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Short-term ensemble forecast for purchased photovoltaic generation

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ABSTRACT

This paper proposes a novel short-term forecasting method for purchased photovoltaic (PV) generation. The proposed method is used to solve emerging problems, such as low accuracy of electricity load forecasting, which are associated with the rapid increase in PV generation. In the present study, hourly PV power is first modeled in the form of state-space models (SSMs), which incorporate a local power model and PV system parameters. Hourly installed PV capacities are then estimated using data that are available on a monthly basis. Finally, using the hourly capacities and weather observations, data assimilation in the SSMs is performed by an ensemble Kalman filter. As a result, the hourly physics-based PV power models are enhanced by monthly PV purchase volumes and significantly outperform an existing operational model. Furthermore, it is possible to simultaneously estimate PV system parameters, such as the coefficient of PV conversion, in the data-assimilation process.

1. Introduction

Since 2012, electric utilities in Japan have been obligated to purchase excess renewable energies at a fixed price, through a government-guaranteed period. Subsequently, the installed capacity of photovoltaic (PV) generation has increased rapidly. Compared with other renewable energies, the Feed-in-Tariff (FIT) rate for PV systems is relatively high (e.g., ¥42/kW h for 20 years). In addition, the installment costs and environmental requirements for the system have been comparatively low. These advantages have led to a boom in investment in PV systems.

The large variability of PV power generation that depends on weather necessitates short-term PV power forecasting in order to maintain the supply-demand balance in the power system. This balance is maintained by system operators through short-term electricity load forecasting. For example, operations of pumped-up hydroelectric and thermal power plants are scheduled two weeks and two days in advance, respectively, according to load forecasts. The uses and importance of short-term PV forecasting is clearly summarized by Wan et al. (2015). However, the difficulty involved in hourly PV power estimation lowers the accuracy of load forecasting. This problem is described in detail as follows. Fig. 1 shows the relationship between electricity load and PV power. PV self-consumption, which is power consumption within houses or firms of PV suppliers, is shown above the load curve indicated by the thick black line. Although PV self-consumption is not part of the load, it decreases and the load curve increases to compensate for the shortfall when the weather changes from clear to cloudy or rainy. The remainder of the PV power, more than 85% of the total PV power generated, is sold to a utility as a power source; this is shown as the area immediately below the load curve. Thus, both sold and self-consumed PV power affects utilities, and due to the influence of weather, PV power is a virtually uncontrollable power source. Since the target of load forecasting is a load that contains such PV power, it is important to accurately forecast PV power generation on an hourly or semi-hourly basis. Hourly PV power forecasting is not an easy task for major utilities, especially those without a remote monitoring system for power-consumption (also referred to as a smart-meter system[1]). The difficulty in proper forecasting is that utilities without a smart-metering system cannot measure the hourly PV power generation which inflows to the power grid. Instead, only reported monthly PV purchase volumes and hourly weather information are available (observational and two-week forecast). Therefore, we must estimate hourly PV power generation based on these data. Major utilities in Japan have used physics-based models for PV forecasting. Since these models do not have a process of model-fitting to observational

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[1] Smart meters that are capable of reporting PV power will be equipped in all households in Japan by 2020 (earliest estimate).

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data, a severe systematic bias problem occurs and it directly leads to a large imbalance penalty.[2]

In the following, we present an overview of PV forecasting technology. Some studies have reported successful removal of systematic bias of satellite-derived solar irradiance using short-term ground measurement (Polo et al., 2015).

Satellite images with cloud motion are commonly used for short-term (within several hours) forecasting (Coimbra et al., 2013), whereas physics-based models are usually used for longer-term (more than six hours) forecasting. Most PV forecasting techniques preliminarily predict solar irradiance using widely available numerical weather prediction (NWP) techniques (Kaur et al., 2016); the results are then used for one-day forecasts (Larson et al., 2016). For forecasting for periods of more than one year, the classical seasonal decomposition model is used to decompose time series data into seasonal components, trend components, and irregular components (Phinikarides et al., 2015). As an example, the Kalman filter has been successfully used to remove the systematic bias of solar irradiance forecasts (Barkhouse et al., 2012).

We herein focus on short-term forecasting, which is our primary interest. Artificial intelligence (AI) methods, such as artificial neural networks (ANNs), has been most commonly used in hourly PV forecasting. For example, several ANNs with distinct topologies have been used for PV forecasting, and two solar modules produced by major manufactures have been tested (Brano et al., 2014). A recurrent neural network has been successfully applied to several hour-ahead PV power forecasting techniques (Yona et al., 2013). For other AI methods, hybrid hourly forecasting using a genetic algorithm to combine the Box-Jenkins autoregressive integrated moving average (ARIMA) and three artificial intelligence methods has been proposed (Yuan-Kang et al., 2014). The hybrid model uses only solar radiation and empirical PV hourly power data. Inman et al. (2013) extensively reviewed existing solar forecasting methods and compared performance of global horizontal irradiance (GHI) forecasting techniques with NWP-based forecast, stochastic forecasts, ANNs, and hybrid forecasting models (ARIMA and ANN). Of all these methods, it is indicated that ANNs can be an alternative approach to physical modeling since the techniques are successfully applied to intra-hour and yearly forecasting. The authors also mentioned the merit of using hybrid methods over traditional approaches. Note that some studies have used actual hourly PV power data as training data. However, these studies considered only a small amount of aggregated power from experimental residential areas or from a few PV firms; this is in contrast to the present study, which considers the total PV power for an entire utility service area.

Forecasting methods which do not require knowledge of PV systems are gaining popularity. The hourly quantile regression model is used for one-day forecasting (Almeida et al., 2015). Forecasting techniques that do not consider solar radiation have been accessed, and ANNs have been demonstrated to outperform ARIMA and k-nearest neighbors algorithms (kNN) (Pedro and Coimbra, 2012). A reforecasting technique for removing systematic bias has also been developed (Chu et al., 2015b). Support vector machines based on weather pattern recognition (Wang et al., 2015) and regularized linear/nonlinear models (Aggarwal and Saini, 2014) have also been developed.

Two basic types of strategies are usually used for PV forecasting of total power: bottom-up strategies, which aggregate locally forecasted PV power generation, and direct strategies, which directly forecast the total PV power generation (Zamo et al., 2014). The mean absolute error (MAE) has been reported to be reduced by more than 3% by using a bottom-up strategy, as compared to a direct strategy. In addition to this accuracy advantage, only the bottom-up strategy is capable of providing precise information regarding local PV power, which would contribute to solving over-voltage problems that occur in power distribution networks. Therefore, we adopted a bottom-up strategy; that is, we first forecast local PV power generation, followed by total PV power.

The most popular ANNs provide a possible means by which to avoid the severe systematic bias problem that occurs in utilities. Although they may fit a nonlinear model to observations very well, ANNs are a black-box approach, and so no reasonable interpretation will be provided for the forecasting results. Therefore, ANNs are not the best choice for a bottom-up approach. Instead, we focused on a data-assimilation technique. Data assimilation incorporates observed data into a simulation model in order to provide better model behavior. The technique is widely acknowledged to be one of the most effective ways of simulating natural phenomena, such as weather, for cases in which related observed data are available. Data assimilation compensates for the weak points of both physics-based and black-box approaches by incorporating observed data into a physics-based model.

The best-known data-assimilation technique (e.g., Pedregal and Trapero, 2010) is the Kalman filter (KF) (Kalman, 1960), although it has a high computational cost derived from full calculation of covariance matrices and is incapable of implementing nonlinear system dynamics (Tippett et al., 2003). Evensen (initial study Evensen, 1994; comprehensive study Evensen, 2003) developed the ensemble Kalman filter (EnKF), which overcame both problems by adopting a Monte Carlo approximation in 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 EnKF and the four-dimensional variational data-assimilation algorithm (4D-Var) have become the most widely used algorithms for data assimilation of weather phenomena. Although PV generation is very closely related to the weather, surprisingly few studies have examined PV forecasting using either the EnKF or the 4D-Var. We applied the EnKF to PV power forecasting and demonstrated its effectiveness for the first time. The EnKF has several variants. The EnKF with perturbed observations (EnKFPO) was the first variant to be introduced and is widely used in many practical applications. However, perturbed observations increase the forecasting error to some extent. In order to reduce this error, the ensemble Kalman square-root filter (EnSRF) was developed (Whitaker and Hamill, 2002). The ensemble transform KF (Bishop et al., 2001) and the ensemble adjustment KF (Anderson, 2001) are similar. In the present study, we use the EnSRF, since it is easily implemented and performs better than the EnKFPO. We will use the term "EnKF" to refer to the EnSRF in this study.

Using EnKF, which can deal with a nonlinear model, it becomes possible to easily enhance an elaborate physics-based model by incorporating observed data. Moreover, it is very easy to add uncertainty information, such as quantiles, to the point estimate, since ensemble members obtained by EnKF represent a prediction distribution. Although most existing forecasting methods provide only point estimates (Espinar et al., 2010), some successful results using non-point forecasts have recently been reported; for example, Chu et al. (2015a) proposed a real-time direct-normal-irradiance forecasting model with prediction intervals. The proposed model achieved high coverage probability in ramp time. Also, non-point forecasts using ANNs, ARMA and kNN were used for forecasting PV power generation (Chu et al., 2015b). For unit commitment for thermal plants, utilities use the forecasted load curve, which fluctuates with PV power. Therefore, interval estimation of PV power is more useful than point estimates for system operators.

In view of the above-mentioned advantages, we adopted SSMs with EnKF as an hourly PV forecasting model. We demonstrated

[2] Imbalance penalties of 53.21 ¥/kW h (summer), 47.03 ¥/kW h (other seasons), and 28.84 ¥/kW h (at night) for forecasting errors greater than 3%, and 15.44 ¥/kW h for forecasting errors within 3%. (http://www.tepco.co.jp/corporateinfo/provide/engineering/wsc/yakkan2604-j.pdf).