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# Impact of Wind Geographical Correlation in Reliability Assessment Studies Using Sequential Monte Carlo Simulations

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**Abstract.** Electrical generation based on the use of renewable energies is emerging in modern grids. In that way, one of the most popular solutions as well in transmission as in distribution grids is certainly coming from wind energy. However, wind resources on a given location randomly fluctuate with time and have thus a major impact on the capacity of the electrical system to continuously face the load. In order to evaluate this impact and to consequently adapt required reinforcements, Monte Carlo simulations are often used. Those approach can be either sequential or not. Nowadays, load shifting solutions (storage, demand side management…) are practically set in order to adapt consumption to time varying generation without involving too consequent investments. In that way, sequential approach is currently preferred when it comes to long-term planning evaluation and adapted time series models are developed to characterize wind generation on a given site. The consideration of the geographical correlation between those models has been recently investigated in some references. This paper proposes to complete those contributions by evaluating the impact of wind geographical correlation on classical reliability indices such as the Loss of Load Expectation (LOLE) or the Expected Energy not Served (EENS).

## Key words

Wind, correlation, reliability, grid.

## 1. Introduction

Nowadays, most of the conventional electrical parks are still using fossil resources like coal or oil. Those primary resources involve the emission of gaseous pollutants like carbon oxides ($CO_x$) or oxides of nitrogen ($NO_x$). Recently, following the Kyoto agreements, a great research effort has been made in order to reduce those emissions worldwide. In this context, one of the most promising alternative resources is certainly wind power. Given the fluctuating behaviour of wind and due to several operating constraints (cost, reliability…) related to electrical systems, it is important to adequately dispatch conventional generation and load shifting solutions in order to face the requirements of modern networks. Practically, in order to undertake adequate investment decisions, reliability evaluation can be accomplished using deterministic (N-1 criterion) or probabilistic methods. Although the deterministic approach presents attractive characteristics like direct implementation, it involves oversized reinforcements of the electrical network. Consequently, probabilistic methods like Monte Carlo simulation are usually used for technical-economic studies. Practically, there are two ways to execute Monte Carlo algorithms: non-sequential and sequential techniques. Non-sequential Monte Carlo simulations generate a large number of system states to provide statistically reliable results but every state is independent from each other [1]. In order to take into account the chronology of wind speed variations and of load profiles, but also to be able to evaluate the benefits arising from load shifting solutions, sequential Monte Carlo simulations [2-4] must be used as they ensure a realistic transition between two successive states for each element of the power system. Currently, given the particular attention paid to storage means in a context of increased dispersed generation, sequential probabilistic approach are generally preferred to the non-sequential ones. Based on historical data of a particular geographic site, time series models are commonly used in sequential Monte Carlo simulations as they permit to generate synthetic wind speed data which mimic the statistical properties of real measurements. Practically, it should be noted that generated wind speed data need then to be transformed in the power domain using the power curves of the considered wind turbines.

In order to sequentially sample wind speeds, *AutoRegressive Moving Average* (ARMA) models are commonly used [5-7] and geographical correlation between wind parks can be considered by means of Cholesky decomposition [6-7]. Practically, to the best authors' knowledge, the sensitivity of the computed reliability indices to the considered geographical correlation level between wind parks has not really been evaluated yet. Consequently, in this paper, the classical LOLE (number of hours per year during which the load cannot be met with the available generation) and EENS (mean energy not served during periods of lack of generation) indices are computed for an academic test grid [8] under extreme wind correlation scenarios (entirely independent or correlated). It is then shown that the consideration of an adequate geographical correlation between wind parks has significant impacts on the computed reliability indices.

## 2. The Implemented Sequential Monte Carlo Simulation

Practically, Monte Carlo simulations can be used to estimate reliability indices by simulating the actual process and random behaviour of the considered electrical system. In theory, those simulations can include system effects which may not be possible without excessive approximation in a direct analytical approach and can generate a wide range of indices within a single study [9]. In fact, there are two basic techniques used when Monte Carlo methods are applied to power system reliability evaluation, these methods being known as the sequential and non-sequential techniques [1-4].

In the present study, a sequential Monte Carlo algorithm has been implemented under *Matlab®* to evaluate the reliability indices of interest. Note that the scope of the study is limited here to the hierarchical level HL-I (aggregated generation and consumption under infinite node hypothesis) and only the capacity of the system to cover the load is evaluated.

*2.A Classical generation and load models*

This Monte Carlo simulation theoretically could incorporate any number of system parameters and states but it has been here assumed that a generation unit was only able to reside in one of the following two states: ***fully available*** and ***unavailable***. The times to failure and times to repair for a yearly sequence are obtained by sampling the appropriate probability distributions. In this procedure, the state residence times are assumed to be exponentially distributed [2-3].

Concretely, a random variable T has thus the following probability density function:

$$f_T(t) = \lambda \cdot e^{-\lambda t} \tag{1}$$

where λ is the mean value of the distribution. Using the inverse transform method [9], the random variable T is obtained by:

$$T = \frac{-\ln(1-u)}{\lambda} \tag{2}$$

where u is a uniformly distributed random number over the interval [0 1].

Practically, both operating and repair times of the considered conventional 2-state model for the generation units are thus exponentially distributed. MTTF and MTTR are respectively the mean times to failure and to repair. Sampling values of the times to failure (TTF) and to repair (TTR) are finally computed following equation (2) as [2]:

$$TTF = -MTTF \cdot \ln(1-u) \tag{3}$$

$$TTR = -MTTR \cdot \ln(1-u') \tag{4}$$

with u and u' two independent uniformly distributed random numbers over the interval [0 1].

From the load point of view, an annual peak load is modulated by use of weekly, daily and hourly modulation rates provided in reference [8].

*2.B Wind generation model*

In this paper, wind speeds are sequentially simulated by means of ARMA time series. Theoretically, ARMA time series models require working on weak-sense stationary processes, *i.e.* stochastic processes for which the mean is constant over time, the variance is finite at each time $t$, and for which the covariance function is independent of the time lag [10]. In practice, collected wind speed data do not verify these properties: it naturally shows seasonal patterns (day/night cycles, seasons), and may contain a trend. Therefore, a pre-processing step must be applied to the raw data in order to remove such effects. Classically, an operation of 'centralization-reduction' is conducted to that end [11]. The idea is to work on a standardized version $X_t$ of the initial wind speed time series $W_t$, obtained by use of the following equation:

$$X_t = \frac{W_t - \mu_t}{\sigma_t} \tag{5}$$

with $\mu_t$ and $\sigma_t$ respectively the mean and the standard deviation of observed wind speed at time $t$.

Practically, a zero mean ARMA process $\{X_t\}$ of order $(p,q)$ can be defined as follows [5,11]:

$$X_t = \sum_{k=1}^{p} \alpha_k X_{t-k} + \varepsilon_t + \sum_{j=1}^{q} \vartheta_j \varepsilon_{t-j} \tag{6}$$

with $\{\varepsilon_t\}$ the process of innovations (a Gaussian white noise $N(0,\sigma_\varepsilon^2)$ of variance $\sigma_\varepsilon^2$), and with $\alpha_k$ and $\theta_j$ non zero constants.

After having obtained the standardized wind speeds thanks to an adequate sampling on the $\varepsilon_t$ residues, those wind speeds are firstly 'de-standardized' and afterwards converted in generated power. In that way, the following power curve is implemented [3]:

$$\begin{cases} P = 0, W_t < v_{ci} \\ P = a + b \cdot W_t^2, v_{ci} < W_t < v_r \\ P = P_r, v_r < W_t < v_{co} \\ P = 0, W_t > v_{co} \end{cases} \tag{7}$$

where, $v_{ci}$, $v_r$, $v_{co}$ are respectively the cut-in, rated and cut-out wind speeds. $P_r$ is the nominal power of the wind generator.

Parameters a and b are defined as [3]:

$$a = \frac{P_r \cdot {v_{ci}}^2}{\left(v_{ci}^2 - v_r^2\right)} \tag{8}$$

$$b = \frac{P_r}{\left(v_r^2 - v_{ci}^2\right)} \tag{9}$$

Finally, note that, in this paper, the time series models established for Swift Current and North Battleford in reference [5] are considered for the simulation of wind generation.

*2.C The implemented algorithm*

For each simulated hour *i*, the state of the studied system is firstly generated. To do so, the state of each classical generation unit is changed if the simulated hour matches the associated TTF (if this unit was operating during the previously simulated state) or TTF+TTR (if the unit was down during the previously simulated state). If the state of a classical unit has been changed then a new value of TTF (if the unit has moved from down to operating state) or TTR (if the unit has moved from operating to down state) is sampled for the considered unit by use of equations (3) or (4). Wind generation during the simulated hour is defined by an adequate sampling on the wind speed time series model related to each wind park, the conversion into power being made via the associated power curve. The load during the simulated hour is obtained by checking the associated modulation rates in the predefined annual profile.

After the generation step, each system state is then analyzed. Indeed, the available generation (wind + classical units) is compared to the load. If the load exceeds the available generation then the number of problematic states $n_p$ is incremented. Simultaneously, for each problematic state *j*, the lack of energy $E_{lj}$ is also evaluated by making the difference between the actual load and the available generation (energy being equal to power in this paper as hourly states are considered).

At the end of the simulation ($i = NS$, $NS$ being the total number of states to be simulated), both reliability indices of interest are evaluated as follows:

$$LOLE = \frac{n_p}{NS} * 8760 \tag{10}$$

$$EENS = \frac{\sum_{j=1}^{n_p} E_{lj}}{NS} * 8760 \tag{11}$$

## 3. Case study and simulation results

The tested grid is based on the one depicted in references [3] and [8]. Practically, the peak load is fixed to 560 kW and 15 conventional generation units are considered (10 units of 32 kW and 5 units of 60 kW). Their MTTF and MTTR are identical and respectively imposed to 2940 h/year and 50 h/year. Two wind generators (20 kW each) are added to the system and, as already mentioned in section 3, are respectively based on Swift Current and North Battleford data. The same power curve is applied for both wind parks with $v_{ci}$ = 3 m/s, $v_r$ = 12 m/s and $v_{co}$ = 25 m/s.

Two extreme correlation scenarios are implemented. The first one considers an entire correlation between the simulated residues $\varepsilon_t$ of the wind speed time series models and the second one is based on an entire independence between those residues.

LOLE and EENS indices are computed for both scenarios. In that way, the number of simulated years NS of the Monte Carlo process is decided by comparing the coefficient of variation β of each index to a fixed tolerance threshold (β < 1% when computed over the last 500 years of simulation) [2]:

$$\beta_{LOLE} = \frac{\sqrt{V(LOLE)}}{E(LOLE)} \tag{12}$$

$$\beta_{EENS} = \frac{\sqrt{V(EENS)}}{E(EENS)} \tag{13}$$

where, V and E are respectively the variance and the expected value of the estimated index.

In the present case, the convergence threshold is reached for NS = 4000 years. Figures 1 (a and b) and 2 (a and b) respectively give the evolutions of LOLE and EENS indices for both investigated scenarios. By analysing the values of those indices, it can be observed that, when the convergence is reached, the LOLE index computed in the "entirely independent" case (LOLE = 1.0855 h/year) is less severe than the one obtained in the "entirely correlated" case (LOLE = 1.1403 h/year). The same observation is made for the EENS index as this index increases from 18.8 kWh/year (in the "independent case") towards 19.5 kWh/year (in the "correlated" one). The degradation of the computed indices in the "entirely correlated" scenario can be explained as follows. Practically, in that case, wind generation is simultaneously reduced for both considered units and, consequently, states of lack of available generation are more severe compared to the ones recorded in the "independent case". Indeed, in this last scenario, a smoothing of the available wind generation is observed as the power decrease of one generator is not necessarily observed for the other one.

In order to have a better idea of the sensitivity of the reliability results between both simulated extreme geographical correlation scenarios, the relative variations of the recorded LOLE and EENS values are also computed and respectively reach 5.05 % and 3.72 %. This result demonstrates the interest of taking into account the existing geographical correlation between wind sites in order to found investments decisions on reliable values of the computed indices.

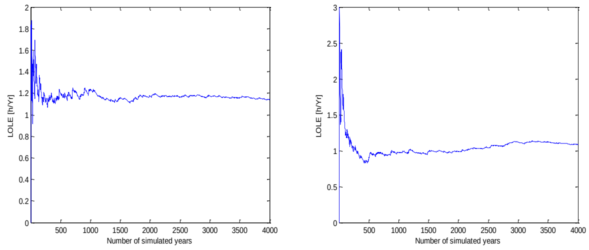


Fig.1. Evolution of the computed LOLE for different simulation lengths: (a) entirely correlated case, (b) entirely independent case

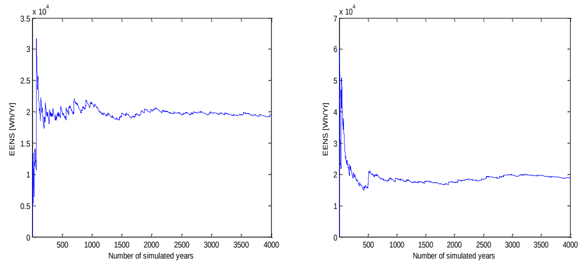


Fig.2. Evolution of the computed EENS for different simulation lengths: (a) entirely correlated case, (b) entirely independent case

## 4. Conclusions

In this paper, a sequential Monte Carlo simulation tool was implemented and wind generation was modelled by means of time series. Two extreme geographical correlation scenarios were investigated in order to evaluate the impact of the correlation level on the computed reliability indices. The study was here conducted on an academic test case [3, 8] and two classical HL-I indices (LOLE and EENS) were evaluated. It was shown that both considered extreme correlation scenarios could lead to relative variations of the collected indices from several %. Consequently, the interest of taking into account adequate geographical correlation between wind sites was pointed out in order to undertake reliable investment decisions.

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