Quantification of Storage Necessary to Firm Up Wind Generation

Samer Sulaeman, Student Member, IEEE, Yuting Tian, Student Member, IEEE, Mohammed Benidris, Member, IEEE, and Joydeep Mitra, Senior Member, IEEE

Abstract—This paper proposes a method to quantitatively determine the sizes of energy storage systems that are intended to mitigate negative impacts of integrating wind energy into power systems. Although the integration of wind power has several advantages, it poses several technical challenges such as variability and uncertainty of wind speed and failures of wind turbine generators (WTGs) which may deteriorate the reliability of power systems. One of the most practical solutions to mitigate these drawbacks is the use of energy storage systems. The method proposed in this paper determines the sizes of the energy storage systems considering the effect of wind power uncertainty and variability, failures of WTGs, wind speed temporal resolution, and correlation with system load. Sizes of energy storage systems are determined based on composite system reliability analysis under operational and technical constraints using the AC power flow model. Monte Carlo simulation is used to emulate the behavior of the system. The proposed method is demonstrated on the IEEE reliability test system (IEEE-RTS) and the results are provided. The results show that the size of an energy storage system is dependent on wind farm characteristics as well as the connectivity with the rest of the system.

Index Terms—Energy storage, reliability, storage sizing, wind power, composite system.

I. INTRODUCTION

INTEGRATION of renewable energy sources has increased in recent years due to several reasons that include environmental concerns, global warming awareness, and economic incentives for reducing the usage of fossil fueled generating units. Although the increased generation from renewable sources reduces overall generating cost, emissions, and consumption of fossil fuels, the intermittency and uncertainty of the output bring about several concerns such as peak load capability and system adequacy [1]–[6]. Also, maintaining the efficiency and reliability of the grid, especially with high penetration of variable generation, has become a challenging task. Several studies have shown that high penetration of wind power could significantly affect power system quality and security due to the intermittency of wind [1], [4]. The integration of energy storage systems with intermittent sources has become a practical solution to overcome these challenges. This is largely because of the rapid growth in deployment and improved technology of energy storage systems.

In the literature, several authors have discussed the economic aspects of energy storage systems in the electricity market [7]–[9]. In [10], dynamic programming with time-shift is used to determine the optimal size of a battery storage in utility load-leveling operations applied on Kansas City Power and Light system. The results show that the optimal size of the battery storage varies with the daily and seasonal load variations. Reference [11] uses Benders decomposition to determine the optimal location and size of a compressed air energy storage system. The optimal size of the energy storage is evaluated based on the capital investment on the energy storage system that leads to the daily operating cost reduction.

Cost of energy storage system is a major factor in the planning of energy storage system projects. In the literature, several authors have summarized and discussed the cost of integrating energy storage systems [21]–[23]. These studies show that the cost of an energy storage system depends on several factors including the size of the energy storage and the type of technology.

A method for quantifying the size of energy storage systems to meet specified reliability targets was proposed by Mitra in [24], [25]. This paper extends this method to quantify the size of the required energy storage to firm up wind power and improve system reliability to a specific target. In this paper, the effect of the input variation (wind speed) on the output power of wind turbine generators (WTGs), forced outages of generating units including WTGs, and other factors (e.g., transmission capacity and power quality constraints) are considered. Correlation between wind generation and load demand is also considered. Considering the above factors, the proposed method determines the amount of storage required to firm up the generation from the wind farm that is added.

S. Sulaeman, Y. Tian, and J. Mitra are with the Department of Electrical and Computer Engineering, Michigan State University, East Lansing, MI 48823 USA, e-mails: samsuru@msu.edu and mitraj@msu.edu.

M. Benidris is with the Department of Electrical and Biomedical Engineering, University of Nevada, Reno, Reno, NV 89557 USA, e-mail: mbenidris@unr.edu.
so as to provide the same level of reliability as a conventional (dispatchable) generating unit of the same nameplate capacity as the wind farm. System reliability enhancement, in terms of reliability indices, is also assessed with respect to wind farm location and the energy storage. Metrics commonly used for reporting bulk power system reliability are utilized in this work: loss of load probability (LOLP), expected demand not supplied (EDNS), loss of load frequency (LOLF), and mean down time (MDT). However, this paper addresses the matter of size only; it is up to the planner to select a suitable technology based on cost and other considerations.

The remainder of this paper is organized as follows. Section II describes the modeling of wind power. Section III discusses the method and expressions for sizing the energy storage. Section IV presents the modeling of power system networks and calculation of reliability indices. Section V provides several case studies, results, and discussions thereof. Section VI provides concluding remarks.

II. MODELING OF WIND POWER

The output of WTGs are known to vary with wind speed and their design characteristics. The first step in modeling wind power is converting the wind speed time-series data into output power. This section describes the calculation of the output power and the failure model of WTGs.

A. Wind Turbine Output Power

Wind turbine power curve provides a quantitative relationship between wind speed and the output power; it describes the operational characteristics of a WTG. The output power that can be extracted from a WTG can be calculated as follows [26].

\[ P = \frac{1}{2} K_p \sigma A v^3, \]  

(1)

where \( P \) is the output power (Watts), \( \sigma \) is the air density (kg/m³), \( v \) is the wind speed (m/sec), \( A \) is the swept area of the turbine (m²), and \( K_p \) is the power coefficient.

The output power curve combines (1) with the physical constraints of WTGs. The output power curve including the physical constraints can be expressed as follows.

\[ P = \begin{cases} 
0 & \text{if } v < v_{\text{cut-in}} \\
\frac{1}{2} K_p \sigma A v^3 & \text{if } v_{\text{cut-in}} \leq v < v_R \\
P_R & \text{if } v_R \leq v < v_{\text{cut-out}} \\
0 & \text{if } v_{\text{cut-out}} \leq v
\end{cases} \]  

(2)

where \( v_{\text{cut-in}} \) is the designed cut-in speed, \( v_{\text{cut-out}} \) is the designed cut-out speed, \( v_R \) is the rated speed, and \( P_R \) is the rated power of the wind turbine.

B. Failure of Wind Turbines

Several studies have shown that the size of turbines and operational and environmental factors could lead to different failure modes of WTGs. Failures of WTGs usually occur due to ageing, worn out parts or manufacturing defects [27]–[29]. The failures of WTGs may be considered independent, both between themselves and of wind speeds. A WTG can be modeled as a Markovian component with two states, up and down, with known failure and repair rates \( \lambda \) and \( \mu \) respectively (\( \lambda \) is the rate of transition from an up state to a down state, and \( \mu \) is the rate of transition from a down state to an up state). The hourly available wind power is then calculated by generating an artificial history of forced outages of WTGs and hourly wind power using Monte Carlo simulation.

III. ENERGY STORAGE SYSTEM

This section presents a method for determining the size of the energy storage that is required to increase the available energy at wind farm locations. Due to transmission line capacity limits and operational constraints, and the uncertainty associated with the overall energy production of wind farms, the output power of a wind farm that is available to the system could be lower than its nameplate capacity. In fact the output variations depend upon several factors such as geographic location, number of WTGs on the farm, differences between WTGs, turbulence and wake effects, and terrain effects [30], [31]. The accuracy of modeling the output power of WTGs also varies with time scales (the frequency of wind speed observation intervals can be 5 minutes, 10 minutes, hourly, etc.). Further, it has been reported that the error in estimating annual energy production of wind power can be up to 12% [30], [32]. Moreover, failures of WTGs have a significant impact on the available power. Thus, in determining the energy storage size, such uncertainty factors should also be considered.

A. Energy Storage Sizing

The proposed method of quantifying the size of the energy storage is based on previous work presented in [24], [25]. Consider a wind-integrated power system that provides supply of availability \( \rho_0 \) to the system load. Now consider that part of the load curtailment, \( P_L \), that can be directly attributed to the variability of wind power. This quantity can be determined from the difference between the nameplate capacity and the capacity value of the wind farm. The capacity value is the amount of load the wind farm can reliably support, given the variability of wind. Firing the wind output consists of adding a storage system that is sufficient to increase the availability of supply to \( \rho_1 \), which is what would be available if there were firm (dispatchable) generation instead of wind. Thus, the power capacity of the required storage unit should be at least \( P_L \). The energy capacity can then be determined as follows.

Define the unavailability reduction ratio \( \alpha \) as [24]:

\[ \alpha = \frac{1 - \rho_1}{1 - \rho_0}. \]  

(3)

The unavailability reduction ratio can be understood thus: suppose that \( \rho_0 = 0.999 \) and that it is required to increase the availability by an additional “9,” i.e., to \( \rho_1 = 0.9999 \); then, \( \alpha = 0.1 \).

Now assume that the storage system that will improve the system reliability to \( \rho_1 \) can sustain a load of \( P_L \) for time \( t_A \). Then, service interruption occurs when the grid supply is
down and the storage has been depleted. The probability of this event can be described by (4).

\[
P\{L_s\} = P\{R > t_A\} \cap L_s \nbar = P\{R > t_A | L_s\}P\{L_s\} = \left(\int_{t_A}^{\infty} f_R(r)dr\right)P\{L_s\}.
\]

(4)

The variables in (4) are defined as follows [24].

\(L_s\): event that the load is curtailed in the absence of storage;
\(L_s\): event that the load is curtailed in the presence of storage;
\(R\): random variable representing the down time (outage duration);
\(f_R(r)\): probability density function of \(R\).

In (4), \(P\{L_s\}\) is clearly 1 - \(\rho_1\), and \(P\{L_s\} = 1 - \rho_0\). From (3) and (4), it is clear that

\[
\int_{t_A}^{\infty} f_R(r)dr = \alpha.
\]

(5)

The solution to (5) can be obtained analytically for simple systems [24], but for more complex systems it is more convenient to use (6), which has been shown to be equivalent to (5) [25].

\[
\int_{0}^{t_A} r f_R(r)dr = (1 - \alpha)\bar{r}
\]

(6)

The solution to (6) can be easily obtained from interruption time statistics generated by using sequential Monte Carlo simulation. Suppose the interruption durations without the storage system are arranged in order of increasing magnitude. If \(\bar{r}\) is the mean interruption duration (given by the mean of all interruption durations), then that time for which the mean of all equal and shorter interruptions is closest to \((1 - \alpha)\bar{r}\) gives the estimate of \(t_A\).

Equation (6) represents the basic relation that quantifies the required energy capacity of the storage system. However, the storage unit itself may not be perfectly reliable. In order to compensate for this, the storage device should have an energy capacity that enables it to provide the required power \(P_L\) for a period of time \((t_S)\) that is given by (7) [24], [25].

\[
t_S = \frac{t_A}{A_S},
\]

(7)

where \(A_S\) is the availability of the storage system. Therefore, the power capacity of the selected storage unit should be at least \(P_L\), and the energy capacity should be at least \(P_L t_S\).

In wind power planning projects, the errors associated with wind power prediction can lead to significant challenges for system planners and operators. Also, wind speed varies with both time and location. For these reasons, wind integration studies are generally conducted prior to the development phase of wind power projects to assess these impacts. With regard to storage system planning projects, several authors have discussed the effect of wind power prediction error on sizing energy storage systems [32]–[35]. Therefore, the available statistical data of wind power may not accurately reflect the long term variation of wind speed [30], [32], [36]. Thus, in the planning phase, additional power may be required to compensate for the long term error associated with wind energy production and estimation. In this work, the additional power of energy storage system \(P_{ESS}\) can be calculated as follows.

\[
P_{ESS} = P_L (1 + \gamma),
\]

(8)

where \(\gamma\) is the anticipated long term error associated with wind energy production and estimation.

B. Energy Storage Operation

In order to evaluate the effect of adding an energy storage device with a rated power of \(P_{ESS}\) on the reliability of the system, the following operation constraints are considered [11]:

\[
0 \leq P_{dis}^i(t) \leq P_r^i \quad \text{for} \quad t \in [0, T], i = 1, 2, \ldots, N_b,
\]

(9)

where \(T\) is the period of the study, \(P_{dis}^i(t)\) is the discharging power of the energy storage device at bus \(i\) at time \(t\) in MW, and \(P_r^i\) is the rated power of the energy storage system at bus \(i\) in MW, and \(N_b\) is the number of buses.

\[
0 \leq P_{chr}^i(t) \leq P_r^i \quad \text{for} \quad t \in [0, T], i = 1, 2, \ldots, N_b,
\]

(10)

where \(P_{chr}^i(t)\) is the charging power of the energy storage system at bus \(i\) at time \(t\) in MW.

The inequalities (9) and (10) constrain the charging and discharging power to remain within the power rating of the energy storage system. The energy constraints of the storage system are imposed by (11).

\[
0 \leq E_{n^i}^i(t) - E_{n^i}^i \quad \text{for} \quad t \in [0, T], i = 1, 2, \ldots, N_b,
\]

(11)

where \(E_{n^i}^i(t)\) and \(E_{n^i}^i\) are the energy state of charge and the energy rating of the storage system respectively at bus \(i\) in MWh. The energy state of charge of the storage system can be expressed as follows.

\[
E_{n^i}^i(t + 1) = E_{n^i}^i(t) - \frac{1}{\eta_{dis}} P_{dis}^i(t) + \eta_{chr} P_{chr}^i(t),
\]

where \(\eta_{dis}\) and \(\eta_{chr}\) are the charging and discharging efficiencies of the storage system respectively.

In the literature, several authors have proposed different operation strategies for energy storage systems [10], [37], [38]. In this work, time-shift technique is applied as described in [10]. The state of charge and discharge of the storage system is represented by means of logic states (i.e., 1 for discharging and 0 for charging). The discharging states represent the hourly down-time statistics of wind power. In the simulation process, the available wind power is evaluated based on the temporal resolution of wind data and the discharging and charging capacities are determined accordingly.

C. Approach for Reliability-based Storage Sizing

Fig. 1 provides an overview of the steps employed in the proposed approach. Reliability evaluation is performed by seeking dispatch solutions that minimize system curtailment, considering wind power uncertainty, forced outages of generation units including WTGs, and system operations constraints (power balance, generation and transmission capacities, and power quality constraints). Details of this model are provided in the next section.
following minimization problem [39].

\[
\text{Loss of Load} = \min \left( \sum_{i=1}^{N_b} C_i \right) \\
\text{subject to}
\]

\[
P(V, \delta) - P_D + C = 0 \\
Q(V, \delta) - Q_D + C_Q = 0 \\
P_G^{\min} \leq P_G \leq P_G^{\max} \\
Q_G^{\min} \leq Q_G \leq Q_G^{\max} \\
V^{\min} \leq V \leq V^{\max} \\
|F(V, \delta)| \leq F^{\max}
\]

\( \delta \) unrestricted

where \( C_i \) is the load curtailment at bus \( i \), \( C \) is the vector of load curtailments \((N_b \times 1)\), \( C_Q \) is the vector of reactive load curtailments \((N_b \times 1)\), \( V \) is the vector of bus voltage magnitudes \((N_b \times 1)\), \( \delta \) is the vector of bus voltage angles \((N_b \times 1)\), \( P_D \) and \( Q_D \) are the vectors of real and reactive power loads \((N_b \times 1)\), \( P_G \) and \( Q_G \) are the vectors of real and reactive power outputs of the generators \((N_g \times 1)\), \( P_G^{\min} \), \( P_G^{\max} \), \( Q_G^{\min} \) and \( Q_G^{\max} \) are the vectors of real and reactive power limits of the generators \((N_g \times 1)\), \( V^{\max} \) and \( V^{\min} \) are the vectors of maximum and minimum allowed voltage magnitudes \((N_b \times 1)\), \( F(V, \delta) \) is the vector of power flows in the lines \((N_l \times 1)\), \( F^{\max} \) is the vector of power rating limits of the transmission lines \((N_l \times 1)\), and \( P(V, \delta) \) and \( Q(V, \delta) \) are the vectors of real and reactive power injections \((N_b \times 1)\). In the foregoing, \( N_b \) is the number of buses, \( N_l \) is the number of transmission lines, and \( N_g \) is the number of generators.

The above model implies that for any encountered scenario (generation and transmission availability and load state) power will be routed through the network in such a manner as to minimize the system load curtailment.

B. Calculation of Reliability Indices

In order to capture interruption times and temporal relationships such as state of charge of the storage system, all indices are determined from sequential Monte Carlo simulation [40].

a) Mean down time (MDT): The MDT is the average interruption duration, denoted by \( \bar{r} \) earlier in this section. By definition,

\[
\text{MDT} = \bar{r} = \int_0^\infty r f_R(r)dr
\]

where the variables are as defined in (4). From the simulation, MDT is estimated using

\[
\text{MDT} = E[\hat{r}] ; \quad \hat{r} = \frac{1}{N_c} \sum_{i=1}^{N_c} T_{dn}^i
\]

where \( E[\cdot] \) is the expectation operator, \( \hat{r} \) is the estimator of MDT, \( T_{dn}^i \) is the duration of \( i \)th interruption encountered during the sequential simulation, and \( N_c \) is the number of cycles simulated. A cycle consists of a service period \( T_{up}^i \) and an interruption period \( T_{dn}^i \); the \( i \)th cycle time \( T_c^i \) equals

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**Fig. 1. General procedure for reliability-based storage sizing.**

IV. NETWORK MODELING AND RELIABILITY EVALUATION

In composite reliability evaluation studies, repetitive solutions of an optimization problem with an objective function of minimum load curtailment are performed. This section describes the formulation and incorporation of the objective function of minimum load curtailment using nonlinear programming and the AC power flow model. Sequential Monte Carlo simulation is used to emulate the behavior of the system and estimate system reliability indices. This consists of sequential assessments of the reliability of the states that the system assumes in successive time steps over the planning horizon. For each such state, the objective is to determine a dispatch that minimizes the load curtailment, subject to the equality constraints of power balance, the inequality constraints of equipment capacity and power quality, and the availability of system components. In this section, the details of system modeling and reliability evaluation are described.

A. System Modeling

For each hour, the system state is defined by the component states and capacities. The output of wind power is determined by the corresponding wind turbine states and hourly output power. Then a feasible dispatch is sought by solving the
$T_{up}^i + T_{dn}^i$. The total period of simulation $T$ is given by $T = N_c T_e = N_c (T_{up}^i + T_{dn}^i)$.

b) Loss of load probability (LOLP): The LOLP index can be estimated as follows.

$$\text{LOLP} = E[\Pi]; \quad \Pi = \frac{1}{T} \sum_{i=1}^{N_c} T_{dn}^i \quad (16)$$

where $\Pi$ is the estimator of LOLP and the other variables are as defined above.

c) Loss of load frequency (LOLF): The LOLF index gives the frequency of service outage and can be estimated as follows.

$$\text{LOLF} = E[\Phi] ; \quad \Phi = \frac{N_c}{T} \quad (17)$$

where $\Phi$ is the estimator of LOLF and the other variables are as defined above. It should be noted that the unit of LOLF is failures per unit time; hence, if time is tracked in hours, (17) will yield LOLF in f/h, and may need to be converted into f/y, which is the customary unit for expressing LOLF. Also, LOLF is related to LOLP and MDT as follows.

$$\text{LOLF} = \frac{\text{LOLP}}{\text{MDT}} \quad (18)$$

d) Expected demand not supplied (EDNS): The EDNS index is the sum of the products of probabilities of failure states and the corresponding load curtailments which can be calculated as follows.

$$\text{EDNS} = \sum_{x_i \in X_f} P\{x_i\} \times C\{x_i\} \quad (19)$$

where $P\{x_i\}$ and $C\{x_i\}$ are the probability of occurrence of state $x_i$ and the system load curtailment in state $x_i$, and $X_f$ is the set of failure states.

Using sequential simulation, EDNS is estimated from

$$\text{EDNS} = E[\hat{d}]; \quad \hat{d} = \frac{1}{T} \sum_{i=1}^{N_c} T_{dn}^i C\{x_i\} \quad (20)$$

where $\hat{d}$ is the estimator of EDNS and $C\{x_i\}$ is the minimum curtailment obtained from the solution of (12) for the prevailing state.

C. Stopping Criterion

In using Monte Carlo simulation to estimate power system reliability indices, a convergence criterion should be applied to stop the algorithm if there is not much change in the reliability indices. In this work, the stopping criterion is applied on the reliability indices as follows.

$$\text{COV} = \frac{\text{Var}(\rho_{N_c})}{E[\rho_{N_c}]} \leq \varepsilon, \quad (21)$$

where $\text{COV}$ is the coefficient of variation, $\text{Var}(\cdot)$ is the variance function, $\rho_{N_c}$ is the value of the estimate of the reliability index of interest (such as LOLP or EDNS) at the end of $N_c$ cycles, and $\varepsilon$ is a pre-specified tolerance.

At intervals of several cycles, the $\text{COV}$ is calculated. If this amount is less than or equal to the specified tolerance $\varepsilon$, the algorithm is terminated; otherwise, the simulation continues.

V. Case Studies

The proposed formulation is applied on the IEEE reliability test system (IEEE-RTS) [41]. The IEEE-RTS has been extensively tested for power system reliability analysis. It consists of 24 buses, 33 transmission lines, 5 transformers, and 32 generating units. The single line diagram of this test system is shown in Fig. 2. The load profile of the IEEE-RTS is used to calculate the hourly load of each bus in the system for a year. For the base case of the IEEE-RTS, the LOLP, LOLF, and EDNS indices are 0.001538, 2.695 f/y, and 0.20151 MW/y respectively.
MTTF lies in the ranges of actual WTGs, as reported in [46]. The MTTR is calculated from the forced outage rates and MTTF of WTGs. The case studies are summarized as follows:

1) Evaluating the effect of the temporal resolutions of the wind speed on system reliability: Due to unavailability of wind speed data for the same site with different temporal resolutions, the effects of correlation and temporal resolution on the system reliability indices are evaluated using three different wind speed data sets for different sites. Three different case studies are considered. These case studies are not intended to compare the results; rather, they impact the extent to which such factors on the planning decisions. In an actual planning study, comparisons should be conducted for wind speed data with different temporal resolutions, at the site under consideration.

2) Energy storage sizing: The proposed method (as explained in section III) is used to determine the power and energy capacities required to firm up the generation from the wind farm that is added, so as to provide the same level of reliability as a conventional (dispatchable) generating unit of the same nameplate capacity as the wind farm.

A. Wind Farm Locations and System Reliability

The selection of wind farm location usually depends on several factors such as wind availability, access to the grid, economic aspects, and reliability enhancement of the grid. In this work, the wind farm candidate locations are evaluated based on how much reliability benefit they can bring to the system i.e., by the extent to which a wind farm at a candidate location reduces the system EDNS. The following three cases are studied:

1) Case study 1: IEEE-RTS reliability indices with wind farm, assuming wind speed data set A.
2) Case study 2: IEEE-RTS reliability indices with wind farm, assuming wind speed data set B.
3) Case study 3: IEEE-RTS reliability indices with wind farm, assuming wind speed data set C.

The temporal resolutions of the wind speed data sets are as follows: 1) wind speed data set A has a temporal resolution of 1 h, 2) wind speed data set B has a temporal resolution of 5 min, and 3) wind speed data set C has a temporal resolution of 10 min. The correlation coefficients between these data sets and the load profile of the IEEE-RTS are as follows: 1) $-0.002$ for data set A, 2) $0.0686$ for data set B, and 3) $-0.1059$ for data set C. Whereas data set A and the load are almost uncorrelated, data set B has positive correlation and data set C has negative correlation with the load. For each case study, the wind power is connected to the load buses and then the reliability indices are calculated. System reliability indices for different wind locations are listed in Table I–III. Buses 21–24 do not have load and are not considered.

The entries in the tables may be understood thus. Each row represents a separate study wherein a 200 MW wind farm as described above is added to the IEEE-RTS at the indicated bus, and the system EDNS, LOLP, LOLF and MDT are evaluated. The best candidate buses are determined by tracking system reliability improvement with respect to wind power location.

Of the indices reported, the EDNS most effectively reflects the extent to which customers are affected by system outages. Therefore, the EDNS index is chosen to determine the best candidate buses to connect the wind farm at. The candidate buses are ranked based on the improvement of the system EDNS index (highest to smallest). In general, system reliability indices improve when wind power is added to the system in every case study which is not surprising. Overall, the system is found to benefit the most from installing the 200 MW wind farm at bus 18, 13, 6, 10 or 9.

B. Storage System Augmentation for Different Wind Datasets

The size of the energy storage $P_{\text{ESS}}$ and the time $t_s$ are calculated as explained in Section III. A prediction error of $\gamma = 5\%$ is assumed for the annual energy production of the
TABLE III
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH 200 MW WIND POWER ADDED AT DIFFERENT BUSES: DATA SET C

<table>
<thead>
<tr>
<th>Wind Power at Bus No.</th>
<th>LOLP (MW/y)</th>
<th>EDNS (MW)</th>
<th>LOLF (f/y)</th>
<th>MDT (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.001188</td>
<td>0.151188</td>
<td>2.171</td>
<td>4.79364</td>
</tr>
<tr>
<td>2</td>
<td>0.001207</td>
<td>0.153582</td>
<td>2.205</td>
<td>4.79410</td>
</tr>
<tr>
<td>3</td>
<td>0.001252</td>
<td>0.159732</td>
<td>2.261</td>
<td>4.84918</td>
</tr>
<tr>
<td>4</td>
<td>0.001262</td>
<td>0.160989</td>
<td>2.272</td>
<td>4.86576</td>
</tr>
<tr>
<td>5</td>
<td>0.001290</td>
<td>0.164816</td>
<td>2.311</td>
<td>4.89139</td>
</tr>
<tr>
<td>6</td>
<td>0.001115</td>
<td>0.140846</td>
<td>2.047</td>
<td>4.77040</td>
</tr>
<tr>
<td>7</td>
<td>0.001525</td>
<td>0.199972</td>
<td>2.657</td>
<td>5.02747</td>
</tr>
<tr>
<td>8</td>
<td>0.001359</td>
<td>0.174072</td>
<td>2.468</td>
<td>4.82253</td>
</tr>
<tr>
<td>9</td>
<td>0.001170</td>
<td>0.148830</td>
<td>2.133</td>
<td>4.79373</td>
</tr>
<tr>
<td>10</td>
<td>0.001152</td>
<td>0.146509</td>
<td>2.117</td>
<td>4.76665</td>
</tr>
<tr>
<td>13</td>
<td>0.001080</td>
<td>0.135374</td>
<td>1.969</td>
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</tr>
<tr>
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<td>2.351</td>
<td>4.86729</td>
</tr>
<tr>
<td>15</td>
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<td>0.171378</td>
<td>2.413</td>
<td>4.85454</td>
</tr>
<tr>
<td>16</td>
<td>0.001136</td>
<td>0.144221</td>
<td>2.091</td>
<td>4.75849</td>
</tr>
<tr>
<td>18</td>
<td>0.001067</td>
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<td>1.940</td>
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</tr>
<tr>
<td>19</td>
<td>0.001160</td>
<td>0.147665</td>
<td>2.121</td>
<td>4.79208</td>
</tr>
<tr>
<td>20</td>
<td>0.001370</td>
<td>0.175437</td>
<td>2.491</td>
<td>4.81614</td>
</tr>
</tbody>
</table>

C. Discussion

As evident from Tables IV, V and VI, the proposed method was effective in firming the reliability of the wind farm using appropriate amounts of storage—the LOLP with storage was improved to the target LOLP, i.e., the same level as that of a conventional unit with the same nameplate capacity as the wind farm. It is also evident from these results how the storage capacity, both in MW and MWh, differ based on factors such as correlation between wind speed and load, and grid access, i.e., strength of interconnection to the grid. The results shown also validate the proposed methodology.

VI. Conclusion

This paper has presented a method for quantifying the amount of energy storage required to firm up wind power. Several case studies were performed to evaluate the reliability indices and determine the sizes and locations of the energy storage systems. Preferred locations for wind injection were also evaluated by comparing the enhancement of system reliability indices at the candidate buses. Sequential Monte Carlo simulation was used to emulate the stochastic behavior of wind power and forced outages of WTGs in calculating the reliability indices and determining the sizes of energy storage systems.

In this work, three wind speed data sets were used. These data sets were utilized to study the effect of correlation between load demand and wind power and temporal resolutions.
on determining the size of the energy storage. The system reliability indices and the rated power of the energy storage systems were calculated for three case studies using the three data sets. These case studies were not intended to compare the results; they only demonstrate the effect of wind speed temporal resolution and correlation with the load on system reliability and determining size of the energy storage system. The results validated the proposed methodology and illustrated the dependence of the required sizes of storage systems on wind characteristics and wind farm location.

REFERENCES


**Samer Sulaeman** (S’11) received the B.Sc. degree in electrical and electronic engineering from University of Al Zawiya, Libya, and the M.Sc. degree in electrical engineering with specialization in power systems from the University of Al Zawiya, Zawiya, Libya, in 1997 and 2005, respectively. He is currently working toward the Ph.D. degree at Michigan State University, East Lansing, MI, USA.

He was in the Department of Electrical and Electronic Engineering, University of Al Zawiya, as an Assistant Lecturer. His research interests include power system reliability, stability, and control, and planning for renewable resources.

**Yuting Tian** (S’14) received the B.S. (Hons.) degree in electrical engineering from Sichuan University, Chengdu, China, in 2013, and the M.S. degree in electrical engineering from Michigan State University, East Lansing, MI, USA, in 2014, where she is currently working toward the Ph.D degree in electrical engineering.

Her research interests include power system analysis, control, reliability and optimization, and distributed energy generation and storage.

**Mohammed Benidris** (S’10–M’14) received the Ph.D. degree in electrical engineering from Michigan State University, East Lansing, MI, USA, in 2014, and the M.Sc. and B.Sc. degrees in electrical engineering from the University of Benghazi, Benghazi, Libya, in 2005 and 1998, respectively.

He is currently an Assistant Professor of electrical engineering with the University of Nevada Reno (UNR), Reno, NV, USA. Prior to joining UNR, he was a Research Associate and a Visiting Lecturer at Michigan State University. Earlier, he was an Assistant Lecturer in the Department of Electrical and Electronics Engineering, University of Benghazi, where he served as the Chair of the Engineering Departments branch of Almaraj. His main research interests include power system reliability, stability and resilience, and cyber-physical systems.

**Joydeep Mitra** (S’94–M’97–SM’02) received the B.Tech. (Hons.) degree in electrical engineering from the Indian Institute of Technology Kharagpur, Kharagpur, India, in 1989, and the Ph.D. degree in electrical engineering from Texas A&M University, College Station, TX, USA, in 1997.

He is currently an Associate Professor of electrical engineering with Michigan State University, East Lansing, MI, USA, the Director of the Energy Reliability and Security Laboratory, and a Senior Faculty Associate with the Institute of Public Utilities. His research interests include reliability, planning, stability, and control of power systems.