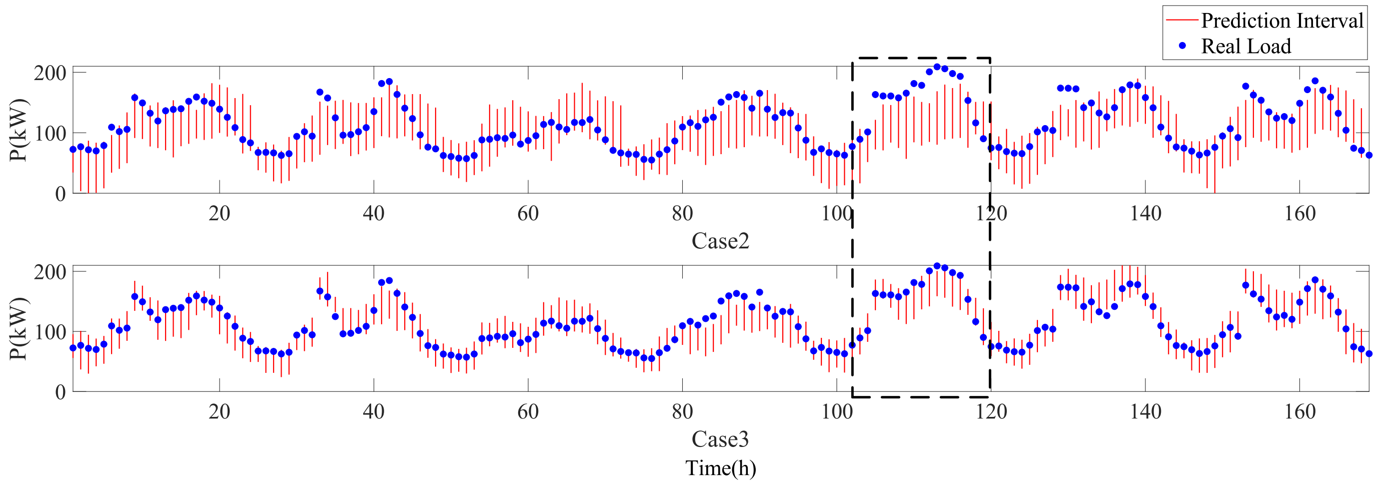

Fig. 2. The coverage of the PIs to the true value in Case 2 and Case 3.

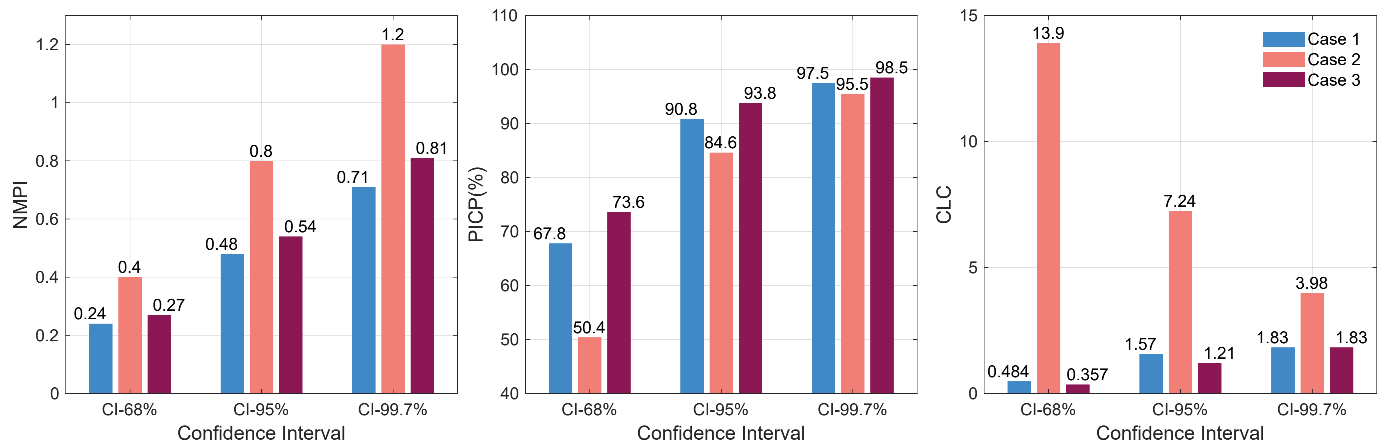

Fig. 3. Quantitative evaluation results of PIs.

output is also the sum of the residential load $P_R(t)$ and the EV charging load $P_{EV}(t)$.

TABLE I
DETERMINISTIC METRICS

Case	1	2	3
MAPE	9.0714%	21.3612%	9.2057%
RMSE	12.0494	25.6835	12.5291

The deterministic performance of three different cases is listed in Tab. I. In Case 1, the GPR-based method achieves reliable accuracy with a MAPE of less than 10%. However, after including EV charging loads, the performance significantly deteriorates, with the MAPE increasing to over 20%. It proves that the increase of EV charging loads in the distribution systems can greatly heighten the unpredictability in load forecasting, and the widely-used features like time indices and weather information may no longer be adequate for accuracy prediction. Then, in Case 3, by including the users' charging habit feature $C_H(t)$, the accuracy can be significantly improved.

Fig. 2 shows forecasting results of one week in the testing set. The PIs from the GPR-based method from Case 2 and 3. The red lines represent the PIs formed by plus and minus two standard deviations, which means the ideal value of coverage probability should be 95%. And the blue dots are the real values. As can be seen, the lengths of PIs in Case 2 are obviously longer than that in Case 3. But the coverage probability is actually lower. As highlighted by the rectangle, some data points in Case 2 are difficult to include within the PIs. Conversely, the majority of data points in Case 3 can be encompassed by the PIs. It is intuitively demonstrated in Fig. 2 that incorporating the user charging habit feature allows the GPR model to more accurately track the uncertain characteristics of the load when integrated with EV charging loads.

Additional quantitative evaluation results are presented in

Fig. 3. As can be seen in Case 1, without the integration of EV charging loads, the proposed GPR-based method can achieve close PICPs with the ideal values while maintaining low NMPIL values. It indicates that the GPR-based method is capable of capturing the complex relationships between the input features and the electrical load. However, the performance of Case 2 is getting worse: the larger NMPIL values indicate that the output PIs are wider, but the PICPs are even worse. It further proves that with the integration of more EV charging loads, the load forecasting task becomes more complex. After the introduction of the new feature, Case 3's performance greatly improved compared to Case 2. The NMPIL values get slightly larger than Case 1, which is reasonable since the integration of EV charging loads improves the uncertainty and unpredictability. The PICP values are even closer to the ideal values. The CLCs of Case 1 and Case 3 are much smaller than Case 2, which means the PIs from Case 1 and Case 3 are much more reliable. The user's charging habit feature can significantly improve the PI quality of the GPR-based load forecasting method.

V. Conclusion

This paper focuses on probabilistic short-term load forecasting. A GPR-based method is proposed and tested on a real residential load data set. To adapt to the unpredictability caused by the increasing penetration of EVs, the EV charging loads are also considered. To increase the forecasting accuracy, the users' charging habit feature is also incorporated. Deterministic and probabilistic metrics are then used for evaluating the forecasting results in terms of the expected values and quality of PIs, respectively. The performance gap between the first two cases in the case study highlights the unpredictability caused by the EV charging loads. Then, by considering the users' charging habit feature, the forecasting accuracy can be greatly increased. The metrics indicate that the proposed GPR-based method can provide not only accurate expected values, but also reliable PIs with relatively short lengths and high coverage probability. Given these favorable characteristics, the proposed probabilistic load forecasting strategy can be applied to enhance the distribution system operation in the future. The predicted load values with PIs will provide valuable insights for system operators amidst growing system uncertainty.

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