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Using the ensemble Kalman filter for electricity load forecasting and analysis

Hisashi Takeda [a, b, *], Yoshiyasu Tamura [b, c], Seisho Sato [d]

[a] Energy Economics Group, Management Strategy Research Office, TEPCO Research Institute, Tokyo Electric Power Company Holdings, Inc., 4-1 Egasaki-cho, Tsurumi-ku, Yokohama-shi, Kanagawa, Japan

[b] Department of Statistical Sciences, School of Multidisciplinary Sciences, The Graduate University for Advanced Studies, 10-3 Midori-cho, Tachikawa, Tokyo, Japan

[c] Department of Statistical Modeling, The Institute of Statistical Mathematics, 10-3 Midori-cho, Tachikawa, Tokyo, Japan

[d] Graduate School of Economics, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo, Japan

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ABSTRACT

This paper proposes a novel framework for modeling electricity loads; it can be used for both forecasting and analysis. The framework combines the EnKF (ensemble Kalman filter) technique with shrinkage/multiple regression methods. First, SSMs (state-space models) are used to model the load structure, and then the EnKF is used for the estimation. Next, shrinkage/multiple linear regression methods are used to further enhance accuracy. The EnKF allows for the modeling of nonlinear systems in the SSMs, and this gives it great flexibility and detailed analytical information, such as the temperature response rate. We show that the forecasting accuracy of the proposed models is significantly better than that of the current state-of-the-art models, and this method also provides detailed analytical information.

1. Introduction

Following the Great East Japan Earthquake of 2011, most nuclear power plants in Japan were shut down due to safety concerns. Consequently, this caused an unprecedented tightening of the supply-demand balance for electricity. The earthquake also caused the public to be more energy conscious, and this has accelerated the widespread use of energy-saving appliances, such as LEDs (light emitting diode). To obtain a low-cost and stable power supply, several incentives have been introduced to facilitate the installation of renewable energy supplies; hence, the number of these installations is growing rapidly. These changes affect the electricity load on various time scales—days, weeks, and years. Under these circumstances, it becomes increasingly important for utilities to properly monitor changes in the electricity load in order to secure a stable power supply and make a proper plan for investing in power facilities. When accurate forecasts are needed, most utilities e.g., [1] use statistical methods, such as MLR (multiple linear regression) or ANNs (artificial neural networks). However, these are not suitable for analyzing the load, since they tend not to provide any insight into the cause of a structural change; for example, regression coefficients estimated using highly correlated explanatory variables are usually very large positive/negative values, but they offer no information on cause and effect. In addition, when covering peak loads with a limited power source, it is important to be able to accurately plan pumped-storage hydropower operations at least a week in advance, and this requires accurate load forecasting.

To solve these problems, our goal is to develop a modeling framework that can be used for both load forecasting and analysis. Utilities require analytical frameworks that can be used to explain the physical or economic rationales behind load changes or inaccurate forecasts to management or system supervisory organizations, such as the Organization for the Cross-regional Coordination of Transmission Operators, Japan. At the same time, the load forecasting should be accurate enough that it can be used in daily operations. Thus far, different methods have been used for each purpose, since in most cases, they are incompatible. A typical load structural analysis is performed by estimating the electricity consumption based on the penetration of electrical appliances, the response to the weather, the stay-at-home rate, and other

* Corresponding author. Energy Economics Group, Management Strategy Research Office, TEPCO Research Institute, Tokyo Electric Power Company Holdings, Inc., 4-1 Egasaki-cho, Tsurumi-ku, Yokohama-shi, Kanagawa, Japan.

E-mail addresses: htakeda@ism.ac.jp, takeda.hisashi@tepco.co.jp (H. Takeda).

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economic statistics. The models used for the analysis are more focused on accountability than accuracy.

Internationally, there have been hundreds of studies of load forecasting, and these have considered the use of many different statistical techniques. Although it is impractical to list all of these techniques here, the following ones are those that are commonly used. The most widely used technique for load forecasting is MLR [2], although machine learning techniques have gained in popularity in recent years; examples include fuzzy inference [3], support vector machines [4], and particle swarm optimization [5]. Singular value decomposition has been used for robust estimations and dimension reduction [6], and the Gaussian process has been used for nonlinear modeling [7]. A large number of neural-network-based methods e.g., [8] have been studied; their main purpose is to handle nonlinearity in a system. SSMs (State-space models) and the Box–Jenkins ARIMA (autoregressive integrated moving average) e.g., [9] have been used since the early days of load-forecasting research.

For load analysis, structural time-series models are commonly used, and these are often used to forecast yearly growth in the load e.g., [10]. However, recent methods use both weather and economic indicators in an attempt to create a forecast that is seamless from short term to long term [11]. In this study, we consider a forecasting horizon of one week, which is considered to be short-term load forecasting. We have thoroughly reviewed all the papers that propose methods for forecasts of up to several weeks. Harvey and Koopman [12] used time-varying splines to model periodic changes in the load, and they showed the necessity of incorporating an evolutionary process in a forecasting model. Taylor [13] developed a scenario-based forecasting model that used 51 different weather ensembles. Several exponential smoothing techniques using SSMs have been developed e.g., [14]. SSMs have been developed for the national load in France [15] and the regional load in the UK [16], and in Section 5.3, we use these results to evaluate the accuracy of our SSMs. We note that one of the advantages of SSMs is that individually created models (submodels or components) can easily be incorporated into a single model; for example, a nonlinear model for temperature effects can be easily incorporated into the load model. Another advantage is that SSMs can be updated recursively, and this is appropriate for modeling the natural evolution of the load components. SSMs have a long history and have been extensively studied; however, thus far, only a few attempts have been made to use them to model nonlinearity. For flexible nonlinear modeling, we use the EnKF (ensemble Kalman filter) as the algorithm for estimating the SSMs. Generally speaking, forecasts obtained from SSMs tends to be less accurate than those produced by the black-box methods that are used by many utilities. Our method was made more accurate by using a shrinkage method, Lasso (the least absolute shrinkage and selection operator) [17], and MLR. In any method, when increasing the forecasting accuracy and stability, it is important to select the proper explanatory variables; for example, using correlation analysis to select input variables has been shown to increase forecasting accuracy [8]. We used the Lasso to select the variables, since it has the additional advantage of reducing over-fitting, as compared with the step-wise methods that are commonly used.

Most of load forecasts that use structured time series models e.g., [16] are based on the KF (Kalman filter) [18], although the KF has a high computational cost and is not capable of implementing nonlinear system dynamics [19]. To handle nonlinear modeling, the extended Kalman filter was developed; however, it also has a high computational cost when approximating the error covariance. Evensen (initial work [20], comprehensive work [21]) developed the EnKF, which overcome both problems by using an ensemble representation for the error covariance. The EnKF adopts a Monte Carlo approximation to the KF, and the result is that the sample mean and variance-covariance matrix are asymptotically the same as those of the KF. The EnKF consists of a linear observation model with Gaussian noise and a linear or nonlinear system model with any type of noise distribution. The nonlinear formulation affords much greater flexibility than does the KF, which can handle only linear models. In addition, the ensemble approximation technique drastically reduces the computational cost, and this allows us to assimilate systems that are too large for previous methods. Since the revolutionary success of Evensen, the EnKF as well as the 4D-Var (four-dimensional variational data-assimilation algorithm) have become the most widely used algorithms for the assimilation of meteorological or oceanographic data. For example, the EnKF has been successfully applied to forecasting ozone concentrations [22], assimilating snow [23] and land surface temperature [24], and building a coupled atmosphere-ocean model [25]. Although the electricity load has a very close relationship with meteorological phenomena, studies using either the EnKF or the 4D-Var have been strangely neglected by scientists. We apply the EnKF to load forecasting and demonstrate its effectiveness for the first time. There are several variants of the EnKF, including the EnKF with perturbed observations (EnKF/PO), which was the first to be introduced and is widely used in many practical applications. However, it is known that perturbed observations increase the forecasting error to some extent. To reduce this error, the EnSRF (ensemble Kalman square-root filter) was developed [26]; the EnSRF does not require perturbed observations. In this paper, we use the EnSRF with Andrews' matrix formulation [27], since it is easily implemented and performs better than the EnKF/PO. Major data-assimilation methods are summarized in Table 1.

The forecasting accuracy was measured in terms of the *MAPE* (mean absolute percentage error).[1] Our aim is to develop SSMs for which the forecasting accuracy has an *MAPE* below 3%; this will ensure that the accountability assigned by the load analysis is correct. We obtained an *MAPE* of 3.05%, and when the Lasso was used, this was reduced to 1.87%. These experimental results show that, compared with the current state-of-the-art methods, the proposed method significantly improves the forecasting accuracy.

We also note that weather response indicators, which are needed for official reports, require additional analyses (e.g., simple regression analysis) in existing methods, but they are directly estimated in our method; this was not discussed in any of the studies that we reviewed.

We have successfully developed a unique modeling framework that can be used for load forecasting and analysis, and thus our goal has been achieved.

The remainder of the paper is structured as follows. Section 2 describes the electricity load and the weather observations that we used in our forecasting experiment. Section 3 introduces the SSMs for the electricity load, the EnKF, and our method of using the Lasso and MLR to enhance forecasting accuracy. Section 4 compares the accuracy of our model with that of existing models found in the literature. Section 5 presents the results of an experiment, and these are discussed in Section 6. Our conclusions are presented in Section 7.

2. Data

2.1. Electricity load

An electricity load model was developed using hourly load data available from the TEPCO (Tokyo Electric Power Company), which covers metropolitan Tokyo and the surrounding area. Load data are

[1] For the mathematical definition, see Section 4.3.