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Adequacy assessment of a wind-integrated system using neural network-based interval predictions of wind power generation and load

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A B S T R A C T

In this paper, a modeling and simulation framework is presented for conducting the adequacy assessment of a wind-integrated power system accounting for the associated uncertainties. A multi-layer perceptron artificial neural network (MLP NN) is trained by the non-dominated sorting genetic algorithm-II (NSGA-II) to forecast prediction intervals (PIs) of the wind power and load. The output of the adequacy assessment is given in terms of point-valued and interval-valued Expected Energy Not Supplied (EENS). Different scenarios of wind power and load levels are considered to explore the influence of uncertainty in wind and load predictions on the estimation of system adequacy.

1. Introduction

Maintaining a reliable power supply is a critical issue in power system design and operation. In general, system reliability consists of the two aspects of system adequacy and system security. The way in which the power system can cope with the evolution in electric demand at any time is defined as "system adequacy".

Assessing the adequacy of a power system is challenging due to the uncertainties associated with energy demand fluctuations, prediction of future weather conditions (e.g. wind speed, solar irradiation, etc.), possible equipment (e.g. generators, lines, etc.) unavailability, failures in electric power transactions, errors (operator errors, dispatcher and relay malfunctions), and other relevant issues [1–3].

Considerable research has been carried out for security, economy, and adequacy assessment of power networks [4–12]. Although Monte Carlo (MC)-based probabilistic methods are still in use, more efficient and faster methods have also been proposed. In [11], the authors propose a two-point estimate method (TPEM) to model the load uncertainty in optimal reactive power dispatch (ORPD) problem. They show that TPEM is a less time consuming technique compared to MC simulation to deal with the probabilistic multi-objective ORPD problem. In [12], ORPD problem is solved for wind-integrated power systems. Both load and wind uncertainties are modeled using probability distribution functions (pdfs).

With increased wind energy production over the last decade, greater attention is being given to the wind energy integration benefits and issues. Intermittent and stochastic characteristics of wind energy bring additional uncertainty to the reliability evaluation of wind-integrated power systems. Therefore, it is critical to take into account this uncertainty in reliability modeling for better assessment of the adequacy of the power systems. In [9], seasonal auto-regressive and moving average (ARMA) time series models are developed to incorporate the chronological nature of the actual wind speed. As the adequacy assessment index, Expected Energy not supplied (EENS) is estimated. Although the authors consider the impact of seasonal changes in wind speed on the adequacy assessment of composite generation and transmission system, uncertainty quantification is not performed for the forecasting models.

Herein a modeling and simulation framework for conducting the adequacy assessment of wind-integrated power systems is presented. As the reliability indicator, EENS is estimated accounting for uncertainties in data and prediction model. EENS can be used to measure the inadequate supply caused by failures in power generator components, which is one type of uncertainty that exists in power grid operation [2–10]. When the renewable energy penetration (e.g. wind) in a power system is significant, EENS can be used

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to measure the inadequate power supply caused by both component failures and changes in wind speed [2–10].

1.1. Contributions

The originality of the present work lies in proposing not only point-valued results, but also interval-valued EENS results to inform decision makers (DMs) on the uncertainty in the predictions. An alternative method to estimate EENS in the presence of interval-valued inputs, i.e. load and wind power, is proposed. Load fluctuations, the volatile and stochastic characteristic of the wind speed, and component failures are considered as sources of uncertainties. Since very few methods have been proposed for estimation of EENS as an interval, this proposed methodology contributes to the development of a novel approach for adequacy assessment when the renewable energy penetration is significant. Interval analysis is one way to take the associated uncertainties into consideration, and provide a measure of the uncertainty in the predicted outputs. The estimated outputs are represented as intervals. Herein, to model and include the stochastic characteristics of load and wind in the adequacy assessment problem, prediction intervals (PIs) are estimated. The estimated PIs for 1-h ahead wind power and load are used as the inputs to estimate both the interval-valued and single-valued EENS.

PIs are provided using multi-layer perceptron artificial neural networks (MLP NNs) trained by the non-dominated sorting genetic algorithm-II (NSGA-II) [13]. The NSGA-II training procedure generates Pareto-optimal solution sets, which include non-dominated solutions for the two objectives- prediction interval coverage probability (PICP) and prediction interval width (PIW).

The wind speed data used in the case study has been collected for a 9-year period for the region of Regina, Saskatchewan, Canada [14]. Then, hourly mean wind speed values are used to determine the time-dependent wind power output of a wind turbine generator (WTG) using its power curve parameters. For load demand, hourly load fluctuations are modeled using the chronological annual load curve of the IEEE Reliability Test System (RTS) [9,15] with the scaled annual peak load value. The generating units in the power system are represented by two-state models, describing operation and failure, and models are sampled by sequential Monte Carlo simulation.

In order to clearly illustrate that the proposed interval-valued EENS estimation method is capable of providing reliable results as an alternative to MC simulation, EENS estimation using a MC simulation method is also discussed in Section 4. In [11,12], the load and wind are modeled as random variables with known probability distributions- normal pdf and Rayleigh pdf, respectively. The method proposed in this paper, instead, does not rely on the assumption that the load and wind data are drawn from given probability distributions, since an empirical approach is used to estimate the PIs. This empirical approach is preferable when distributional assumptions are not met, or cannot be verified, in the data at hand. Note that a comparison between TPEM [11] and the proposed PIs model is feasible, however it is beyond the scope of the present paper.

1.2. Paper organization

The paper is organized as follows. Section 2 briefly introduces the definition of PIs and the use of NSGA-II for training a NN to estimate PIs. In Section 3, the methodology for interval-based estimation of EENS is given. In Section 4, experimental results on the case study are given, and EENS estimation using MC simulation is discussed. Finally, Section 5 concludes the paper with a summary and discussion for future work.

2. Methodology to estimate load and wind power PIs

In the following sub-sections, the main phases of the methodology are described. The application of the framework is shown on a case study taken from the literature [9]. In Fig. 1, a flowchart of the methodology proposed for the adequacy assessment of wind-integrated power systems is depicted.

2.1. Wind power generation

Hourly wind speed data have been collected for the region of Regina, Saskatchewan, Canada for a 9-year period (1 Jan. 2003 to 31 Dec. 2011) [14]. Since wind power is a function of wind speed, forecasts of power are generally derived from wind speed. To conduct the adequacy assessment over one-year time horizon, for each hour in the year (8736 h) the hourly means are calculated over 9 years of wind speed values. The so obtained one-year time series of wind speed $V(t), t = 1, \ldots, 8736$, are then transformed in wind power $P(t)$ values using a quadratic characteristic curve (power curve) taken from the literature [16,17]. Fig. 2 shows a typical power curve of a WTG. V_{ci}, V_r, and V_{co} denote the cut-in speed, rated speed, cut-off speed, respectively, whereas Pr is rated output power. When the wind speed is less than a threshold minimum, known as the cut-in speed, the power output is zero. Between the cut-in and the rated speed, there is a rapid growth of power produced. A constant output (rated power Pr) is produced when the wind speed is between the rated speed and the cut-off speed, whereas beyond the cut-out speed the WTG is shot down for safety reasons, hence, it produces zero power. For the mathematical expressions of the power curve, the reader is referred to [16,17].

2.2. Load modeling

The load duration curve (LDC) on an annual basis (8736 h) is created by manipulating the hourly load values from the IEEE-RTS [12]. One year (8736 h) load data, i.e. a load value $L(t)$ for each hour $t = 1, \ldots, 8736$, have been generated with the following formula [18]:

$$L(t) = \bar{L}(t) + \bar{L}(t)\left(\frac{\sigma}{100}\right)X^{norm} \tag{1}$$

where $\bar{L}(t)$ is the expected value of load for hour t, calculated using the following equation.

$$\bar{L}(t) = P_w(t) \times P_d(t) \times P_h(t) \times L_{\max} \tag{2}$$

where L_{max} is the peak load in a year, $P_w(t)$ is the weekly peak load as a percentage of the annual peak, $P_d(t)$ is the daily peak load as a percentage of the weekly peak and $P_h(t)$ is the hourly peak load as a percentage of the daily peak. The system peak load L_{max} is set to 185 MW [9]. σ is the load forecasting uncertainty error (standard deviation) expressed as a percentage of the hourly peak load, and X^{norm} is defined as [18]:

$$X^{norm} = \sqrt{-2ln(R_1)}\cos(2\pi R_2) \tag{3}$$

where R_1 and R_2 are two random numbers drawn from the standard uniform distribution on the open interval (0,1), and X^{norm} is a normally distributed random number [18,19]. The load forecasting error σ is set to 5%.

2.3. Estimation of NN-based PIs

Based on the hourly wind power and load values over a 1-year horizon, a data-driven strategy to perform short term (1-h ahead) prediction of both load and wind power with uncertainty quantifi-