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Estimating future balancing power requirements in wind–PV power system

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ABSTRACT

This paper presents a general model—based on the Monte Carlo simulation—for the estimation of power system uncertainties and associated reserve and balancing power requirements. The proposed model comprises wind, PV and load uncertainty, together with wind and PV production simulation. In the first stage of the model, wind speed and solar irradiation are simulated, based on the plant disposition and relevant data. The second stage of the model consists of wind speed, PV power and load forecast error simulation, based on the associated statistical parameters. Finally, both wind and PV forecast error are combined with the load forecast error, resulting in the net uncertainty. This net uncertainty, aggregated on a yearly level, presents a dominant component in balancing power requirements. Proposed model presents an efficient solution in planning phase when the actual data on wind and PV production is unavailable.

1. Introduction

High penetration of renewable generation introduces several difficulties in power system operation. Variable and uncertain power output from both wind power plants (WPPs) and photovoltaic power plants (PVs) requires additional operating reserve in schedule planning in order to ensure sufficient flexibility for deviations in forthcoming period. Furthermore, increase in operating reserves is followed by their higher usage, resulting in additional balancing power used for accommodating renewable generation. Both increase in operating reserves and balancing power requirements is one of the major changes introduced by recent increase in renewable generation presence, and is expected to follow future growth of renewable generation [1].

This issue has been a dominant topic in numerous studies (extensive review of integration studies is available in Ref. [2]) and scientific publications introducing various approaches in assessing the impact of future renewable generation on power system operation. On the solution side, a wide range of measures has been proposed, from simple changes in reserve forecasting and procurement to renewable generation control enhancement for balancing purposes [3]. Within related publications a distinction between variability and uncertainty in terms of origin is highlighted, allowing for their separate consideration in subsequent analyses. In this sense, the model presented in this paper focuses on uncertainty and, together with variability assessment, enables a complementary approach to the assessment of renewable generation impact on operating reserve requirements and usage.

Impact of renewable generation uncertainty on power system operation has been extensively researched in recent years. In case of wind power, operational reserve planning has been investigated in Refs. [4,5] focusing on uncertainty, while [6,7] examined variability. Photovoltaic (PV) power uncertainty and variability followed wind power in a similar way [8,9]. In case of wind and PV generation mixture, conclusions cannot be extrapolated from separate investigations but require a specific approach ([10] in case of variability). A common starting point in all publications is a statistical analysis of renewable generation forecast error which, on its own, provides an insight in impact of renewable generation on operating reserves [11–13], but can serve as an input in a detailed power system operation simulation, for example [4,5,8]. While a statistical analysis of forecast error provides useful insight in current forecast performance, the issue of future performance of mixed power system remains unknown, unless major simplifications are introduced.

For an assessment of future renewable generation impact on

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power system operation, a method presented in Ref. [14] is a simple but practical approach. However, authors assume a normal distribution of wind power forecast error in a weather based model, while it was recognized that wind power forecasting is highly dependent on the forecast value [15,16]. This specificity arises from the non-linearity of the wind to power transformation, and this issue has been addressed appropriately in Ref. [12], but only for current system uncertainty estimation. While the drawbacks of the models for wind power uncertainty assessment are reduced to several issues, PV uncertainty is almost uncovered topic in existing publications. Such circumstances perhaps arise from recent penetration of PVs compared to wind power plants, but in any case require a closer attention. Model presented in this work aims at setting out these drawbacks and introducing further novelties required for estimation of balancing power requirements in mixed power systems.

Major scientific contributions introduced in the here proposed model are:

- Parallel simulation of hourly power output and forecast error which allows for a conditional forecast error modeling and thus capturing a well recognized conditional wind power forecast error distribution.
- Presented model comprises both wind and PV power plants together with load forecast error, providing a generality in terms of power system development scenarios.
- Together with wind power plant production simulation, a detailed model for PV power plant production simulation is presented as well, introducing a novelty in terms of a simple framework based on several statistical parameters.

Each of the mentioned contributions is further elaborated in related sections. As a final remark on the proposed model capabilities, a complete model is based on weather and disposition data which are easily obtainable, enabling its wide practical applicability.

The paper is organized in the following manner. First section gives a general overview of the stochastic processes modeling techniques, pointing out a general simulation procedure used later in a model development. Second section provides a detailed description of each component of the proposed model in the context of stochastic process simulation procedure. Within each components description, a thorough review of related work is given as well. Finally, proposed model is validated on a practical case study.

2. Stochastic processes

Stochastic process is a collection of random values used for describing the evolution of some random variable and, in this sense, forecast error is a typical example of a stochastic process. Therefore, the existing knowledge on stochastic process modeling can be used for the forecast error simulation.

Each stochastic process is described with different mathematical parameters, and a basic task set for a model used for stochastic process simulation is to provide which parameters are preserved and to which extent. Among others, typical parameters that require preservation are: autocorrelation and correlation among variables in the process as well as the statistical distribution of these variables. Since the purpose of the model proposed in this paper is the estimation of yearly balancing power requirements, autocorrelation is not of importance. Namely, the characteristic of all series simulated with proposed model (forecast error, wind speed, clearness index) display an autocorrelation function with exponential decay vanishing within couple of days (wind speed, [17]) or hours (wind speed forecast errors, [18]). On the other hand, correlation and statistical distribution require preservation since they determine the state of simulated system in specific hour. Fig. 1 displays a principal depiction of the stochastic process simulation procedure applied in the proposed model. In its essence, proposed model reflects a Copula theory based multivariate random number generation with arbitrary marginal distributions. Following paragraphs describe each component in the depicted procedure.

The multivariate Gaussian copula cumulative distribution function can be determined with [19]:

$$C(u_1, u_2, \ldots, u_N) = \Phi_N\left(\Phi^{-1}(u_1), \Phi^{-1}(u_2), \ldots, \Phi^{-1}(u_N)\right) \tag{1}$$

where Φ_N is the multivariate standard normal cumulative distribution function (CDF), and Φ^{-1} is the inverse cumulative distribution function of the univariate standard normal distribution. Gaussian copula density function can be written as:

$$c(u_1, \ldots, u_N) = \frac{1}{\sqrt{\det R}} \exp\left(-\frac{1}{2} \begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_N) \end{pmatrix}^T \left(R^{-1} - \mathbf{I}\right) \begin{pmatrix} \Phi^{-1}(u_1) \\ \vdots \\ \Phi^{-1}(u_N) \end{pmatrix} \right) \tag{2}$$

where R is the correlation matrix and $\mathbf{I}$ is the identity matrix. Arbitrary multivariate cumulative distribution function can be generated based on its marginal distributions and copula function (Sklar's theorem):

$$F(x_1, x_2, \ldots, x_N) = C(F_1(x_1), F_2(x_2), \ldots, F_N(x_N)) \tag{3}$$

The second component in the procedure enables for obtained series to be transformed to a series with a desired distribution and standard deviation unachievable with the first component. After generating random sample from multivariate Gaussian copula

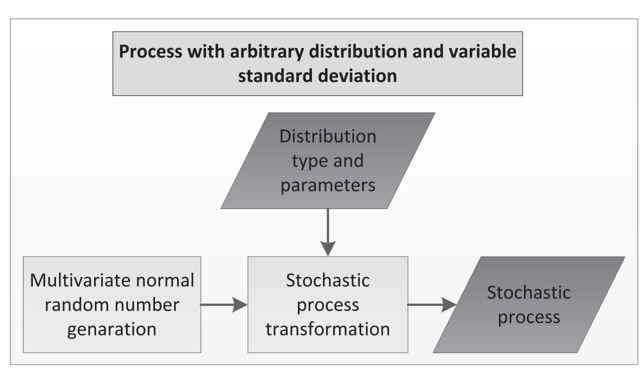

Fig. 1. Stochastic process simulation procedure.