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Reliability assessment of a standalone wind-conventional/energy storage system using probabilistic production simulation method

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Abstract: This paper presents a reliability evaluation technique for a small standalone system including wind and conventional resources integrated with an energy storage system. A battery bank is considered as the energy storage system. The focus in this analysis is on the effect of battery modeling and its performance on system reliability. In this way, this paper presents an accurate model for the electrochemical batteries, which takes into account all the influential characteristics of the battery related to reliability studies, such as depth of charge, efficiency of charge, and rate of discharge. The proposed reliability evaluation method is based on the combination of a probabilistic production simulation technique as an analytical method and time series technique, in the domain of adequacy studies. By using the probabilistic production simulation technique, not only can the reliability of wind-conventional resources be assessed, but the fuel consumption can also be analyzed. On the other hand, by using the time series approach, the time variation of wind speed and operating constraints of the battery bank can be considered in evaluating the reliability indices. In this paper, a typical lead–acid battery bank is used. It is shown how the accurate modeling of the battery bank can affect the reliability indices. Beneficial results are obtained for different operating strategies and wind penetrations and are then compared.

Key words: Battery modeling, time series simulation, probabilistic production simulation, reliability, wind, conventional generating source

1. Introduction

In recent years, the deployment of renewable energy resources such as wind has had rapid growth due to the environmentally friendly nature of these resources on one hand and the increasing cost of fossil fuels on the other. Many renewable energy resources are atmosphere-dependent and thus have intermittent generation. Therefore, they require additional sources of energy to constantly supply the load in off-grid applications. In addition to conventional generating sources, an energy storage device is one of the best choices of complementary energy sources in such applications [1]. In this case, electrochemical batteries are used widely, owing to the growth of their technology and modular design [2]. To use such a system more efficiently and economically, system unit sizing studies play an important role. Various unit sizing techniques of the system have been reported [3–6]. System modeling is considered as the first step in the unit sizing procedure. Reliability and economic studies, as essential components of these techniques, are the second step and are affected by the system modeling. Modeling and reliability studies have received more attention in this body of research. Hence, this paper focuses on the effect of more accurate modeling for the energy storage system on the reliability.

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There are many techniques for reliability evaluation and power generation planning in functional generation zones. These techniques are based on the risk model obtained by combining the load and generation models [7]. The risk can also be expressed by means of quantitative indices, which are calculated by analytical or simulation methods. Both the analytical technique [8,9] and Monte Carlo simulation (MCS) [10–12] have been employed by researchers for the reliability evaluation of renewable energy-based systems without storage. However, the intermittent nature of renewable energy systems calls for the integration of conventional sources and appropriate energy storage systems in order to maintain system reliability. In this way, reliability evaluation studies of renewable energy systems integrated with conventional sources [13–17] and storage systems [18–23] have been extended in the literature. In this regard, the simulation-based method is computationally cumbersome, in which the wind speed is predicted through a time series analysis of the past data [23,24]. More precisely, the simulation-based method requires a rather complex prediction model and a large amount of past wind data [16,17], which might not be available for all regions. In [15] both analytical and MCS methods were used and compared for the reliability evaluation of small isolated wind/diesel systems. It was also demonstrated that the analytical method, in spite of its computational superiority with respect to MCS, can be used to provide acceptable results for the system adequacy. However, with the presence of storage systems, especially when their realistic behavior is taken into consideration with respect to the changes imposed by wind speed fluctuation over time, the analytical method cannot consider the above factors in the evaluation of the reliability indices. For these reasons, this paper uses a combination of analytical and time series techniques in which modeling of the system components is done using the time series technique. This approach can remove the disadvantages of the analytical method related to reliability evaluations of the system being studied and is also simple, requiring a limited range of historical weather data. In this paper, loss of load probability (LOLP) and expected energy not supplied (EENS) are considered as reliability indices. These indices were assessed using the probabilistic production simulation (PPS) technique [14,18]. In the PPS technique, the fuel consumption can also be scheduled.

In [18–23] and other studies, the effect of the accurate behaviors of the storage system were not investigated in detail. In other words, an overly ideal model of the storage system (with no operating restrictions) has been used. This paper proposes an appropriate model for a popular type of the electrochemical batteries with all the influential characteristics related to reliability studies taken into account. This model is suitable for the reliability evaluation technique presented in this paper and with this combination the impact of storage system behaviors can be investigated in detail. Several models for electrochemical batteries have usually been proposed for dynamic studies in certain applications [25,26]. They are voltage models based on the terminal voltage for the simulation of the electrochemical behaviors. The application of the battery is a very important criterion in the production and estimation model. This paper concentrates on presenting an appropriate model for time series simulation of charging/discharging behavior of the battery in reliability studies. In the adequacy studies of the given generation system, an appropriate model is required for the battery capacity as a source of generation and consumption in which the influential characteristics, such as depth of charge (DOC), efficiency of charge, and rate of discharge of the battery, are viewed while respecting the time series approach with hourly intervals. The model is eventually used in the aforementioned reliability analysis. In this paper a lead–acid battery is used.

Modeling of other system components, such as conventional units, can also have an important role in the accuracy assessments, which are not within the scope of this paper. In sum, the following items can be counted as the contributions of this research paper:

- This paper proposes an appropriate model of the electrochemical batteries that can be utilized in reliability studies.
- This paper presents a reliability assessment method with these features:
  - It is simple and needs a limited range of historical wind speed data.
  - It considers wind speed fluctuations and nonlinear time-varying behaviors of the battery bank.
  - In this technique, the fuel consumption of conventional units can be scheduled.

In Section 2, an appropriate model is proposed for the lead–acid battery. Section 3 describes the reliability evaluation technique used in these studies, including the time series approach with system component modeling and reliability evaluation and the proposed hybrid method. In Section 4, a case study is demonstrated with a detailed discussion of the results.

2. Battery modeling

Reliability evaluation of renewable resources integrated with a battery bank greatly depends on battery bank operation in off-grid applications. The typical structure of a standalone wind-conventional/battery energy storage system (WCBES) is shown in Figure 1. Because of the fluctuating nature of the wind resources and changes in operating conditions, the performance of the battery changes over time. It can be simulated with the use of an appropriate model for the battery bank. Having done this, the available capacity of the battery bank can be obtained in time series format related to generation and demand time series.

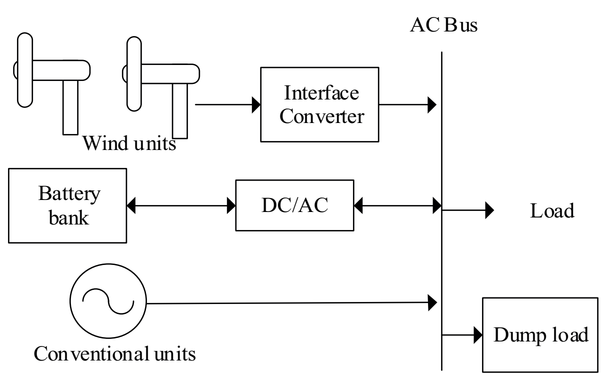


Figure 1. Structure of a typical standalone WCBES system.

In [25] a dynamic model based on terminal voltage for the lead–acid battery was presented. In the adequacy studies of a generation system, the available capacity of system components is modeled on the basis of their stochastic behaviors in a steady-state condition and their dynamic models are not considered. In this way, an appropriate model is required for the battery as a source of generation and consumption, in which the influential characteristics of the battery are considered to assess the available capacity of the battery bank. For this reason, in this paper, a capacity model based on the mathematical equations of the battery (based on [25]) is proposed, whose parameters can be estimated by reducing the error of simulation and experimental results in this application, which is a priority of this paper. This is done by comparing the terminal voltage profile of the battery in simulation and experimental tests.

In the charging/discharging process, the numerical values of the current and its time are basic parameters that affect the battery behaviors. With these, other parameters such as temperature, β (fundamental parameter in chemical processes), and the DOC can be obtained. The DOC indicates the battery state during discharge as compared with its available-charge state (which is not the full-charge state). DOC is a parameter normalized to 1, given by:

$$DOC = DOC_0 - \frac{Q_e}{C(I,\beta)}, \quad Q_e = \int_{t_0}^{t} I_m dt, \tag{1}$$

where I is the constant discharge current in A, which is captured from the battery from time t_0 to $t.Q_e$ is the exchanged capacity within the battery in Ah. I_m is battery current in A, which has a positive sign for discharging processes ($I_m = I$) and a negative sign for charging processes. β is electrolyte temperature in $^\circ$C. DOC_0 is the initial DOC based on available capacity in t_0. $C(0\ ,\ \beta)$ and $C(I\ ,\ \beta)$ are the nominal capacity of the battery and available capacity of the battery at the given β and I, respectively. In the charging process (I = 0), DOC is an indicator of how full a battery is with reference to the nominal capacity, and in the discharging process, DOC is an indicator of how full the battery is with reference to the actual discharge regime. $C(I\ ,\ \beta)$ is obtained from an empirical relation as follows [25]:

$$C(I,\beta) = K\frac{K_c C_0^*(1+\frac{\beta}{-\beta_f})^\varepsilon}{1+(K_c-1)(\frac{I}{I^*})^\delta}, \tag{2}$$

where β_f is the electrolyte freezing temperature in $^\circ$C, which depends mainly on the electrolyte specific gravity and changes in different states of charge. I^* is a current that flows in the battery for a typical use, e.g., the nominal current. ε, K, K_c, and δ are empirical quantities that for a given battery with a certain I^* are considered as constant values. $C_0(\ I)$ is an empirical function of discharging current and is obviously equal to the battery capacity at 0 $^\circ$C, ($C_0(\ I^*) = C_0^*$). The capacity of the battery is zero in β_f, because in this point the battery is not able to transfer any current. Therefore, Eq. (2) is used for $\beta > \beta_f$.

A simple dynamic relation between electrolyte temperature and ambient temperature can be considered. Therefore, the electrolyte temperature can be obtained by the following equation:

$$\begin{aligned} &\tfrac{d\beta}{dt} = \tfrac{1}{C_\beta}\left[P_{loss} - \tfrac{(\beta-\beta_a)}{R_\beta}\right] \\ &R_i = R_{i0}\left[1+K_i(1-DOC)\right]\ , \\ &P_{loss} = R_i I_m^2 \end{aligned} \tag{3}$$

where P_{loss} is heating power generated inside the battery by conversion from electrical or chemical energy in W, which is calculated as the wasted power through the internal resistance of battery, R_i. R_{i0} and K_i are constant parameters. C_β and R_β are thermal capacity (Wh/$^\circ$C) and thermal resistance ($^\circ$C/W) of battery, respectively. β_a is ambient temperature in $^\circ$C.

The quantity parameters of Eqs. (1)–(3) must be estimated by comparing the terminal voltage profile of the battery in simulation and experimental results under different conditions in the charge and discharge processes. Since the battery is linear electric bipolar, its more natural model would be constituted by an electromotive force in series with the internal resistance.

$$V_b = E \pm R_i I_m, \quad E = E_m - K_e(273+\beta)(1-DOC), \tag{4}$$

where E is the electromotive force function of the given battery in V. E_m and K_e are constant parameters estimated along with other parameters. Positive and negative signs are applied for charging and discharging processes, respectively. The capacity model is based on mathematical Eqs. (1)–(4).

Figure 2 shows variations of charge status in the charging and discharging process for an ideal model (with no operating restrictions) and proposed model (capacity model) of a typical lead–acid battery for a constant ambient temperature, 25 °C. These variations are illustrated based on charge/discharge rates C/25, C/42, and C/95. Here, the charge/discharge rate is total capacity per charging/discharging current (i.e., 25, 42, and 95 A). The solid lines in this figure represent the DOC of the battery for the ideal model and the dotted lines represent the DOC for the proposed model. Figure 2a shows the simulated behavior of the given battery in the discharging process with initial state $DOC_0 = 100\%$ and $\beta_f = -53.88$ °C. It can be seen that the DOC associated with the proposed model is less than the DOC associated with the ideal model. This shows the influence of the discharge rate, which reflects the impact of the discharging current on the available capacity of the battery. Meanwhile, this difference increases along with discharging current. Figure 2b shows the variation of DOC in the charging process. In this process, by comparing the DOC corresponding with the ideal model and the proposed model, it can be demonstrated that the charging efficiency is not 100%. This efficiency depends on the charging current, battery status, and temperature. This figure shows that a higher charging current results in lower charging efficiency. Furthermore, charging efficiency drops with the increasing DOC. The initial

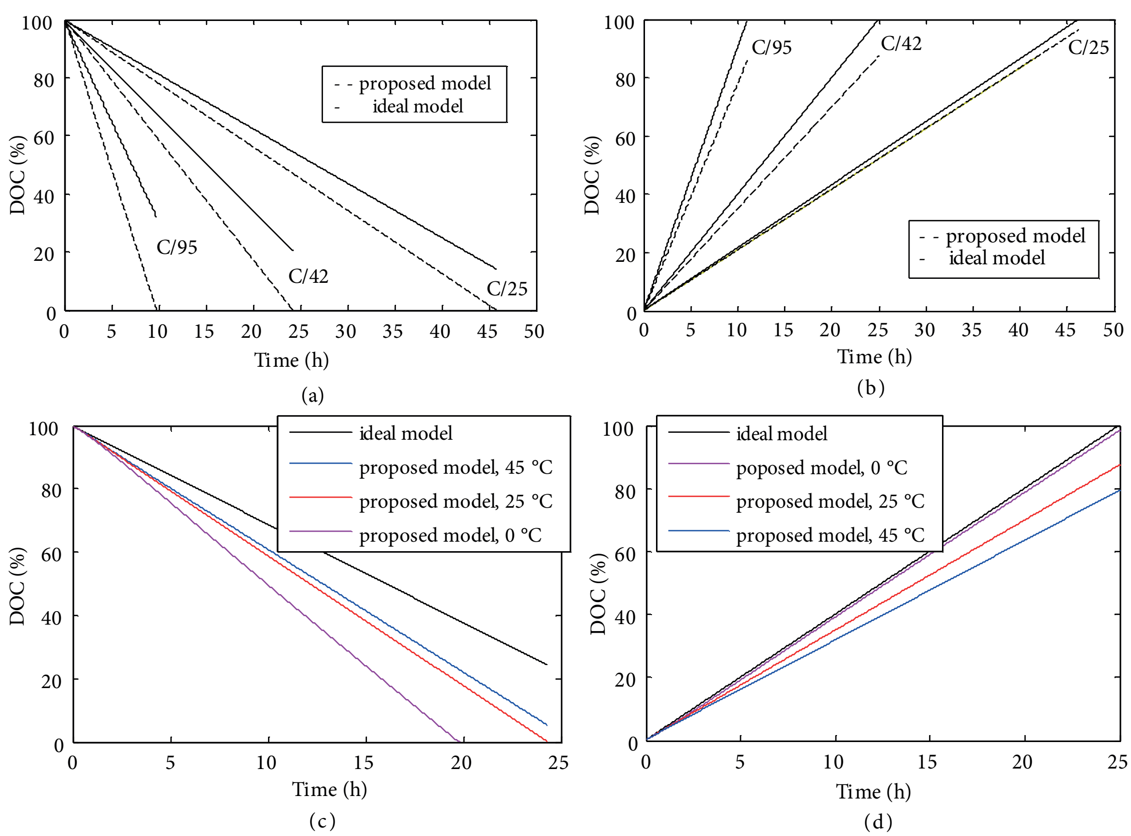


Figure 2. Variations of DOC versus time for the proposed and ideal models: a) at different discharge rates, b) at different charge rates. For ambient temperatures 0, 25, and 45 °C in c) discharging process and d) in charging process.

states in Figure 2b are $DOC_0 = 0$ and $\beta_f = -9.44$ °C. Figures 2c and 2d further illustrate the effect of temperature on the charging/discharging processes. These figures are based on charge/discharge rate C/42 at different temperatures, for example 0, 25, and 45 °C. Figure 2c presents the behavior of the simulation model in the discharging process with initial state $DOC_0 = 100\%$. Any decrease in ambient temperature quickly drops the discharging time and the DOC. Figure 2d shows the changes of DOC in the charging process. It is observed that the charging efficiency decreases as the ambient temperature increases.

It is shown in Figure 2 that the DOC is dependent on the charging/discharging current, I, and the electrolyte temperature, β. In other words, DOC and β can be calculated given their previous values and current I. Based on this, an appropriate model of the battery is obtained that simulates its electrochemical behaviors and then provides DOC along with time.

3. Reliability evaluation for WCBES

In this section, a suitable reliability evaluation method is proposed to consider the battery model given previously in calculating reliability indices. The method is a combined approach based on the time series and analytical techniques to evaluate the reliability of a standalone WCBES. The system reliability is evaluated based on LOLP and EENS. These indices are assessed using the PPS technique. In the PPS method the reliability indices can be calculated by convolving the load and generation models. By using time series modeling of the generation system, energy storage system, and demand, the wind speed fluctuations and nonlinear behaviors of batteries can be taken into account in the reliability evaluations. Meanwhile, according to the proposed method, it is possible to use a limited range of historical wind speed data, for example for 1 year, and also a certain forced outage rate (FOR) for the generating units. In this section, the time series modeling and reliability approach are briefly described.

3.1. Time series technique

Time series simulation is an approach used to study and show a set of observed or reproduced data in time. According to this method, the wind speed is predicted based on a large amount of the past wind data, which might not be available for all regions [24]. This paper does not exclusively deal with the prediction of the wind speed by time series analysis. Rather, the time series model will be used to display the wind speed variation over time. In this regard, using the recorded data for 1 year in hourly-intervals for specific regions, the stochastic characteristics of the wind speed are obtained. The same characteristics are further used to reproduce the wind speed time series and the corresponding wind power time series. Similarly, load time series can be modeled. Based on these two time series, the time series associated with the charging/discharging of the battery bank can also be obtained. Thus, with appropriate battery modeling, the time series state of charge related to the battery bank during charging/discharging processes can be determined in cyclical use.

3.1.1. Generation time series model

The generation system consists of variable speed wind turbines and conventional sources. The electric output of wind energy conversion systems depends on wind characteristics as well as on the aeroturbine performance. In variable speed types, the possibility of capturing maximum power from the wind exists at any rate. The output power time series of the wind turbine generator is calculated as follows:

$$P_{wt}(h) = \begin{cases} (A + BV(h) + CV^2(h))P_{rat}, & V_{ci} < V(h) < V_r \\ P_{rat}, & V_r < V(h) < V_{co} \\ 0, & V_{ci} > V(h) or V(h) > V_{co} \end{cases}, \quad (5)$$

where P_{wt} is the output power time series, v is the wind speed time series, and V_r and P_{rat} are the rated turbine speed and power, respectively. V_{ci} and V_{co} are turbine cut-in and cut-out speeds, respectively, and A, B, and C are constants determined from V_r, V_{ci}, V_{co}, and the other system parameters. h is the time in hours [7].

The conventional generating sources are usually used to maintain the system stability and improve reliability in standalone systems. Conventional sources such as diesel or biodiesel consume fuel to generate electrical power. Thus, contrary to the production of renewable resources, their production does not have an intermittent nature. This paper thus assumes that fuel is available. The capacity and time series of output power concerning the conventional units can be easily determined by the generation strategies that will be explained in Section 3.1.3.

3.1.2. Load time series model

To study the adequacy assessment of the generation system, the entire demand is considered as a single load in off-grid applications. The most common model used in this study is based on the hourly peak of power consumption. By recording peak load for the given site during the study period, for example for 1 year, the time series load model is obtained. In this paper, two load models are considered, the IEEE-RTS model [27] based on the climate in eastern Iran and the uniform model. Figure 3 shows the load duration curve (LDC) of load models.

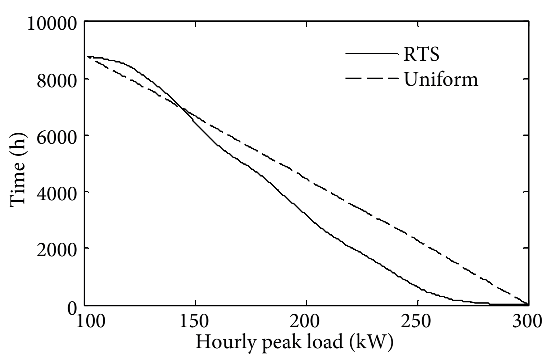


Figure 3. Load duration curves of RTS and uniform load models.

3.1.3. Battery time series model

Many significant works have been performed in using renewable energy resources in off-grid applications [28]. In order to provide adequate reliability for consumers, in large- or small-scale off-grid applications, usually hybrid generation systems are considered. For example, wind/diesel power systems are utilized to supply a wide range of energy needs at different penetration levels [29]. Over the past few years, wind energy has been increasingly used to reduce diesel fuel consumption, providing economic, environmental, and security benefits to the energy supply. In this case, energy storage systems are extensively employed in such systems [30]. It is important to investigate the possible impacts of energy storage on the reliability of relatively large systems that include significant amounts of wind power. In addition, the forecasting of fuel consumption of the conventional generating units can be also carried out. In this way, many significant strategies based on practical conditions have been introduced [31]. Each strategy is planned based on a certain scenario. Three different scenarios are used in this paper and they are explained as follows.

Scenario 1 is introduced for a small standalone system for which the transportation of conventional sources of fuel to its region can be costly or even risky. Based on this scenario, a generating unit corresponding to wind resources integrated with an energy storage system is considered. The stored energy in the storage system can be used to supply load. The conventional source appears to improve the reliability benefits during the needed time, and the amount of energy received and the consumable fuel are evaluated for the entire period, which could be, for example 1 year, to achieve a certain reliability index. The time series associated with battery power in a standalone system can be obtained as follows:

$$P_b(h) = \begin{cases} -P_{dch-\max}, & (P_{out}(h) - P_l(h)) \leq -P_{dch-\max} \\ P_{out}(h) - P_l(h), & -P_{dch-\max} < (P_{out}(h) - P_l(h)) < P_{ch-\max} \\ P_{ch-\max}, & (P_{out}(h) - P_l(h)) \geq P_{ch-\max} \end{cases}, \quad (6)$$

where $P_{out}(h)$ is the output power of wind units at time h, $P_l\ (h)$ is the load power at time h, and P_{ch-max} and $P_{dch-\max}$ are the maximum admissible charging and discharging power. The sign of $P_{dch-\max}$ signifies the power direction. Note that the simulation period is 1 year, which is broken into 1-h intervals.

Scenario 2 is introduced for a standalone remote area where the fuel of conventional sources is available. Unlike Scenario 1, conventional sources are utilized as basic units of the generating system. This scenario can be useful to maintain system stability. This may be used for a remote area with sensitive and critical loads. According to this scenario:

$$P_b(h) = \begin{cases} -P_{dch-\max}, & (P_{out}(h) + P_{cg}(h) - P_l(h)) \leq -P_{dch-\max} \\ P_{out}(h) + P_{cg}(h) - P_l(h), & -P_{dch-\max} < (P_{out}(h) + P_{cg}(h) - P_l(h)) < P_{ch-\max} \\ P_{ch-\max}, & (P_{out}(h) + P_{cg}(h) - P_l(h)) \geq P_{ch-\max} \end{cases}, \quad (7)$$

where P_{cg} is the time series associated with the output power of conventional sources.

Scenario 3 is similar to Scenario 1 with the difference that the hourly wind energy dispatch is restricted to a certain percentage of the hourly demand. The surplus wind energy can be stored in the battery bank. It is assumed that the sum of wind power and the battery power is limited to a restriction coefficient and the rest of the demand is supplied by reliable conventional sources. It is done in order to improve system stability specifically in the face of sensitive loads. To determine the appropriate restriction coefficient, a detailed stability analysis is required for a given system operation and wind conditions. Here, the restriction coefficient is demonstrated by the penetration factor (PF), and this paper does not intend to analyze the system stability and just samples of restriction coefficient considered in reliability studies. In this case, the time series associated with battery power is calculated by:

$$P_b(h) = \begin{cases} -P_{dch-\max}, & (P_{out}(h) - PF \times P_l(h)) \leq -P_{dch-\max} \\ P_{out}(h) - PF \times P_l(h), & -P_{dch-\max} < (P_{out}(h) - PF \times P_l(h)) < P_{ch-\max} \\ P_{ch-\max}, & (P_{out}(h) - PF \times P_l(h)) \geq P_{ch-\max} \end{cases}. \quad (8)$$

Based on the battery power, the available energy that can be exchanged within the battery bank is described by:

$$E_{ex}(h+1) = \begin{cases} E_{\min}, & E_{ex}(h) + P_b(h) \leq E_{\min} \\ E_{ex}(h) + P_b(h), & E_{\min} < E_{ex}(h) + P_b(h) < E_{\max} \\ E_{\max}, & E_{ex}(h) + P_b(h) \geq E_{\max} \end{cases}, \quad (9)$$

where $E_{\max}$ and $E_{min} = DOC_{min} \times E_{\max}$ are the maximum and minimum admissible energy of the battery bank in Wh, respectively, and DOC_{min} is the minimum admissible DOC. They are determined by size selection of the battery bank. The battery bank energy at $h = 1$ is assumed to be E_{min}.

By using Eq. (9) and battery voltage based on Eq. (4), the charging/discharging currents of the battery are specified. With Eq. (1) the battery status and then the battery bank status are determined. Consequently, the battery bank energy is obtained by:

$$E_b(h+1) = \begin{cases} E_{\min}, & DOC(h+1) \leq DOC_{\min} \\ DOC(h+1) \times E_{\max}, & DOC_{\min} < DOC(h+1) < DOC_{\max} \\ E_{\max}, & DOC(h+1) \geq DOC_{\max} \end{cases}, \quad (10)$$

where E_b is the battery energy time series. $DOC_{\max}$ and DOC_{min} are the maximum and minimum admissible DOC values, respectively. The available power time series of the battery bank during discharge is expressed as follows:

$$P_{ach}(h) = \begin{cases} E_b(h) - E_{\min}, & (E_b(h) - E_{\min}) \leq P_{dch-\max} \\ P_{dch-\max}, & (E_b(h) - E_{\min}) \geq P_{dch-\max} \end{cases}, \quad (11)$$

where $P_{ach}(h)$ is the available power of the battery bank at time h. It should be noted that, unlike P_b, P_{ach} is a positive mathematical variable that bears no physical meaning. P_{ach} represents the amount of power that can potentially be drawn from the battery when production is insufficient. Figure 4 illustrates the participation of the proposed model for the battery in the simulation algorithm, as will be explained in Section 3.3.

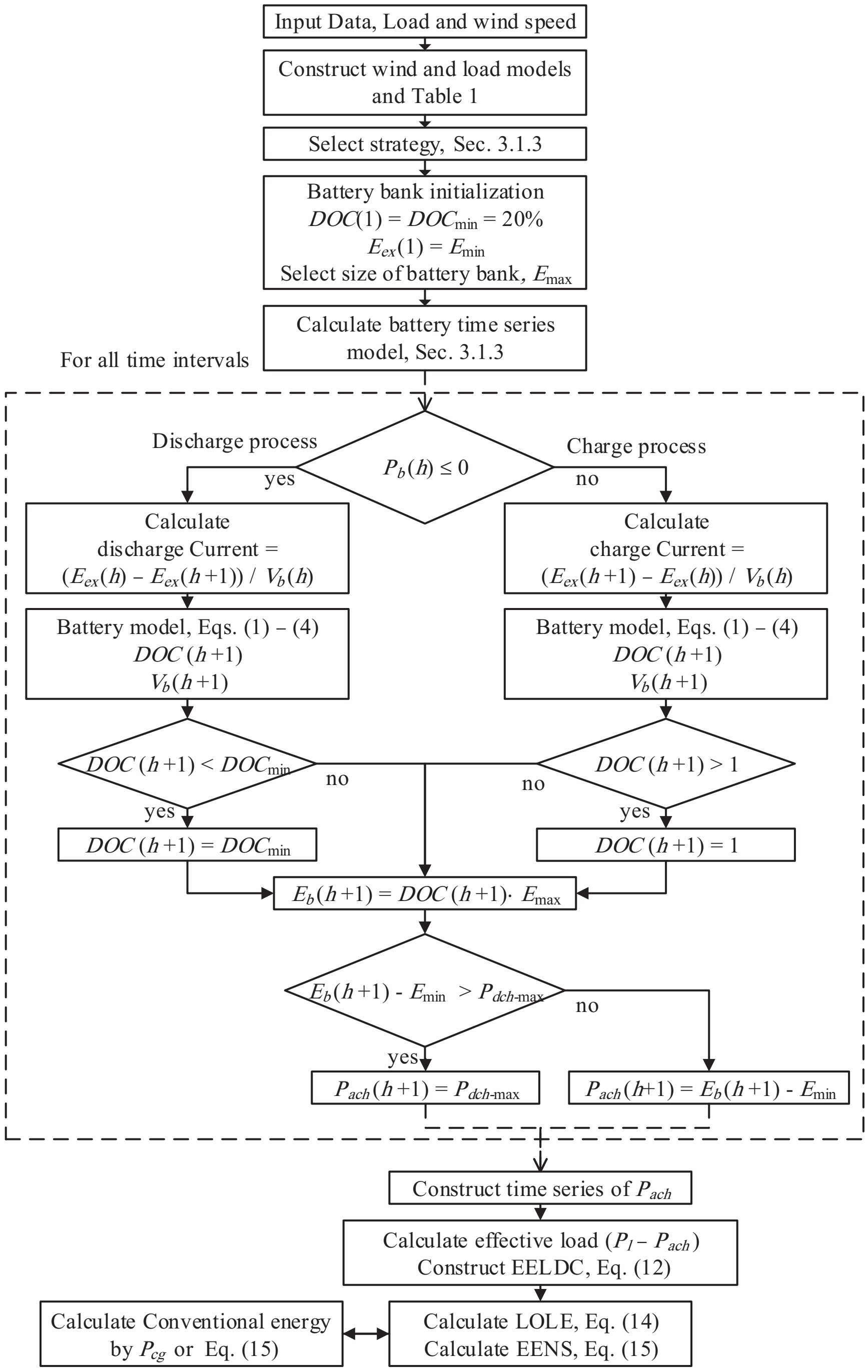


Figure 4. Reliability evaluation framework using proposed method.

3.2. Reliability indices

In this paper, the generating system contains renewable energy and conventional sources. To assess the system reliability, this paper assumes that the continuity of service of the conventional source in the production process is favorable and is quickly used to improve the appropriate level of reliability in the time required. Therefore, in this section, the focus is on the reliability model of the wind units.

For wind turbines located at one site, the output power of all turbines depends on the same characteristic with respect to wind speed, so the risk models of these must be considered together. Therefore, all wind turbines can be considered as one aggregated unit [11]. In the multistate model [7], all the states are given in the capacity-in probability table, as shown in Table 1. The capacity value of each state is derived from the power output curve of the wind turbine. The probability in each state is obtained from a combination of the Weibull probability distribution function [7,32] for the wind speed data and the FOR of the wind turbine. Table 1 provides the probability of the generated power being less than or equal to a given value. In this table, n is the number of wind turbines with the same FOR, p is the number of wind turbines that work successfully, and q is the number of wind turbines under repair. V_1, V_2, and V_3 are wind speeds that divide the nonlinear part of the wind power curve (first piece of Eq. (5)) into four equal sections, and then P_{avei} is the average output power in the ith section.

Table 1. Multistate model of wind power system.

State	Probability of success $p+q=n$ $p=0,..,n$	Probability	Expected output power
1	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_{co} < v \mid v < V_{ci})$	0
2	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_{ci} < v < V_1)$	$\sum_{i=0}^{p} P_{ave1}^{(i)}$
3	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_1 < v < V_2)$	$\sum_{i=0}^{p} P_{ave2}^{(i)}$
4	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_2 < v < V_3)$	$\sum_{i=0}^{p} P_{ave3}^{(i)}$
5	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_3 < v < V_r)$	$\sum_{i=0}^{p} P_{ave4}^{(i)}$
6	$(1\text{-}FOR)^p\,FOR^q$	$P_r\,(V_r < v < V_{co})$	$\sum_{i=0}^{p} P_{rat}^{(i)}$

In the PPS method the basic purpose is to form an equivalent LDC (ELDC). This curve is the convolution of the probability of each generating state and LDC that can be expressed as follows:

$$f^{(i)}(x) = \sum_{s=1}^{N_s} p_s f^{(i-1)}(x - C_s), \quad \sum_{s=1}^{N_s} p_s = 1, \tag{12}$$

where C_s is the generating capacity-in at state s. p_s is the probability of C_s. N_s is the number of states. x is the value of power per kW. $f^{(i)}$ (x) is the ELDC after the ith generating unit. $f^{(i-1)}$ is the old ELDC in the ith step. $f^{(i-1)}(x - C_s)$ is ELDC when the sth state of the ith unit with capacity-in C_s experiences failure.

The captured energy from the ith unit can be calculated as follows:

$$E_{eg}^{(i)} = \sum_{s=1}^{N_s} [Tp_s \int_{x^{i-1}}^{x^{i-1}+C_s} f^{(i-1)}(x)dx], \tag{13}$$

where T is the investigated period. x^{i-1} is total capacity of generating units before the ith unit.

In this paper, the LOLP and EENS are considered as the reliability indices by convolving the load with the generation and battery output. The LOLP is the expected duration (on ELDC) within a certain period of time, for example 1 year, for which the load demand exceeds the total generated power.

$$LOLP = f^{(n)}(C_t) \tag{14}$$

$$EENS = T \int_{C_t}^{X_{\max}+C_t} f^{(n)}(x)dx \text{ or } \quad EENS = E_{load} - E_{eg} \tag{15}$$

Here, the number of generating states is n and the total capacity of them is C_t. $f^{(n)}$ (x) is the ELDC when the convolution process has finished for all the generating states. $X_{\max}$ is the maximum value of the load power per kW in period T. The maximum equivalent load is $X_{\max} + C_t$. E_{load} is the total load energy calculated in period T. E_{eg} is the total captured energy from the generating units [33].

3.3. Hybrid method

According to the proposed technique, the storage energy system is considered as a load system. Therefore, the time series associated with the effective load power is obtained by $P_l - P_{ach}$. In this regard, the load duration curve is replaced with an effective load duration curve. Furthermore, according to Eq. (12), the equivalent ELDC is constructed. Consequently, by considering each state of Table 1, the system reliability indices can be calculated based on Eqs. (14) and (15). Figure 4 illustrates the proposed algorithm for reliability evaluation of the system under study.

4. A case study

The analysis carried out in this paper is applied to a sample from a standalone system consisting of two types of variable speed wind turbines with diesel generators and a battery storage system according to Figure 1. In this section, effect of wind penetration and battery bank modeling on evaluating the reliability indices and also the performance of the battery bank in the three mentioned scenarios are investigated. It is assumed that the two wind power units have equal cut-in, rated, and cut-out wind speeds and FOR. In this paper, the FORs of the individual conventional units and battery bank are not considered. The parameters associated with this system are given in Table 2. This table presents the rated power of individual generating units. The hourly wind speed data at the height of 60 m are available in 2008–2009 for Khaf (region 1) and Afriz (region 2) from Iran. The same data are used to specify the parameters of the Weibull probability distribution function by the maximum likelihood estimate technique [32] as shape factor = 2.01 and scale factor = 9.10 for region 1 and shape factor = 1.554 and scale factor = 6.1 for region 2. The root mean cube of the wind speed for an area is significant in determining the wind potential. In other words, the wind energy collected over the year is commensurate with this [34]. In this case, the root mean cube amounted to 10 and 8 m/s for regions 1 and 2, respectively, indicating the good potential of the wind energy in these regions.

Table 2. The parameters of the system under study.

Wind energy conversion system	
Rated powers	250, 500 kW
Height of hub	60 m
Cut-in wind speed	3.5 m/s
Cut-out wind speed	25 m/s
Rated wind speed	12 m/s
V_1, V_2 , V_3	5.63, 7.75, 9.87 m/s
A , B , C	0.124, –0.412, 0.012
FOR	5%
Conventional generating system	
Rated powers	20, 50 kW
Load (IEEE-RTS & uniform)	
Annual peak load	300 kW
Vented, tubular-plate, deep-cycle lead–acid battery	
Battery capacity	1220 Ah
Nominal voltage	2 V

In the battery modeling, the root mean square error method [32] is used for estimating the battery parameters based on available experimental data. In other word, the parameters of the battery model are estimated in reducing the error of terminal voltage of the battery in simulation and experiment conditions. In this regard, Figure 5 presents a sample of the experimental and simulation results for a constant charge/discharge rate in ambient temperature, 25 °C. Figure 5a shows terminal voltage variation of the given battery in the discharging process by discharge rate C/100. In this case, $DOC_0 = 100\%$ and full-discharge time is approximately 9 h. Figure 5b illustrates terminal voltage variation by charge rate C/21 and $DOC_0 = 20\%$. In this test, the charging process is done during 8 h, in which the final DOC is up to 34%. According to Eq. (2), the parameter K is dependent on charge status and then electrolyte freezing temperature [34]. Therefore, K must be updated for the different DOCs. For example, Table 3 shows K for five different DOCs in the charge and discharge processes. Meanwhile, ε is not the same for the charge and discharge processes as can be seen in the table.

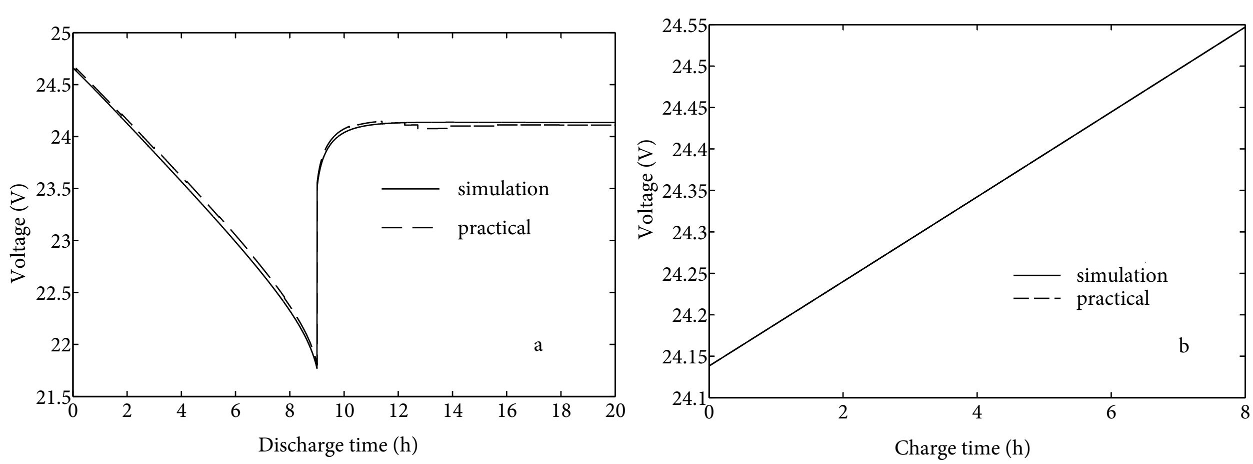


Figure 5. Comparison of simulated and measured battery voltage for a constant current during a) discharge process and b) charge process.

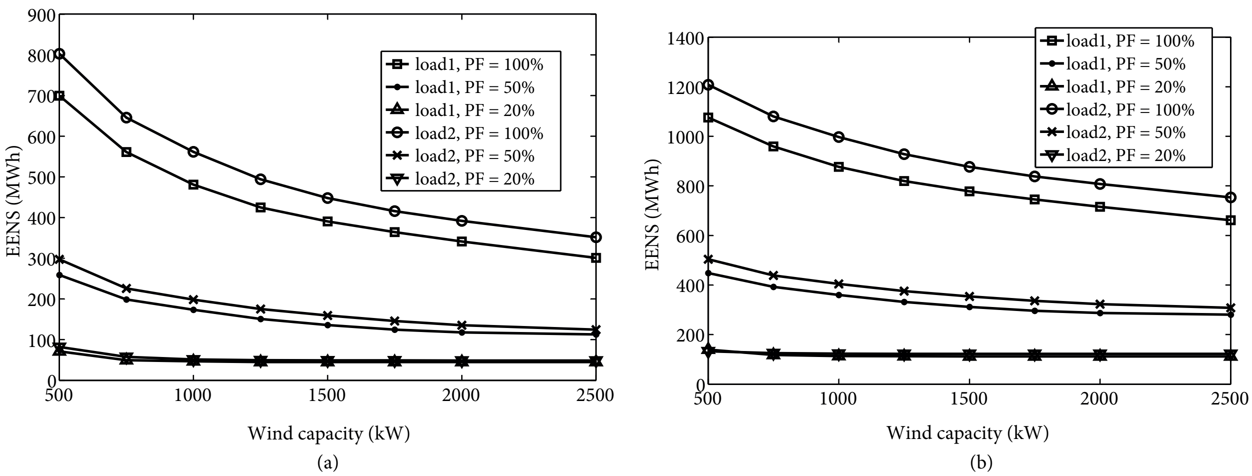


Figure 6. Variation of EENS versus wind capacity by wind penetrations of 100%, 50%, and 20% for two load models in a) region 1 and b) region 2.

The other estimated parameters are $K_c = 1.2577$, $\delta = 0.7789$, $C_0^* = 797$, $I^* = 44.3$, $E_m = 2.18$, $K_e = 0.839 \times 10^{-3}$, $R_{i0} = 125 \times 10^{-5}$, $K_i = 0.25$, $C_\beta = 15$, and $R_\beta = 0.2$, and these parameters can be applied to all conditions. Meanwhile, in the following studies of this section, a constant ambient temperature of 25 °C is assumed for the battery bank. This is an optimal working temperature for the selected battery.

Table 3. Estimated parameters of the given battery.

Lead–acid 1220 Ah		Discharge process $\varepsilon = 0.7472$	Charge process $\varepsilon = 0.139$
DOC (%)	Freezing point (β_f) °C	K	
100 % (fully charged)	–53.88	1	1.1361
75%	–40	0.9291	1.1197
50%	–23.33	0.7749	1.0826
25%	–15	0.6417	1.0452
0 (fully discharged)	–9.44	0.5077	1

4.1. Effect of wind penetration on reliability index

In this section, the impact of the wind capacity on the EENS is analyzed regardless of the storage. This work is performed in regions 1 and 2, and also for two load models, the RTS model (Load 1) and the uniform distributed model (Load 2). Figures 6a and 6b show the variations of EENS versus wind capacity at different PFs such as 100%, 50%, and 20% for two load models in regions 1 and 2, respectively. The EENS increases with the increasing PF so that the wind capacity goes up and the production of the conventional unit is also reduced to supply the load. The difference of the evaluated EENS for RTS and uniform load models reduces at a lower

PF. In other words, the sensitivity of system adequacy to load model decreases when wind penetration drops to supply the load. In this case, it is assumed that the adequacy of conventional sources is at an appropriate level. These figures also show that EENS associated with the RTS load model is evaluated at lower levels compared with the uniform load model. It is also evident from Figure 3 that the uniform model curve is above the RTS model curve for more hours. By comparing Figures 6a and 6b, it can be seen that the EENS associated with region 1 is lower than the corresponding curves of region 2. This is because in region 1 the root mean cube of the wind speed data is greater than that in region 2. Thus, it is very important to pick the right place.

4.2. Effect of realistic operational characteristics of battery bank on reliability index

In [18–23] and other studies, the effect of the accurate behavior of electrochemical batteries on reliability studies was not investigated in detail. In other words, an overly ideal model of the battery bank (with no operating restrictions) has been considered. However, the realistic behavior of the battery bank and its changes imposed by wind speed fluctuation over time can affect the evaluation of the reliability indices. In other words, the proposed model of the battery relatively limits the reliability benefits of the battery bank. In this regard, Table 4 provides a comparison between the proposed methods in [18,22,23] and the one in this paper based on EENS variation versus battery bank capacity. In a study performed by Karaki et al. [18], an analytical method for evaluating the reliability index of the wind/battery was developed assuming that the battery bank would be fully charged and discharged in a fixed cycling manner, for example once in 2 days. In [22,23] a simulation method was used for the wind/battery. In this case, the total capacity of the wind system was 750 kW and the reliability studies were done in region 1 for the RTS load model. Table 4 shows the improvement in our work with respect to the proposed model of the battery.

Table 4. EENS versus storage capacity for comparing the methods proposed in [18,22,23] with the method presented in this paper considering battery model.

Storage capacity (MWh)	EENS (MWh)		
	Based on [18], analytical method	Based on [22,23], simulation-based method	Based on proposed method
2	635.94	166.81	194.38
2.5010	585.96	152.06	180.62
3.0012	535.98	141.08	172.23
3.5014	486.01	132.04	164.17
4.0016	436.21	123.96	156.40
4.5018	387.01	117.31	150.85
5.0020	338.27	112.04	145.68
6.0024	241.03	102.95	137.20

Figure 7 shows variations of LOLP and EENS versus storage capacity in order to illustrate the impacts of considering or ignoring the modeling of the battery. In this case, reliability studies are done for the RTS and uniform load models for different PFs based on Scenario 3. Obviously, the LOLP and EENS associated with the proposed model seem to be at a higher level than when they are connected with the ideal model. In this regard, the ideal model of the battery is the battery time series model with no operating restrictions. Owing to the fact that with small PF amounts the wind energy output is more likely to be restricted, the charging and discharging currents drop and possibly lead to an increase in energy efficiency. Therefore, the difference of the evaluated indices corresponding to the two battery models has dropped.

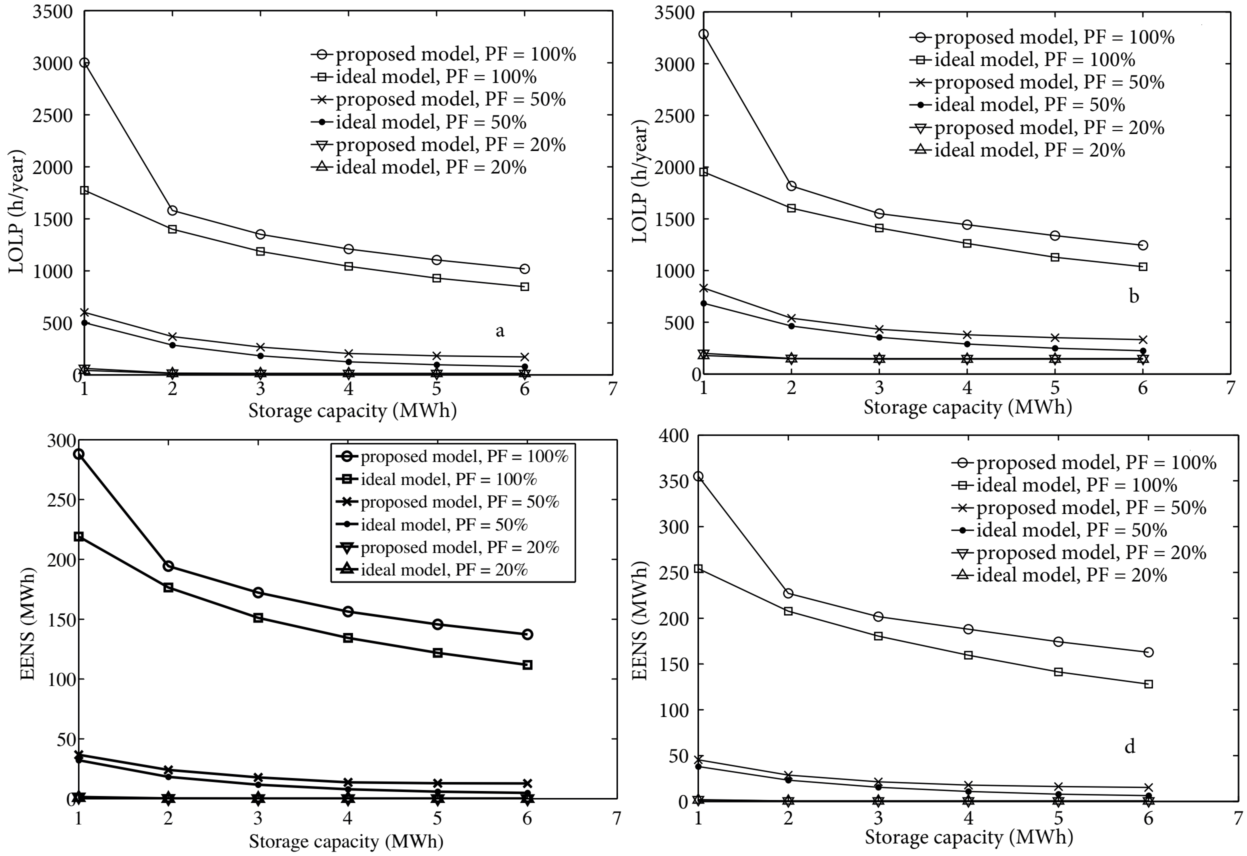


Figure 7. Effect of energy storage modeling on LOLP with a) RTS load model, b) uniform load model and on EENS with c) RTS, d) uniform load models, versus storage capacity for wind penetrations of 100%, 50%, and 20% in region 1.

4.3. Effect of different scenarios on energy storage capacity

In this section, the relationship between the battery bank capacity and LOLP is investigated for the system under study with different scenarios. This part concentrates on investigating the impact of any increase in the storage capacity and also the battery modeling in the reliability evaluation. In this case, the total capacity of the wind energy conversion system is 1 MW and the total capacities of the conventional energy system in Scenarios 1, 2, and 3 are respectively 210, 120, and 220 kW. In this study, the installed capacities of generation units have been selected for the same adequacy level. Figures 8a and 8b show the variations of LOLP versus battery bank capacity for the two load models. In Scenario 3, the hourly wind energy dispatch is restricted to PF = 50% of the hourly load. It is shown that the variations of LOLP in Scenario 2 are larger than the others. The battery modeling greatly affects the LOLP in these three scenarios. The differences in the reliability evaluation are relatively high because of considering the proposed model of the battery bank based on the uniform load model. By comparing Figures 8a and 8b, this case can be distinguished.

4.4. Effect of different scenarios on the employment of sources and facilities

The mentioned scenarios can be applied in special conditions and locations and each of the scenarios affects the employment of sources and facilities. This section provides a quantitative comparison of the scenarios. It was stated in Section 4.2 that excessive wind energy could be stored in the energy storage system, as the added wind capacity increases if the storage capacity is available. For two load models both located in region 1, Table 5 shows the energy not stored (ENS) and the conventional energy (CE) for different installed capacities of generating units in the three scenarios for the same reliability benefit. In this case, Figure 9 shows the LOLP index for the different scenarios. In Scenario 3, the hourly wind energy dispatch is restricted to PF = 50%. According to Table 5, the energy of conventional sources decreases when the added wind capacity increases in all three scenarios for the two load models. For each wind capacity, most of the conventional generating energy is related to Scenario 3, because in this scenario the participation of the wind/battery is limited to supplying the load. In this scenario, excessive wind energy, which cannot be stored, is larger than the others. In this case, the available energy for saving and future use is increased, which can develop the gain of charging and discharging restrictions. For the minimum PFs, this is intensified.

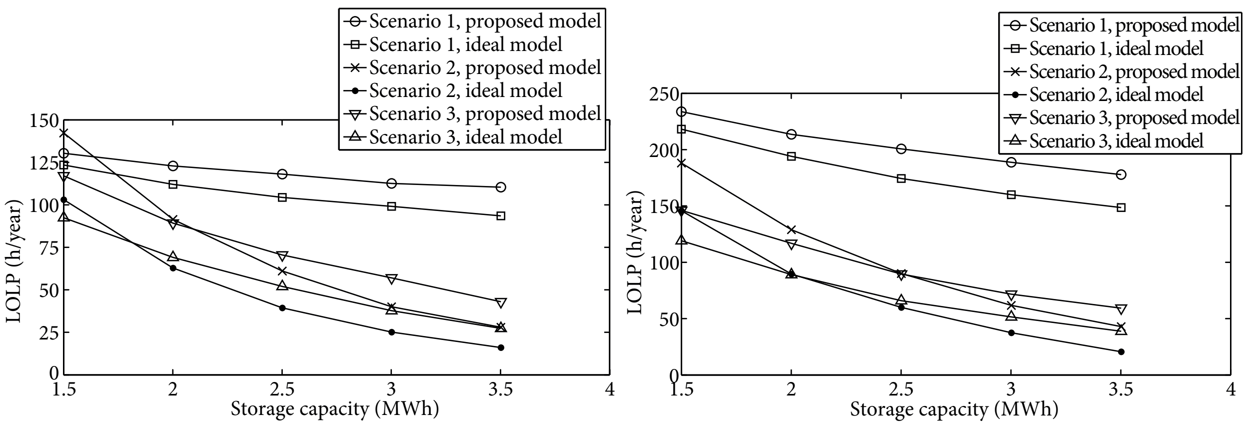


Figure 8. Effect of battery modeling on LOLP versus storage capacity in three scenarios with a) RTS load model and b) uniform load model.

Table 5. Effect of different scenarios on consumed energy.

Wind capacity (kW)	Energy factor (MWh)	Load 1			Load 2		
		S1	S2	S3	S1	S2	S3
500	ENS	20.91	243.7	829.36	17.68	213.13	776.8
	CE	326.94	501.47	857.7	363.63	674.55	939.46
750	ENS	398.73	735.21	1618.7	351.5	699.9	1560.4
	CE	151.8	415.44	830.57	183.37	577.85	907.9
1000	ENS	914.32	1296.2	2422.5	852.61	1250.7	2364.2
	CE	79.01	236.1	817.23	90.32	380.44	893.73
1250	ENS	1494.6	1911.8	3237.6	1426.6	1850.1	3177.2
	CE	45.28	155.62	811.72	54.72	285.62	887.4
1500	ENS	2123.1	2533.5	4054.6	2047.7	2468.8	3993.2
	CE	21.9	76.64	808.73	28.8	160.25	883.54

According to Table 5, increasing the wind capacity and PF reduction tend to increase the ENS. It can be seen that in Scenario 1 it is lower than in the others. Figures 7 and 8 show that the excessive capacity of the battery bank does not have a remarkable effect on improving reliability. Due to the high cost of this system, in optimum size selection studies, the utilization of the installed capacity is investigated, which is beyond the scope of this paper. This paper introduces an index to compare the mentioned scenarios in Section 3.1.3, which is

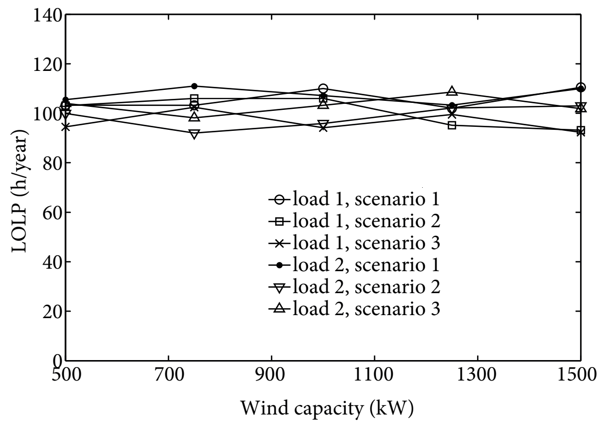
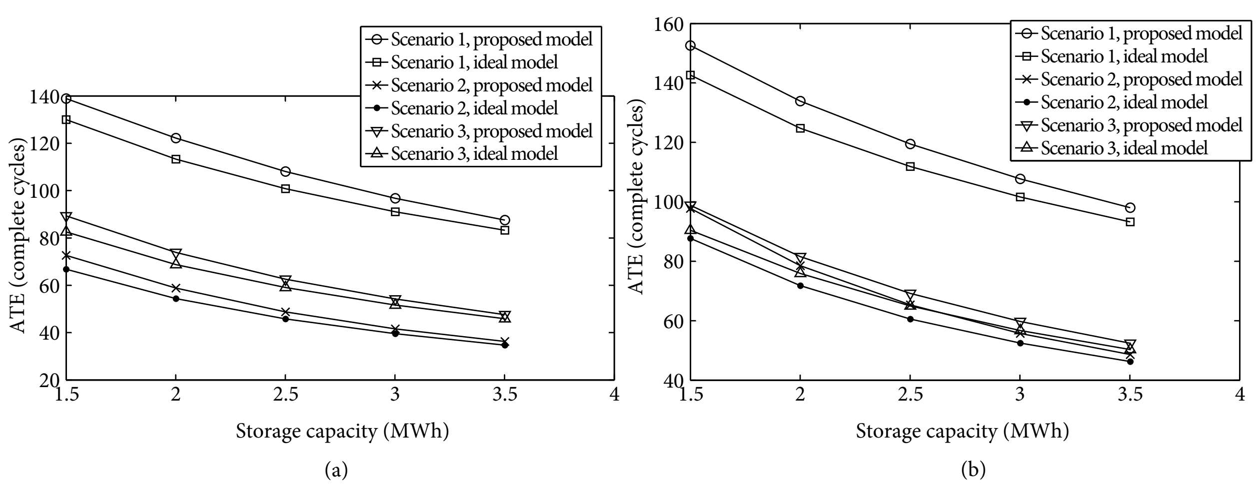


Figure 9. LOLP versus wind capacity in Table 5 for two load models in region 1.

about utilizing the installed capacity of the battery bank. The utilization of the battery bank corresponding to nominal capacity can be defined by normalizing the annual throughput-energy index ($ATE = \int_0^T Idt/C(0,\beta)$), where T is the period of study and C is the installed capacity of the battery bank. Here, the unit of ATE corresponds to the number of complete charge/discharge cycles in 1 year. Using the proposed model of the battery that considers the charge and discharge restrictions, the smaller amount of surplus energy can be transmitted into the storage system and used to supply the load and then greatly affect the ATE. This analysis could be useful for evaluating more accurate ATE in such applications. Figures 10a and 10b show the variations of ATE versus battery bank capacity for the RTS and uniform load models. In this study the capacity of the generating units is the same as in the previous section. It is shown that the ATE decreases as the added storage capacity increases and Scenario 2 obviously has the lowest value of ATE among the others. According to the installed capacity of the conventional sources in the three scenarios, the contribution of wind units is raised in Scenario 2. Thus, little energy can be transmitted into the battery bank. In other words, there are fewer chances for saving energy and therefore more wind energy is used to supply the load directly. Although the installed capacity of conventional sources in both Scenarios 1 and 3 is almost equal, it is Scenario 1 that has



(a) (b)

Figure 10. Effect of different scenarios on energy storage performance with a) RTS load model and b) uniform load model.

the highest value of ATE among the scenarios. This is because in Scenario 3 the contribution of wind energy and storage energy is limited to PF = 50%.

5. Conclusion

In this paper, a method for the simulation production and determination of reliability of a standalone hybrid energy system integrated with energy storage systems is proposed. This method is a combination of PPS and time series simulation in the domain of adequacy evaluation. Using this method, the fluctuation nature of the wind speed and nonlinear behaviors of the energy storage device can be considered in the reliability evaluation. The fuel consumption of the conventional generating units can also be analyzed. The electrochemical battery as an energy storage system is utilized. In this way, all of the influential characteristics of the battery are considered by an appropriate model in the reliability studies. According to the nonlinear electrochemical behavior of the battery, a capacity model for a typical lead–acid battery has been introduced. The proposed approach has potential applications in the power industry, especially in power system planning for a system with high penetration of renewable energy and battery.

As for the subject of the first part of this study, it is pointed out that the adequacy indices are highly dependent on wind energy penetrations and the charging/discharging restrictions taken from the proposed model of the battery. The influence of these restrictions depends on the wind energy dispatch restrictions. Three different scenarios are considered. They can be operated in special conditions and locations. Based on the reliability indices and performance indices, all three scenarios for the two load models are analyzed and compared. Studies show that the reliability index variation from the energy storage in Scenario 2 is larger than that of the other scenarios. The battery bank with appropriate modeling considerably affects the LOLP in all three scenarios. In another study, the mentioned scenarios have been compared from the perspective of the employment of sources and facilities. The utilization of the battery bank corresponding to the available capacity was analyzed to know how much of the total battery bank capacity can be used. This is useful in the unit sizing approach.

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