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# Application and comparison of wind speed sampling methods for wind generation in reliability studies using non-sequential Monte Carlo simulations

F. Vallée*,†, J. Lobry and O. Deblecker

*Faculté Polytechnique de Mons, Department of Electrical Engineering Bvd. Dolez, 31 B-7000 MONS, Belgium*

## SUMMARY

Given the actual context of increased dispersed generation and highly loaded lines, probabilistic methods are more and more required to take into account the stochastic behavior of electrical network components (possible spate of outages by use of the electrical network near its physical limits) in reliability studies. To implement those probabilistic methods, numerical Monte Carlo simulations are typically used and can be divided in two categories: sequential and non-sequential techniques.

This paper deals with two wind speed sampling methods adapted for non-sequential Monte Carlo simulations, among which an original approach based on the combination of a mean statistical law (for a large geographical area like a country) and Normal distributions (to characterize smaller wind speed zones inside the country). Both proposed techniques are then applied on a self-developed non-sequential Monte Carlo simulation only taking into account generation units outages and load changes (hierarchical level HL-I). Finally, the collected simulation results allow, not only, to evaluate the impact of sampling methods on the collected reliability indices but also to decide which proposed technique will lead to the most interesting situations (larger wind power fluctuations from one state to the other) for the electrical network operation management. Note that our simulations are applied to the Belgian production park. Copyright © 2008 John Wiley & Sons, Ltd.

KEY WORDS: Weibull distributions; wind energy; reliability; adequacy evaluation; Monte Carlo simulation

## 1. INTRODUCTION

The major characteristic of a Monte Carlo method is to simulate the random behavior of the considered electrical system. Typically, two kinds of Monte Carlo simulations can be found in the literature, based on the stochastic dependence between consecutive states. In that context, the introduction of wind models in an electrical network reliability study will have to be imagined in agreement with the chosen Monte Carlo method. In case of a non-sequential approach (consecutive states totally independent), a random wind speed drawing is to be implemented to model wind generation in the proposed reliability study.

In this paper, two wind speed sampling methods well adapted for non-sequential Monte Carlo simulations are applied in a reliability study limited to hierarchical level I (HL-I) [1].

Here, the focus is more particularly axed on an original sampling method based on the combination of a single mean distribution for the considered country and of normal noises $N(m,\sigma)$ to particularize smaller wind regions inside the country. This new method is then compared with a classical one funded on the inversion of *Weibull* Cumulative Distribution Functions.

The paper will thus be organized as follows. After a brief description of the existing sampling method, advantages and drawbacks to be associated with this solution are listed tending to demonstrate the interest (especially when the geographical correlation level between wind parks is to be taken into account) of defining a new sampling method. This last one is based on the computation of a global statistical distribution and on the characterization of each considered wind region with a particular normal noise. Finally, both wind speed sampling methods are introduced in an HL-I reliability study and, in that way, applied to the Belgian wind park that was

*Correspondence to: F. Vallée, Faculté Polytechnique de Mons, Department of Electrical Engineering Bvd. Dolez, 31 B-7000 MONS, Belgium.
†E-mail: francois.vallee@fpms.ac.be

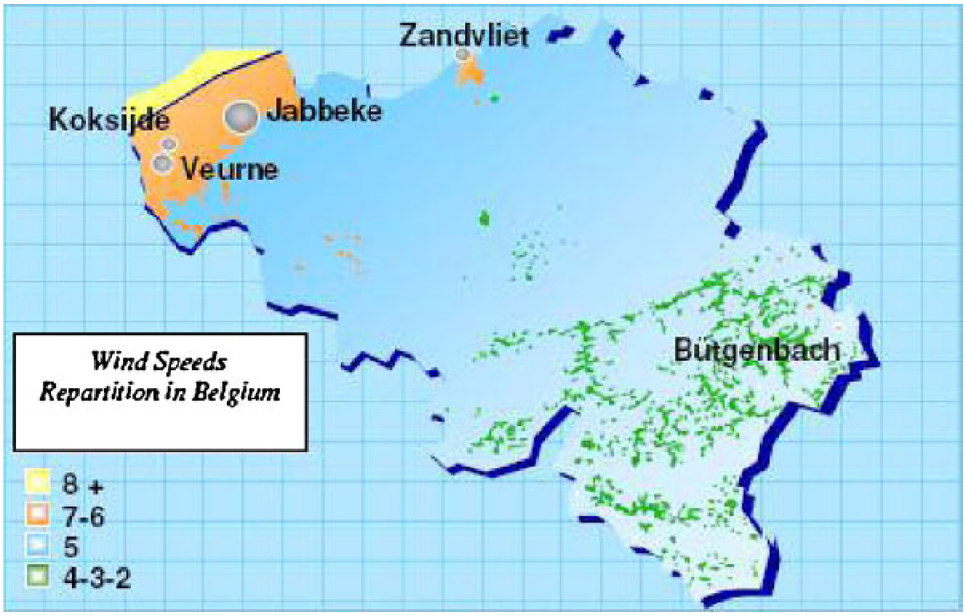


Figure 1. Belgian wind speeds repartition [2].

operating by the year 2004. The simulation results are compared and lead to some interesting results in terms of wind modeling for reliability studies.

## 2. WIND SPEED DRAWING METHODS

In this paper, the definition of wind geographical areas is based on annual mean wind speed values. So, as illustrated in Figure 1 [2], Belgium can be divided into three geographical regions: the Polders ($W_{mean/year} > 6$ m/second), the Center (4 m/second $< W_{mean/year} < 6$ m/second) and the Ardennes ($W_{mean/year} < 4$ m/second). Consequently to this geographical division of the country, wind speed measurements are imperative to characterize each wind region and have been collected for Uccle (Center), Ostende (Polders), and Saint-Hubert (Ardennes) thanks to the database owned by the *Belgian Royal Institute of Meteorology* (IRM).[1] In Figure 2(a), the histogram of measured wind speeds is established for Uccle and follows, based on a least square estimation (for the adjustment of scale and shape parameters of the Weibull law; *cf.* paragraph II.A) and a $\chi^2$ critical validation of the adjustment [3], a *Weibull* distribution. Note that the same approach is applied for Saint-Hubert (Figure 2(b)) and Ostende (Figure 2(c)); also leading to *Weibull* distributions (with, of course, changed parameters).

### *2.1. Single Weibull distribution by wind geographical region: direct sampling method*

The first sampling method has already been published in scientific literature [4]. Practically, it associates a single *Weibull* law by wind region and can be presented as follows:

- √ Drawing of an uniformly distributed number $\nu$ between [0,1].
- √ This random number $\nu$ is then applied to the inverse of the *Weibull Cumulative Distribution Function* (1) to determine the associated wind speed $W$:

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[1]The data given by the *Royal Institute of Meteorology* are based on one typical year. By definition, a typical year is a year that has never existed but that correctly fit the observed weather trends for a larger period of time (the 1990s for our case).



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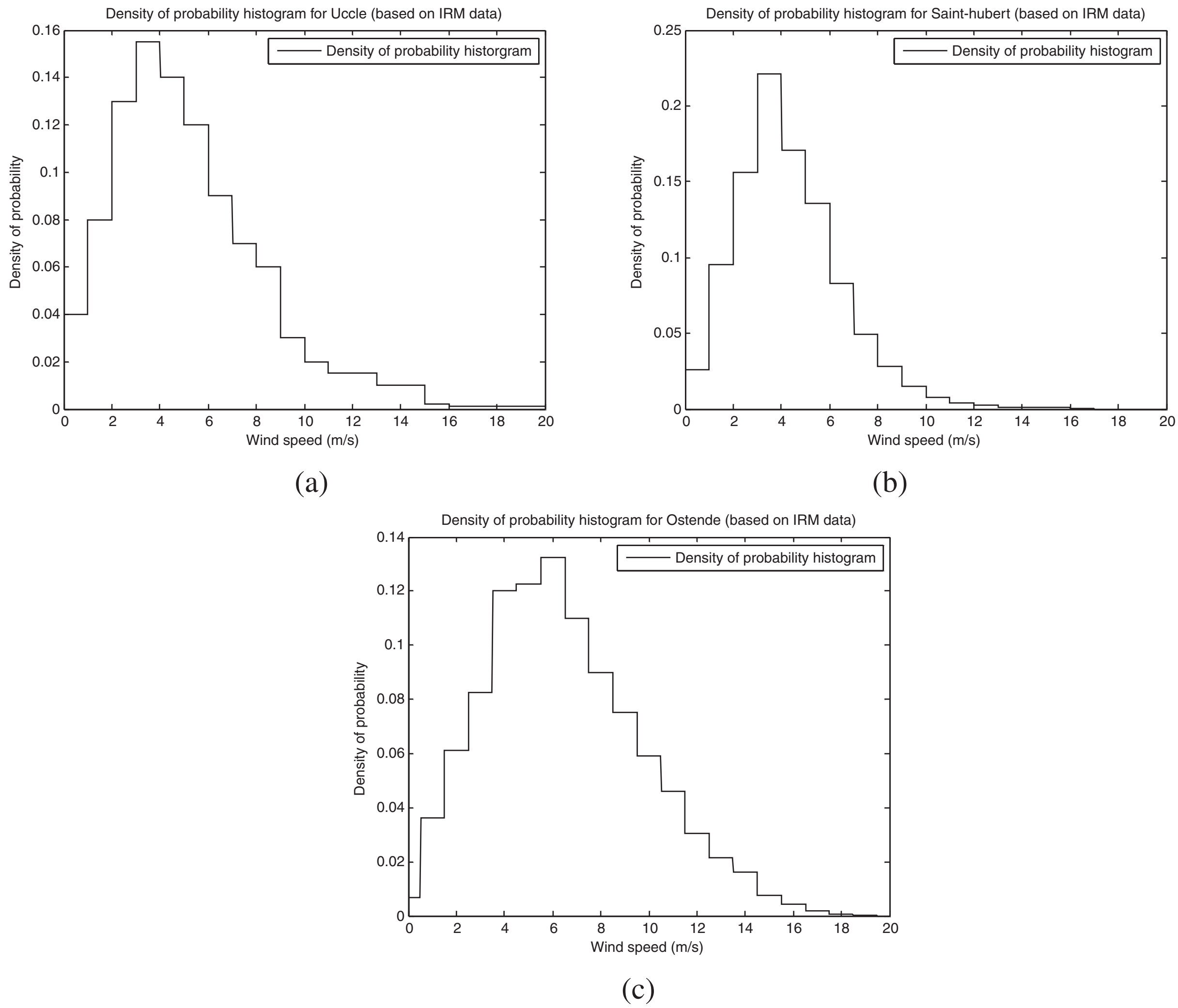


Figure 2. Probability density histogram (based on IRM data) established for Uccle (a), Saint-Hubert (b), and Ostende (c).

$$W = A\left[(-\ln(1-v))^{\frac{1}{B}}\right] \tag{1}$$

with, $A$ the scale parameter and $B$ the shape parameter.

The first proposed sampling method is illustrated, for Uccle, Saint-Hubert, and Ostende, in Figure 3. It can be observed on these results that simulated wind speeds and measured histograms nearly follow the same statistical evolution. Moreover, remark that the $A$ and $B$ parameters are determined thanks to least squares estimation between simulated and measured histograms (2) [3].

$$S = \min\left(\sum_i \left(p_{\mathrm{IRM}}(W_i - W_{i-1}) - p_{\mathrm{draw}}(W_i - W_{i-1})\right)^2\right) \tag{2}$$

where $S$ is the least square estimator, $p_{\mathrm{IRM}}(W_i - W_{i-1})$ and $p_{\mathrm{draw}}(W_i - W_{i-1})$ are respectively the IRM measured and the directly drawn densities of probability included in the wind speed interval $[W_{i-1}, W_i]$.



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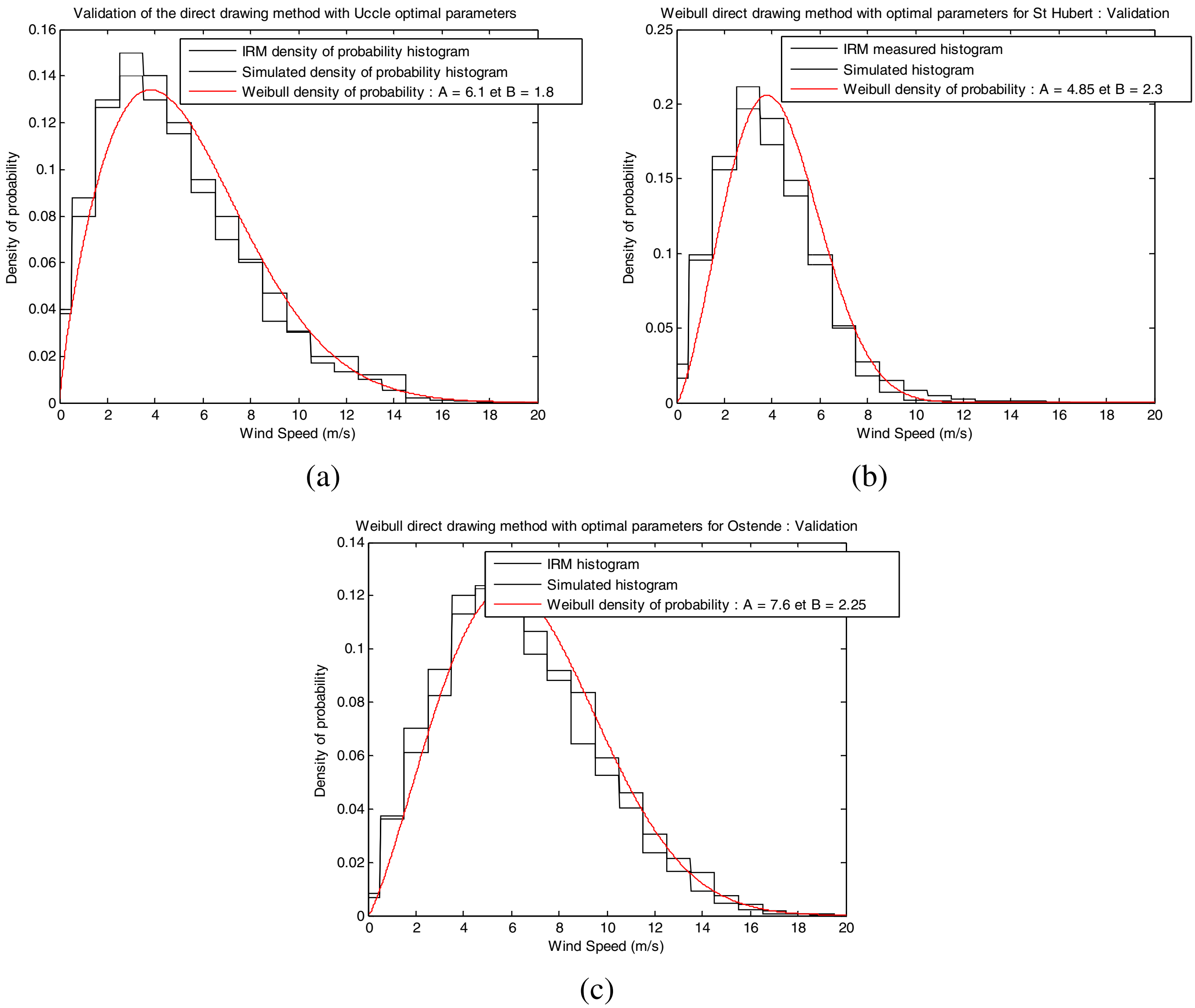


Figure 3. Direct drawing method for Uccle (a), Saint-Hubert (b), and Ostende (c).

Also note that this first proposed drawing method is classically justified by a property of *Cumulative Distribution Functions* that implies to find back the initial statistical law by a uniform drawing on the distribution function if this last one is *well adjusted*. In that way, our least squares adjustment has been critically validated by use of a $\chi^2$ statistical test [3].

However, even if justified and validated, this classical sampling method presents some drawbacks:

- √ Indeed, the correlation level to be associated between each wind park of the same region must be discussed. If we refer to the worst case, a complete dependence between wind parks (a single wind speed drawn for each region) must be considered, as it will lead to greater wind power fluctuations from one simulated hour to the other [4]. Nevertheless, by definition of the direct sampling method and, as a different *Weibull* distribution is associated to each wind region (inside the same country), there will always be an independency level between wind regions related to the use of the direct sampling method.
- √ Moreover, each geographical region is here based on an identical annual mean wind speed value. Given the narrowness of Belgium, the choice of a single *Weibull* distribution for each of these regions can be justified as the distribution of hourly wind speeds around the annual mean wind speed will be approximately the same all over each considered region. On the opposite, in



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case of a larger country (and, thus, possible larger wind regions inside this country), the association of a single *Weibull* law for each wind region (being still based on an identical annual mean wind speed) could lead to errors as, for possibly larger wind speed regions inside the considered country, the distribution of hourly wind speeds can change from one site to the other in the same wind region (even if the same annual mean wind speed is still calculated all over the wind region) and, thus, a single *Weibull* law associated to each defined wind region is no more sufficient in this last case.

### 2.2. Combination of a mean distribution and of a normal noise N(m,σ) characteristic of each wind region

To introduce a dependency level between wind regions inside the country, the idea is to introduce a mean distribution for the entire country and to particularize this last one by adding, for each wind region (inside the considered country), a normal noise (the normal noise parameters being different for each wind region) to the single drawn mean wind speed. This mean distribution is, here, obtained by calculating, for each hour, the arithmetical mean wind speed between the IRM data for the three considered sites (Uccle, Ostende, and Saint-Hubert). We, so, compute 8760 (IRM data are given, on hourly basis for a single typical year) hourly mean wind speeds. The results are then classified (intervals of 1 m/second given the precision of the data collected by the IRM) and presented, for Belgium, as a histogram in Figure 4. A least square adjustment has been made on the resulting law, leading to a *Weibull* distribution with $A = 5.25$ and $B = 3.55$.

The obtained *Weibull* law has been critically validated by mean of a $\chi^2$ adjustment test and, thus represents the evolution of the mean wind speed throughout the country. However, note that, *Weibull* distributions being non stable distributions, the sum of such laws (as the mean distribution has been obtained by adding the realizations of three different *Weibull* distributions; each considered wind speed region being, indeed, characterized by a different *Weibull* law) does not necessarily give back a *Weibull* one and generally has no name [5]. Nevertheless, even if the arithmetical mean distribution does not follow a *Weibull* evolution, the proposed sampling method stays valid on condition that mean wind speeds are obtained thanks to a well adjusted mean distribution (which is, in the general case, no more a *Weibull* law).

Jointly to this mean distribution, normal noises $N(m,\sigma)$ are introduced for each wind region and model the hourly difference between the arithmetical mean wind speed histogram (previously obtained by calculating the hourly arithmetical mean wind speeds between the three considered sites) and the IRM measured histogram of each wind region (3), (4) and (5).

$$B_{\text{uccle}}(j) = W_{\text{mean}}(j) - W_{\text{uccle}}(j) \tag{3}$$

$$B_{\text{sthubert}}(j) = W_{\text{mean}}(j) - W_{\text{sthubert}}(j) \tag{4}$$

$$B_{\text{ostende}}(j) = W_{\text{mean}}(j) - W_{\text{ostende}}(j) \tag{5}$$

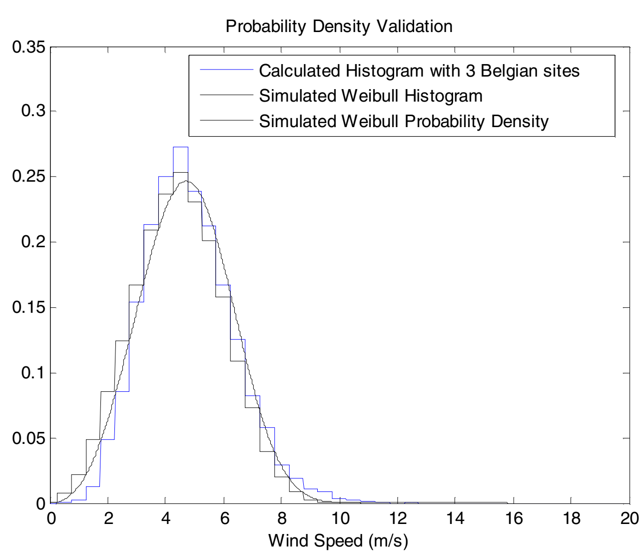


Figure 4. Calculated (blue) and simulated (dashed) mean *Weibull* histograms + simulated *Weibull* density of probability.



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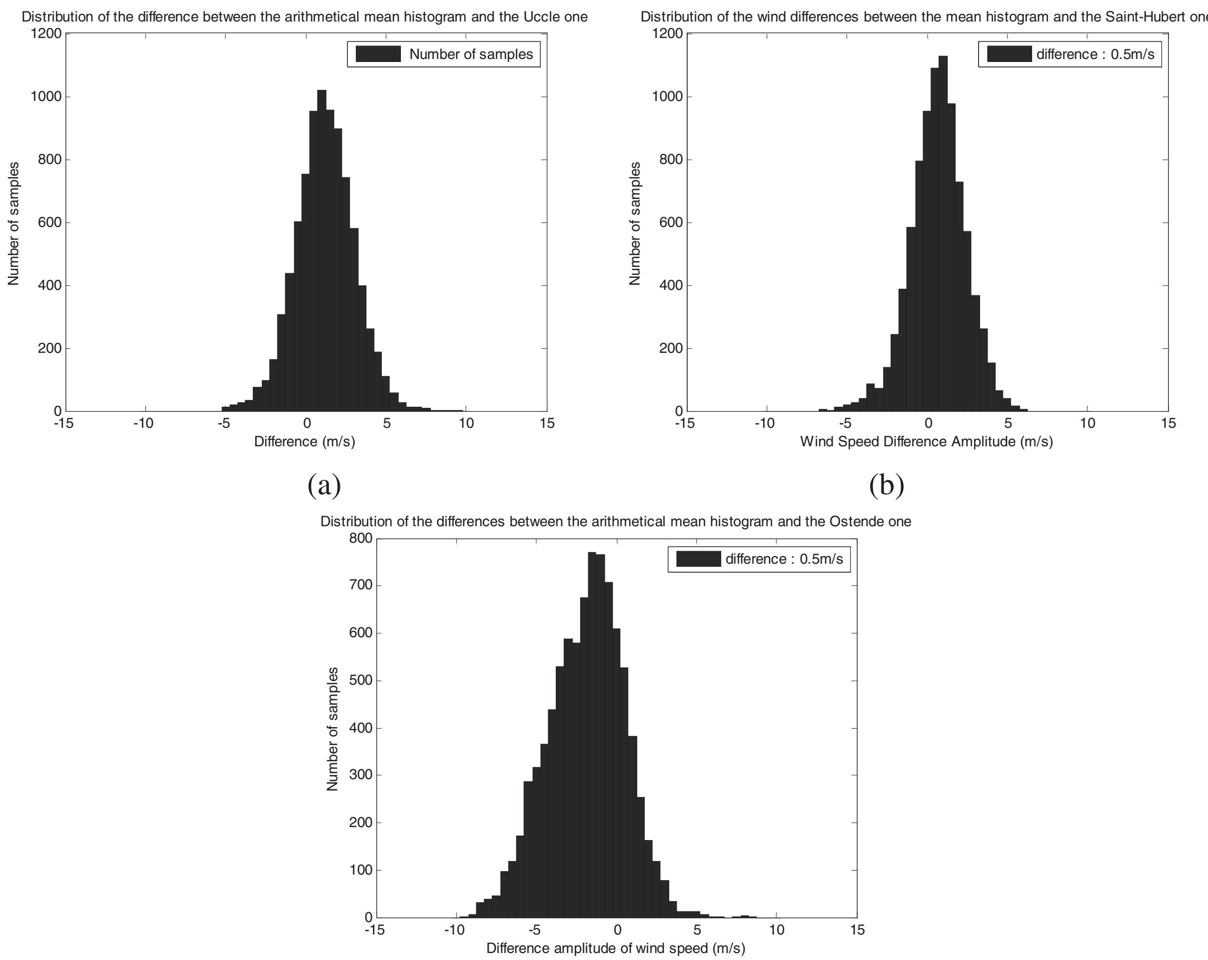
where $j$ represents the hour, $W_{site}$ the wind speed at the considered site, $W_{mean}$ the wind speed extracted from the arithmetical mean distribution and $B$ is the hourly difference between these two wind speeds.

Figure 5(a) illustrates, for Uccle, the histogram of the calculated hourly differences $B_{uccle}$. This last one follows the evolution of a Normal distribution and its parameters have then been determined thanks to a method of moments [6]. The obtained Normal distribution for Uccle can be expressed as $N(1.2098, 1.8325)$ and is validated, in Figure 6(a), where this simulated distribution perfectly fits the one extracted from the calculated histogram $B_{uccle}$. Note that the same approach has been followed for Saint-Hubert (Figures 5(b) and 6(b) and Ostende (Figures 5(c) and 6(c) and has also led to normal noises. Indeed, Saint-Hubert is characterized by a Normal distribution $N(0.6688, 1.6987)$ while Ostende gives $N(-1.8786, 2.3839)$.

Finally, as illustrated, for Belgium, in the flow chart of Figure 7, wind speeds in each region will be obtained by jointly drawing a single mean wind speed (for the entire country) on the mean distribution (in our particular case, a *Weibull* law) and by adding to this last one a normal noise characterizing the considered region (respectively $B_{uccle}$ for Uccle, $B_{sthubert}$ for Saint-Hubert, $B_{ostende}$ for Ostende).

The proposed algorithm of Figure 7 has been implemented for the three Belgian wind regions and is validated, in Figure 8, by comparing, for each site, the measured IRM histogram with the drawn one.




(a) (b) (c)

Figure 5. Calculated distribution of the differences between the arithmetical mean histogram and (a) the Uccle IRM one, (b) the Saint-Hubert IRM one, (c) the Ostende IRM one.



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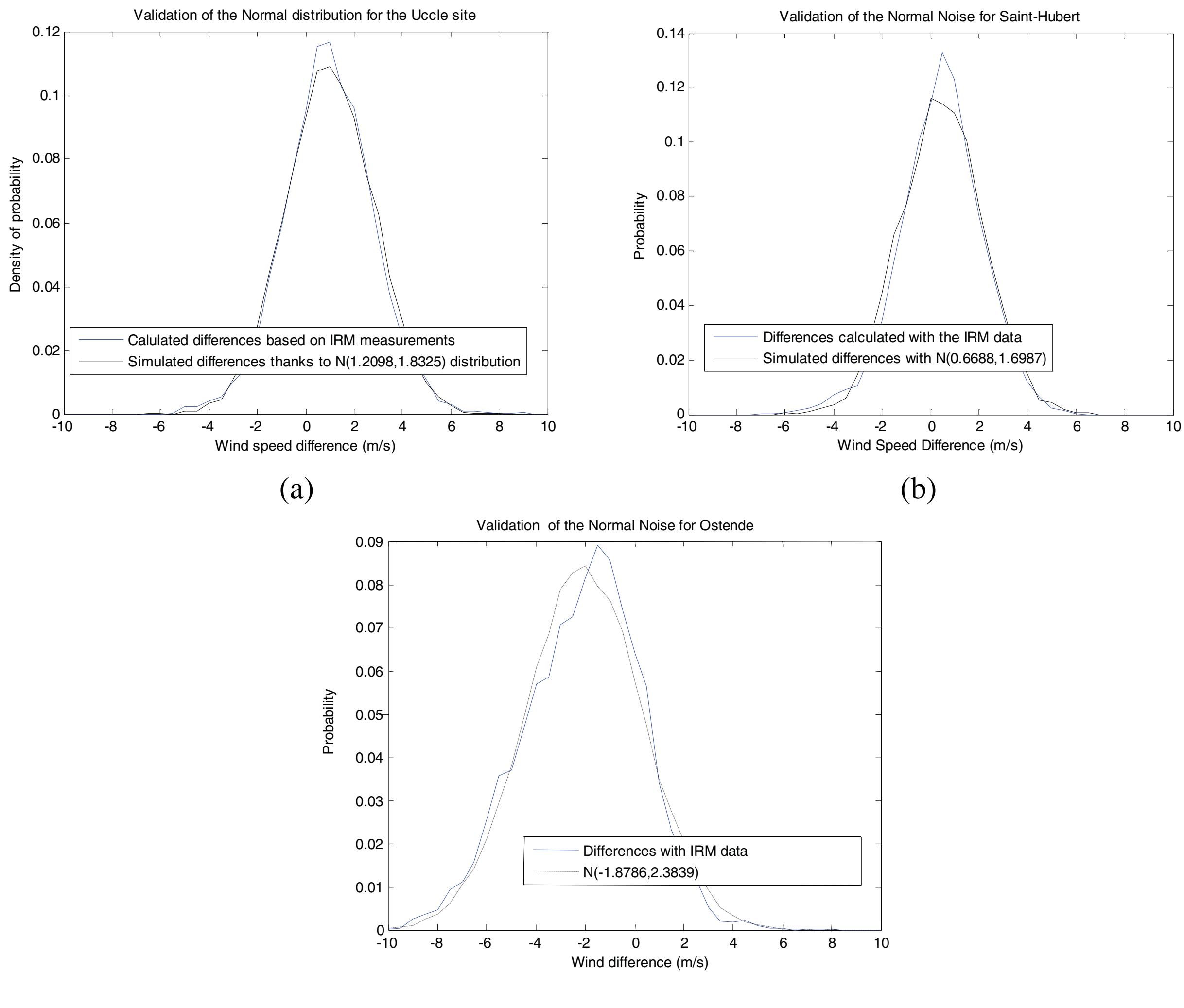


(c)

Figure 6. Validation of the normal distribution for wind speed differences (between the hourly wind speed at the considered site and the global arithmetical mean wind speed) for (a) Uccle, (b) Saint-Hubert, and (c) Ostende.

Also note that, in the way it is defined here, the second proposed drawing method introduces a higher correlation level between wind sites as the same single mean wind speed is considered for the entire country (this last one being then particularized thanks to the normal noises defined for each wind region inside the country) and will thus, lead to higher hourly global wind power fluctuations when taking wind production into account for reliability studies (worst case in terms of power flows on the electrical network). Moreover, in this second approach, thanks to the modeling of the differences in relation to a global mean evolution, wind speed regions can here be defined on basis of the corresponding Normal distribution characteristics (which could be an interesting result in case of large countries).

Point out that a single wind speed is sampled for each wind park. In other words, it implies that all the turbines inside the park are facing the same wind speed. By doing this, we do not consider, as parameters, the direction of the wind and the associated interactions between turbines. Indeed, taking into account turbines interactions inside the park could lead to a smoothing of the produced power from one simulated hour to the other. Therefore, as the worst case is to be considered in order to study the reliability of the electrical system, this last one has thus to face the most fluctuating wind conditions. Those conditions are obtained when wind speed is supposed to be constant all over the wind park.



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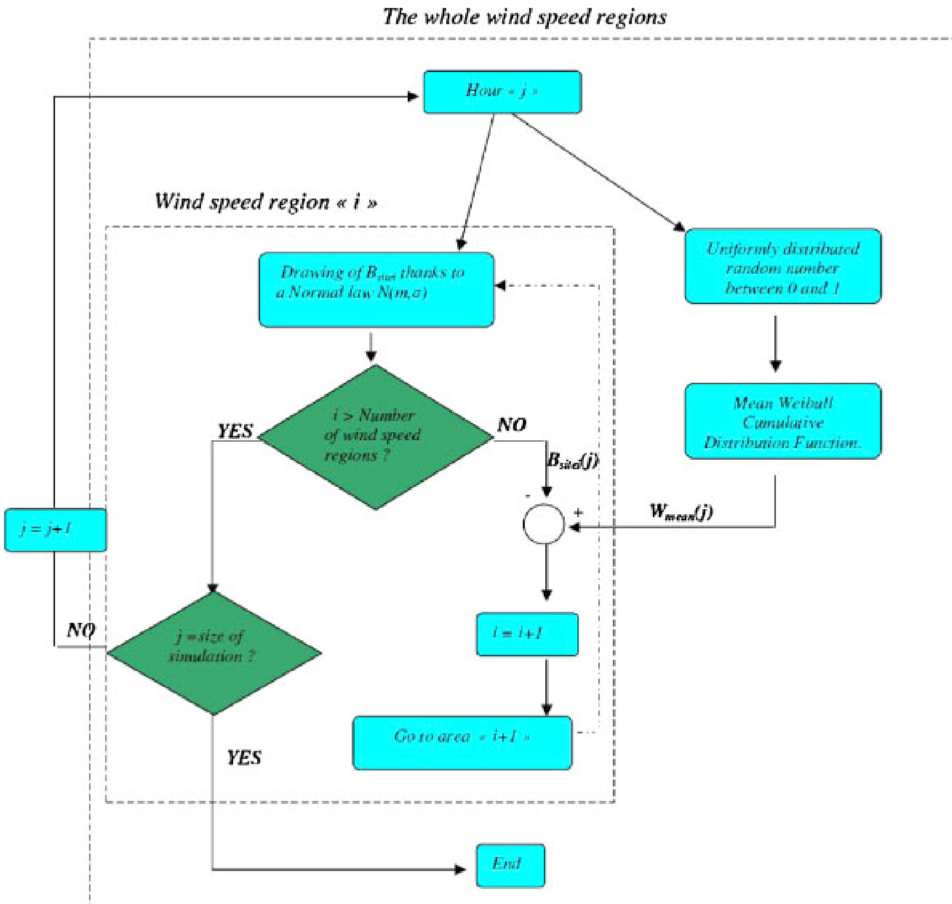


Figure 7. Flow chart: second drawing method (mean *Weibull* + normal noise).

## 3. SIMULATION RESULTS

### 3.1. The considered Belgian wind park

Both proposed sampling methods have been introduced in a HL-I *non-sequential Monte Carlo simulation* and have been compared based on the Belgian production park established by the year 2000 [4]. Moreover, the considered wind parks are the ones that were operating in Belgium by 2004 and are listed in Table I [7]. At that time, the installed on-shore capacity was only reaching 46.6 MW. Nevertheless, in our simulations, to consider a rather significant wind penetration, the 300 MW offshore project *C-Power* is also taken into account. In this way, note that the IRM does not dispose of any measurement point in the *North Sea* and that the *Weibull* parameters accepted for the offshore park are thus, $A = 9$ and $B = 2.025$ [8]. In that way, offshore wind speeds will always be directly drawn on the associated *Weibull* law, whatever the drawing method used for the on-shore wind speeds.

Concerning the operation of the wind turbines, mainly fixed speed squirrel cage and variable speed doubly-fed asynchronous structures can be found in Belgium; the actual trend being 60% of installed doubly-fed wind generators for only 40% of fixed speed ones [9]. So, in order to calculate the power distribution of each wind park presented in Table I, two Power–Wind characteristics are considered and established in Figure 9. The first one is based on the speed control characteristic of a classical doubly-fed wind generator like the one installed in Schelle and is made up of the four usual control areas [10]. Next to that first P–W characteristic, a second one is also established for an asynchronous fixed speed generator.

Finally, it can be observed in Figure 9 that the variable speed structure starts producing power at a lower cut-in wind speed compared to the fixed speed case; both topologies behaving thus differently in reliability studies.



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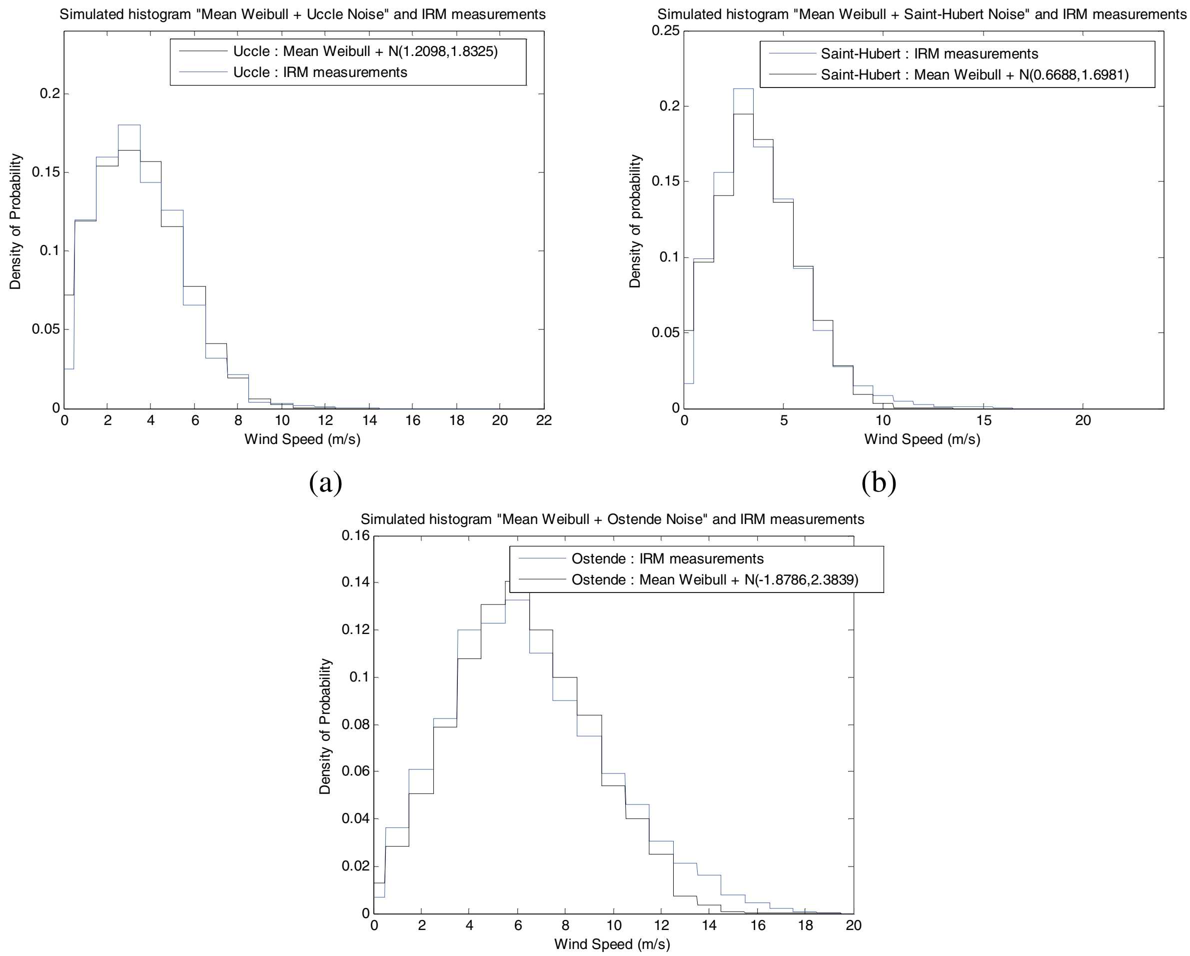

(c)

Figure 8. Second wind speed drawing method. Validation for Uccle (a), Saint-Hubert (b), and Ostende (c).

Table I. Belgian wind park in 2004 + C-Power project [7].

| Site | Installed power | Situation | Weibull |
|---|---|---|---|
| Bütgenbach | 8 MW | South | Saint-Hubert |
| Gembloux | 6 MW | Center | Uccle |
| Hoogstraten | 12 MW | Center | Uccle |
| Kasterlee | 0.66 MW | Center | Uccle |
| Pathoekeweg | 3 MW | North | Ostende |
| Rodenhuize | 4 MW | Center | Uccle |
| Schelle | 4.5 MW | Center | Uccle |
| Wondelgem | 4 MW | Center | Uccle |
| Zeebrugge | 4.5 MW | North | Ostende |
| Thornton bank (C-Power) | 300 MW | Off-shore | Off-shore |



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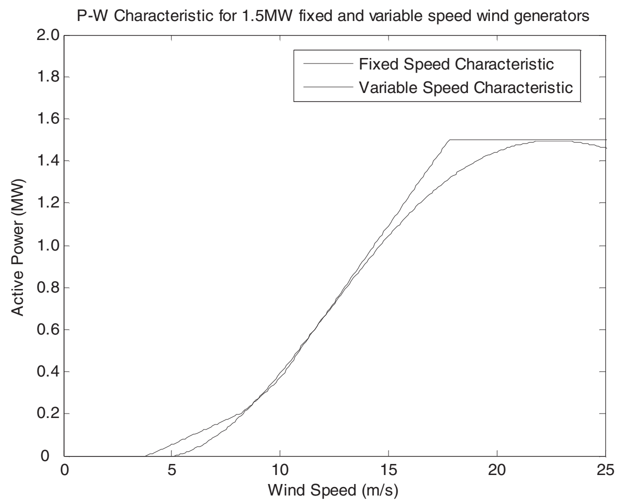


Figure 9. P–W characteristic established for 1.5 MW doubly-fed (dotted) and 1.5 MW fixed speed asynchronous wind generators (continuous).

### 3.2. The HL-I non-sequential Monte Carlo developed simulation tool and the well-being analysis

In the present study, a non-sequential Monte Carlo method has been developed under *Matlab*® to evaluate the reliability indices of interest. This Monte Carlo simulation theoretically could incorporate any number of system parameters and states but it has been assumed, in our calculations, that a generation unit was only able to reside in one of the following two states: fully available and unavailable. Moreover, in the established non-sequential simulation, only hourly uncorrelated states are considered as it is supposed that a generation unit outage state does not condition or influence its state during the next or previous hours of simulation (and inversely). Finally, at the start of each hour, a uniformly distributed random number ($u$) on the interval [0,1] is drawn for each generation unit in order to decide its operation state, using the following procedure:

- √ If $u \leq$ FOR, the unit is decided to be unavailable.
- √ If $u >$ FOR, the unit is decided to be fully available.

In the present study, the events recognized by the established program are thus the changes in load[2] and the possible failure of a generating unit. Each simulated system state can then be defined in terms of available margin, which is the difference between the available production capacity and the load. Indeed, given the difficulty for network operators to sometimes analyze probabilistic techniques (lack of information in indices like *Loss of Energy Expectation* and *Loss of Load Probability*), the idea here is to combine probabilistic and deterministic techniques. So, by proceeding to a well-being analysis [1], reliability indices are defined, for each generated state (probabilistic approach), by subtracting the larger unit capacity (application of the deterministic *Lost of the Larger Unit* criterion) to the available production park. By doing so, it is now possible to analyze the severity associated to each simulated fault state (which was not necessarily the case with classical probabilistic indices like *LOLE* and *LOEE* [11]). Also note that, to implement the well-being analysis, the total available system capacity must be superimposed on the load during each simulated hour to define [1,12,13]:

- √ Healthy state: the total available capacity minus the largest production unit remains greater than the corresponding hourly load.
- √ Marginal state: the total available capacity is greater than the corresponding hourly load but becomes less than that same load when the capacity of the largest unit[3] is subtracted of the available production park.

[2]The load is determined as a base value (required 100% of the time) to which a random normal distributed contribution, comprised between the base and peak load values, is added.
[3]Here, to analyze the impact of the *Belgian* law on the nuclear stopping (exploitation licence ended in 40 years), we subtract the larger nuclear unit (*Tihange: 2937 MW*) to the available production park to define the required margin.



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√ At risk state: the total available capacity is directly less than the corresponding hourly load value.

Three well-being indices are then defined as [2]

$$\text{Probability of health} = P(\mathrm{H}) = \frac{n(\mathrm{H})}{N \times 8760} \quad (6)$$

$$\text{Probability of margin} = P(\mathrm{M}) = \frac{n(\mathrm{M})}{N \times 8760} \quad (7)$$

$$\text{Probability of risk } (LOLP) = P(\mathrm{R}) = \frac{n(R)}{N \times 8760} \quad (8)$$

where $n$(H), $n$(M), and $n$(R) are respectively the total number of hourly healthy, marginal and risky simulated states; $N$ being the total amount of simulated years.

### *3.3. Impact of wind production on the HL-I reliability*

To quantify the impact of wind generation on the HL-I reliability of the Belgian electrical network, two case studies are investigated and compared. So, in the first step, the developed Monte Carlo tool is launched with the entirely defined wind park (see Table I). Then, to have a comparison point (in terms of ''reliable'' behavior) between wind production and classical units, a second approach consists to replace each considered wind production park (*cf*. Table I) by a thermal unit (with the *Forced Outage Rate* of a thermal unit equal to 0.025 [14]). The nominal power of each introduced thermal unit equals the installed capacity of the wind park that the thermal unit replaces.

Also note that, when taking the entire wind production park into account, both proposed wind speed sampling methods are applied. In our case, given the narrowness of Belgium, and to be in the worst case of highly fluctuating global wind energy, all the wind parks of the same wind region are supposed to be entirely correlated. Consequently, this hypothesis implies that only one single wind speed is drawn for each wind region and, thus, that:

√ During the considered hour, one different single random number is drawn, for each wind region (a single random number per region), in case of *Weibull* direct sampling method.
√ During the considered hour, each of the three established different normal noises is applied to its corresponding wind region, in case of *''Mean Weibull + Normal Noise''* sampling method.

The collected results are presented, for each considered case, in Table II. Several observations can be made on the basis of the calculated ''Well-being'' indices:

√ The introduction of an additional production unit (wind or thermal unit) reduces the risk of meeting critical situations of load non-recovering. This observed fall of the LOLP values when adding an additional unit is quite logical as the installed capacity is, in each case, increased while the load characteristics stay unchanged.
√ The ''Well-being'' indices calculated with wind production are nearly equal, whatever sampling method be used. This result is not surprising, here, in the way that both sampling techniques have been implemented to simulate the same experimental histograms of wind densities of probability. However, note that the *''Mean Weibull + Normal Noise''* sampling method implies a larger correlation level between wind regions and, thus, an increased *''all or nothing''* behavior for wind production. Therefore, it is not surprising to observe, in this last case, slightly worsened LOLP and $P$(M) values. Indeed, with the *''Mean Weibull + Normal Noise''* method, the drawing of a reduced mean wind speed will quasi immediately lead to a limited wind production level all over the country, while the independency between wind regions involved by the direct drawing method will, *de facto*, imply a smooth evolution for the global hourly wind production (and, thus, a better behavior from reliability point of view).
√ From a reliability point of view, the fluctuating behavior of wind power makes this last one (LOLP = 0.0046) less efficient than thermal production with an identical installed capacity (LOLP = 0.0038). Indeed, as illustrated in Figure 10, the simulated



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Table II. Simulation results quantifying the impact of wind production on HL-I reliability.

| | $P$(H) | $P$(M) | $P$(R) = LOLP |
|---|---|---|---|
| Belgian production park (year 2000 [4]) | 0.7536 | 0.2415 | 0.0049 |
| Belgian production park (year 2000 [4]) + 346.6 MW wind production (Weibull direct sampling method) | 0.7620 | 0.2334 | 0.0046 |
| Belgian production park (year 2000 [4]) + 346.6 MW wind production (« Mean Weibull $\pm N$(m,$\sigma$) » sampling method) | 0.7614 | 0.2339 | 0.0047 |
| Belgian production park (year 2000 [4]) + 346.6 MW thermal production | 0.7978 | 0.1984 | 0.0038 |

global wind production fluctuates, from one hour to the other, between zero and the installed capacity (346.6 MW) while the corresponding thermal units will operate almost all the time (to within about the associated FOR) at nominal power. In that way, Table III computes the nominal capacity of the thermal unit that would lead to the same *"Well-being"* indices than the ones obtained with the entire Belgian wind production. So, a ratio 1:5 is pointed out between the installed wind and thermal capacities to end up in the same reliability indices. This result confirms, thus, the limited interest (compared to classical thermal units) of wind production from the load covering point of view.

For HL-I reliability studies, the limits of wind power are, thus, mainly caused by the fluctuating behavior of this last kind of production. Moreover, when considering additional network constraints like line overloading (hierarchical level HL-II), it will be imperative to draw wind speeds in order, not only, to simulate realistic hourly wind power fluctuations, but also, to calculate the worst wind power fluctuations that could be faced by the network. So, Table IV summarizes, for each proposed wind speed drawing methods, the simulated number $N_0$ of zero wind power hours (all the wind turbines are simultaneously down) and the *Annual Simulated Wind Energy* (ASWE) [4]. In each simulated case, the ASWE indicator is nearly almost the same. This conclusion is quite logical as both drawing techniques cover the same measured wind histograms. However, as already mentioned, it can also be seen that the high correlation level, implied by the definition of a mean global distribution (here, a mean *Weibull* one) valid for all the wind regions, leads to higher $N_0$ values with the *"Mean Weibull distribution + Normal Noise"* sampling method. Thus, to correctly model wind production and, simultaneously, introducing a correlation level between wind regions, combining a mean distribution (increased correlation level as this distribution is valid for all the country) and normal noises defining each wind region (more realistic in terms of wind modeling, especially for large territories or countries) seems the better wind speed drawing method to be considered for a *non-sequential Monte Carlo simulation*.

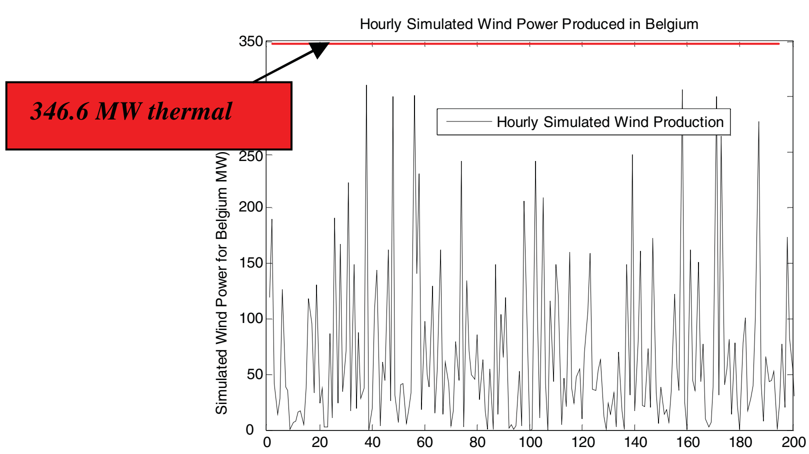


Figure 10. Hourly evolution of the global wind production in the Belgian case.



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Table III. Equivalent thermal unit for the installed Belgian wind production.

| | $P$(H) | $P$(M) | $P$(R) = LOLP |
|---|---|---|---|
| Belgian production park (year 2000 [4]) + 346.6 MW wind production | 0.7620 | 0.2334 | 0.0046 |
| Belgian production park (year 2000 [4]) + 68.5 MW thermal production | 0.7619 | 0.2335 | 0.0046 |

Table IV. Impact of the chosen wind speed drawing method and of the considered correlation level for wind production statistical modeling.

| | $N_0$ (Hours) | ASWE (GWhour/year) |
|---|---|---|
| Direct drawing method + 100% correlated sites (over the same wind region) | 22997 | 587.08 |
| Direct drawing method + independent sites (over the same wind region) | 13 | 586.42 |
| "Mean Weibull + Normal Noise" method + 100% correlated sites (over the same wind region) | 25771 | 587.56 |
| "Mean Weibull + Normal Noise" method + independent sites (over the same wind region) | 11882 | 586.94 |

## 4. CONCLUSION

In this paper, simulation results for hierarchical level HL-I have been developed and compared pointing out not only the importance of the correlation level between wind parks when making reliability studies, but also, the necessity of choosing a well adapted wind speed sampling method in order to make the most accurate estimation for the impact of wind production.

So, two wind speed sampling methods adapted for *non-sequential Monte Carlo simulations* have been presented and compared. The first technique was implemented *via* a direct drawing on *Weibull* distributions associated to wind speed regions. Unfortunately, that well-known method was implicitly introducing an independency level between wind regions. To avoid this drawback and to test the electrical system under highly fluctuating wind power (worst case), a second original sampling method based on the combination of a mean distribution, which is generally ordinary (but can be, in some cases like the Belgian one, particularized to a global *Weibull* law) and normal noises has been introduced. Simulation results have then shown the increased interest of such a method in terms of wind statistical modeling (possibility to define wind regions based on Normal distributions around a mean trajectory) and of highly correlated simulation schemes (worst case in terms of network constraints as larger wind power fluctuations are introduced by this second proposed wind speed sampling method).

## 5. SYMBOLS

| | |
|---|---|
| $m$ | Mean value |
| $\sigma$ | Standard deviation |
| $W$ | Wind speed [m/second] |
| $A$ | Scale parameter |
| $B$ | Shape parameter |
| $S$ | Mean square estimator |
| $p$ | Density of probability |
| $B$ | Hourly difference between two wind speeds [m/second] |
| FOR | Forced Outage Rate |
| $P$(H) | Probability of healthy state |
| $P$(M) | Probability of marginal state |
| $P$(R) | Probability of risky state |



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| | |
|---|---|
| $N$ | Total number of simulated years |
| $n$(H) | Total number of healthy state hours (hour) |
| $n$(M) | Total number of marginal state hours (hour) |
| $n$(R) | Total number of risky state hours (hour) |
| LOLP | Loss of Load Probability |
| ASWE | Annual Simulated Wind Energy [GWhour/year] |
| $N_0$ | Number of zero wind power hours (hour) |

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