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Reliability constrained planning and sensitivity analysis for solar-wind-battery based isolated power system

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ABSTRACT

Isolated hybrid power systems have emerged as a practical substitute to grid extension for electrification of remote areas. Increased penetration of renewable energy sources (RES) such as solar and wind can commendably cut down system operating costs but can create reliability issues owing to their unpredictable nature. Thus, an effective storage integration is needed in order to ensure reliability standards. This paper presents reliability and cost-based sizing of solar-wind-battery storage system for an Isolated hybrid power system (IHPS). In order to analyze system reliability, dual reliability indices, *Probability of risk* and *Probability of health* have been used in this work. These reliability indices provide a better assessment of system reliability when RES are being used. The objective function for optimal planning is based on minimization of Total life cycle cost (TLCC). Considering variable nature of solar and wind sources, modelling of solar irradiance and wind speed has been done using Beta and Weibull probability density functions (pdf) respectively. The hardware availability modelling of generators has been done based on their respective forced outage rates. Monte-Carlo simulation (MCS) has been used for conducting reliability evaluation. For solving optimal sizing problem, a nature inspired algorithm called as Particle Swarm Optimization (PSO) has been employed. Sensitivity analyses are performed by studying the effect of addition/removal of RES-based generators and storage units on system reliability. In order to assess the additional investment required to improve reliability standards, a new index termed as *Incremental cost of reliability* has been used in this paper. A case study has been carried out for an IHPS located in Jaisalmer, India. The results have been suitably analyzed to facilitate a deeper insight into system planning.

Keywords:

Isolated power system;
Reliability;
Renewable energy sources;
Particle swarm optimization;
Monte-Carlo simulation;

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Introduction

In spite of several policy initiatives taken by countries across the world, approximately 13% of world's population still has no grid availability [1]. This hampers socio-economic development in these areas. The power to rural areas can be supplied in three ways [2]:

- By providing an extension of central grid.
- Using fossil fuel-based generators.
- Using a hybrid power system with renewable energy sources.

In geographically inaccessible areas, the cost of laying down grid could be excessively high. Isolated power systems are seen as a workable substitute to grid extension for providing electricity access in these areas. For isolated applications, hybrid power system employing RES-based distributed generators (DGs) can prove to be an attractive option in comparison with fossil fuel-based generators. A hybrid power system comprises of various kinds of energy sources which have specific features in terms of costs and reliability. A careful analysis is thus required to have an optimal and reliable

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Nomenclature

DG	Distributed generator
ICR	Incremental cost of reliability
PDF	Probability density function
PVA	Photovoltaic Array
RES	Renewable energy sources
RSE	Risk state expectation
TLCC	Total life cycle cost
WTG	Wind turbine generator
$P(Risk)_{\max}$	Upper limit for risk state probability (percent)
$P(Health)_{\min}$	Lower limit for healthy state probability (percent)
$SOC_{\min}$ and $SOC_{\max}$	Lower and upper limit for *SOC* respectively
$O_{B\_dis\_\max}$	Upper limit for power which can be obtained from battery during discharging, kW
$O_{B\_ch\_\max}$	Upper limit for power which can be supplied to battery during charging, kW
$I_{B\_dis\_\max}$ and $I_{B\_dis\_\max}$	Maximum permissible value of charging and discharging current respectively, A

system planning. There are two major issues associated with IHPS based on RES:

i. Intermittent nature of RES
ii. High capital cost

The first issue can be counteracted with the integration of storage units in right combination [3]. As far as the second issue is concerned, the RES have high capital cost but yield the advantage of very low operating costs. Due to this reason, economic analysis with RES is carried out not on the basis of initial capital cost but *TLCC*. This requires extensive planning so that optimum combination of units which fetches minimum cost without compromising on system reliability is obtained. The focus of work presented in this paper is the incorporation of these two criteria *viz*. Reliability and Economics. The two criteria are conflicting in nature and call for a judicious compromise for optimal system planning.

Different reliability indices have been used in system planning studies. Loss of power supply probability (LPSP) is the most commonly employed reliability index and has been widely used [4–6]. Loss of load probability (LOLP) has also been used for reliability analysis [7–9]. Expected energy not served (EENS) [10–12] is another important reliability assessment parameter and has been used by Khalili *et al*. In a further analysis, a sensitivity analysis has been performed to show the application of demand response program in reducing unused energy [13]. Though probabilistic indices have been widely used by researchers, they are unable to reflect information about capacity reserve condition. Hence, probabilistic techniques are found to be inadequate for reliability assessment of isolated power systems. System Well-Being Criteria comprising of healthy, risk and marginal system states offers a better approach for system planning [14]. Paliwal *et al*. have used dual reliability indices for reliability evaluation with RES integration [15-16]. The authors have further added a dimension in reliability assessment by introducing separate indices for grid-connected and islanded operation [17].

Cost analysis is an integral part of optimal sizing problem of IHPS. Katsigiannis *et al.* [18] have used LCOE as deciding economic criteria for optimal planning of IHPS. LCOE has also been used by Tariq [19]. Wang and Singh [20] have used Annualized capital cost (ACC) for economic evaluation of hybrid generation system comprising of wind turbine generator (WTG) units, photovoltaic arrays (PVA) and storage batteries. Annual costs have also been used as economic parameter by Meschede *et al.* [21]. Techno-economic evaluation has been performed by Candia *et al.* [22] considering the variability of renewable generation. TLCC [23] is also considered as important financial tools to compare alternative projects.

Lamyae et. al. [24] have worked on finding the most optimum sizing configuration on the basis of cost of energy from each constituent generation technology. Yu *et al*. [25] have proposed a fuzzification of multiple objective functions to come up with an optimal solution. Lozano *et al*. [26] have used cost of energy as the basis for selecting optimum hybrid system configuration. Asserting on the importance of storage units for counteracting the intermittency of renewable sources in standalone hybrid systems, Xia *et al.* [27] have performed a cost benefit analysis with storage. Storage planning has also been considered in [5, 28]. Sensitivity analysis is indispensable for optimal power system planning. It is imperative to understand the impact of variation of different parameters on system performance and cost.

Aziz *et al.* [29] have performed a sensitivity analysis by varying the parameters such as PV degradation, fuel pricing and load growth.

1.1. Research gaps

Based on literature survey following conclusions can be drawn:

i. Majority of papers reported on optimal sizing are based on economic evaluation parameters. However, not much literature is available on conduction of sensitivity analyses.
ii. There are few literatures which report sensitivity analysis. However, they are focused merely on economic considerations and do not take system reliability into consideration. Reliability is a very important parameter when RES are being considered owing to their variable nature. It has been asserted that reliability and cost considerations are conflicting in nature. Thus, it is essential to know the impact of addition/ removal of RES and storage units on system reliability and cost.
iii. For reliability assessment, the parameters such as LOLP, LOLE and EENS have been frequently used. However, with RES, it is not sufficient to assess merely the present reliability state. It is essential to have the knowledge of redundancy in system.
iv. Many papers have asserted on importance of energy storage in rendering dispatchability to RES. However, the integration of storage incurs additional cost. Thus a careful economic evaluation in order to justify the economic viability of RES integration and storage considering different scenarios is required. This aspect is missing in majority of papers.
v. There is a strong need to have a single parameter which can embody reliability and cost evaluation in one framework. This will facilitate system planners to have a quick assessment of additional investment needed to increase system reliability.

1.2. Contributions and organization

This paper presents reliability and cost-based sizing of solar-wind-battery storage for an isolated power system. The prime objective of optimal sizing problem is to determine configuration of hybrid system comprising of solar-wind-battery storage with minimum *TLCC* ensuring defined standards of reliability. The major contributions of work reported in this paper can be summarized as follows:

i. In this paper, in addition to optimal sizing problem, sensitivity analyses are being conducted. These analyses can serve to provide an insight into optimal sizing results with greater clarity. The sensitivity analyses have been conducted considering two different cases:
   - *Case: I* Effect of replacement of smaller units with larger units of same capacity on system reliability.
   - *Case: II* Effect of variation of component sizes around optimal values

   The sensitivity analyses serve following purpose:
   - Provides an in depth understanding of effect of variation of component size on technical (dual reliability indices) and economic parameters. Thus an optimum hybrid system configuration which has requisite reliability standards and is economically justifiable can be achieved.
   - Provides due justification to why a specific component size has been chosen.
ii. In order to have an understanding of redundancy in system, dual reliability indices are being used in this paper. The indices used are *P(Risk)* and *P(Health)* which provide an enhanced quantitative assessment of system well-being.
iii. In order to establish a suitable correlation between reliability and economics, a new index called as *Incremental cost of reliability* has been introduced in this paper.

The stochastic behavior of RES has been accounted for by modelling solar irradiance through Beta and wind speed through Weibull probability density function respectively. The reliability evaluation has been performed using MCS. The system status is investigated for all time slots and reliability indices are calculated. Optimal sizing of isolated hybrid power system has been carried out using Particle Swarm Optimization. A schematic depicting planning framework is presented in Figure 1.

The organization of paper is as follows: Section 2 deals with the modelling of system components i.e. RES and battery storage. Section 3 explains reliability evaluation using MCS. Section 4 elaborates formulation of objective function. The optimization technique i.e. PSO is also explained here. Section 5 describes case study wherein optimal sizing and sensitivity analyses are

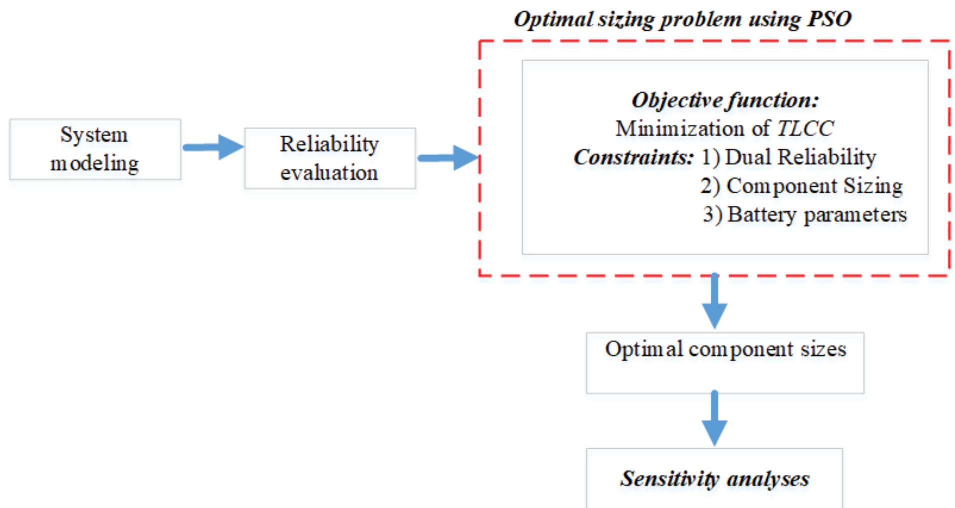

Figure 1: Schematic of planning framework

carried out for an isolated solar-wind-battery storage-based hybrid power system located in Jaisalmer, Rajasthan, India. In Section 6, pertinent conclusions have been presented.

2. System modelling

The generation of power from solar and wind is hugely correlated to meteorological conditions such as wind speed and solar irradiance. In this paper, modelling of wind speed and solar irradiance is carried out using Weibull and Beta distributions respectively [4, 14]. Battery model for determining state of charge (*SOC*) characteristics and lifetime is based on charge/discharge operations through battery. Battery charging efficiency has been determined using a fuzzy logic-based model [30].

2.1. PV system model

The PV system model is composed of two parts *viz.* solar irradiance model and power model which are explained as follows.

2.1.1. Solar irradiance model

Solar irradiance is regarded as random variable and follows Beta probability distribution function [4, 14] which is expressed as:

$$f_b(s) = \left\{ \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)} (1-s)^{\beta-1} \; for \;\; 0 \le s \le 1, \alpha \ge 0, \beta \ge 0 \right\} \quad (1)$$
$$= 0, otherwise$$

where, s = Solar irradiance in kW/m^2, $f_b(s)$ = Beta distribution function for s, α,β = Parameters of Beta distribution function, Γ = Gamma function.

2.1.2 PV array power model

The characteristic of a PV cell can be obtained for different irradiance levels and temperatures using following relations [15, 31]:

$$T_C = T_A + s.\frac{N_{OT} - 20}{0.8} \quad (2)$$

$$I = s\left[I_{SC} + K_i\left(T_C - 25\right)\right] \quad (3)$$

$$V = V_{OC} K_v T_C \quad (4)$$

Where, T_c= cell temperature, °C, T_A = Ambient temperature, °C, N_{OT} = Nominal operating temperature of cell, °C, I = PV module short circuit current at conditions other than Standard test condition (STC), A, K_i = Short circuit current temperature coefficient, A/°c, V = Open circuit voltage at conditions other than STC, V, Kv = Open circuit voltage temperature coefficient, V/°c. The maximum power from a PV array comprising of N modules can be calculated as [15, 31]:

$$O_{PV}(s) = N\, FF.V.I \quad (5)$$

Where, FF = Fill factor of PV module

2.2 Wind turbine model

The model of wind turbine comprises of two parts *viz.* wind speed model and power model which are explained in following subsections.

2.2.1 Wind speed model

The two parameter Weibull distribution is most widely used for modelling wind speed and is given by [4, 14]:

$$f_w(\nu) = \frac{k}{c}\left(\frac{\nu}{c}\right)^{k-1} e^{-\left(\nu/c\right)^k} \quad for\ \nu > 0, c > 1\ and\ k > 0 \tag{6}$$

where, v =Wind speed in m/s, $f_w(\nu)$ = Weibull probability density function for wind speed ν, k = Shape parameter of Weibull distribution, c = Scale parameter of Weibull distribution.

2.2.2 Wind turbine power model

The electrical power generated from a WTG is a function of wind speed and design parameters of WTG unit. The output power from WTG units for wind speed can be calculated as [4, 14]:

$$O_{WT^{(t)}} = \begin{cases} 0 & for\ 0 \le \nu \le V_{cut\_in} \\ a + b\nu^m & for\ V_{cut\_in} \le \nu \le V_{rated} \\ P_{rated} & for\ V_{rated} \le \nu \le V_{cut\_off} \\ 0 & for\ \nu \ge V_{cut\_off} \end{cases} \tag{7}$$

2.3 Battery storage model

The battery models used in this paper are described as follows.

2.3.1 State of charge model

Battery storage will undergo charging/discharging operation based on power availability from generators and loading conditions. Thus, energy availability in battery and consequently battery *SOC* of the following time slot has to be calculated based on charging/discharging operation occurring in preceding time slot. In present work, battery *SOC* model proposed in [32] has been adopted. The battery *SOC* for succeeding time slot is evaluated as:

$$SOC^{t+1} = SOC^{t}\left[1 - \frac{\sigma}{24}\right] + \frac{O^{t}_{B}\, l(t)\eta_B}{C_B} \tag{8}$$

where, SOC^{t+1} = *SOC* of Battery for $(t+1)^{th}$ time slot, SOC^t = *SOC* of Battery for t^{th} time slot, O^t_B = charging/discharging power during t^{th} time slot, kW, η_B = Efficiency of battery charging and discharging in charging and discharging mode respectively,σ = self-discharge rate of battery, %/day, C_B = Rated battery capacity, kWh, $l(t)$ = Length of t^{th} time slot, hours.

2.3.2. Lifetime model

Battery storage forms a crucial component of hybrid systems comprising of only RES-based generators. The replacement costs associated with battery storage constitutes a substantial portion of total life cycle costs of a hybrid system configuration. The lifespan of battery is described in terms of cycle life and float life. Batteries in hybrid power systems that include stochastic sources such as wind and solar undergo a very asymmetrical pattern of charge and discharge operations. Thus useful life of battery is constrained with two independent limitations of cycle life and float life. The procedure used in this work to evaluate battery life is explained as follows:

i. Calculate number of cycles of battery operation for period under study at specified depth of discharge.
ii. Calculate number of years to end of battery cycle life.
iii. Number of years to end of battery life after which battery needs replacement is chosen as the minimum of battery cycle life and battery float life.

2.3.3 Fuzzy model for charging efficiency

Battery charging efficiency with respect to a particular *SOC* has been calculated using a fuzzy logic-based model [16, 30]. A fuzzy system can be efficiently used for approximating charging efficiency. The block diagram for determination of battery charging efficiency using fuzzy logic controller is presenting in Figure 2. The implementation has been explained in detail in [30].

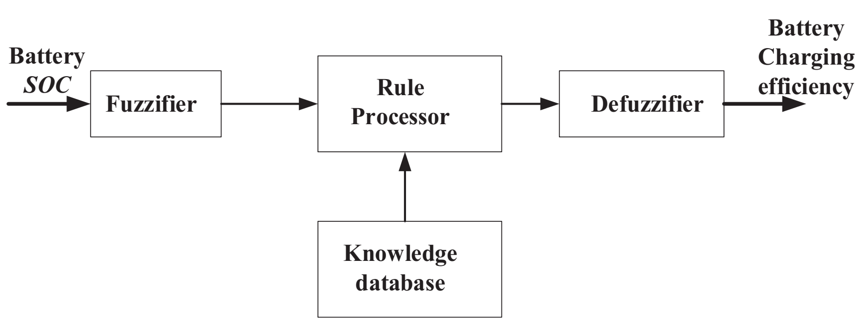

Figure 2: Implementation of Fuzzy Logic for determination of battery charging efficiency [30]

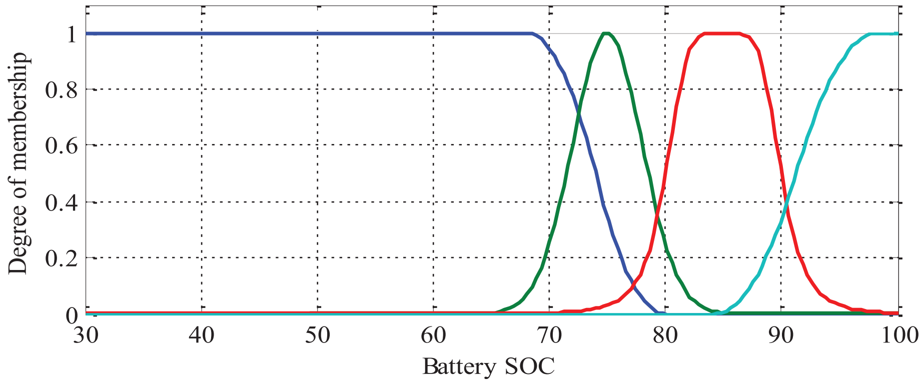

Figure 3: Membership function plot for battery *SOC* [30]

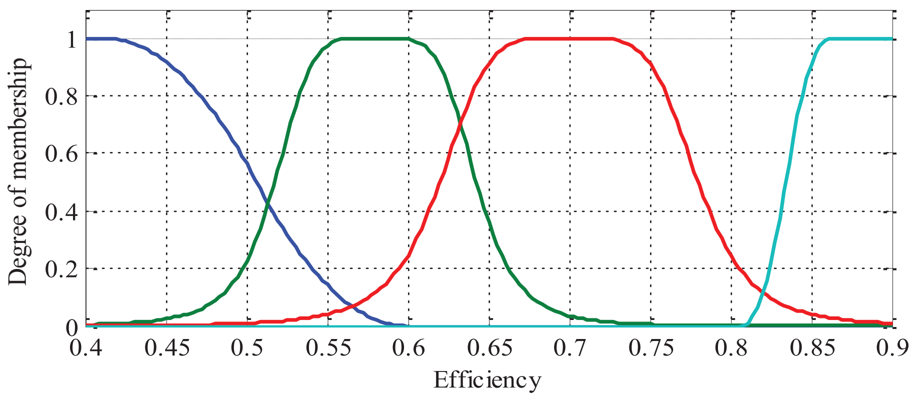

Figure 4: Membership function plot for battery charging efficiency [30]

The input variable in fuzzy logic controller is battery *SOC*. Based on the value of SOC, fuzzy logic controller provides a probable value of charging efficiency. Four membership functions are formulated for SOC viz. Low, Medium, High and Very high. Four membership functions are formulated for charging efficiency viz. Very Low, Low, Medium and High. The formulation of membership functions is based on experimentation conducted on lead acid battery [33]. Figure 3 and Figure 4 represent membership function plots for input and output variable respectively.

In present work, centroid method has been used owing to its capability to produce a result which is sensitive to all the rules executed. The inference rules used in the model are presented in Table 1.

Table 1: Inference rules for Fuzzy model

Battery SOC	Battery efficiency
Very high	Very low
High	Low
Medium	Medium
Low	High

3. Reliability assessment using Monte Carlo simulation

The reliability assessment using MCS [5, 34-35] can be summarized as follows:

i. The period under study is divided into number of time slots.
ii. For each time slot under study, generating units, RES and load are modelled as follows:

- ***Hardware availability modelling of generating units***
  Depending on its forced outage rate(FOR), the probabilities of a generating unit residing in up/down states are identified as availability and unavailability respectively [36]. The operating profile which comprises of hardware availability status based on FOR can be generated using suitable probability distribution function. In present work, up and down states have been simulated using exponential distributions.
- ***Modelling of wind speed and solar irradiance***
  As explained in Section 2.1.1 and 2.2.1, solar irradiance and wind speed data is

synthetically generated from Beta and Weibull pdfs respectively.

- ***Load modelling***

  The MCS requires sequential load data which is obtained in the similar way as for RES modelling i.e. by using suitable pdfs or by employing time series method [37]. However, in present work, it is assumed that load remains constant for a particular time slot and step change is assumed from one-time slot to another.

iii. For each time slot, the output from generating units is determined based on their hardware availability status and wind speed/solar irradiance.

iv. The power output from generating units as calculated in previous step is compared with the load of respective time slot.

v. The power flow through battery is evaluated. If output power from generating units is surplus, the battery enters charging mode. Based on the present *SOC* of battery, the battery charging efficiency is determined based on Fuzzy logic based model explained in Section 2.3.3. However, in case of any deficiency from generating units, battery goes into discharging mode. The charge/discharge operation of battery is restricted by limits of battery SOC and charging/discharging current flowing through the battery. Depending upon charge/discharge operation of battery in considered time slot, the energy availability status of battery for successive time slot is evaluated.

vi. The system state is then examined with respect to dual reliability indices i.e. Probability of risk state, *P(Risk)*and Probability of health state, *P(Health)*. The calculation of these indices had been explained in [16].

vii. *Steps iii-vi* are repeated chronologically for all time slots.

viii. The simulation is repeated for N years based on defined accuracy standards.

The steps involved in MCS are illustrated in Figure 5.

4. Optimal sizing problem formulation

The optimal sizing of hybrid system components is performed based on objective function and constraints as explained in subsequent subsections.

4.1 Objective function

The objective is to minimize TLCC which are the costs incurred through ownership of a project over project's lifespan. The objective function is expressed as follows:

$$Minimize \quad TLCC \tag{9}$$

wherein, *TLCC* = Present worth of total costs of incurred during project lifespan, \$.

The expression for TLCC can be written as:

$$TLCC = CC + OM + RC + OC_U - SV \tag{10}$$

where, *CC*= Capital cost in \$, *OM, RC,* OC_U, *SV* = Present worth of O&M cost, replacement cost, utility outage cost and salvage value respectively in \$. The different cost components associated in determination of TLCC along with the assumptions made are computed as explained in [16].

4.2 Constraints

The various constraints used in optimal sizing problem are as follows:

4.2.1 Dual reliability constraint

In this paper, system well-being criterion has been applied using dual reliability constraints [16]. The probabilistic indices such as LOLP, LOLE are unable to reflect information about capacity reserve condition. System well-being criterion provides information regarding reserve margin available in the system [14]. Hence it serves as a more appropriate method of assessing system reliability particularly for system comprising of RES based-DGs. Assessment of system well-being is incorporated by imposing dual reliability constraint as follows [16]:

$$P(Risk) \leq P(Risk)_{\max} \tag{11}$$

$$P(Health) \geq P(Health)_{\min} \tag{12}$$

The reliability indices are evaluated using MCS as explained in Section 3.

4.2.2 System components sizing constraint

The number of PV, WTG and battery units is subjected to following constraints:

$$N_{PV_{\min}} \leq N_{PV} \leq N_{PV_{\max}} \tag{13}$$

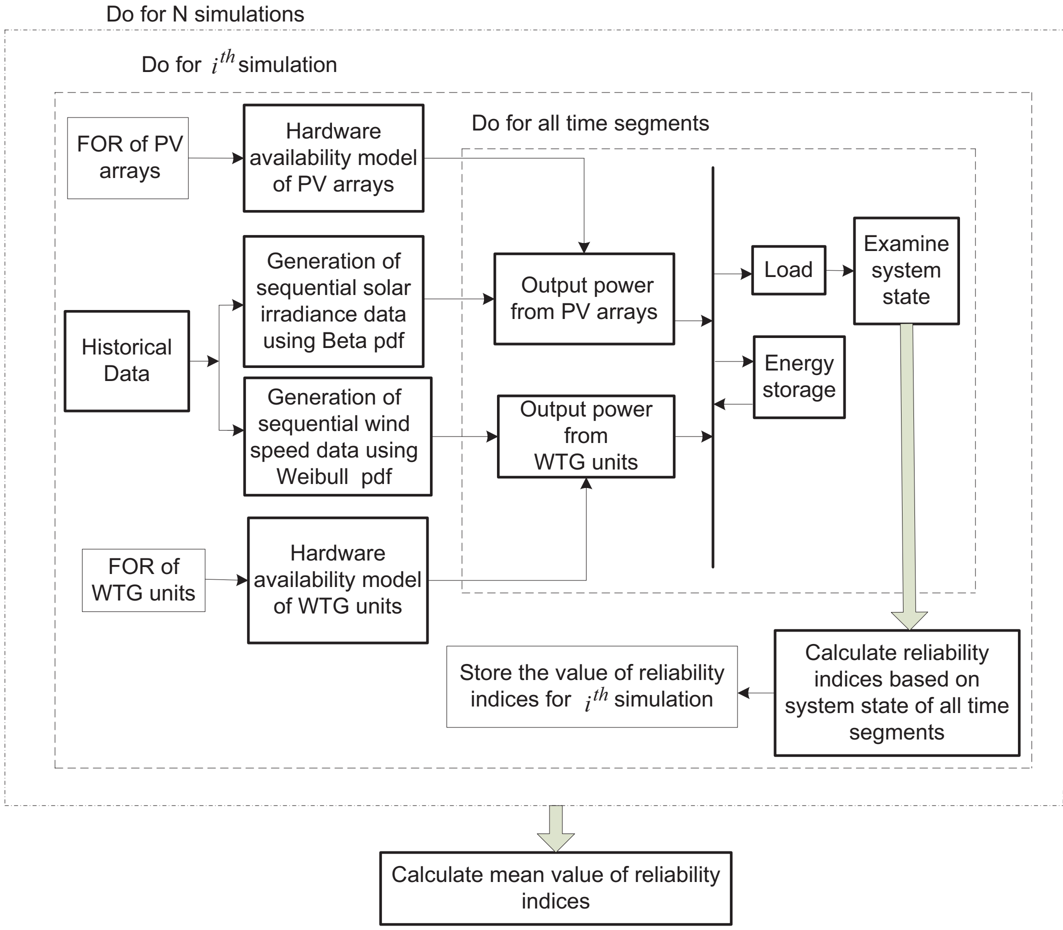

Figure 5: Monte Carlo simulation for reliability evaluation

$$N_{WT_{\min}} \leq N_{WT} \leq N_{WT_{\max}} \tag{14}$$

$$N_{B_{\min}} \leq N_B \leq N_{B_{\max}} \tag{15}$$

where, $N_{PV_{\min}}$ and $N_{PV_{\max}}$ = Lower and Upper bounds of PV array units respectively, $N_{WTG\min}$ and $N_{WTG\max}$ = Lower and Upper limits of WTG units respectively, $N_{B\min}$ and $N_{B\max}$ = Lower and Upper limits of battery storage units respectively.

4.2.3 Constraint on battery parameters

SOC of battery is to be restricted within minimum and maximum values as specified by the manufacturer.

$$SOC_{min} \leq SOC \leq SOC_{max} \tag{16}$$

$$O_B\_dis\_\max \leq O_B \leq O_B\_ch\_\max \tag{17}$$

$$I_B\_dis\_\max \leq I_B \leq I_B\_ch\_\max \tag{18}$$

where, SOC_{min} and SOC_{max} = Lower and upper limit for SOC respectively, $O_B\_dis\_\max$ = Upper limit for power which can be obtained from battery during discharging, kW, $O_B\_ch\_\max$ =Upper limit for power which can be supplied to battery during charging, kW, $I_B\_dis\_\max$ and $I_B\_ch\_\max$ =Maximum permissible value of charging and discharging current respectively, A.

4.3 Optimization technique

The optimal sizing of hybrid system is carried out using Particle Swarm Optimization. PSO offers a variety of advantages over other techniques [31, 38–40]. In order to improve computational efficiency of PSO, it has been suitably modified by author in their previous work [16] and has been used in this paper. Readers are encouraged to refer to [16] for a more detailed discussion on implementation of modified PSO. The flowchart for implementation of PSO is presented in Figure 6.

Implementation of PSO algorithm can be explained in following steps:

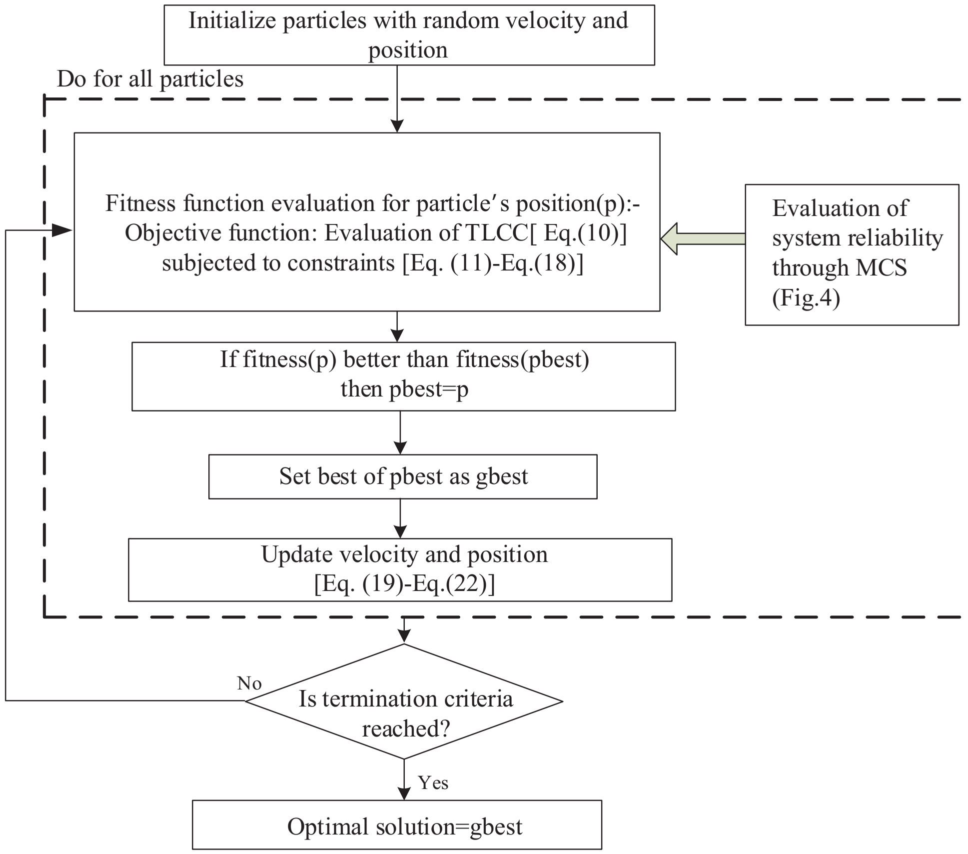

Figure 6: Implementation of PSO

Step 1: Evaluate the fitness of each particle based on objective function i.e. TLCC (explained in Section 4.1). The decision variables are N_{PV}, N_{WTG} and N_B.

Step 2: Update *pbest* value for each particle and *gbest* value of whole swarm.

Step 3: Based on *Step 2*, update the velocity and position of each particle is. The updation of particle's velocity and position are carried out using adaptive PSO model [16] as follows:

$$v_{id}(t+1) = x[v_{id}(t) + C_1.\varphi_1.(pbest_{id}(t) - x_{id}(t)) + C_2.\varphi_2.(gbest_d(t) - x_{id}(t))] \quad (19)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (20)$$

$$x = \frac{2}{4 - \varphi - \sqrt{\varphi^2 - 4\varphi}} \quad (21)$$

$$\varnothing = C_1 + C_2 \quad (22)$$

where, v_{id}, x_{id}, $pbest_{id}$ and $gbest_d$ represent velocity, position, personal best and global best respectively of d^{th} dimension of i^{th} particle, φ_1 and φ_2 are uniformly distributed random numbers in the interval [0, 1], χ is the constriction factor, C_1 and C_2 are acceleration coefficients.

5. Results and discussion

For optimal sizing study, IHPS located in Jaisalmer, Rajasthan, India has been considered. The peak load has been considered to be 70 kW and the category of consumers is residential. The chronological load data has been obtained from [41]. The data for solar irradiance and ambient temperature for site has been taken from [42] and wind speed data has been obtained from [43]. All the technical and economic parameters considered in the analysis have been obtained from [16]. The study period is one year.

The optimal sizing problem is solved using Particle Swarm Optimization. The component sizes are determined with respect to following reliability standards:

$$P(Risk)_{max}=0.2\%,\ P(Health)_{min}=95\%$$

A system is assumed to reside in healthy state if the battery has enough capacity to supply the peak load for 5 continuous hours. The results of optimal sizing problem for hybrid PV-wind-storage system are given in Table 2. Figure 7 presents the convergence characteristics of PSO.

Table 3 shows dual reliability indices calculated through MCS (3000 simulations each with 5 different seeds) for optimal component sizes presented in Table 2. It is evident from Table 3 that dual reliability indices comply with the specified values of $P(Risk)_{max}$ and $P(Health)_{min}$.
Figure 8 shows average solar power output obtained through MCS for considered hybrid system configuration over a span of 24 hours for the first day of January.

Similarly, Figure 9 and Figure 10 show average output power from WTG units and load profile respectively for the same time slot. The solar radiation and wind speed data have been generated synthetically from Beta, given by Eq. (1), and Weibull, given by Eq. (6), density functions, respectively.

As it is apparent from Figure 8, solar power output is available only for a fraction of a day. Figure 9 suggests that although wind power output is available

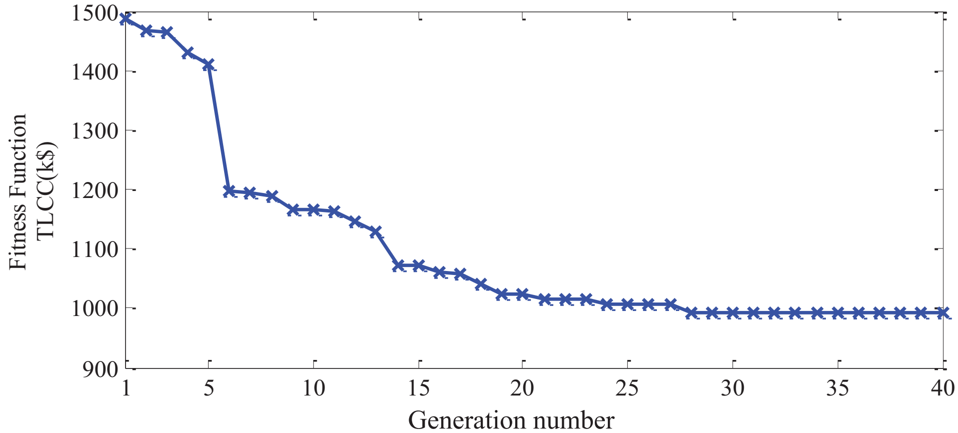

Figure 7: Convergence characteristics of PSO

Table 2: Optimal system configuration

Component	Number of units	Size/unit
N_{PV}	3	30 kW
N_{WTG}	12	20 kW
N_B	17	26.4 kWh

Table 3: Reliability indices for optimal system configuration

Reliability index	Value
P(Risk) (%)	0.17
P(Health) (%)	99.64

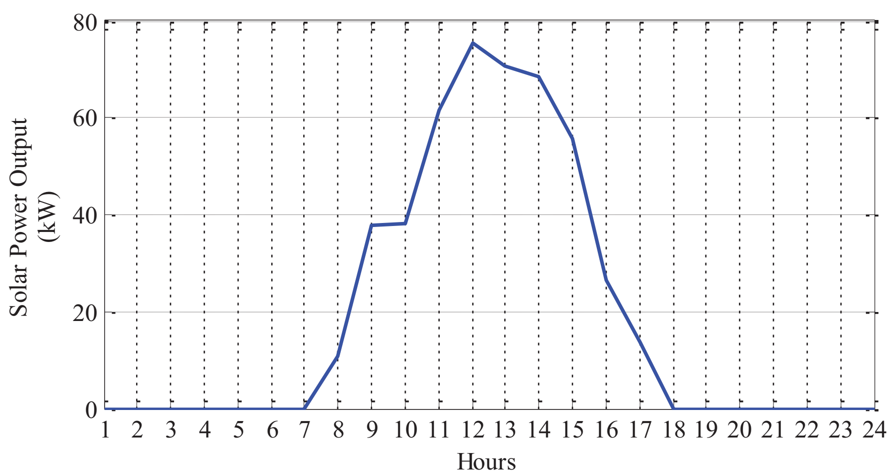

Figure 8: Average solar power output over 24 hours for first day of January

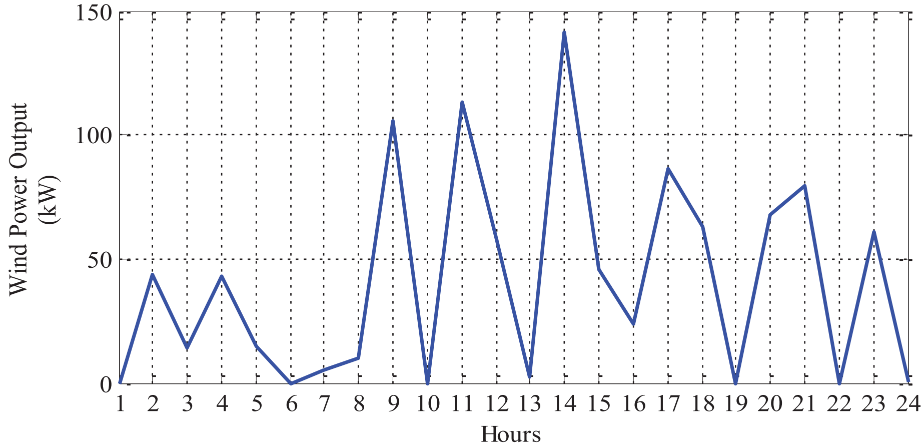

Figure 9: Average wind power output over 24 hours for first day of January

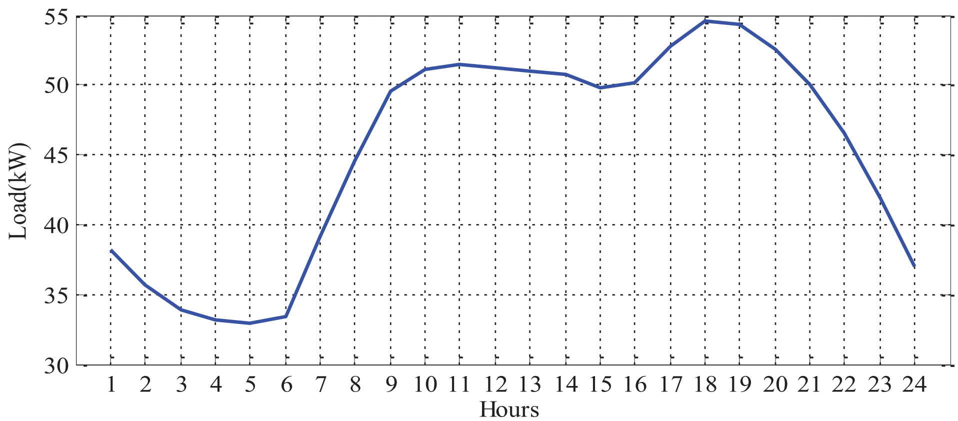

Figure 10: Load profile over 24 hours for first day of January

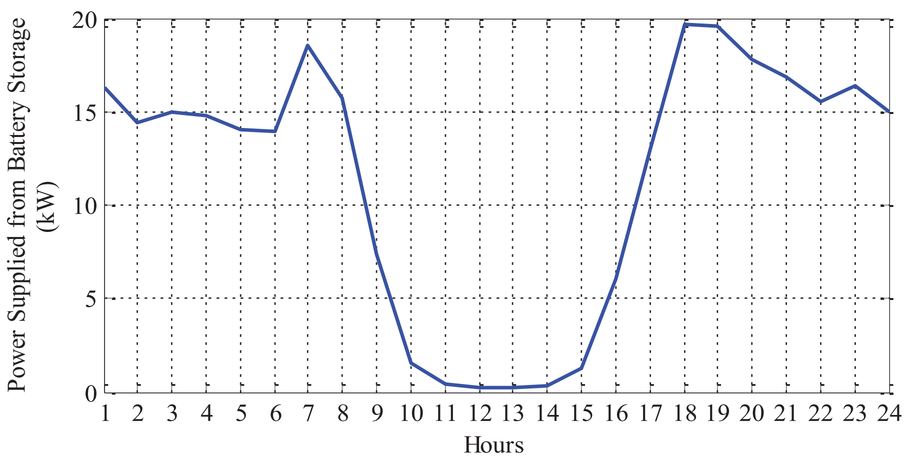

Figure 11: Power supplied by battery storage units

throughout the period of 24 hours, the availability is highly intermittent. Thus, in order to maintain supply reliability, integration of storage is essential. This is further reflected in Figure 11 which shows the output power supplied by battery storage units.

For emphasizing the importance of storage system, the sharing of power between PV array, WTG units and battery storage for a day is shown in Figure 12. Figure 12 clearly suggests the positive impact of storage system on system reliability. During the non availability of sun, storage system share the load along with WTG units. This smoothens out the effects of intermittency of wind sources. On the other hand, when the sunshine is available, storage systems charge themselves to facilitate system reliability. Table 4 shows the contribution of PV, WTG and storage system in meeting the load demand over the entire year. It is apparent from Table 4 that system reliability will deteriorate significantly in the absence of battery storage.

The system planning incorporating RES is complicated due to unpredictable nature of these sources. Thus sensitivity analyses must be carried out in order to assist system planners in coming up with an optimum system planning. Thus, in the present work, two types of sensitivity studies have been carried out:

Table 4: Contribution of energy sources

Source	Percentage of energy supplied
PV	37.8057
WTG	47.8238
Battery storage	14.2993
Percentage of unserved energy = 0.0711	

Case:I Effect of replacement of smaller units with larger units of same capacity on system reliability.

The effect of considering PV and WTG units of larger ratings but same total capacity on system adequacy is given in Table 5. The twelve 20 kW WTG units are replaced by two 120 kW WTG units and three 30 kW PV arrays are replaced by one 90 kW PV array.

Replacement of multiple small units with fewer large units of equivalent capacity should have had a considerable impact on system reliability since the outage of a single large unit can lead to significant loss of generating capacity resulting in huge energy deficit. However the results as reported in Table 5 suggest that replacing small units by equivalent large capacity unit leads to only marginal deterioration in reliability. This is attributed to the reason that stochastic nature of RES overpower the effect of forced outage rate. The effect would have been more pronounced with conventional generating units.

Case:II Effect of variation of component sizes around optimal values (presented in Table 2) on system reliability.

With the aim of studying the impact of addition/ removal of RES and storage on system reliability with respect to optimal system configuration presented in Table 2, following different scenarios have been studied:

Scenario1: WTG and storage capacity is assumed constant at the base level and PV capacity is varied.

Table 5: Reliability indices considering units of large rating

Reliability index	Value
P(Risk) (%)	0.19
P(Health) (%)	97.31

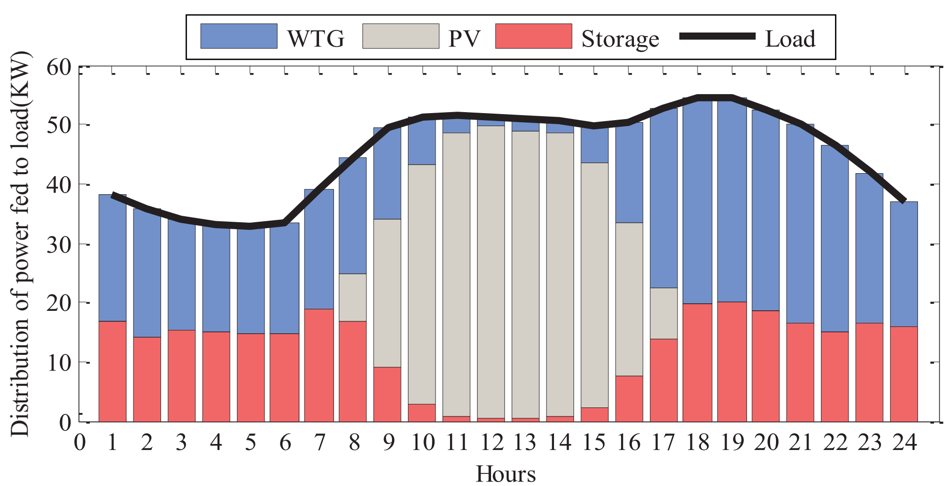

Figure 12: Contribution of sources for supplying load over 24 hours for first day of January

Scenario 2**:** PV and storage capacity is assumed constant at the base level and WTG capacity is varied.

Scenario 3**:** PV and WTG capacity is assumed constant at the base level and storage capacity is varied.

Figure 13(a)-Figure 13(c) show the impact of capacity variation of different sources on reliability of IHPS. Risk state expectation (RSE) indicates the total number of hours during the study period for which the generation is inadequate to supply the load indicating the 'risk state' [36]. So for every time segment (each time segment has length of one hour), RSE is evaluated by determining whether total available power from all the sources and storage (if present) is adequate to supply the load. All those hours for which the source adequacy is not met are summed up to get RSE during the study period. As specified earlier, the study period is one year. As can be seen from Figure 13, the incremental benefits obtained in system reliability by capacity addition through different RES and storage systems are not of the same degree. This is quite unlike the conventional diesel generator units where capacity addition results in proportional increase in reliability. From Figure 13(c), it can be seen that addition or removal of storage units results in almost linear variation in system reliability. However, same is not the case with PV arrays and WTG units. The capacity addition of PV arrays or WTG units

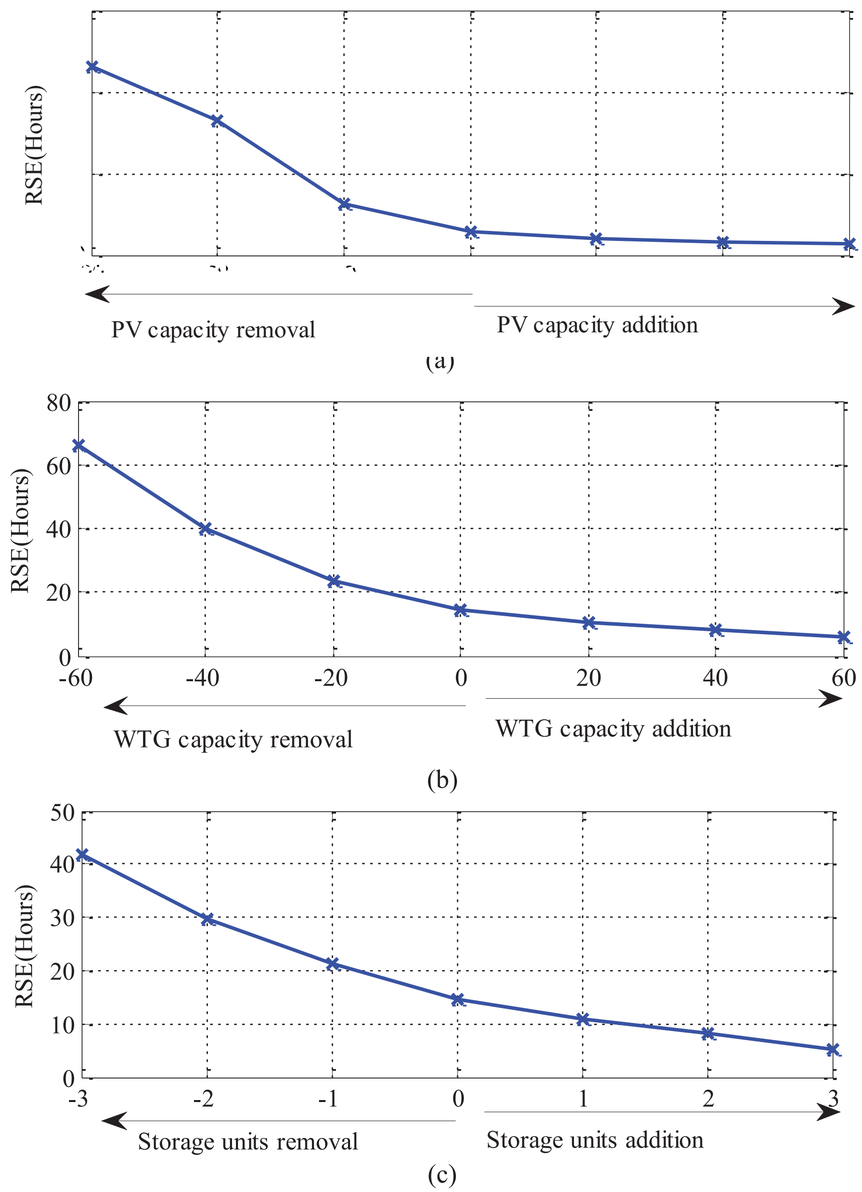

Figure 13(a)-(c): Impact of unit addition/removal on system reliability improves the system reliability only up to a certain level. Beyond that, further capacity addition does not yield a significant improvement in reliability suggesting the saturation to capacity addition. This can be a very important consideration in system planning indicating that a suitable mix of RES along with storage system has to be determined in order to achieve appreciable improvement in reliability.

Figure 14 shows a comparison of impact of different sources on RSE. It can be observed from Figure 14 that reduction in PV capacity affects the system reliability considerably, followed by WTG and storage. This can be chiefly attributed to the fact that solar power although available only during sunshine hours is more reliable and predictable in comparison with highly intermittent and unpredictable wind power.

This can also be observed from average solar and wind output profile over 24 hours presented in Figure 8 and Figure 9 respectively. Storage capacity reduction does affect system reliability, however at a lesser degree in comparison with the generators. This is due to the reason that storage is merely a buffer and can aid system reliability only in presence of adequate generation. If generation is insufficient, it is not only incapable of meeting the load demand but also there is not enough power to charge the battery storage. Thus, storage units might not get adequately charged to provide required backup when desired. Thus, storage capacity has to be adequately planned in conjunction with generating units in order to ensure optimum reliability standards.

In order to give an insight into economic viability of capacity addition from the perspective of reliability, incremental cost of reliability has been calculated for different sources. Incremental cost of reliability is the cost required to be paid in order to improve reliability by a certain degree. In the present work, **Incremental Cost of Reliability(ICR)** has been calculated as:

$$ICR = \frac{\text{Additional investment required over project lifespan}}{\text{Reduction in RSE over project lifespan}} \quad (23)$$

Table 6 presents incremental cost of reliability for considered sources for different capacity additions. The analysis has been done by providing capacity additions above the optimal values(presented in Table 1).

It can be observed that there is a substantial difference between ICR of different sources. The capcity addition of PV arrays has highest ICR owing to its highly capital intensive structure. WTG units can offer a cost effective solution by providing lower ICR. Storage units provide lowest ICR. However, they have to be judiciously planned in combination with capacity of generators as discussed earlier.

A peculiar feature which can be observed from Table 6 is that ICR increases with capacity addition of PV arrays and WTG units. This is due to the fact that as the generator capacity increases, the improvement in reliability is not of the same degree. This is a characteristic very typical to RES-based sources. If solar irradiance/ wind is not available, the load demand cannot be met no matter how large the generating capacity is. Thus, with capacity addition, although the cost increases linearly, there is not a proportionate increase in reliability. This leads to high ICR.

The ICR with storage unit addition shows an irregular pattern. As evident from Table 6, it increases with capacity addition up to two units and shows a decrement thereafter. This can be explained as follows:

Table 6: Incremental cost of reliability($/Sec)

Unit Addition Source	I unit	II unit	III Unit
PV	7.841	16.324	41.55
WTG	2.112	4.247	4.35
Battery storage	1.312	2.32	1.08

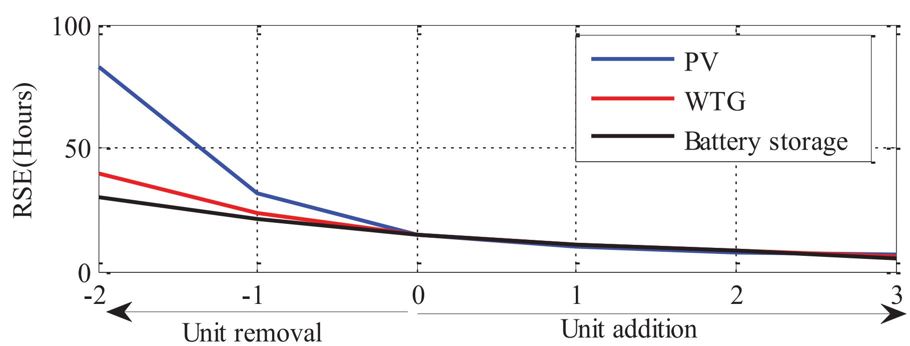

Figure 14: Comparison of impact of different sources on RSE

While calculating ICR, TLCC has been used. TLCC incorporates the replacement costs of battery units during project lifespan. With increase in storage capacity, the number of charge/discharge operations of battery storage decreases. This leads to increase in battery life thereby minimizing the replacement costs. The decrease in replacements costs leads to reduction in TLCC and hence ICR reduces.

6. Conclusion

This paper presents planning formulation for isolated hybrid system incorporating RES-based DGs and storage. Dual reliability indices, *P(Risk)* and *P(Health)* have been used to ensure optimum system planning with requisite reliability standards. A case study has been carried out for a site located in India. A realistic analysis is being provided by considering meteorological parameters of site under consideration. The reliability constrained optimization problem based on minimization of *TLCC* has been solved using PSO. The main focus of this work is to conduct sensitivity analyses to enable a thorough understanding of planning. Two types of analyses have been conducted: (i) Analysis when smaller units are being replaced by larger units of same capacity (ii) Analysis with component sizes varied around their optimal values.

The first analysis provides a very useful insight which is particularly of importance when instead of conventional generators, RES-based generators are being used. The results indicate that contrary to belief, when units of lesser capacity of RES are being replaced by fewer large units, there is no significant degradation in system reliability. This is accredited to variable nature of RES. This information can facilitate better economic planning as deployment of fewer larger units can prove to be a more economical option.

The second analysis can be utilized to have an understanding of impact of addition/removal of PV, wind and battery units. In the present case study, it can be seen that PV unit has maximum impact on system reliability, followed by wind and battery storage units.

Further, in this paper a new index termed as *Incremental cost of reliability* has been introduced. The results suggest that PV present highest ICR followed by wind and storage. Case II of sensitivity analysis and ICR should be used in conjunction to determine the optimum component addition while balancing reliability and cost.

Maintaining system reliability in presence of RES is a major issue in system planning. The optimal sizing model and sensitivity analyses presented in this paper can provide a useful tool for efficient system planning with enhanced reliability standards and optimum cost. Nevertheless, the analysis presented in this paper can be further extended in following research areas:

i. Incorporation of various government schemes and incentives in economic evaluation.
ii. Use of more sophisticated load models.
iii. Analysis with priority customers.

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