IOWA STATE UNIVERSITY

Department of Electrical and Computer Engineering

Have no fear! The room you're looking for is right here.

Short-term Load Forecasting Considering EV Charging Loads with Prediction Interval Evaluation

Feixiang Zhang

IOWA STATE UNIVERSITY

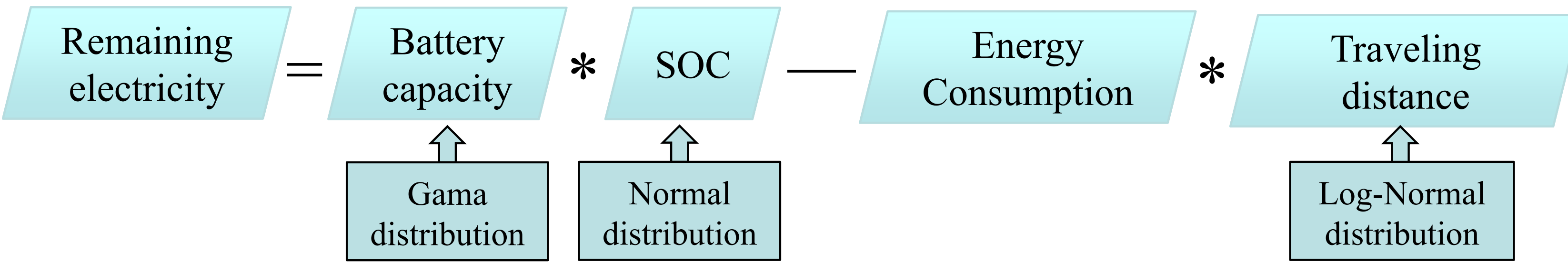
Menu

- Background
- EV Model Considering Ambient Temperature
- Load Forecasting Based on Gaussian Process Regression

Background

- 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**.
- Conventionally, utilities relied heavily on the expected values obtained from the load forecasting process for decision-making. But load forecasting, which **deals with randomness**, is fundamentally a **stochastic** rather than a deterministic problem. 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).
- Besides, the rapid growth of **electrical vehicles** (EVs) eventually alters users' load profiles. To enhance the power system operation in response to the growing penetration of EVs, some researchers have been concentrating on EV charging load prediction.
- Therefore, **it's significant to develop a method to evaluate the prediction interval of load with EVs.**

EV Model Considering The Ambient Temperature



- Energy consumption considering ambient temperature e_0 (kWh/mile) :

$$e_0 = b + v_1 v + v_2 v^2 + c_e^T P_e + aA + h_e H_e + t_1 T + t_2 T^2 + t_3 T^3$$

- Therefore, the remaining battery electricity E:

$$E = E_0 - e_0 * l$$

- Considering the range anxiety a_1 obeying $U(0.15, 0.3)$, the driver decides to charge when:

$$E < a_1 * C_0$$

EV Model Considering The Ambient Temperature

Starting charging time → Charging Time Duration → Charging power

- A **kernel density estimation (KDE)** is used for fitting the probability density function of the starting charging time *CT*.
- Charging power P_{char} (kW) : Uniform distribution $U(4.5, 5.5)$
- Charging time duration T_C (h):

$$T_C = \frac{0.8 * C_0 - E}{P_{char}}$$

- 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 timeseries charging load of all the EVs:

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

Load Forecasting Based on Gaussian Process Regression

Definition of GP:

A Gaussian Process is a collection of random variables, any finite number of which have (consistent) **joint Gaussian distributions**. GP is written as:

$$p(x) \sim \mathcal{GP}(m(x), k(x, x'))$$

Meaning: the function $p(x)$ is distributed as a GP with mean function $m(x)$ and covariance function $k(x, x')$.

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

GPR:

Training dataset:

$$\begin{bmatrix} p(x(1)) \\ \vdots \\ p(x(N)) \end{bmatrix} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma}) = \mathcal{N}\left([\boldsymbol{\mu}], \begin{bmatrix} k(x(1), x(1)) & \cdots & k(x(1), x(N)) \\ \vdots & \ddots & \vdots \\ k(x(N), x(1)) & \cdots & k(x(N), x(N)) \end{bmatrix}\right)$$

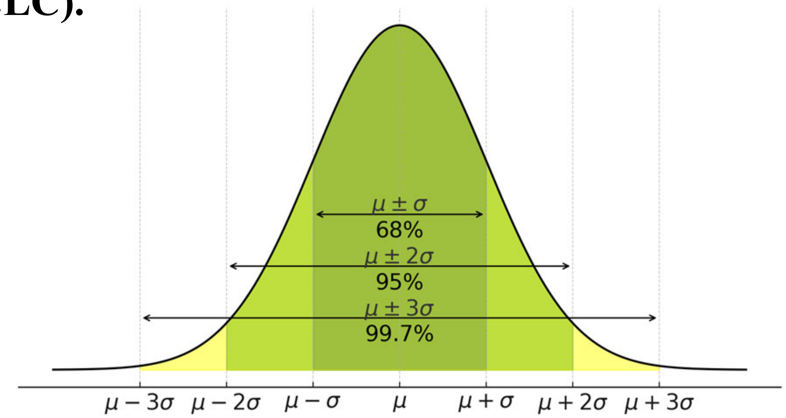
For a new independent variable $p(x(*))$

$$\begin{bmatrix} p(x(1)) \\ \vdots \\ p(x(N)) \\ p(x(*)) \end{bmatrix} \sim \mathcal{N}\left(\begin{bmatrix} \boldsymbol{\mu} \\ \mu_* \end{bmatrix}, \begin{bmatrix} \boldsymbol{\Sigma} & \boldsymbol{\Sigma}_{N*} \\ \boldsymbol{\Sigma}_{N*}^T & \Sigma_{**} \end{bmatrix}\right)$$

Forecasted load: $p(x(*)) \sim \mathcal{N}\left(m(x(*)), k(x(*))\right); m(x(*)) = \boldsymbol{\Sigma}_{N*}^T \boldsymbol{\Sigma}^{-1} D,\ k(x(*)) = \Sigma_{**} - \boldsymbol{\Sigma}_{N*}^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\Sigma}_{N*}$

Load Forecasting Based on Gaussian Process Regression

- **How to evaluate the forecasting results:**
- The deterministic metrics: mean absolute percentage error (**MAPE**) and root mean squared error (**RMSE**).
- Quantitative evaluation of prediction intervals (PIs): **normalized mean PI length (NMPIL), PI coverage probability (PICP), coverage-length-based criterion (CLC).**



Normal distribution with mean value μ, standard deviation σ.

$$NMPIL = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{p^U(X_i) - p^L(X_i)}{p^*(t)}\right)$$

$$PICP = \frac{1}{n}\sum_{i=1}^{n} c_i$$

$$CLC = \frac{NMPL}{\sigma(PICP, \eta, \alpha)}$$

$$\sigma(PICP, \eta, \alpha) = \frac{1}{1 + e^{-\eta}(PICP - \alpha)}$$

where $p^U(Xi)$, $pL(X_i)$ are the upper and lower bonds of the PI. $p^*(t)$ is the real value of the load. c_i=1 if the actual value lies in the PI. Otherwise c_i=0.

Load Forecasting Based on Gaussian Process Regression

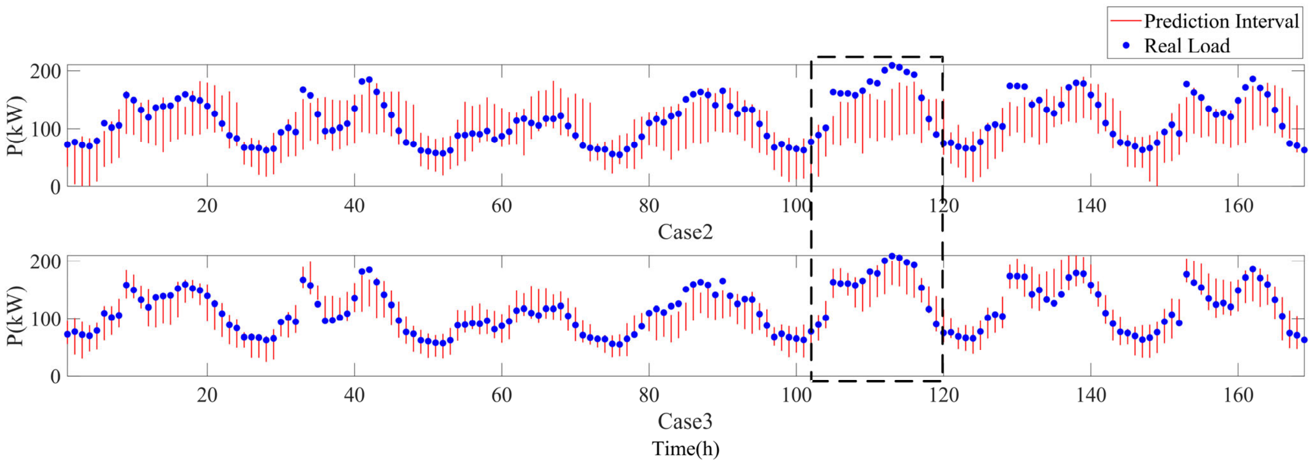
Forecasting results

Three scenarios: Case 1: The historical data without EVs is used to forecast the EV-free loads.

Case 2: The historical data with EVs is used to forecast the loads including EV charging loads.

Case 3: Based on Case 2, the user's charging habit feature *CH*(*t*) is included in the input feature set X.

CH(*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.

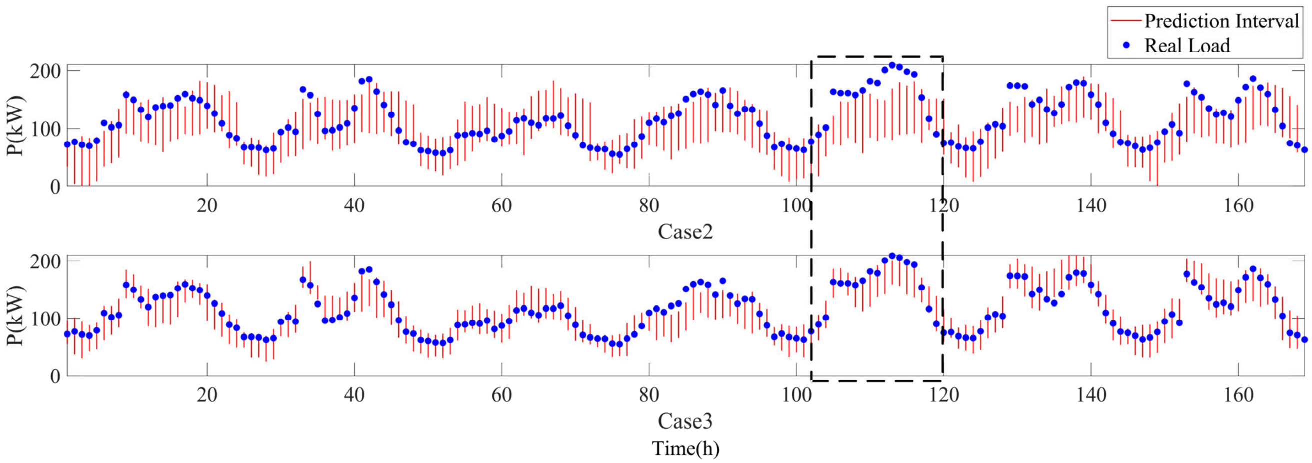


Forecasting results of one week in the testing set.

Load Forecasting Based on Gaussian Process Regression

Forecasting results

- The MAPE and RMSE of Case 3, almost the same as Case 1, are only half of Case 2.
- Some data points in Case 2 in the rectangle are challenging to include within the PIs. Most data points in Case 3 can be encompassed by the PIs.
- The user charging habit feature allows the GPR model to more accurately track the uncertain characteristics of the load.

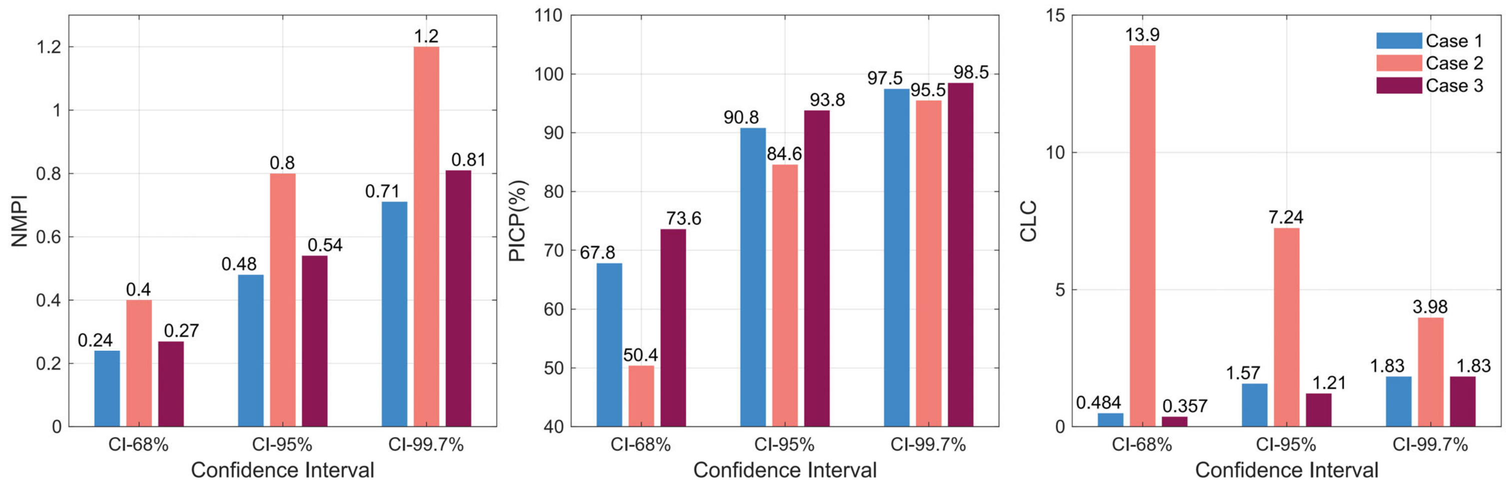


Partial forecasting results with 95% coverage probability.

Load Forecasting Based on Gaussian Process Regression

Forecasting results

- Case 1 can achieve close PICPs with the ideal values while maintaining low NMPIL values.
- Case 2 has the larger NMPIL values while the PICPs are even worse.
- Case 3's performance greatly improved compared to Case 2.



Quantitative evaluation results of NMPI, PICP, and CLC

Conclusion

- This paper focuses on probabilistic short-term load forecasting using the GPR method.
- The EV charging load performance gap between the first two cases in the case study highlights the unpredictability caused by the EV charging loads. The forecasting accuracy can be greatly increased by considering the users' charging habit feature.
- 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.

Thank You!
Q&A