

Quantification of Storage Necessary to Firm Up Wind Generation

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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. Also, according to [11], the trade-off between the capital cost of the energy storage and the daily system operating cost becomes insignificant as the energy storage investment increases. This can be attributed in part to the high variation of wind power and high cost and limited operating lifespan of energy storage systems [8], [12], [13]. Due to these factors, several management and control systems have been proposed to optimize their operation [14]–[16]. In [17], a predictive control method is proposed for controlling the charging and discharging of a battery storage system; this work concluded that the size of the required battery storage system to mitigate the hourly variation of wind power that leads to minimum operating cost should be around 75% of nameplate capacity of the wind farm. In practice, different types and sizes of energy storage systems have been deployed for different applications such as energy management, backup power, load leveling, frequency regulation, voltage support, and grid stabilization [18], [19]. However, large scale adoption and deployment of energy storage technologies is still limited, largely due to the aforementioned factors [13], [20].

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,

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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].

$$P = \frac{1}{2} K_p \sigma A v^3, \quad (1)$$

where P is the output power (Watts), σ is the air density (kg/m^3), v is the wind speed (m/sec), A is the swept area of the turbine (m^2), 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.

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

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 λ and μ respectively (λ is the rate of transition from an up state to a down state, and μ 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 ρ_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. Firming the wind output consists of adding a storage system that is sufficient to increase the availability of supply to ρ_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 α as [24]:

$$\alpha = \frac{1 - \rho_1}{1 - \rho_0}. \quad (3)$$

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 ρ_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).

$$\begin{aligned} P\{L_s\} &= P\{\{R > t_A\} \cap L_{\bar{s}}\} \\ &= P\{R > t_A \mid L_{\bar{s}}\} P\{L_{\bar{s}}\} \\ &= \left(\int_{t_A}^{\infty} f_R(r) dr \right) P\{L_{\bar{s}}\}. \end{aligned} \quad (4)$$

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

$L_{\bar{s}}$: 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 $P\{L_{\bar{s}}\} = 1 - \rho_0$. From (3) and (4), it is clear that

$$\int_{t_A}^{\infty} f_R(r) dr = \alpha. \quad (5)$$

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].

$$\int_0^{t_A} r f_R(r) dr = (1 - \alpha) \bar{r} \quad (6)$$

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].

$$t_S = \frac{t_A}{A_S}, \quad (7)$$

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.

$$P_{ESS} = P_L(1 + \gamma), \quad (8)$$

where γ 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]:

$$0 \leq P_{dis}^i(t) \leq P_r^i \quad \text{for } t \in [0, T], i = 1, 2, \dots, N_b, \quad (9)$$

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.

$$0 \leq P_{chr}^i(t) \leq P_r^i \quad \text{for } t \in [0, T], i = 1, 2, \dots, N_b, \quad (10)$$

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).

$$0 \leq En^i(t) \leq En_r^i \quad \text{for } t \in [0, T], i = 1, 2, \dots, N_b, \quad (11)$$

where $En^i(t)$ and En_r^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.

$$En^i(t+1) = En^i(t) - \frac{1}{\eta_{dis}} P_{dis}^i(t) + \eta_{chr} P_{chr}^i(t),$$

where η_{chr} and η_{dis} 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.

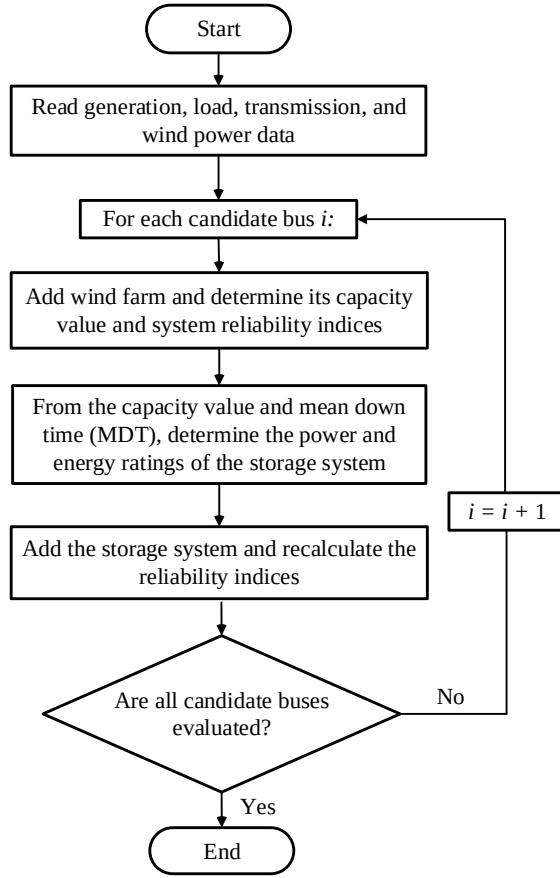


Fig. 1. General procedure for reliability-based storage sizing.

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

following minimization problem [39].

$$\text{Loss of Load} = \min \left(\sum_{i=1}^{N_b} C_i \right) \quad (12)$$

subject to

$$\begin{aligned} P(V, \delta) - P_D + C &= 0 \\ Q(V, \delta) - Q_D + C_Q &= 0 \\ P_G^{min} &\leq P_G \leq P_G^{max} \\ Q_G^{min} &\leq Q_G \leq Q_G^{max} \\ V^{min} &\leq V \leq V^{max} \\ |F(V, \delta)| &\leq F^{max} \\ \delta &\text{ unrestricted} \end{aligned} \quad (13)$$

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 ($N_b \times 1$), δ 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 ($N_t \times 1$), F^{max} is the vector of power rating limits of the transmission lines ($N_t \times 1$), 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_t 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,

$$\text{MDT} = \bar{r} = \int_0^\infty r f_R(r) dr \quad (14)$$

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

$$\text{MDT} = E[\hat{r}]; \quad \hat{r} = \frac{1}{N_c} \sum_{i=1}^{N_c} T_{dn}^i \quad (15)$$

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

$T_{up}^i + T_{dn}^i$. The total period of simulation T is given by $T = N_c T_c = N_c (T_{up}^i + T_{dn}^i)$.

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 Π 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 Φ 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.

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

where COV is the coefficient of variation, $\text{Var}(\cdot)$ is the variance function, ρ_{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 ε is a pre-specified tolerance.

At intervals of several cycles, the COV is calculated. If this amount is less than or equal to the specified tolerance ε , 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.

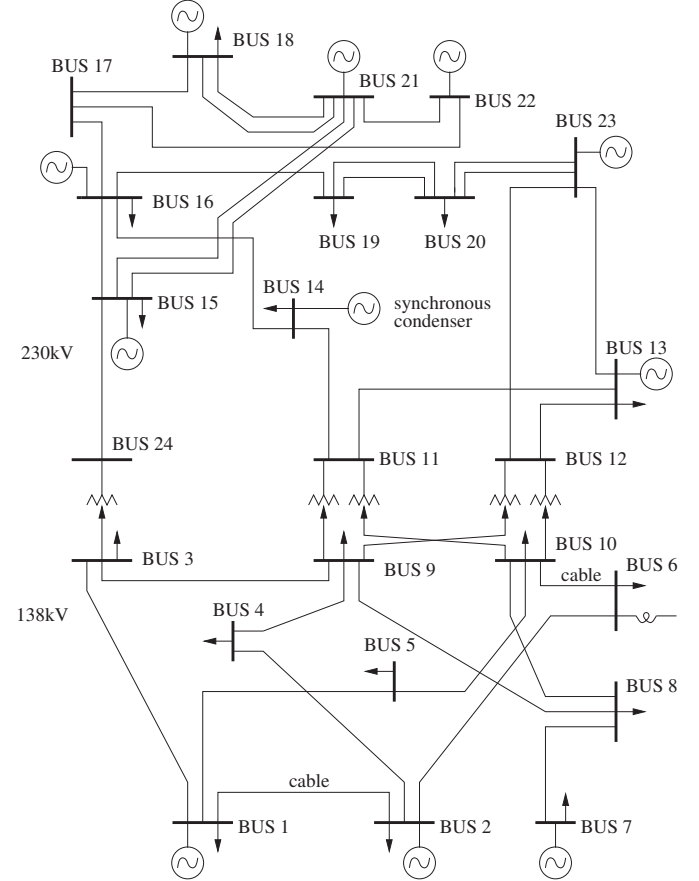


Fig. 2. Single line diagram for IEEE-RTS

In this study, a wind farm with 200 MW capacity is added to the system at the load buses assuming that all WTGs are identical (100 WTGs with nameplate capacity of 2 MW each). Actual observed wind speed data sets are used to calculate the output of WTGs. In the following case studies, three wind speed data sets are used to evaluate the effects of different correlations between the wind power and the load profile, and different temporal resolutions on the system reliability indices: *data set A* [42], *data set B* [43], and *data set C* [44]. The wind speed data sets are utilized to calculate the output of WTGs using equations (1) and (2) as described in section II.

A typical wind turbine characteristic is assumed (type Vesta V90-2.0 MW [45]). The reliability data of the WTGs are as follows: The mean time to failure (MTTF) and mean time to repair (MTTR) are 3600 h and 150 h respectively [2]. The

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 illustrate the impact of considering 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.

TABLE I
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH 200 MW WIND POWER ADDED AT DIFFERENT BUSES: DATA SET A

Wind Power at Bus No.	LOLP	EDNS (MW/y)	LOLF (f/y)	MDT (h)
1	0.001054	0.135182	3.079	3.00000
2	0.001071	0.137305	3.120	3.00641
3	0.001114	0.142770	3.228	3.02261
4	0.001122	0.143889	3.240	3.03302
5	0.001143	0.147287	3.285	3.04749
6	0.000988	0.125983	2.892	2.99239
7	0.001517	0.198447	2.639	5.03714
8	0.001201	0.155500	3.467	3.03375
9	0.001038	0.133087	3.042	2.99047
10	0.001025	0.131022	3.012	2.98240
13	0.000950	0.121135	2.770	3.00578
14	0.001161	0.149592	3.341	3.04280
15	0.001185	0.153112	3.418	3.03686
16	0.001011	0.128986	2.955	2.99695
18	0.000938	0.119248	2.737	3.00110
19	0.001032	0.132050	3.020	2.99238
20	0.001209	0.156707	3.496	3.02918

TABLE II
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH 200 MW WIND POWER ADDED AT DIFFERENT BUSES: DATA SET B

Wind Power at Bus No.	LOLP	EDNS (MW/y)	LOLF (f/y)	MDT (h)
1	0.000991	0.120629	1.960	4.42908
2	0.001007	0.122628	1.974	4.46960
3	0.001047	0.127766	2.036	4.50344
4	0.001055	0.128817	2.054	4.50049
5	0.001078	0.132020	2.083	4.53337
6	0.000919	0.112048	1.814	4.43826
7	0.001496	0.195424	2.601	5.03883
8	0.001137	0.139781	2.204	4.51906
9	0.000971	0.118663	1.915	4.44386
10	0.000954	0.116734	1.878	4.45101
13	0.000887	0.107531	1.773	4.38240
14	0.001094	0.134194	2.122	4.51602
15	0.001120	0.137520	2.157	4.54845
16	0.000937	0.114838	1.860	4.41344
18	0.000876	0.105768	1.749	4.38536
19	0.000963	0.117694	1.894	4.45565
20	0.001147	0.140924	2.223	4.51867

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_{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

Wind Power at Bus No.	LOLP	EDNS (MW/y)	LOLF (f/y)	MDT (h)
1	0.001188	0.151188	2.171	4.79364
2	0.001207	0.153582	2.205	4.79410
3	0.001252	0.159732	2.261	4.84918
4	0.001262	0.160989	2.272	4.86576
5	0.001290	0.164816	2.311	4.89139
6	0.001115	0.140846	2.047	4.77040
7	0.001525	0.199972	2.657	5.02747
8	0.001359	0.174072	2.468	4.82253
9	0.001170	0.148830	2.138	4.79373
10	0.001152	0.146509	2.117	4.76665
13	0.001080	0.135374	1.969	4.80599
14	0.001306	0.167412	2.351	4.86729
15	0.001337	0.171378	2.413	4.85454
16	0.001136	0.144221	2.091	4.75849
18	0.001067	0.133227	1.940	4.81907
19	0.001160	0.147665	2.121	4.79208
20	0.001370	0.175437	2.491	4.81614

wind farm. The unavailability reduction ratio α is determined for each instance in the following manner. The wind farm is replaced by a conventional unit with the same nameplate capacity as the wind farm, i.e., 200 MW. Typical reliability characteristics are assumed for the conventional unit. Then, the system LOLP is calculated using the conventional unit instead of the wind farm, at the same location. This LOLP is deemed the target LOLP, since it is intended to use storage to firm up the wind supply by increasing its reliability to the same level as that of a conventional unit. Now α is determined by dividing the target LOLP by the LOLP obtained from wind injection.

Then, the energy storage system is added to the grid at the candidate buses in presence of wind power. The storage system is sized as described in section III-A. The power capacities P_{ESS} of the storage systems for data sets A, B and C are found to be 153.3 MW, 150.15 MW and 157.5 MW; these values differ because a higher positive correlation between wind and load requires a lower P_{ESS} . Then using α as calculated above, t_A is determined as described in section III-A. The storage system is assumed to have 0.99 availability. From t_A and $A_S = 0.99$, t_S can be determined. But since the simulation is performed in hourly increments, t_S is rounded off to the nearest hour. The energy capacity of the storage system is given by $P_{ESS}t_S$.

The charging and discharging efficiencies of the storage are assumed 90% and 87.5% respectively [11]. During the simulation, the storage system logic described in section III-B is implemented. For the three case studies, the P_{ESS} , target LOLP, α , t_S , and the LOLP achieved with storage integration at each of the five selected locations are shown in Tables IV, V and VI.

TABLE IV
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH WIND POWER AND
ENERGY STORAGE AT DIFFERENT BUSES: DATA SET A

Wind Power at Bus No.	Target LOLP	P_{ESS} (MW)	α	t_S (h)	LOLP with Storage
18	0.00036	153.3	0.38	4	0.0003726
13	0.00039	153.3	0.41	4	0.0003808
6	0.00044	153.3	0.45	3	0.0004153
10	0.00053	153.3	0.52	3	0.0005445
9	0.00057	153.3	0.55	3	0.0005845

TABLE V
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH WIND POWER AND
ENERGY STORAGE AT DIFFERENT BUSES: DATA SET B

Wind Power at Bus No.	Target LOLP	P_{ESS} (MW)	α	t_S (h)	LOLP with Storage
18	0.00036	150.15	0.41	6	0.0003434
13	0.00039	150.15	0.43	5	0.0003856
6	0.00044	150.15	0.48	4	0.0004208
10	0.00053	150.15	0.56	3	0.0005217
9	0.00057	150.15	0.59	3	0.0005369

TABLE VI
SYSTEM RELIABILITY INDICES FOR IEEE-RTS WITH WIND POWER AND
ENERGY STORAGE AT DIFFERENT BUSES: DATA SET C

Wind Power at Bus No.	Target LOLP	P_{ESS} (MW)	α	t_S (h)	LOLP with Storage
18	0.00036	157.5	0.34	8	0.0003686
13	0.00039	157.5	0.36	6	0.0004154
6	0.00044	157.5	0.40	6	0.0004300
10	0.00053	157.5	0.46	5	0.0005922
9	0.00057	157.5	0.49	4	0.0005836

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.

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