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A sparse heteroscedastic model for the probabilistic load forecasting in energy-intensive enterprises

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ABSTRACT

The energy-intensive enterprises (EIEs) account for a significant part of the total electricity consumption in most industrial countries. In the smart grid environment, electric load forecasting in EIEs plays a critical role in the security and economical operation of both the main grid and the EIEs' micro-grid. However, the accuracy of such forecasting is highly variable due to the strong stochastic nature of the load in EIEs. In this circumstance, probabilistic forecasts are essential for quantifying the uncertainties associated with the load, thus is highly meaningful for assessing the risk of relying on the forecasts and optimizing the energy systems within EIEs. This paper focuses on the day-ahead probabilistic load forecasting in EIEs, a novel sparse heteroscedastic forecasting model based on Gaussian process is developed. With the proposed model, we can provide predictive distributions that capture the heteroscedasticity of the load in EIEs. Since the high computational complexity of Gaussian process hinder its practical application to large-scale problems such as load forecast, the proposed model employs the $\ell_{1/2}$ regularizer to reduce its computational complexity, thereby enhancing its practical applicability. The simulation on real world data validates the effectiveness of the proposed model. The data used in the simulation are obtained in the real operation of an EIE in China.

1. Introduction

In many industrial countries, the electrical energy consumption in *energy-intensive enterprises* (EIEs) constitutes for a significant part of the country's total energy use. These EIEs includes steel plants, alumina plants, petrochemical plants, cement plant, etc. In many cases, EIE has its own *self-generating power plant*, thus forming a *micro-grid*. This micro-grid is connected to the *main grid* through the substations or feeders, as in Fig. 1. Since the electric load in EIEs is affected by the start-up and shut-down of some high power consuming production units, e.g., electric furnace in steel plant, the load in EIEs is highly volatile and sharply fluctuating. Because the micro-grid in EIEs are connected to the main grid, these uncertain burst loads pose several challenges to both utilities and EIEs, such as stability, power quality, and especially power dispatching [1–3]. Specifically, from the viewpoint of utilities, the uncertain burst loads from EIEs may have an adverse impact on the power quality, e.g., large fluctuations in voltage and frequency. From the viewpoint of the EIEs, the burst load reduces the operational efficiency of their own self-generating power plant, so EIEs have to purchase additional burst loads following capability, spinning reserves, and some other ancillary services from the main grid, thus increasing its energy costs [2]. In the smart grid environment, optimized scheduling among self-generating power plant, shiftable loads, energy storages, and utility power supply has a great potential to address these challenges [3]. Because of the existence of high uncertainties in EIEs' energy consumption, a stochastic scheduling model is more appropriate than a deterministic one for the EIEs' energy system. This is due to the fact that the former could introduce caution, flexibility and robustness in the solution. Such a stochastic scheduling model leads to the requirement of probabilistic load forecasting in EIEs. In addition to the point prediction values, probabilistic load forecasting also provides the predictive distributions of the future load, thus quantifying the uncertainties associated with the EIEs' load. This information of uncertainties is the stepping stone for a stochastic scheduling model. Furthermore, probabilistic forecasts can also be used to improve the dynamic demand response, investigate the power flow [4,5], and evaluate the system reliability [6].

Various techniques have been proposed for the electric load forecasting. However, almost all of them focus on the main grid or the metropolitan power grid [7–14]. As stated above, the load characteristic of EIEs is significantly different from that of the main grid, so the existing load forecasting methods in literatures for the main grids are not appropriate for the load forecasts in EIEs. To the best of our knowledge [15,16] are the only previous works that address the load forecasting in EIEs. In [15], a gradient-boosting

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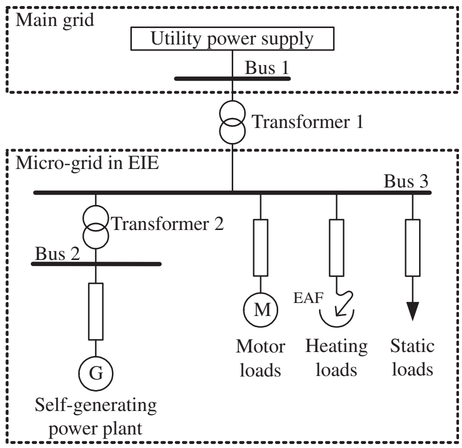

Fig. 1. Diagram illustrating a micro-gird in EIE.

ensemble learning algorithm for non-stationary time series is established, and applied to the load forecasts in a large scale steel plant. In [16], a template-based technique along with template scaling and equivalence algorithms is proposed to solve the EIEs' load modeling problem, and is applied to an oil refinery facility. Although these two methods show some promising results, they only provide the point forecasts, but not the probabilistic forecasts.

From a statistical point of view, probabilistic load forecasting for EIEs is a probabilistic regression problem. Gaussian process (GP) is a powerful tool for probabilistic regression [17]. Since GP is a fully probabilistic model, it can give predictive distributions, i.e., probabilistic forecasts, rather than merely point predictions. Standard GP simply assumes that the variance in data is Gaussian and its level is uniform throughout all data points. However, this assumption is unreasonable for some real applications such as load forecasting in EIEs. In following sections, we will show that although the uncertainty associated with the load in EIEs can be quantified by Gaussian distributions, the level of such uncertainty cannot be assumed to be uniform due to the start-up and shut-down of some high power consuming production units. Consequently, the variances of the load series in EIEs can be time varying, i.e., the load series in EIEs is a *heteroscedastic* time series. In such a circumstance, standard GP may misestimate the variances of this time series, thus giving poor predictive distributions. Furthermore, since the misestimation of the variances makes the GP oversmooth or undersmooth, the point prediction performance is also affected. Heteroscedastic Gaussian Process (HGP) is an extension of the standard GP, it models the uncertainty level using a second GP in addition to the GP governing the noise-free output [18]. This way, HGP handles the non-uniform and input-dependent uncertainty levels, thereby capturing the local volatility of the load in EIEs. Therefore, HGP is suitable for the probabilistic load forecasting in EIEs.

A major limitation of HGP is its high computational complexity. One HGP consists of two standard GP *base models*, each of them costs $\mathcal{O}(N^3)$ for training and $\mathcal{O}(N^2)$ for predicting, where N is the number of training points. This high computational complexity severely limits its scalability to large problems. When training a load forecasting model for EIEs, in general, there is a large amount of data available from the supervisory control and data acquisition (SCADA) system. In this case, the high computational complexity of HGP makes its training and real-time forecasting intractable, thus hindering its practical application. Therefore, from a practical viewpoint, we have to reduce the computational complexity of HGP before applying it to the probabilistic load forecasting in EIEs.

To address the above issues, this paper presents a new approach for the probabilistic load forecasting in EIEs. To effectively handle the heteroscedasticity in EIEs' load series and the large-scale forecasting problems, the proposed method is developed to be a sparse heteroscedastic model, referred to as SHGP. In SHGP, to deal with the heteroscedasticity, a heteroscedastic GP model is employed to model and predict the variances. To handle the large-scale problems, SHGP reduces the computational complexity by sparsifiying its base models. The newly introduced $\ell_{1/2}$ regularizer [19] is employed for this sparsification. Compared to the popular regularizers such as ℓ_1 [20], $\ell_{1/2}$ regularizer generally gives more sparse solutions. By benefiting form this sparse nature of $\ell_{1/2}$ regularization, SHGP has a significantly lower computational complexity compared to HGP. Considering the schedule horizon of the self-generating power plant in EIEs, we focus on the day-ahead forecasting, i.e., 24 h forecasting horizon.

The remainder of this paper is organized as follows. A detailed description of the proposed SHGP model is presented in Section 2. Section 3 analyzes the load characteristics of EIEs, and shows how to select the input features for model training. Section 4 contains the description of the numerical experiments and the discussion of the results. The data used in the experiments are obtained from the real operation of a steel plant in China. Section 5 concludes the paper.

2. Sparse HGP based on $\ell_{1/2}$ regularization

Because of its heteroscedastic property, HGP is suitable for the probabilistic load forecasting in EIEs. However, when applying HGP to a practical load forecasting system, an important issue must be addressed. That is, the high computational complexity of the standard HGP makes the training and real-time forecasting intractable for large problems. To address this issue, we present a sparse HGP model, which reduces the computational complexity. We refer to this sparse HGP model as SHGP. In this section, we show how to establish this SHGP model using $\ell_{1/2}$ regularization. Before introducing the proposed model, we give a brief review of HGP in Section 2.1. In Section 2.2, we present the proposed SHGP model.

2.1. A brief review of HGP

The probabilistic load forecasting in EIEs is a probability regression problem, which can be formulated as: at time stamp t, given forecasting horizon h and a set of input feature $\mathbf{x}_{t+h|t}$, forecast the future load distribution $p(y_{t+h}|\mathbf{x}_{t+h|t})$ at time stamp $t+h$. As mentioned earlier, this paper focuses on the day-ahead forecast, i.e., we only perform the single-step ahead forecasting. Therefore, the forecasting model can be expressed as

$$p(y_{t+h}|\mathbf{X}_{t+h|t}) = g(\mathbf{X}_{t+h|t}),$$

where g denotes the probabilistic forecasting model. The input features form the D dimension input vector $\mathbf{x}$, while the actual electric load measurements form the corresponding real valued target y.

HGP is a heteroscedastic regression model, which takes into account the input-dependent noise. Given a dataset $\mathcal{D} = (\mathbf{X}, \mathbf{y})$ consisting of N input vectors $\mathbf{X} = \{\mathbf{X}_n\}_{n=1}^N$ and corresponding targets $\mathbf{y} = \{y_n\}_{n=1}^N$, in HGP we assume that the relationship between the input vector and the target is given by

$$y_n = f(\mathbf{X}_n) + \epsilon_n, \quad (1)$$

here $\epsilon_n \sim \mathcal{N}(0, \sigma_n^2)$ is the input-dependent noise, which models the time changing variance, thus hitting the heteroscedasticity. f is the latent function. By placing a Gaussian process prior on f and assuming a noise rate function $\sigma_n^2 = r(\mathbf{X}_n)$, the predictive distribution $p(y_*|\mathbf{x}_*,\mathbf{X},\mathbf{y})$ at a testing point $\mathbf{x}_*$ is a Gaussian distribution, which is given by