Modeling of Wind Farm in Reliability Study by Means of Monte Carlo simulation

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Abstract
The present study undertakes reliability and capacity credit analysis of wind farms generation. The capacity credit of wind power generation (WPG) express how much conventional power can be replaced by wind power. Reliability analyses of power systems are conventionally done by using either the analytical method based on the contingency enumeration approach or Monte Carlo simulation. In this approach, the software tool Monte Carlo Simulation (MCS) is applied to simulate the behavior of the corresponding system. The basic concepts and their application in composite power system reliability evaluation are illustrated by application to a small practical test system designated as the Roy Billinton Test System (RBTS). An auto regressive moving average (ARMA) time series model is used to simulate hourly wind speeds and the out put of the wind farm.

Keywords: reliability; wind power; Monte Carlo Simulation; Time Series

1. Introduction
Unlike other renewable energy sources wind energy has become competitive with conventional power generation sources. It can be replaced fossil fuels and economize using fossil sources. WPG can also contribute to overall system reliability, and help in reducing customer cost of electric power interruption. The behavior of wind energy sources is different from conventional energy sources. The wind speed is very variable in time and because of that WPG randomly fluctuates between zero and the wind farm’s rated capacity. Therefore, the reliability evaluation of power systems including WPG is not easy and it needs specific approach.

The basic function of an electric power system is to provide reliable and economic supply of power to all the consumers. It is a challenging work for power system planners and operators to design and operate the system with an optimum balance between reliability level and investment cost. The continuously increasing application of wind power in conventional power systems has created more challenges in system planning and operation.

Power system reliability evaluation is an important process in system planning and designing in order to ensure healthy system operation in the future analytical methods and simulation techniques are used in power utilities to determine adequate generating capacity. The most obvious deficiency of analytical methods is that the chronological characteristics of wind velocity and its effects on wind power output cannot be considered. Then sequential Monte Carlo simulation has been proven to be a more effective approach to incorporate these considerations in the adequacy assessment of systems including WPG. Monte Carlo simulation can be used to estimate the system reliability indices by simulating the actual process and random behavior of the system. The basic approach to system reliability evaluation can be represented...
The evaluation process consists of three parts: a) generation modeling, b) load modeling, and c) risk modeling. It can combine the equivalent wind system generation unit with other generation units to obtain total generation model. Expected Energy Not Supplied (EENS), Loss Of Load Expectation (LOLE), are considered as reliability indices. The simulated performance index reflects only system overload problems. Reliability indices obtained using the sequential technique can, therefore, be realistically used to forecast future system reliability.

a) Modeling of wind speed

By using of the local wind data, we consider a time series that can be defined in terms of the following variables: [2]

\[ y_t = \frac{ow_t - \mu_t}{\sigma_t} \]  

\( ow_t \): is the observed wind speed at hour \( t \)

\( \mu_t \): is the mean observed wind speed at hour \( t \)

\( \sigma_t \): is the standard deviation of observed wind speed at hour \( t \)

\[ y_t = \sum_{i=1}^{a} \varphi_i y_{t-i} + \alpha_t - \sum_{j=1}^{m} \theta_j \alpha_{t-j} \]  

Where \( \varphi_i, \theta_j \) are the auto regressive and moving average parameters of the model respectively and \( \alpha_t \) is a normal white noise with zero mean. [3]

Because the data of sample wind site is available for one year we can use equation 1 to produce. The simulated hourly wind speed is obtained from equation 3

\[ SW_t = \mu_t + \sigma_t y_t \]  

b) WPG model

The relation between power output from the wind turbine generation and available wind speed is shown by the power curve in figure 5. It can also be mathematically expressed by equation 4.

\[ P(SW_t) = \begin{cases} 0 & 0 \leq SW_t < V_{ci} \\ (A + B \times SW_t + C \times SW_t^2) \times P_r & V_{ci} \leq SW_t < V_r \\ P_r & V_r \leq SW_t < V_{co} \\ 0 & SW_t \geq V_{co} \end{cases} \]  

Where \( V_{ci}, V_r, V_{co}, P_r \) are the cut in speed, rated speed, cut out speed and rated power output of the wind turbine, respectively. The constants \( A, B \) and \( C \) as expressed in [4].

3. RBTS model

The RBTS is utilized to model of the wind farm that has reasonable generation system adequacy [5]. The generating units ratings and reliability data for the RBTS are shown in Table 1.
Table 1. Units specification of RBT

<table>
<thead>
<tr>
<th>Rated power (MW)</th>
<th>Type</th>
<th>λ Failure rate (Failure/year)</th>
<th>r Repair time (hours)</th>
</tr>
</thead>
<tbody>
<tr>
<td>40</td>
<td>Thermal</td>
<td>6</td>
<td>45</td>
</tr>
<tr>
<td>40</td>
<td>Thermal</td>
<td>6</td>
<td>45</td>
</tr>
<tr>
<td>10</td>
<td>Thermal</td>
<td>4</td>
<td>45</td>
</tr>
<tr>
<td>20</td>
<td>Thermal</td>
<td>5</td>
<td>45</td>
</tr>
<tr>
<td>5</td>
<td>Hydro</td>
<td>2</td>
<td>45</td>
</tr>
<tr>
<td>5</td>
<td>Hydro</td>
<td>2</td>
<td>45</td>
</tr>
<tr>
<td>40</td>
<td>Hydro</td>
<td>3</td>
<td>60</td>
</tr>
<tr>
<td>20</td>
<td>Hydro</td>
<td>2.4</td>
<td>55</td>
</tr>
<tr>
<td>20</td>
<td>Hydro</td>
<td>2.4</td>
<td>55</td>
</tr>
<tr>
<td>20</td>
<td>Hydro</td>
<td>2.4</td>
<td>55</td>
</tr>
</tbody>
</table>

The RBTS load model is in basis of IEEE-RTS chronological load profile but annual peak load is 185 MW. The hourly load model is illustrated in Fig. 4.

4. Monte Carlo simulation

Monte Carlo algorithm, one of the strongest tools in engineering issues, enable to solve complex problems in which random variables by many nonlinear equations related to each other. In this approach a two state model is considered for the modeling of system. The overall procedure for the system reliability evaluation using a sequential simulation approach is briefly summed up in the following steps:

1. Specify the initial state of each component (generating units). Normally it is assumed that all components are initially in the normal state (up state).
2. Simulate the duration of each component residing in its present state using the inverse transform method [6]. The time between failures of component and the repair duration are modeled as exponential random variables. If we have an exponential distribution function, i.e., $f_i(t) = e^{-\lambda t}$, then the sample value of the state duration ($T$) is $T = -\frac{1}{\lambda} \ln u$, where $u_i$ is a uniformly distributed random number $[0,1]$ corresponding to the $i$-th component, and $\lambda$ is a failure rate or repair rate depending on the current state of the $i$-th component.

$$T_{up} = -\frac{1}{\lambda} \ln u \quad (5)$$

$$T_{down} = -\frac{1}{\mu} \ln u \quad (6)$$

3. Repeat step 2 in a specific time span (one year). A chronological up and down state for each unit is then constructed and chronological hourly load model for individual delivery points are constructed and incorporated in the analysis.

4. The simulated operation is assessed for
each hour. At the end of simulation the delivery points and system reliability predictive indices are calculated and updated.

\[ \text{LOLE} = \frac{1}{N} \sum_{y=1}^{N} \sum_{h=1}^{8760} t_y \quad \text{(hours / year)} \]

\[ t_y = \begin{cases} 1 & \text{if Load} > \text{Generation in hour } h \\ 0 & \text{otherwise} \end{cases} \]

\[ \text{EENS} = \frac{1}{N} \sum_{y=1}^{N} \sum_{h=1}^{8760} t_y' \quad \text{(hours / year)} \]

\[ t_y' = \begin{cases} \text{load} - \text{Generation} & \text{if Load} > \text{Generation in hour } h \\ 0 & \text{otherwise} \end{cases} \]

5. Case study

In order to exhibition a practical sample study, one of the wind farm in Iran is modeled and analyzed. This site consists of 27 wind turbines. The rated output of each turbine is 660 kW. Simulation approach is done by considering wind regime and technical characteristics of the wind turbines.

The basic system model considered for the study is shown in fig.5.

![Fig.5. Basic system model](image)

6. Result of simulation

Total generation of the wind farm is illustrated in Fig 6. Because of intermittent behavior of wind source the wind power generation is variable.

![Fig. 6. Total WPG capacity](image)

The considered risk index is obtained for the RBTS, then by adding the wind farm to the RBTS the simulation process is repeated.

Figs. 7 and 8 show the magnitude of the risk indices before and after adding the wind farm.

![Fig. 7. LOLE changes before and after adding WPG](image)

![Fig. 8. EENS changes before and after adding WPG](image)

Table 2. The magnitude of LOLE obtained from 2 methods

<table>
<thead>
<tr>
<th>index</th>
<th>LOLE</th>
</tr>
</thead>
<tbody>
<tr>
<td>analytical method</td>
<td>0.23</td>
</tr>
<tr>
<td>Monte Carlo method</td>
<td>0.28</td>
</tr>
</tbody>
</table>

7. Sensitive analyses

In this section the effective parameters on the reliability of system are evaluated. Monte Carlo simulation can be used to study the sensitivity of the system indices to the factors.

a)sensitivity of the risk indices to the wind speed

In the simulation procedure, LOLE and EENS indices is computed to various wind speed. Table 5 illustrates the index...
changes against wind speed.

Table 1. The changes of risk indices against increasing wind speed average

<table>
<thead>
<tr>
<th>Wind speed average growth</th>
<th>-1</th>
<th>-0.5</th>
<th>0</th>
<th>0.5</th>
<th>1</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOLE</td>
<td>0.45</td>
<td>0.42</td>
<td>0.3</td>
<td>0.5</td>
<td>0.52</td>
</tr>
<tr>
<td>EENS</td>
<td>4</td>
<td>3.8</td>
<td>2.4</td>
<td>4.5</td>
<td>5.4</td>
</tr>
</tbody>
</table>

b) Impact of load changes on system reliability

It is supposed that RBTS has 3% annual load growth. So if we don’t increase the capacity, reliability of the system decreased. WPG is used in order to increasing of capacity generation. Figs 9, 10 show the magnitude of LOLE and EENS by addition the wind farm when the peak load reaches to 190.5 MW.

![Fig. 9. EENS at 190.5MW peak load](image)

![Fig. 10. EENS at 190.5MW peak load](image)

It can use a 5.5MW conventional capacity such as thermal power plant to compensate the load growth.

8. Conclusion

It becomes increasingly important to develop realistic reliability evaluation techniques that are practically useful for electric power industries that are expected to include rapidly growing proportion of wind generation in the coming years. Sequential simulation is ideally suited to the analysis of the intermittent generating sources such as wind power. The quantitative reliability analyses presented in this paper can be used to determine the wind power installed capacity that can be injected into a power system, and assist system planners to create potential transmission reinforcement schemes to facilitate wind power additions to the power system. Power system reliability analysis associated with wind power is demonstrated in this paper. The results show that totally the reliability of WPG lower than other conventional units and the Sensitivity of the system reliability to the wind speed is high.

References


