Probabilistic Assessment of the Impact of Wind Power Generation on Voltage Sags in Composite Systems

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Abstract—This paper presents a methodology to assess the impact of wind power generation on the voltage sags in generation and transmission composite systems. The proposed methodology is based on probabilistic techniques to model uncertainties associated with fault scenarios and wind speed fluctuations. The probabilistic technique used to represent the uncertainties is the non-sequential Monte Carlo Simulation. The voltage sags resulting from fault scenarios were evaluated using symmetrical components technique. The combination of these two techniques was used to estimate the nodal and systemic indices associated with the frequency of voltage sags. The proposed methodology to evaluate these indices was tested on the IEEE Reliability test system of 24 buses. The tests results demonstrate that the wind generation has a significant impact on the frequency indices related to voltage sags.

Keywords—power quality; voltage sags; wind power generation, probabilistic methods; Monte Carlo simulation; Clustering.

I. INTRODUCTION

Currently, constraints associated with the greenhouse gas emissions have motivated the use of the renewable energy resources such as: wind, solar, biomass, tide, waves, small hydro stations, etc. The wind energy generators have achieved large penetration in power systems around the world due to the advances in the construction of large scale turbines and the low operational costs compared with conventional thermal generators.

A common issue related to all renewable energy resources is the variability of the primary energy source (wind speed, solar irradiance, water inflows, etc.). In the wind power generation, the stochastic behaviour of the wind speed introduces significant uncertainties in several areas of the power system planning and operation, such as: voltage and reactive power control, optimal generation dispatch, reliability, short-circuit levels, etc. The short circuits are the main cause of voltage sags. That is, a reduction in the RMS voltage between 0.1 and 0.9 pu with duration in the interval from half cycle to one minute [1], [2]. Consequently, the fluctuations in the power output of the wind turbines have potential to cause power quality problems in sensitive loads such as power electronic devices and microprocessor-based controls. On the other hand, the severity of the voltage sags is also affected by the pre-fault conditions. Due to this, wind power generation has a double impact on the voltage sags profile of an electrical network: (i) pre-fault: changes in the base case voltage profile caused by random variations in the wind speed; (ii) post-fault state: variations in the fault currents. A suitable assessment of these two factors must be carried out in a probabilistic framework to accurately recognize the stochastic nature of the wind power generation. The main advantage of the probabilistic methods is the ability to combine severity and probability to provide a true assessment of the system risk [3], [4].

Probabilistic methods have been used for decades in reliability studies to evaluate indices such as: frequency, duration and expected load curtailments [3], [4]. The probabilistic methods have also been applied in power quality studies associated with voltage sags [5]-[12]. These applications are based on two methods: analytical [5], [6], [7], [9], [11] and Monte Carlo Simulation (MCS) [8], [10], [12].

The probabilistic assessment of voltage sags through the analytical method is usually based in two techniques: critical distances [5], [6] and fault positions [9]. Furthermore, other analytical techniques have been proposed to reduce the computational cost of the fault position method and to obtain the probability distributions related to the voltage sags in specified load points [7], [11]. These techniques are based on the proposed approach in [13] to evaluate post-fault voltages due to short circuits along lines. On the other hand, the application of Monte Carlo Simulation in the probabilistic voltage sag assessment has been based on state space representation, that is, non-sequential MCS [10], [12].

The computational effort of the analytical approaches to carry out a probabilistic analysis of voltage sags is usually lower than the one associated with MCS. However, the MCS is more flexible to represent systems' operations issues [3], [4].

In spite of the high penetration of wind power generation in electric networks and of the significant number of publications on the probabilistic voltage sag analysis, the impact of wind power generation on the voltage sag profile has not been assessed in a probabilistic framework. In this way, the main aim of this paper is to carry out a probabilistic assessment of voltage sags in composite system (generation and transmission) considering uncertainties associated with
wind power generation. The proposed method is based on the combination of MCS [3], [4] and Component Symmetrical methods [14], [15]. The MCS method is used to model uncertainties related to fault scenarios such as: number of faults in a given period, location, type (three-phase, two-phase or single-phase), resistance, etc. On the other hand, the Symmetrical Component method is applied to calculate the fault currents and voltages resulting from the fault scenarios sampled using the Monte Carlo Simulation method. The combination of these two approaches is used to obtain the expected values and probability distributions of nodal and global indices associated with voltage sags. The proposed methodology was tested in the IEEE Reliability Test System with 24 buses (RTS) [16], [17]. The results obtained in this test system demonstrate that the integration of wind power generation in the electric network has significant impact on the voltage sag profile.

II. VOLTAGE SAG EVALUATION

In this paper the post-fault voltage and currents are evaluated using the symmetrical components method [14], [15]. This method is suitable for fault analysis in composite systems due to transposition of transmission lines and absence of structural imbalances such as single-phase and two-phase laterals that exist in distribution systems. The fault analysis based on symmetrical components consists basically in building the bus impedance matrix for each sequence network (zero, positive and negative) and by using compensation techniques to model the connection of the fault impedance through a nodal current injection. In practice, the bus impedance matrix is not explicitly evaluated, because only their LU factors are necessary to estimate fault currents based on partial inversion technique. In the voltage sag assessment it is required to simulate fault along the lines because there is an uncertainty associated with the fault position. In this paper, short-circuits along transmission lines are simulated using the approach proposed by Z. X. Han [13]. The main advantage of the method proposed by Z. X. Han is that the faults along the lines are simulated without the need of creating an additional bus to represent the fault connection point. Due to this, the structures of the bus admittance matrix and their LU factors are preserved. Consequently, it is possible to simulate faults in any position of the line without recalculate the LU factors of the bus admittance matrix.

III. MODELING FAULT SCENARIOS

A short circuit can occur in any location on a transmission line. Therefore, the fault position modeling is carried out using the uniform distribution. That is, a uniform random number \( U \) is generated in the interval \([0,1]\). Next, this number is multiplied by the line length \( l \) to obtain the fault position \( l_{\text{fault}} \), regarding to the sending node, in accordance with the following equation:

\[
I_{\text{fault}} = U \times l
\]  

(1)

The selection of the type of fault is carried out using a uniform random number generator. The more likely types of faults in a transmission line are: three-phase, phase-to-phase, double-phase to ground and single-phase to ground. The probabilities associated with each type of fault are showed in Table I.

<table>
<thead>
<tr>
<th>Fault Type</th>
<th>Probability (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single-Phase to Ground</td>
<td>90.1140</td>
</tr>
<tr>
<td>Double-Phase-to-Ground</td>
<td>4.4594</td>
</tr>
<tr>
<td>Phase-to-Phase</td>
<td>4.0827</td>
</tr>
<tr>
<td>Three-Phase</td>
<td>1.3439</td>
</tr>
</tbody>
</table>

The probabilities of the type of faults are used to divide the interval \([0,1]\) in subintervals. The widths of the subintervals are equal to the corresponding probabilities for each type of fault as showed in Fig. 1.

![Visualization of the intervals that determine the fault type.](http://example.com/fig1)

The definition of the type of fault is carried out sampling a uniform random number in the interval \([0,1]\) and comparing this number with the type of fault subintervals. The subinterval in which the random number is located will indicate the fault type. For example, if the random number is 0.4, then the sampled type of fault is a single-phase to ground.

The number of faults experienced by each component (line, cable or transformer) is determined considering that the failure rates are constant in a study period (e.g. a yearly period). This hypothesis is frequently used in reliability and power quality studies in electrical networks [3], [4], [10]. In this way, the number of faults for each component can be sampled using a random number generator with Poisson distribution [10]. Additionally, if the faulted equipment is a transformer, then it is necessary to determine the terminal (primary or secondary) in which the fault has occurred. This terminal is defined considering that the probability of fault is equally distributed between the primary and secondary terminals. In this way, the faulted terminal is identified sampling a random number with uniform distribution and comparing this number with the probability of fault in a terminal. If the random number is lower than 1/2 then the fault is in the primary. Otherwise, the fault is in the secondary. Finally, the resistance of fault is modelled as a random variable with uniform distribution between a minimum and maximum values.

IV. MODELLING WIND POWER GENERATION

A. Power Flow and Short Circuit

Currently, there are four configurations used in the construction of wind turbines [19]:
The current status of the wind turbines technologies is characterized by an evolution from DFIG and other types of induction generators to the FCPC due to its flexibility to control the output current [20]. Furthermore, the preferred topology for the construction of large scale turbines is the FCPC. Consequently, the impact of this type of wind generator on the power system performance tends to be higher. Due to this, in this paper the impact of the wind generation on the voltage sags profile will be assessed considering the wind generators based on the FCPC.

In the FCPC topology, squirrel cage induction generators, permanent magnet synchronous generators or wound rotor synchronous generators are connected to the grid through a full-capacity converter. The utilization of the power converter enables the operation in a full speed range and decouples the generator from the electric network. Additionally, the nominal capacity of the converter must be equal to the generator capacity [19].

In power flow studies the FCPC converter can be modelled as a PQ bus due to the capacity of the converter to control the power factor. On the other hand, in short circuit studies the FCPC is modelled as [15]:

i) positive sequence network: independent current source with the value given by:

\[ I_{k}^{\alpha} = \alpha d_{k}^{\text{pre}} \]  

(2)

ii) negative sequence network: open circuit.

iii) zero sequence network: open circuit.

Where:

- \( k \) is the bus in which the FCPC is connected;
- \( I_{k}^{\alpha} \) is a positive sequence fault current injected into the bus \( k \) by the FCPC;
- \( \alpha \) is a constant associated with the fault current control;
- \( I_{k}^{\text{pre}} \) is the injected current into the bus \( k \) by the FCPC in the pre-fault state.

\[ I_{k}^{\text{pre}} = P_{k}^{\text{FCPC}} - jQ_{k}^{\text{FCPC}} \]

\[ E_{k}^{*} \] is the conjugate of the complex nodal voltage in the bus \( k \);

\[ P_{k}^{\text{FCPC}} (Q_{k}^{\text{FCPC}}) \] is the active (reactive) power produced by the FCPC.

The FCPC model for fault analysis is based on the fact that the full-converter can supply a constant and balanced current even on unbalanced conditions such as single-phase and double-phase faults. Furthermore, the full-converter can be controlled to supply a specified short circuit current during a fault. Therefore, electric utilities usually demand higher short circuit currents of the FCPC to aid the fault detection by the protection devices [15]. The control of the FCPC fault current is represented in the model by the constant \( \alpha \) which have value lower or equal to three. In this paper, the main concern is to assess the maximum impact of wind turbine in voltage sag profile. Due to this, the current limit for the full-converter during a fault is not considered. In other fault studies related to FCPC it must be considered.

**B. Wind Speed Uncertainties**

The wind speed fluctuations can be modelled in the MCS using a Weibull distribution [26]. In this model, a wind speed must be sampled based on this distribution for each randomly selected fault scenario. Consequently, a new pre-fault state must be obtained due to the changes in the power output of the wind generator caused by the wind speed sampling. However, this procedure is computationally intensive due to:

i) A power flow study must be carried out to achieve the new pre-fault state.

ii) It is necessary to rebuild the sequence admittance matrices for each pre-fault state since the load admittances are function of the voltages magnitudes of the pre-fault state, that is:

\[ Y_{k}^{\text{load}} = \left( P_{k}^{\text{load}} - Q_{k}^{\text{load}} \right) / V_{k}^{2} \]  

(3)

where:

- \( Y_{k}^{\text{load}} \) is the admittance of the load connected to the bus \( k \).
- \( P_{k}^{\text{load}} (Q_{k}^{\text{load}}) \) is the active (reactive) power associated with the load connected to the bus \( k \).
- \( V_{k} \) is the magnitude of the nodal voltage in the bus \( k \).

iii) LU factors of the sequence admittance matrices must be evaluated for each pre-fault scenario due to the modifications in these matrices caused by the load admittances.

An alternative to overcome the problem described above is to use clustering techniques to reduce the number of states resulting from wind speed fluctuations [22]. Consequently, the number of the pre-fault scenarios will be decreased. Clustering techniques are used in power systems reliability studies to model the load duration curve [4]. In this paper, the clustering techniques have been applied in the wind speed data obtained from the Triunfo station of the SONDAS project located in the Brazil’s Northeast. The wind speeds are measured in intervals of ten minutes and were collected in the yearly period from April 2005 up to April 2006. There are 52560 (365×24×60/10) measurements in the wind speed data. The clustering analysis in the wind speed data was applied considering that the number of clusters is equal to 15. This number of clusters was selected aiming to establish a compromise between computational cost and accuracy. The probabilities, centroids...
and number of elements of each cluster are presented in Table II. The clusters showed in this table were obtained using the k-means algorithm [4]. The Fig. 2 shows the graphic of the measured wind speed in descending order and their respective clusters. From this figure, it can be concluded that the clustered data are well fitted to measured data.

**TABLE II. CLUSTER ANALYSIS RESULTS FOR THE WIND SPEED DATA**

<table>
<thead>
<tr>
<th>Index</th>
<th>Frequency</th>
<th>Probability (%)</th>
<th>Centroid (m/s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>4628</td>
<td>8.8052</td>
<td>12.8108</td>
</tr>
<tr>
<td>2</td>
<td>2637</td>
<td>5.0171</td>
<td>4.6155</td>
</tr>
<tr>
<td>3</td>
<td>4513</td>
<td>8.5864</td>
<td>6.8488</td>
</tr>
<tr>
<td>4</td>
<td>5301</td>
<td>10.0856</td>
<td>11.7571</td>
</tr>
<tr>
<td>5</td>
<td>486</td>
<td>0.9247</td>
<td>22.2981</td>
</tr>
<tr>
<td>6</td>
<td>4880</td>
<td>9.2846</td>
<td>8.8401</td>
</tr>
<tr>
<td>7</td>
<td>4788</td>
<td>9.1096</td>
<td>7.8657</td>
</tr>
<tr>
<td>8</td>
<td>3839</td>
<td>7.304</td>
<td>5.7759</td>
</tr>
<tr>
<td>9</td>
<td>3811</td>
<td>7.2508</td>
<td>13.9972</td>
</tr>
<tr>
<td>10</td>
<td>2898</td>
<td>5.5137</td>
<td>15.3094</td>
</tr>
<tr>
<td>11</td>
<td>1875</td>
<td>3.5674</td>
<td>16.8878</td>
</tr>
<tr>
<td>12</td>
<td>5037</td>
<td>9.5833</td>
<td>9.7952</td>
</tr>
<tr>
<td>13</td>
<td>1093</td>
<td>2.0795</td>
<td>19.0257</td>
</tr>
<tr>
<td>14</td>
<td>1287</td>
<td>2.4486</td>
<td>3.061</td>
</tr>
<tr>
<td>15</td>
<td>5487</td>
<td>10.4395</td>
<td>10.7687</td>
</tr>
</tbody>
</table>

**Fig. 2.** Measured and clustered wind speed data in ascendent order.

**V. MONTE CARLO SIMULATION ALGORITHM**

Using the models presented in sections III and IV, the voltage sags probabilistic indices can be estimated based on the following conceptual algorithm:

i) Read input data related to the electric network and wind speed.

ii) Cluster the wind speed data.

iii) Repeat the steps (iv)-(xviii) for the number of wind speed clusters.

iv) Evaluate the power output of the wind turbines for the current cluster.

v) Obtain the pre-fault state through the power flow solution.

vi) Build the sequence admittance matrices.

vii) Evaluate the LU factors of the sequence admittance matrices.

viii) Repeat the steps (ix)-(xvi) for a specified number of simulations.

ix) Repeat the steps (x)-(xv) for each component.

x) Sample the number of faults experienced by the component using the Poisson distribution.

xi) Repeat the steps (xii)-(xv) for the sampled number of faults.

xii) Select a fault location for the circuits or a terminal for transformers.

xiii) Select the fault type.

xiv) Evaluate the post-fault voltages.

xv) Update the voltage sag indices for the current fault scenario.

xvi) Update the samples of the annualized voltage sag indices.

xvii) Evaluate the mean values of the annualized voltage sag indices based on the simulated samples.

xviii) Update the voltage sag indices for the clusters.

xix) Evaluate expected voltage sag indices based on the clusters probabilities.

The conceptual algorithm described above was used to estimate the nodal frequency of voltage sags and the SARFI (System Average RMS – Variation – Frequency Index). The average values of the indices, for a sample of $N^\text{Sim}$ simulations, are estimated as:

$$\tilde{E}[NFVS_{p,c}^{x}] = \left( \sum_{i=1}^{N^\text{Sim}} NFVS_{p,c}^{x}(S^i) \right) / N^\text{Sim}$$  \hspace{1cm} (4)

$$\tilde{E}[SARFI_{c}^{x}] = \left( \sum_{i=1}^{N^\text{Sim}} SARFI_{c}^{x}(S^i) \right) / N^\text{Sim}$$  \hspace{1cm} (5)

Where:

$NFVS_{p,c}^{x}(S^i)$ is the nodal frequency of the voltage sags with magnitude lower than $x\%$ in the load bus $p$ for the simulation $S^i$.

$SARFI_{c}^{x}(S^i)$ is the value of the $SARFI^{x\%}$ index for the simulation $S^i$. This index is the average value of the $NFVS_{p,c}^{x}(S^i)$ for all load buses of the system.

$\tilde{E}[NFVS_{p,c}^{x}]$ and $\tilde{E}[NFVS_{p,c}^{x}]$ are the mean values of the indices $NFVS_{p,c}^{x}$ and $SARFI^{x\%}$ for the wind speed cluster $c$, respectively.
Finally, the expected values of the indices, based on the clusters probabilities, are given by:

\[ E[NFVS_{p,\%}] = \sum_{i=1}^{N_{clus}} P_{wind}^{c} \times E[NFVS_{p,\%}] \]  

\[ E[SARFI_{\%}] = \sum_{i=1}^{N_{clus}} P_{wind}^{c} \times E[SARFI_{c,\%}] \]  

Where:

\( N_{clus} \) and \( P_{wind}^{c} \) are the number of wind speed clusters and the probability of the wind speed cluster \( c \), respectively:

\[ E[NFVS_{p,\%}] \] and \( E[SARFI_{c,\%}] \) are the expected values of the indices \( NFVS_{p,\%} \) and \( SARFI_{c,\%} \), respectively.

VI. RESULTS

A. Definition of the Test System and the Case Studies

The proposed methodology for the probabilistic assessment of voltage sags was tested in the RTS. This assessment was based on two case studies:

i) Case #1 (base case): original RTS without installed wind power generation.

ii) Case #2: RTS with wind power generation sitting and sizing based on [24]. That is, two wind farms installed in the buses 3 and 10. In this paper were used Vestas wind turbines of 3.3 MW with FCPC [25]. The installed capacity in each wind farm of [24] is 90 MW (50×1.8 MW). Thus, 27 Vestas turbines were required to obtain this capacity approximately (27×3.3 = 89.1 MW).

Additionally, the tests were performed under the following assumptions: (i) since the numbers of customers in each load bus of the RTS are not available, the weights for the SARFI index are the kVA of the load buses; (ii) the number of simulations for each cluster is 200; (iii) the fault resistance interval is [1, 5]; (iv) the probability and centroids of the wind clusters used in the simulations are showed in Table I; (v) the probabilities of the type of fault are presented in Table II; (vi) in the FCPC model for fault analysis, the constant \( \alpha \) is 3.

B. Assessment of the System Indices

The expected values of the indices \( SARFI_{90\%} \), \( SARFI_{80\%} \), and \( SARFI_{70\%} \) are presented in Table III. From this table, it can be noticed that the installation of the wind power generation causes a significant reduction in the SARFI indices. For example, the reduction in the index \( SARFI_{90\%} \), regarding to the case #1, is around 42%. This result indicates that the wind power generation has a potential to decrease the vulnerability of loads to voltage sags.

The Table IV shows some statistics associated with the SARFI90% index for the case studies #1 and #2.

![Fig. 3. Individual Probability Distribution of the SARFI90\% index for case #1.](image)

From this table it can be concluded that the uncertainties associated with the fault scenarios and wind speed fluctuations cause significant variation in the SARFI90% index. However, the variability associated with the case #2 is lower than the case #1. For example, the ratio between the standard deviation and the mean for the cases #1 and #2 are around 49% and 15%, respectively. That is, the installation of wind turbines can reduce the dispersion of the SARFI90% index around its mean value. This dispersion can be quantified by the variation coefficient (the ratio of the standard deviation to the mean). For this case study it is around 36% Detailed information about this distribution can be found in Table IV.
SARFI\(^{90\%}\) index for the case #1 is bigger than the one of the case #2. The reduction in the expected values of the \(\text{NFVS}_{p}^{90\%}\) index demonstrates that the wind power generation can decrease the vulnerability of the load buses regarding to voltage sags. The most suitable explanation to this tendency is that the insertion of the wind generation causes an increasing in the base case voltage profile thereby the voltage sag vulnerability was decreased. The same effect may occur in distribution networks after the wind distributed generation be installed.

Fig. 4. Expected \(\text{NFVS}_{p}^{90\%}\) index for the case studies #1 and #2.

VII. CONCLUSIONS

This paper presented a probabilistic approach to assess the impact of wind power generation on the voltage sag profile of generation and transmission composite systems. This impact was analysed through the computation of the following indices: NFVS (Nodal Frequency of Voltage Sags) and SARFI (System Average RMS – Variation – Frequency Index). These indices were evaluated based on the combination of symmetrical components method (to estimate post-fault voltages) and Monte Carlo Simulation method (to model uncertainties in the wind speed and fault scenarios). The proposed methodology was tested in the IEEE Reliability Test System (RTS) of 24 buses. The tests results showed that there are large variations around the mean value of the SARFI index due to the uncertainties associated with wind speed fluctuations and fault scenarios. From the results, it can be concluded that the connection of the wind generation in composite systems has a potential to reduce the susceptibility of the loads regarding to voltage sags.

REFERENCES