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Wind power scenario generation through state-space specifications for uncertainty analysis of wind power plants

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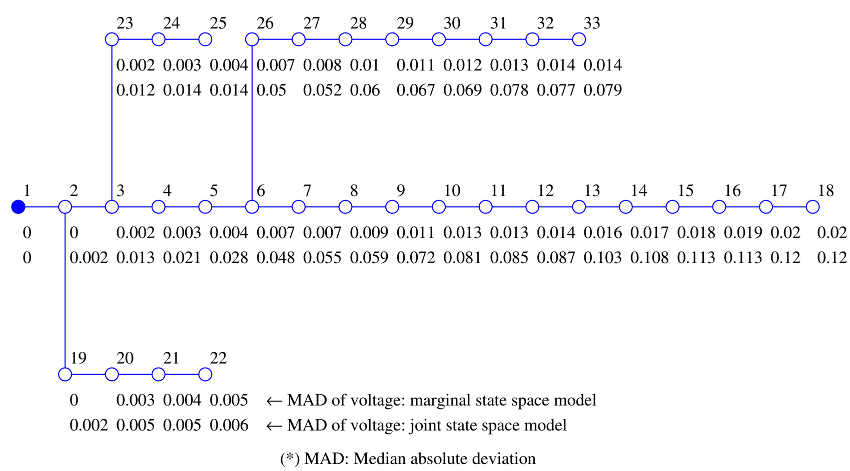
HIGHLIGHTS

- State space representations for simulating wind power plant output are proposed.
- The representation of wind speed in state space allows structural analysis.
- The joint model incorporates the temporal and spatial dependence structure.
- The models are easily integrable into a backward/forward sweep algorithm.
- Results evidence the remarkable differences between joint and marginal models.

GRAPHICAL ABSTRACT



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ABSTRACT

This paper proposes the use of state space models to generate scenarios for the analysis of wind power plant (WPP) generation capabilities. The proposal is rooted on the advantages that state space models present for dealing with stochastic processes; mainly their structural definition and the use of Kalman filter to naturally tackle some involved operations. The specification proposed in this paper comprises a structured representation of individual Box–Jenkins models, with indications about further improvements that can be easily performed. These marginal models are combined to form a joint model in which the dependence structure is easily handled. Indications about the procedure to calibrate and check the model, as well as a validation of its statistical appropriateness, are provided.

Application of the proposed state space models provides insight on the need to properly specify the structural dependence between wind speeds. In this paper the joint and marginal models are smoothly integrated into a backward–forward sweep algorithm to determine the performance indicators (voltages and powers) of a WPP through simulation. As a result, visibly heavy tails emerge in the generated power probability distribution through the use of the joint model—incorporating a detailed description of the dependence structure—in contrast with the normally distributed power yielded by the margin-based model.

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1. Introduction

Uncertainty analysis of a wind power plant (WPP) provides knowledge about the reliability of its design parameters, its integration into the power system, and ultimately about decisions resting on its estimated performance [1]. Essentially, these analyses aim at producing probabilistic distributions of selected performance indicators (voltages, powers, etc.) subject to the uncertain variation of independent variables. Wind speed is arguably the most significant of those variables in a WPP. Its random variations—with involved both temporal and spatial dependencies—makes scenario generation through simulation a most valuable tool to facilitate the uncertainty analysis.

Cross-sectional sampling is a first suite of methods for simulating wind speed to investigate WPP performance. They are the basis of Monte Carlo analyses in which time as a variable is of no interest. In these analyses the extraction of samples is not necessarily sequential. Indeed, vector operations are indicated to improve sampling speed [2]. In the wind power literature, several versions appear. The simplest rest on drawing unstratified samples of the probability distribution [3], or stratified through Latin hypercube-sampling (LHS) [4,2] or lattice sampling [5] to improve performance. They are simple to use because they do not necessarily require parameter estimation. If the marginal distribution is obtained through a kernel estimation, the distribution parametric specification can be avoided [2]. Even so, they may accurately model simple spatial dependence between pairs of machines by using a linear transformation based on the Cholesky decomposition of the correlation matrix [3,2]. Alternatively, where the dependence structure is more involved, copula methods have been applied, but following the same time independence [6,2].

At times it is necessary not only to focus on the probabilistic properties of the wind power sample, but also to show the longitudinal dependence structure, which stands for sequential sampling. That is the case when the wind power must be confronted to other stochastic processes—electricity price being the most relevant [1]—or when the evolution of a power system is investigated [7–9]. Box–Jenkins's ARMA models—with the property of resting in past values to regress the actual wind speed—have been favored in such cases. Indeed, Billinton et al. claimed that any individual wind speed process may be modeled by ARMA$(n, n-1)$ models [9]. And Torres et al. after intensive research concluded that other more parsimonious ARMA specifications also represented these processes adequately [10].

However, the ability to incorporate a sequential dependence makes ARMA-based models more complex to employ than their cross-sectional counterparts. The two major problems are the parameter estimation of individual wind speed series and the incorporation of spatial cross-correlation between sources. The first issue requires trial and error procedures as well as expert judgment, and it has been sufficiently covered in the related literature; including the classical work by Box and Jenkins [11]. The second issue, the correlation, has been addressed in the wind power literature in two ways: one resting on forcing the correlation to estimated individual models, and other using compound models covering several wind speed sources simultaneously. An instance of the first approach is reported in [12], where Gao et al. proposed a modification of the random number generation to affect the MA errors in such a way that the correlation was forced. The model was complex because it required a heuristic search of the appropriate seeds. Also following the individual path, Morales et al. proposed in [13] a methodology based on Nataf's method, popularized in [14], to obtain correlated samples of wind speed after having estimated the individual models. The correlation was incorporated by employing a technique of transformation similar to that in [3,4]. Alternatively other authors have recently followed the compound model path by employing vector autoregressive (VAR) models. For instance, in [15] VAR(p) models were employed for simulating wind speeds subject to directional components. Correia et al. restricted their analysis to VAR(1) models [16], and Hill et al. to VAR(2) [17]. The common feature in these studies is that the authors employed VAR, but not VARMA, models. That is, the error regression was not considered, though it has been stated in [9,10] that it is a fundamental component.

A recent addition to the previous specifications of wind speed autoregressive models is that of Chen and Yu in [18]. They proposed the translation of an AR model into state space (SS) form. Indeed, AR models are but a subfamily of the more general SS models. The ensuing advantages of using Chen and Yu's approach, rather than Box–Jenkins's, were detailed by Durbin and Koopman in [19, Section 3.2.1]. First and foremost, the problem can be structurally analyzed. This is in contrast with Box–Jenkins approach, which does not investigate the structure of the problem. This structural analysis makes the SS approach really flexible for incorporating trends and seasonalities. By contrast, Box–Jenkins approach requires a previous deseasonalizing and detrending. In addition, Durbin and Koopman cite other superior features of SS models compared with ARMA specifications, such as for instance the treatment of missing observations, the easy incorporation of explanatory variables, the possibility of time-varying regression coefficients, and the use of Kalman filter to naturally forecast forward in the future (the subject of [18]).

This paper contributes to the literature on wind power scenario generation by proposing a SS representation of the wind speed. The contributions with respect to previous works are the following:

1. First, Section 2.2 generalizes the SS model in [18] to also consider the contribution of previous unobserved errors. The ensuing generalized model exhibits a structure that makes it susceptible to easy expansions.
2. The use of Kalman filtering to estimate those marginal SS model parameters is favored by the transformation of the original dataset into Gaussian random variables. This paper shows that the method proposed in [20] though proving to be useful is incomplete, for it cannot cope with calm wind speeds. A solution to this problem is offered in Section 2.1.
3. This paper shows in Section 2.3 that a joint SS model can be easily built, preserving the structure of the marginal models. The joint model expands the VAR formulations in [15–17], by incorporating the MA terms, as advised in [9,10]. Further, it completes the marginal state space model in [18] by integrating the spatial dependence between sources through the use of a multivariate white noise into the transition equation, with covariances estimated from the original data.
4. Finally, this paper shows how to integrate the model into a backward–forward sweep algorithm to obtain the simulated performance of a WPP (Section 3.2). Moreover, clear evidence about the error of employing non-dependent wind speeds to simulate the aggregated power generation of a WPP is provided: Though there may be no deviations on the mean node voltages and generated power, the extreme and more probable values are visibly different.

2. State space model characterization

This section describes the proposed procedure for building the SS model of wind speed of a WPP. The model is built in a normalized space, starting with an uncorrelated SS model in which the marginal distributions are independent, and ending with the specification of the correlation.