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Modeling of uncertainty of solar irradiance forecasts on numerical weather predictions with the estimation of multiple confidence intervals

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ABSTRACT

One-day-ahead solar forecasting by numerical weather prediction is expected to be an effective tool to improve the operation of an electrical system that integrates a large amount of solar power generation. The purpose of this study is to develop a new empirical method to model the prediction uncertainty of the solar irradiance forecast on numerical weather prediction. The proposed method comprises of four steps. First, predicted and measured solar irradiances are transformed into Gaussian random variables using data observed in a modeling window in the near past. Second, a multivariate normal joint distribution model is estimated using data in the same window. Next, a distribution of irradiance of the next day conditional on one-day-ahead forecast is derived. Finally, multiple confidence intervals both temporally and spatially are estimated by using the conditional distribution. A solution to select an appropriate length for the modeling window is presented. The multivariate normality assumption is checked by evaluating the joint hit rate of the estimated multiple confidence intervals numerically.

1. Introduction

Unit commitment (UC) of power generation units is made based on the demand forecast one day ahead because sufficient generation units need to operate to follow the varying load at any moment, and some thermal units such as coal power plants take a long time before starting operation. As a large number of intermittent renewable electricity generation plants are in operation, the fluctuation of their output is superimposed on the variation of demand, and the load following requirements to thermal units becomes greater still. Against this background, an increasing number of studies on advanced electrical system operation have been performed, making use of forecast techniques. Most of the early studies have focused on wind power, but the number of studies on solar power has grown recently. For example, Ummels et al. [1] and Wang et al. [2] simulated the UC and economic load dispatch (ELD) of power grid with wind power generation integrated on large scale. Masuta et al. [3] and Brancucci et al. [4] simulated the UC and ELD under a large-scale penetration of solar power generation with the help of one-day-ahead irradiance prediction and evaluated the impacts of over- and underprediction on system performance. It is also investigated to incorporate prediction uncertainty into UC and ELD based on wind and solar forecast. The utilization of confidence intervals [5,6] and probabilistic simulation [7] have been two important approaches of incorporating uncertainty into UC and ELD.

The confidence interval prediction for solar forecasts [8] was developed by Lorenz et al. [9] and Marquez et al. [10]. Marquez et al. [10] assumed a normal distribution in prediction error resulting from the irradiance forecast by a neural network model. However, this assumption does not always hold for solar prediction because solar irradiance has natural bounds [11,12], and various methods of interval prediction have been proposed. Bacher et al. [11] applied quantile regression to evaluate the confidence intervals of solar irradiance forecast as a local constant for each hour in a year. Ohtake et al. [13] used a numerical weather prediction (NWP) provided by a mesoscale model (MSM) to forecast global solar irradiance 33 h ahead and estimated confidence intervals based on

Abbreviations: CI, clearness index; CREST, Core Research for Evolutional Science and Technology; ELD, economic load dispatch; GHI, global horizontal irradiances; GPV, grid point value; JMA, the Japan Meteorological Agency; JST, the Japan Science and Technology Agency; MSM, mesoscale model; NWP, numerical weather prediction; SVR, support vector regression; UC, unit commitment.

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the relationship between predicted clearness indices and prediction errors. Saez et al. [14] applied fuzzy quantile regression to 1-h-ahead forecasts of wind, solar, and electricity demand. Fonseca et al. [15] compared the Gaussian distribution and Laplacian distribution assumed for solar forecast error and showed that the Laplacian distribution assumption is more suitable to solar forecasts with small forecast error. A confidence interval prediction combining volatility estimate and kernel density estimate has also been proposed [12]. Yamazaki et al. [16] proposed a confidence interval prediction using a normal kernel density estimate combined with Just-In-Time modeling. Confidence interval prediction in these studies is developed to estimate the uncertainty of point forecasting [17] and the uncertainty of multiple forecasts such as joint distribution of forecast errors at multiple points both temporally and geographically is not modeled.

Many models have been used for the probabilistic forecast of solar irradiance, such as adaptive linear regression models [11], neural network models [10], and stochastic differential equation models [18]. Iversen et al. [18] developed stochastic differential equations that considered the cyclicality and boundedness of solar irradiance and derived a partial differential equation for the distribution function of forecast values, while confidence intervals were obtained by Monte Carlo simulation in this work. Both stochastic irradiance time series and confidence intervals can be obtained by the method proposed by Iversen et al. [18]; it is difficult to apply this approach to deterministic forecast methods such as NWP. Pinson et al. [19] proposed an uncertainty model for the wind forecast, combining multivariate normal distribution and non-linear conversion of prediction errors, and used it to generate a stochastic time series of hourly wind power output that accounts for both the interdependence structure of prediction errors at different hours and the predictive distribution of wind power production. This modeling approach can be applied to deterministic forecast methods as well, but the quantile points of forecast distribution are necessary to construct the conversion functions.

The purpose of this study is to develop a model of forecast uncertainty of one-day-ahead solar irradiance forecast on NWP [20] assuming multivariate normality of clearness indices transformed by nonlinear mappings, and to develop a method to estimate multiple confidence intervals. Multiple confidence intervals are confidence intervals estimated at more than one points (both temporally and geographically) keeping joint distribution characteristics. Fig. 1 shows a flow diagram of the proposed method. Let K be the number of points for which multiple confidence intervals are estimated. In Step 1, clearness indices both forecast and measured are transformed into random variables that follow the standard normal distribution by using nonlinear transforms constructed from their observed distributions in the preceding N days. The number N must be chosen carefully for the proposed multivariate normal distribution approximation to be valid. In Step 2, the joint distribution of K-pairs of transformed clearness indices is modeled assuming 2K-dimensional multivariate normal distribution whose covariance matrix is computed using the transformed clearness index values in the preceding N days. In Step 3, the distribution of K transformed clearness indices in the following day conditional on the one day ahead forecast values is derived, which is K-dimensional multivariate normal distribution. In Step 4, K confidence intervals for clearness indices in the following day are estimated using the conditional distribution and the inverse transformation. Steps 1–4 are performed once a day successively.

The rest of the paper is organized as follows.

Section 2 is a brief description of solar irradiance forecast used in this study. Section 3 provides a mathematical description of Steps 1–4 in Fig. 1. In Section 4, the sensitivity of the parameters of the conditional distribution of clearness indices in the following

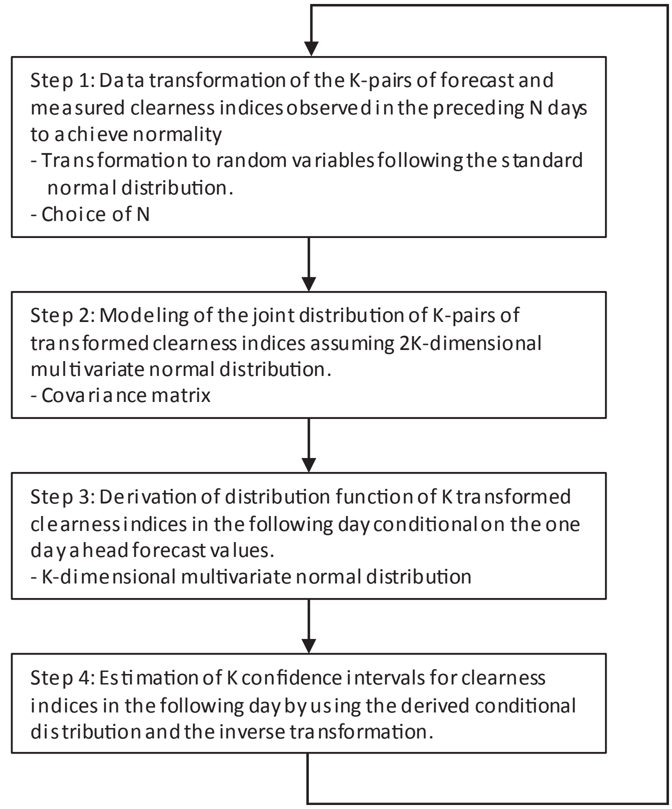

Fig. 1. Flow diagram of the proposed method.

day to the number N is examined. The result provides useful information for the selection of the number N. In Section 5, the proposed model is used to estimate the multiple confidence intervals of solar irradiance at different hours and the multiple confidence intervals of solar irradiance at different places. Joint hit rates of multiple confidence intervals are evaluated to validate the multivariate normal distribution assumption. Finally, the conclusion is presented in Section 6.

2. Solar irradiance forecast

In this study, hourly solar irradiances at forty-two points in Japan are predicted through the year 2010 by means of a support vector regression (SVR), whose inputs are the extra-terrestrial global horizontal irradiances (GHI) and grid point values (GPV) for the next 33 h computed by the GPV-MSM system of the Japan Meteorological Agency (JMA). These values include the ground GHI, ambient temperature, air relative humidity, and cloudiness [15,21]. The forty-two points are the locations of the ground observational stations where GHI is observed constantly. They are divided into 10 regions, which approximately correspond to the service areas of the ten principal electric companies. In Kanto region, for example, the six stations are located at Tokyo, Tsukuba, Choshi, Maebashi, Utsunomiya, and Kofu. The average GHIs predicted and measured at these six points are used in Section 4. In Section 5, the average GHI predicted and measured in the Tohoku region, adjacent to the Kanto region to the north and containing seven observational stations, and in the Kyusyu region, which is in the western part of Japan and contains seven observational stations, are used for the estimation of multiple confidence intervals at different hours, as explained in Subsection 5.1. GHIs predicted and measured at Tokyo, Tsukuba, and Choshi are used for the estimation of multiple