Multi-objective optimization of photovoltaic/wind/biomass/battery-based grid-integrated hybrid renewable energy system

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Abstract

The variable nature of the renewable energy resources (RES) complicates their modelling, operation, and integration to the grid. Therefore, it is difficult to choose optimal RES with a proper energy storage system (ESS) for the economic and reliable operation of the grid-integrated hybrid renewable energy system (HRES). There is a need to solve this optimal HRES problem using efficient algorithms due to the high cost and model complexity involved. In this study, optimal photovoltaic, wind, biomass, and battery-based grid-integrated HRES is proposed using a multi-objective artificial cooperative search algorithm (MOACS) to minimise annual life cycle costing and loss of power supply probability. ESS is chosen to provide a backup power supply for at least 30 min during peak load condition. A probabilistic approach is used to consider the time-varying nature of the RES and load while solving optimal HRES design problem by employing MOACS. A comparative analysis is provided at the end, which shows that MOACS can provide a better optimal design of HRES.

1 | INTRODUCTION

In 2020, the total installed power generation in India reached 361.17 GW. The majority of the generation comes from the combustion of fossil fuels. The installed capacity of the renewables is only 10%–20%. As of now, the power generation from the installed wind and solar sources are 36.3625 and 29.5 GW, respectively. To improve the reliability of the power supply, biomass generation can be added to wind and photovoltaic (PV) hybrid system. India is a land of agriculture; the issue with agricultural residue is its inefficient usage, and these are burnt in the open fields in a majority of the areas causing pollution, health issues and soil infertility. It is estimated that 1800–2500 MW of power can be generated by these residues. The demand is rising each day and fossil fuels are depleting. There is a need to achieve the objective of reducing emissions in the environment while ensuring cost reduction with an increase in the installed generation capacity [1]. This has resulted in renewed interest and attention towards the usage of renewable-based hybrid energy systems. The percentage growth of renewable energy resource (RES) is about 24% according to the Ministry of Power, India. Due to the variable nature of the renewable sources, the key concerns for designing a hybrid renewable energy system (HRES) are power management, the system’s reliability and economic feasibility. To handle these sensible concerns, there is a need to achieve multiple objectives and design a renewable energy-based hybrid system using a proper methodology [1].

In recent years several investigations have been carried out on optimal sizing of the HRES. A majority of these studies are focused on the modelling of off-grid HRES [2–6]. By integrating these systems into the utility grid, the system becomes more reliable since the grid acts as a backup to the HRES. However, integration of HRES to the grid still remains a challenging job due to the intermittent, variable, and stochastic nature of the RES, which cause frequency deviation, load mismatch, and voltage instability [7, 8]. Therefore, energy storage systems (ESS) gained more importance in the integration of HRES to the grid [9–11]. Different methods are employed for the optimal design of grid-integrated HRES. In [12], the authors proposed a methodology to minimise the power fluctuations of HRES by introducing pumped energy storage. Basaran et al. [13] presented a PV, wind, and battery-based grid-integrated system designed to power small loads. The authors did not consider cost optimisation or reliability but only focused on energy transfer aspects. El Bidiari et al. [14] presented a fuzzy...
logic-grey wolf optimization technique with an objective to minimise the operating cost of the HRES system. But proper mathematical modelling of the sources is not considered in the system design. In [15, 16], the PV-battery grid-integrated system is designed based on cost minimisation and maximisation of the utilisation of the sources. However, detailed cost analysis and the time-varying nature of the renewable sources and load are not considered. Singh and Kaushik [17] proposed a methodology based on the ABC algorithm considering the annualised cost of the system as the objective for optimal HRES design. In [18], the authors proposed a PV, wind and battery hybrid grid-integrated micro-grid system, which reduces the annual cost and maximise the reliability without considering the varying nature of the load. Detailed discussion on artificial cooperative search (ACS) algorithm for optimisation was carried out by authors in [19]. To design a reliable grid-integrated HRES system, proper mathematical modelling is required [20, 21], and the stochastic nature of the resources should be characterised. Probability density functions (PDFs) are needed to model the stochastic nature of resources [24–26]. In [27, 28], the authors used PDFs for the analysis of the HRES. Tina and Gagliano [29] used PDF to compute power produced by a PV system equipped with a tracking system and a wind energy conversion system. But they did not consider the design of HRES. The inclusion of biomass generation in HRES, which improves the reliability [21], is not considered in many of the above-mentioned optimal HRES designs.

To overcome the drawbacks in the existing literature, in this study, a PV-wind-biomass-based grid-integrated system with ESS presented in Figure 1 is proposed using a multi-objective ACS (MOACS) algorithm. Optimal HRES is designed based on the key essentials of annual cost minimisation and reliability maximisation (reliability measured in terms of loss of power supply probability (LPSP)) [2, 4, 5]. Solar and wind-based power generation in HRES are intermittent in nature. Hence, one of the major challenges of HRES design involving solar and wind generations is satisfying the load demand at all times irrespective of generation uncertainty. Therefore, the minimisation of LPSP [30, 31], which is a measure of reliability in serving the load demand, is considered as an objective in this study. Detailed mathematical modelling of RES is considered for optimal HRES design. The battery ESS (BESS) is chosen to supply the peak load demand for at least 30 min during the non-availability of power from renewable energy sources. Further, the results obtained with the MOACS are compared with the standard multi-objective algorithm Nondominated sorting genetic algorithm II (NSGA-II) [32] as well as improved multi-objective harmony search (IMOHS) [33] algorithm.

The main contributions of this work are summarised as

1. Consideration of the probabilistic nature of the generation and load in optimal HRES design.
2. Probabilistic models are blended with a multi-objective meta-heuristic algorithm to develop a probabilistic approach for the optimal design of grid-integrated hybrid renewable energy system using locally available resources to fulfil the load demand.
3. Proposal of MOACS, which is based on ACS algorithm proficient to deal single-objective optimisation problems. MOACS, which is capable to solve multi-objective optimisation problems, is employed to find the optimal sizing of the grid-integrated hybrid renewable energy system by minimising the annual life cycle costing (ALCC) and LPSP.
4. Comparison of the performance of MOACS with NSGA-II and IMOHS.

This study is organised into six sections. Modelling of renewable energy sources using probabilistic power generation models for solar, wind, and load is explained in Section 2, the problem formulation is discussed in Section 3, the proposed approach using the MOACS algorithm is presented in Section 4. Results obtained by the MOACS, NSGA-II, and IMOHS algorithms are discussed in Section 5, and finally, the conclusion of this work is presented in Section 6.

# 2 Modelling of Grid-Integrated Hybrid System

The proposed system consists of biomass, wind, PV, and a utility grid. For the efficient design of the HRES system, accurate modelling of sources and load is required. Mathematical modelling of renewable sources is complex as the power generation from these sources is highly dependent on meteorological conditions. Hence, in this work, probabilistic models are used in HRES design to account for their time-varying and stochastic nature. In this section, modelling of the HRES system is briefly presented.

## 2.1 Modelling of the solar PV system

Weibull PDF is used to characterise the stochastic behaviour of the solar irradiance as it provided a good fit (less K-S error and high $R^2$ value [25]) for the irradiance data of the chosen site compared to beta, gamma, lognormal and generalized extreme value distribution (GEV) PDFs. At any time frame $t$, the Weibull distribution for the solar irradiance $s$ (W/m$^2$) is given by Equation (1), the shape parameter ($k$) and the scale factor ($\lambda$) are calculated at time frame $t'$ using the maximum
likelihood estimation (MLE) method:

\[
    f(v_t) = \frac{k'}{\varepsilon'} \left( \frac{v'}{\varepsilon'} \right)^{k'-1} \cdot \exp \left( - \left( \frac{v'}{\varepsilon'} \right)^{k'-1} \right)
\]

for \( \varepsilon' > 1; k' > 0 \) \( \text{(1)} \)

To analyse the solar PV output power, the continuous PDF is divided into different states for a particular time frame. Solar irradiance will be within limits in each state, the probabilities of all possible states for that particular hour are obtained, and these probabilities are used to obtain power generation in the \( \text{th} \) time segment. The average power output of the solar PV array for a particular time frame \( \text{th} \) or hour is given by

\[
P_{\text{pv}}(t) = \sum_{i=1}^{N_v} P_{\text{pv},i} \times P_i(v_t)
\]

(2)

For a given state, during any particular time frame or any particular hour, the solar irradiance probability is given by

\[
P_i(v_t) = \begin{cases} 
\int_{0}^{t_{s1}+t_{s2}} f(v_t) \, dv_t \text{ for } st = 1 \\
\int_{t_{s1}+t_{s2}}^{t_{s2}+t_{s3}} f(v_t) \, dv_t \text{ for } st = 2, \ldots, (N_v - 1) \\
\int_{t_{s1}+t_{s2}}^{\infty} f(v_t) \, dv_t \text{ for } st = N_v
\end{cases}
\]

(3)

If the power generated by PV array with the average solar irradiance (i.e. if a state represents solar irradiance (W/m²) is lying between 0 to 100, then the average \( (I_s) \) will be 50 W/m²) for \( \text{th} \) state is calculated as

\[
P_{\text{pv},i} = N_v \cdot \eta_{\text{app}} \cdot ff \cdot I_s(u) \cdot V_a(u)
\]

(4)

\[
ff = \frac{(V_a \cdot I_s)}{(V_{\text{oc}} \cdot I_{\text{sc}})}
\]

(5)

The variation of \( I_s \) and \( V_a \) with temperature and irradiance [22] is given by Equations (6) to (8):

\[
I_s(u) = I_{sc} + k_i \cdot (T_{\text{cell}}(u) - T_{\text{sc}}) \cdot (f/\tau_{\text{sc}})
\]

(6)

\[
V_a(u) = V_{\text{oc}} + k_v \cdot (T_{\text{cell}}(u) - T_{\text{sc}})
\]

(7)

\[
T_{\text{cell}}(u) = T_s + (s/\tau_{\text{sc}}) \cdot (T_{\text{Noc}} - T_{s\text{Noc}})
\]

(8)

2.2 Modelling of the wind energy system

Weibull PDF is suited to express the wind speed stochastic behaviour [23], as it provides a good fit for the wind speed distribution at the chosen site. Weibull PDF for the wind speed \( v \) (m/s) for any time frame \( \text{th} \) can be expressed as

\[
f(v_t) = \frac{k'}{\varepsilon'} \left( \frac{v'}{\varepsilon'} \right)^{k'-1} \cdot \exp \left( - \left( \frac{v'}{\varepsilon'} \right)^{k'-1} \right)
\]

for \( \varepsilon' > 1; k' > 0 \) \( \text{(9)} \)

The average output power of the wind turbine (WT) for a particular time frame \( \text{th} \) or a particular hour is given by

\[
P_{\text{wt}}(t) = \sum_{i=1}^{N_v} P_{\text{wt},i} \times P_i(v_t)
\]

(10)

The power generation of the WT depends on the velocity of the wind at that particular time. Therefore, the power generated by WT at the average wind speed \( v_{\text{th}} \) for any state \( st \) is determined as

\[
P_{\text{wt},i} = \begin{cases} 
\rho_{\text{air}} \cdot N_w \cdot \frac{v_{t}^3 - v_{\text{th}}^3}{v_{\text{th}}^3} \text{ for } v_{t} < v_{\text{th}} < v_{\text{t}} \\
\rho_{\text{air}} \cdot N_w \text{ for } v_{t} < v_{\text{th}} < v_{\text{t}} \\
0 \text{ else}
\end{cases}
\]

(11)

2.3 Modelling of biomass gasifier

A thermochemical conversion technology is used to convert biomass into clean and cool gas by partial combustion under a restricted air supply. This produced gas is used as an input for biomass into clean and cool gas by partial combustion under a restricted air supply. This produced gas is used as an input for

\[
E_{\text{bio}} = N_{\text{bio}} \times P_{\text{bio}} \times t_w
\]

(13)

The maximum rating of the gasifier depends on the total available biomass in a year, the calorific value of biomass and on the efficiency of the biomass gasifier, which is given by

\[
p_{\text{bio}}^{\text{max}} = \frac{\text{total agrimate} \times 1000 \times C V_{\text{bio}} \times \eta_{\text{bio}}}{365 \times 860 \times t_{\text{bio}}}
\]

(14)
2.4 Load modelling

A normal probability distribution function is used to describe the probabilistic character of the load [26], as it follows a normal PDF. Normal PDF for load demand (kW) over any time frame \( 't' \) is described as

\[
f(x|\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}
\]  

(15)

\( P_l(l_x) \) (probability of load demand of a given state during any time frame \( 't' \)) is given by

\[
P_l(l_x) = \left\{ \begin{array}{ll} \int_{0}^{(l_x,l_{x+1})/2} f(x|\mu, \sigma^2) \, ds & \text{for } st = 1 \\ \int_{(l_x-1,l_{x+1})/2}^{(l_x,l_{x+1})/2} f(x|\mu, \sigma^2) \, ds & \text{for } st = 2 \ldots (N_l - 1) \\ \int_{(l_x-1,l_{x+1})/2}^{\infty} f(x|\mu, \sigma^2) \, ds & \text{for } st = N_l \end{array} \right.
\]

(16)

The hourly average load demand for a time segment \( 't' \) is formulated as

\[
P_l(t) = \sum_{st \text{ is}} N_l P_l(l_x) \]

(17)

2.5 Modelling of battery

Lead–acid batteries are used in this study because of their short response time, low self-discharge rate (3%–20%), high cycle efficiency (70%–85%), and low capital cost. BESS is chosen to supply the peak load demand for at least 30 min [10]. To operate BESS in a reliable and efficient way, a complete study of battery requirements while charging and discharging, energy loss, and efficiency is required. If the total energy generated from the PV, biomass, and wind is more than the energy demand, then the battery bank will charge, and whenever there is an energy deficit to meet the load, the energy stored in the battery will supply the deficit energy to the load. The state of charge (SOC; which represents the amount of energy stored in the battery) controls the performance of the HRES.

2.5.1 State of charge

The original SOC of battery in charging mode is given by

\[
SOC_{org}(t + 1) = SOC(t) + \frac{I_{bat}(t) \cdot \Delta t}{C_{bat}}
\]

(18)

But due to battery self-discharging rate (sdr; which depends on the health state of the battery and accumulated charge) and battery charge efficiency factor \( \eta_c \) the actual SOC of the battery is less than \( SOC_{org} \) and is described as

\[
SOC(t + 1) = SOC(t) \cdot (1 - sdr) + \frac{I_{bat}(t) \cdot \Delta t \cdot \eta_c(t)}{C_{bat}}
\]

(19)

The charge efficiency factor is described as

\[
\eta_c(t) = 1 - \exp\left[ a \cdot (SOC(t) - 1) \right]
\]

(20)

where working condition parameters of the battery \( a, b, I_{bat} \) are considered as 20.73, 0.55, and 10, respectively. The charging current \( I_{bat}(t) \) at any time \( t \) can be derived for HRES (which gives the amount of excess power generated by RES after supplying the load) and is given by

\[
I_{bat}(t) = \frac{P_{pv}(t) + P_{wt}(t) \cdot \eta_c + N_{bio} \cdot P_{bio}(t) \cdot \eta_c - (P(t) \cdot \eta_{in})}{N_{bat} \cdot N_{bat'} \cdot V_{bat}}.
\]

(21)

To convert AC power generated by biomass and wind into constant voltage DC power, a rectifier is used. In the discharging process (when power obtained from RES is not adequate to supply the load), SOC is given as

\[
SOC_{org}(t + 1) = SOC(t) - \frac{I_{bat}(t) \cdot \Delta t}{C_{bat}}
\]

(22)

The actual SOC is less than the original SOC due to the self-discharge rate. The actual SOC is given as

\[
SOC(t + 1) = SOC(t) \cdot (1 - sdr) - \frac{I_{bat}(t) \cdot \Delta t}{C_{bat}}
\]

(23)

where

\[
I_{bat}(t) = \frac{P_{pv}(t) \cdot \eta_{in} - (P_{pv}(t) + P_{wt}(t) \cdot \eta_c + N_{bio} \cdot P_{bio}(t) \cdot \eta_c)}{N_{bat} \cdot N_{bat'} \cdot V_{bat}}
\]

(24)

BESS is operated subjected to the constraints as follows:

\[
SOC_{min} \leq SOC(t) \leq SOC_{max}
\]

(25)

and

\[
I_{bat,max}(t) = \max\left\{ 0, \min\left[ I_{max}, C_{bat} \cdot (c \cdot (SOC_{max} - SOC(t)) \right. \right.

(26)
the battery, \( \varepsilon \) is considered to be 0 while discharging, and it is chosen as 1 while charging.

3 | PROBLEM FORMULATION

Due to the high load demand, many of the conventional grids are unable to give continuous supply to a load, which results in power cuts in many areas. In addition, the depletion of fossil fuels is a major issue in recent years, which leads to an increase in focus on renewable technologies for power generation. In this work, a grid-integrated HRES is designed with an objective to reduce the cost and increase the reliability by reducing LPSP. The objectives are formulated as given in the following subsections.

3.1 | Annual life cycle costing

Minimisation of the total ALCC of the HRES integrated into the grid is one of the objectives in this study, which includes the total costs of PV, wind, biomass, battery, inverter (all costs are annualised), and also the grid sale and purchase cost (annual). The objective function is formulated as

\[
\text{ALCC} = \left( \sum_{\text{PV, wind, biomass, inverter}} C_x \right) - C_{gs} + C_{gp} \tag{27}
\]

The total cost (annualised) of each component (PV/wind/battery/biomass/inverter) includes capital, replacement, maintenance, and salvage costs (all costs are annualised) of that component. The detailed cost analysis for any component is given as

\[
C_x = C_{acap}^x + C_{amx}^x + C_{asg}^x + C_{arp}^x \tag{28}
\]

where \( x \) could be PV/wind/biomass/battery/inverter.

3.1.1 | Annualised capital cost

The annualised capital cost of any component (wind, PV, biomass, inverter, and battery bank) is computed by using the present worth factor (PWF) and capital cost as shown in Equation (29):

\[
C_{acap}^x = C_{acap}^x \times \text{PWF} \tag{29}
\]

\[
PWF = \frac{1 + f}{i - f} \times \left( 1 - \left( \frac{1 + f}{1 + i} \right)^n \right) \tag{30}
\]

3.1.2 | Maintenance cost

The repair, running and any other costs that are included in the maintenance cost of each component are expressed as

\[
C_{amx}^x = C_{amx}^x \times N_x \tag{31}
\]

3.1.3 | Annualised salvage cost

The salvage value of a component at the end of the lifetime of the project is treated as the salvage cost of that component. In this work, the salvage cost of every component is taken as 10% of its capital cost. The annualised salvage cost is formulated as

\[
C_{asg}^x = C_{asg}^x \times \text{PWF} \tag{32}
\]

3.1.4 | Annualised replacement cost

When the lifetime of the project is more than the lifetime of a component, then replacement of that component is required. PV panels, WTs, and biomass do not require replacement. In the designed HRES, the battery bank needs to be replaced every 5 years. For each replacement, the annualised replacement cost is

\[
C_{arp}^x = C_{arp}^x \times \left( \frac{1}{1 + f} \right)^n \times \frac{1}{\text{PWF}} \tag{33}
\]

3.1.5 | Energy purchased from grid and energy sold to the grid

Apart from these cost functions, in grid-integrated HRES, the bi-directional power flowing from the grid plays an effective role in the operation of the HRES. The total cost of energy purchased from the utility grid is given as

\[
C_{pg} = C_{pg} \times \sum_{i=1}^{8760} (P_g(t)) \tag{34}
\]

For grid-integrated system, the total cost of the energy sold to the grid is

\[
C_{gs} = C_{gs} \times \sum_{i=1}^{8760} (P_g(t)) \tag{35}
\]

The further unit cost of the electricity produced by the HRES is expressed as

\[
\text{Unitcost} = \frac{\text{ALCC} (Rs/yr)}{\text{Load served (kWh/yr)}} \tag{36}
\]
3.2 Loss of power supply probability

Minimisation of LPSP [2, 31] (which can be described as the probability of HRES not being able to serve the load demand) is considered as another objective in this study.

\[ f_2 = LPSP = \sum_{t=1}^{8760} \left( \frac{P_{\text{need}}(t) - P_{\text{supplied}}(t)}{P_{\text{total,load}}} \right) \]  
(37)

The following constraints are considered in this study.

\[ N_{\text{min}}^{pv} \leq N_{pv} \leq N_{\text{max}}^{pv}, N_{\text{min}}^{w} \leq N_{w} \leq N_{\text{max}}^{w} \]
\[ tP_{gp}(t) \leq p_{\text{max}}^{gp}, P_{\text{dump}} \leq p_{\text{max}}^{\text{dump}} \]  
(38)

3.3 Operational strategy (run for one year)

Weibull PDF and normal PDF are chosen to model the stochastic nature of wind power, solar power and load considering a typical day (24 hourly PDF’s) for every month. The hourly average power obtained from PV, wind and average load demand is computed as explained in Section 2. Using 288 PDF’s (12 months × 24 PDF’s) each for irradiance, wind speed and load, data for 8760 h is synthesised. The power balance equation is shown in Equation (39).

\[ \Delta P_1(t) = (P_{gp}(t) + P_{bat}(t)\eta_{inv} + N_{bio}P_{bio}(t)\eta_{inv}) - P_L(t)\eta_{inv} \]  
(39)

The following strategy is used in this work for the HRES operation, which is depicted in the flowchart shown in Figure 2.

1. If power from RES is more than the load that is needed to be served (i.e. \( \Delta P_1(t) > 0 \)), the battery bank will be charged with the remaining power available after serving the load. If still there is any excess power, then it will be pumped into the grid. The amount of power sold to the grid is described as

\[ P_{gp}(t) = (\Delta P_1(t) - P_{\text{bat,c,max}(t)}\eta_{inv}) \]  
(40)

The time frame chosen in this work is 1 h. The maximum power sold to the grid should not be greater than the maximum allowable limit of the grid (\( P_{gp}^{\text{max}} \)). If it exceeds \( P_{gp}^{\text{max}} \), the remaining power is wasted in the dump load.

(i) If the power generated by the RES is not enough to meet the load (i.e. \( \Delta P_1(t) < 0 \)), then the energy stored in the battery will be used to serve the load up to its maximum limit, and \( \Delta P_2(t) \) is given as follows:

\[ \Delta P_2(t) = (P_{gp}(t) + P_{bat}(t)\eta_{inv} + N_{bio}P_{bio}(t)\eta_{inv}) + P_{\text{bat,d,max}(t)}\eta_{inv} \]  
(41)

FIGURE 2 Flowchart for operational strategy

(ii) If \( \Delta P_1(t) < 0 \) & \( \Delta P_1(t) > 0 \), the energy delivered from the battery bank is able to meet the deficit power (\( \Delta P_1(t) \)).

(iii) If \( \Delta P_1(t) < 0 \) & \( \Delta P_2(t) < 0 \), the energy delivered from the battery bank is also not sufficient to serve the load. Then, the remaining power will be purchased from the grid. Power purchased from the grid is expressed as

\[ P_{gp}(t) = P_L(t) - (P_{gp}(t) + P_{bat}(t)\eta_{inv} + N_{bio}P_{bio}(t)\eta_{inv} + P_{\text{bat,d,max}(t)}\eta_{inv} \]  
(42)

Nevertheless, the maximum amount of power purchased from the grid should not exceed the maximum grid purchased power \( P_{gp}^{\text{max}} \). If it exceeds, then the remaining deficit power will be treated as a loss of power that is accounted for in LPSP.

3.4 Multi-objective formulation

If \( f_1, f_2, f_3, \ldots, f_n \) are the objective functions, which are conflicting in nature, the multi-objective optimisation problem will be given...
as
\[
\min \{ f_1(x), f_2(x), \ldots, f_n(x) \} 
\]  

where \( x \in \mathbb{R}^n \) and \( n \) are the total numbers of objectives and decision variables, respectively, confined to the feasible search space \( R \). As these objective functions \( f_1, f_2, f_3, \ldots, f_n \) are conflicting with each other, it is hard to get the single optimal solution, which consists of all optimised objectives. Therefore, multiple non-dominated solutions (set of non-dominated solutions in objective space is referred as Pareto front) can be obtained by using suitable algorithms. In HRES, the objective functions \( f_1 \) (ALCC) and \( f_2 \) (LPSP) are conflicting in nature. Hence, a powerful algorithm is required to find the optimal sizing of the grid-integrated HRES by minimising the two objective functions.

4 | ACS ALGORITHM

In this work, the ACS algorithm [19], which is able to solve single-objective optimisation problems, is modified as a MOACS to solve the optimal HRES problem. In this section, a detailed explanation of the basic ACS algorithm and the modifications done to it to solve the multi-objective problem is given. In addition, the application of MOACS for optimal HRES design is explained.

4.1 | ACS algorithm

ACS algorithm is inspired by the natural species or superorganisms (e.g., bird species, honey bees, butterflies). Many of the superorganisms will go for seasonal migration in different areas to reach for food because the food available in that area is very vulnerable to climatic changes and is highly varied in nature. The steps of the algorithm are explained below [19].

**Step 1**: Initially define the objective function and initialise the population and its decision variables, boundary limits.

The objective function can be defined as

Minimise \( f(x) \)

Subjected to \( X_i, \text{LOW} \leq X_i \leq X_i, \text{UP} \) \((i = 1,2 \ldots D)\)

Initialise the two superorganisms randomly subjected to their boundary limits by using the following equation [19].

\[
A_{(i,j)} = \text{low}_j + \text{rnd}. (\text{up}_j - \text{low}_j) \\
B_{(i,j)} = \text{low}_j + \text{rnd}. (\text{up}_j - \text{low}_j) 
\]

where \( i = 1, \ldots, N \), where \( N \) is the population size and \( j = 1, \ldots, D \), dimension of the problem is \( D \). Fitness value \( f(x) \) will be evaluated for each sub-superorganism \( \langle A, B \rangle \).

**Step 2**: Two superorganisms \( \langle A, B \rangle \), which consists of random solutions (sub-superorganisms) of related problem, migrate to productive feeding areas. These superorganisms are used to detect the predator and prey randomly by using two random variables. If \( \text{rnd}1 < \text{rnd}2 \), then the predator will be initialised with superorganism \( A \), and a key value of ‘1’ is assigned for the predator; otherwise, the predator will be initialised with superorganism \( B \), and a key value of ‘2’ is assigned for the predator. Similarly, the prey is also initialised.

**Step 3**: The superorganisms cooperate with each other and also they interact biologically. When they are trying for the global minimum of the problem, they undergo cooperation and biological interaction with each other. The organisms, which are involved in the biological interaction, are known as active individuals. Their interaction depends on the scale factor \( R \). The predator superorganism is updated by the biological interaction as follows:

\[
X_{(i,j)} = \text{predator}_{(i,j)} + R.(\text{prey}_{(i,j)} - \text{predator}_{(i,j)}) 
\]

where scale factor \( R \) can be computed as follows:

\[
\text{if } \text{rnd} < \text{rnd} \\
R = 4.\text{rnd}.(\text{rnd} - \text{rnd}) \\
\text{else} \\
R = \Gamma (4.\text{rnd}, 1) 
\]

where the shape parameter is 4 and the scale parameter is 1 with a gamma distribution (\( \Gamma \)).

**Step 4**: The newly obtained superorganism \( \langle X \rangle \) is updated with the predator for active individuals by using the mapping rule subjected to the boundary limits. Then, fitness is calculated for each sub-superorganism of the new superorganism, and it is compared with the predator superorganism. The sub-superorganisms of the predator will be updated if new superorganisms have better fitness according to the objective function. The updated predator will be transferred into \( A \) if the key value is 1 or transferred into \( B \) if the key value is 2.

**Step 5**: Repeat steps 2–4 up to the maximum number of iterations.

4.2 | MOACS algorithm

ACS algorithm is modified as MOACS to solve multi-objective problems by using the non-dominated sorting and crowding distance principle. The steps of MOACS are discussed in this section.

**Step 1**: Initialise population and decision variables within boundary limits as discussed in the above section, which is given by Equation (44). Calculate individual fitness \( f_1(x), f_2(x), \ldots, f_n(x) \) for both superorganisms \( \langle A, B \rangle \). Rank sub-superorganisms of \( A \) and \( B \) using the non-dominated sorting principle [32]. For similar ranked solutions, assign crowding distance as described in [32]. Fitness, rankings, and crowding distances of superorganisms \( \langle A, B \rangle \) are stored in other memory location.

**Step 2**: Determine the predator and prey and initialise key values as discussed in step 2 of Section 4.1.

**Step 3**: The new superorganism \( \langle X \rangle \) will be formed with the biological interactions between the two superorganisms.
depending on passive individuals (based on mapping) controlled by the scale factor \( R \) as shown in Equations (45) and (46). The detailed explanation for this is given in steps 2 and 3 of the above section.

**Step 4:** Calculate the individual fitness for each sub-superorganism in \( X \).

**Step 5:** To get the best population between the predator and \( X \), combine them and rank them based on their fitness values using the non-dominated sorting principle and crowding distance \([32, 33]\). Sort the combined population (size \( 2N \)) based on ranking and crowding distance, and choose the best ranked \( N \) solutions (if the ranks are the same for the two solutions, then the solution that has more crowding distance will be sorted out to be the best solution) from them as predator superorganism.

**Step 6:** The updated predator will be transferred into \( A \) if the key value is 1 or transferred into \( B \) if the key value is 2.

**Step 7:** Repeat steps 2–6 until the maximum number of iterations is reached. The best-compromised solution from the Pareto front (related to the predator), which comprises of rank one solutions, is obtained using a max-min approach \([33]\).

### 4.3 Proposed probabilistic approach

The proposed probabilistic approach, which uses MOACS for optimal HRES design, is explained here. The main steps involved to implement the MOACS algorithm for the above-stated optimisation problem for the grid-integrated HRES is given as follows:

(i) Initialise control parameters of the MOACS algorithm that are population size (chosen as \( N = 50 \)), maximum iteration number (\( \text{iter}_{\text{max}} = 300 \)), number of variables to be optimised, input data of annual horizontal irradiance data, wind speed data, and annual load demand.

(ii) Superorganisms \( A \) and \( B \) are generated randomly using Equation (44) subjected to the boundaries described by Equation (38). Typical solution vectors of \( A \) and \( B \) is given by Equation (47).

\[
\begin{bmatrix}
N_{\text{sol}}^1 & N_{\text{we}}^1 & N_{\text{bio}}^1 \\
\vdots & \vdots & \vdots \\
N_{\text{sol}}^N & N_{\text{we}}^N & N_{\text{bio}}^N
\end{bmatrix}
\]

(iii) For each guess solution vector (sub-superorganism) of \( A \) and \( B \), perform the following steps.

- Measure the power generated by the solar PV modules, WT, and biomass using Equations (2), (10) and (13).
- Compute \( \Delta P1(\delta) \) and \( \Delta P2(\delta) \) using Equations (39) and (41).
- Obtain ALCC and LPSP of the sizing components as stated in the flowchart shown in Figure 2.

Follow the same procedure for the rest of the solutions (sub-superorganism) of \( A \) and \( B \).

(iv) Follow steps 2 and 3 in Section 4.2 to select prey, predator and obtain a new population. Compute ALCC and LPSP for each sub-superorganism of the new population \( X \).

(v) Follow steps 5 and 6 in Section 4.2 to update the predator.

(vi) Repeat the procedure explained in (ii) to (v) until the maximum iteration number is reached. The best-compromised solution from the predator, which provides a good trade-off between ALCC and LPSP, has been chosen as the optimal sizing configuration of HRES. Flowchart for application of MOACS for HRES design is shown in Figure 3.

### 5 RESULTS AND DISCUSSIONS

A hamlet (a group of houses) near Gangadevipalli around 120 km from Kadapa (latitude-4°34’24.1 and longitude – 78°19’44.9) Andhra Pradesh, India, is chosen as a site for optimal HRES design, which has a peak load of 100 kW and an average load of 50 kW. The inputs for the designing of the grid-integrated HRES are solar irradiance, temperature, and wind speed at a given site collected from the National Institute of Wind energy \([34]\). Hourly load demand data is collected from the local substation. The efficiencies of rectifier and inverter are taken as 95% and 97%, respectively. To produce one unit of energy from biomass gasifier, 1.5 kg of residue is required and the cost of the residue is taken as Rs. 0.30 /kg \([21]\). To serve the peak load for at least 30 min, the required capacity of the ESS is 249.5 kWh (four batteries in series (\( N_{\text{b}} \)) and 26 parallel paths (\( N_{\text{p}} \)). The SDR of battery is considered as 0.02%, \( V_{\text{bat}} \) is 12 V, \( V_{\text{oc}} \), \( V_{\text{av}} \), \( V_{\text{r}} \) are 2.7, 25, 11 (m/s). \( V_{\text{oc}}, I_{\text{st}}, k_{\text{v}}, k_{\text{p}} \), and \( T_{\text{ep}} \) of PV panel are available in \([23]\). Seventeen number of 300 Wp solar panels have been used to build 5 kW array. The cost of energy sold to the grid and energy purchased from the grid is taken as Rs. 6 /kWh. Grid purchase capacity is taken as 10 kWh, and grid sale capacity is chosen as 20 kWh. A low value of grid purchase capacity is considered to limit dependency on the grid power. The capital, annual maintenance, and replacement costs of the equipment used in this study is given in Table 1.

### 5.1 Grid-integrated hybrid renewable energy system

In the absence of grid integration, if power obtained by the RES is not enough to meet the load, the energy stored in the battery will be used to serve the load. If the battery bank is unable to meet the deficit power, then the remaining power will be treated as a loss of power supply (LPS). By integrating HRES into the grid, the remaining power will be purchased from the grid. If the remaining power is more than the maximum grid purchased power, then balance deficit power, which is equal to the difference of remaining power and maximum grid purchased power, will be treated as LPS. This is quite small implying enhancement in reliability due to grid integration. Even though the hybrid system is linked with the grid, the priority of the renewable sources is to reach the load demand. The proposed probabilistic approach and the operational strategy
TABLE 1  Cost specifications

| Component                  | Rated capacity | Capital cost (Rs) | Annual maintenance cost (Rs) | Replacement cost (Rs) |
|----------------------------|----------------|------------------|-----------------------------|-----------------------|
| Wind turbine (WT) generator| 5 kW           | 500,000          | 25,000                      | –                     |
| PV                         | 5 kWp          | 350,000          | 10,000                      | –                     |
| Biomass gasifier           | 10 kW          | 623,000          | 10,000                      | –                     |
| Battery/unit               | 12 v, 200 Ah   | 15,000           | 1000                        | 15,000                |
| Inverter                   | 100 kW         | 100,000          | 10,000                      | –                     |

TABLE 2  Optimal sizes of HRES

| Algorithm         | Photovoltaic (PV) units (N_{pv}) | Wind units (N_{w}) | Biomass gasifier units (N_{bio}) | Grid purchase capacity (kW(h)) | Grid sale capacity (kW(h)) | Loss of power supply probability | Annual life cycle cost (Rs) | Unit cost (Rs) |
|-------------------|----------------------------------|-------------------|----------------------------------|-------------------------------|----------------------------|---------------------------------|---------------------------|----------------|
| S-I (without biomass) | MOACS 242                        | 24                | –                               | 10                            | 20                         | 0.10                            | 2,185,265.1               | 4.95983        |
|                   | NSGA-II 256                       | 23                | –                               | 10                            | 20                         | 0.11                            | 2,174,637.7               | 4.95455        |
|                   | Improved multi-objective harmony search (IMOHS) 258 | 23            | –                               | 10                            | 20                         | 0.11                            | 2,178,439.7               | 4.95723        |
| S-II (with biomass) | MOACS 280                        | 17                | 3                               | 10                            | 20                         | 0.04                            | 2,115,934.8               | 4.47895        |
|                   | NSGA-II 287                       | 16                | 3                               | 10                            | 20                         | 0.05                            | 2,104,026.5               | 4.47235        |
|                   | IMOHS 264                        | 17                | 3                               | 10                            | 20                         | 0.05                            | 2,107,228.7               | 4.47450        |

employed are not dependent on the sizes of renewable sources and load. Modelling of wind speed and irradiance is dependent on the site but not on wind and PV generator sizes. Hence, the approach is scalable and flexible enough to accommodate generation sources of different types and sizes for designing large-scale HRES. In this study, two scenarios are considered while designing the HRES system, which demonstrates the flexibility of the approach in accommodating different types of sources using MOACS, IMOHS [33] and NSGA-II [32] algorithms.

Scenario I (S-I): HRES system integrated into the grid, which includes wind, PV, and battery.

Scenario II (S-II): HRES system integrated into the grid, which includes the battery, PV, wind, and biomass generation.

(i) Scenario-I (without biomass gasifier)

In this scenario, the hybrid system consists of PV and wind generators integrated into the grid with ESS. Table 2 presents the optimal solution, which has reasonably less objective function values $f_1$ (ALCC) as well as $f_2$ (LPSP). In Table 2, RE sources are represented in units, which means each unit of the solar panel is equal to 300 W (i.e. 242 units means 242*300 W = 72.6 kW); similarly, each unit of the wind model is equal to 5 kW, and each unit of biomass model is equal to 10 kW. As seen from Table 2, by using the optimal HRES system obtained with MOACS, the LPSP is 10%. On the contrary, LPSP with optimal HRES design using IMOHS and NSGA-II is 11% and per unit cost obtained from all algorithms is almost the same indicating that MOACS gave a better-compromised solution. LPSP in this scenario is high, which is expected as grid purchase capacity is limited to 10 kWh. The optimal front obtained in this scenario is shown in Figure 4. As seen from Table 4, the majority of the generation comes from the wind generator to meet the load demand since the PV generation is not available at night time.

(ii) Scenario-II (with biomass gasifier)

In the case of scenario I, the biggest challenge is the moderate reliability of the system (indicated by high LPSP). LPSP is high as the peak load of the system occurs in the evening, and due to the unavailability of solar energy, the system is unable to meet the load effectively resulting in more LPS. To overcome this, in scenario II, biomass is included in the system, which is operated from 5 PM to 5 AM daily. By including biomass in the system, the LPSP and cost of the system can be reduced because biomass feed is available at a lower price. The optimal front obtained in this scenario is shown in Figure 5. MOACS algorithm is used to obtain optimal sizes of the grid-integrated HRES, and then the results are compared with the results obtained by IMOHS and NSGA-II.

As shown in Table 2, the introduction of biomass into the hybrid system (scenario II) improves the reliability, compared to scenario I by reducing the LPSP to 4% from 10%. Also, the unit price is reduced because of the low cost of biomass. MOACS algorithm gave better optimal results, compared to other algorithms (which can be seen from the additional 1% decrease in LPSP with almost the same per-unit cost). Table 3 shows the detailed ALCC calculations and costs, and Table 4 shows the energy production and power balance for the HRES system designed using MOACS. To figure out the effectiveness of the optimal grid-connected HRES design, energy balance (energy generation from different sources, energy exported to the grid,
the energy imported from the grid, and energy not served to the load) is carried out, which is mentioned in Table 4. The energy balance should be equal to 0, which means that the generated power (power from RES and purchased from the grid) after losses should be equal to the load served, energy sold to the grid, and annual dump. Table 4 shows that there is a proper energy balance of the HRES for both scenarios.

### 5.2 Comparison of MOACS with IMOHS and NSGA-II

The performance of MOACS is compared with multi-objective algorithms IMOHS and NSGA-II. The population size, number of decision variables and their limits are considered the same for all the algorithms. The algorithms are executed for 50 runs, and the final non-dominated solutions (Pareto front solutions) obtained with each algorithm are stored as the outcome for each run. It is more complex to find out the quality of multi-objective optimisation solutions, compared to single-objective optimisation. An efficient multi-objective optimisation algorithm should obtain rank one solutions closer to the optimal true Pareto front, and the non-dominated solutions of the Pareto front should be uniformly distributed with less spacing between them. The non-dominated solutions should cover a large range of values for every objective. By considering all these aspects, some comparison metrics such as convergence metric (\(C\)-metric) and spaced metric (\(Sp\)-metric) are used to find out the quality of the multi-objective optimisation algorithm. Since the true optimal Pareto front is not known, in this study, the comparison is done by plotting the Pareto fronts obtained with each algorithm and considering the \(C\)-metric and \(Sp\)-metric [32, 33]. \(Sp\)-metric is used to quantify how uniformly the solutions in the Pareto front are distributed. In addition, the box plot is used to assess the quality of the obtained results.

\[ I_C(A, B) = \frac{\text{size}\{b \in B, \exists a \in A : a \leq b\}}{|B|} \]  

### TABLE 3 ALCC of HRES designed using MOACS pertaining to S-II

| Costs (Rs/year) | PV | WT | Battery | Biomass | Inverter | Total |
|-----------------|----|----|---------|---------|---------|-------|
| Capital cost    | 348,913.35 | 502,364 | 92,198.58 | 110,460.49 | 59,101.65 | +1,113,142.69 |
| Replacement cost | – | – | 235,377.59 | – | – | +233,399.39 |
| O and M cost    | 168,674.7 | 425,000 | 104,000 | 207,390.00 | 10,000 | +915,064.69 |
| Salvage cost    | 25,154.79 | 36,217.77 | – | – | – | –61,378.29 |
| Purchased energy cost | +108,863.20 | | | | | |
| Sold energy cost | –195,157 | | | | | |
| ALCC            | 2,115,934.8 | | | | | |

### TABLE 4 Energy balance for HRES

| Component | S-II | | | | S-I | After inverter (kWh/year) | Production (kWh/year) | Balance |
|-----------|------|---|---|---|---|---|---|---|
| WT        | 268,520.22 | 255,094.209 | 508,495.1 | 535,258.09 | 0.00 | 498,606.67 | 18,143.87 | 526,638.97
| PV        | 143,021.51 | 135,870.43 | 355,458 | 508,495.1 | 492,15 | 493,471.78 | 493,471.78 | 33,167.19
| Biomass   | 127,458 | 121,085.1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| (-)Battery waste | 3741.64 | 355,458 | 355,458 | 355,458 | 355,458 | 355,458 | 355,458 | 355,458 |
| Total     | 535,258.09 | 508,495.1 | 508,495.1 | 508,495.1 | 498,606.67 | 473,676.27 | 473,676.27 | 473,676.27 |
| Purchased from grid | 18,143.87 | 526,638.97 | 526,638.97 | 526,638.97 | 526,638.97 | 526,638.97 | 526,638.97 | 526,638.97 |
| (-)Load   | 493,471.78 | 33,167.19 | 493,471.78 | 493,471.78 | 493,471.78 | 493,471.78 | 493,471.78 | 493,471.78 |
| Loss of power supply power | 20,112.92 | 51,685.44 | 51,685.44 | 51,685.44 | 51,685.44 | 51,685.44 | 51,685.44 | 51,685.44 |
| (-)Dump   | 32,526.17 | 30,498.17 | 30,498.17 | 30,498.17 | 30,498.17 | 30,498.17 | 30,498.17 | 30,498.17 |
| Overall balance | 0.00 | | | | | | | |
Here, size \((y)\) gives the number of elements present in set \(y\) and \(|B|\) refers to the size of set \(B\).

\(I_C(A, B) = 1\) indicates that all the decision vectors in \(B\) are weakly dominated by decision vectors in \(A\). \(I_C(A, B) = 0\) indicates that no decision vector in \(B\) is weakly dominated by decision vectors in \(A\). Similarly, in other direction, \(I_C(B, A)\) also will be computed.

**Sp-metric:** Spacing metric measures the range of (distance) variation of neighbouring decision vectors present in the Pareto front and is given as follows:

\[
SP = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} \left( d_i - d_j \right)^2}
\]

where \(d_i = \min\left( \sum_{k=1}^{m} |f_i^k - f_j^k| \right), i, j = 1, ..., n.\) and \(n\) is the number of decision vectors in the Pareto front.

Sp-metric ‘0’ means that all the non-dominated solutions present in that specified set are spaced in equal distance. The visualisation of the distribution of obtained samples can be done by means of the box plot. By executing the algorithms for 50 runs, 50 C-metric average values for a pair of \(IC(MOACS, NSGA-II), IC(NSGA-II, MOACS), IC(MOACS, IMOHS)\) and \(IC(IMOHS, MOACS)\) are obtained. The two edges of the box plot are the boundary limits (upper, lower) of the average C-metric values, and the central mark is the median.

Figures 6 and 7 illustrate the box plot (distribution) of the 50 average C-metric results of both the scenarios, and Table 5 shows the C-metric results. From Table 5, it is evident.
that MOACS is significantly better than the other two algorithms. From Figures 6 and 7, it is evident that $I_C (MOACS, NSGA-II)$ median is higher, compared to $I_C (NSGA-II, MOACS)$, and $I_C (MOACS, IMOHS)$ median is higher, compared to $I_C (IMOHS, MOACS)$. As per the C-metric analysis, $I_C (MOACS, NSGA-II)$ is the ratio of the number of solutions of NSGA-II (which are weakly dominated by solutions of MOACS) to the total number of MOACS solutions. In the case of scenario-II, $I_C (MOACS, NSGA-II)$ equal to 0.166667 indicates that 16.67% of Pareto front solutions of NSGA-II are dominated by the Pareto front solutions of MOACS, whereas $I_C (NSGA-II, MOACS)$ equal to 0.115333 indicates that 11.53% solutions of MOACS are dominated by solutions of IMOHS. For the same scenario, $I_C (MOACS, IMOHS)$ and $I_C (IMOHS, MOACS)$ equal to 0.22066 and 0.15247, respectively, indicate that on average, 22.06% of solutions of IMOHS are dominated by solutions of MOACS, whereas 15.24% solutions of MOACS are dominated by solutions of IMOHS. It implies that MOACS has better search capability in finding superior Pareto front solutions. From Figures 4 and 5, it is evident that the Pareto set obtained by the MOACS have wider range of functional values, compared to that obtained with NSGA-II and IMOHS. Table 6 shows the results of the Sp-metric values obtained with the three algorithms. Sp-metric with MOACS is less, compared to that obtained with NSGA-II and IMOHS, indicating that MOACS is capable of finding better evenly distributed solutions. From Figures 8 and 9, it can be seen that median values are less with MOACS indicating that the Pareto front solutions obtained have better diversity, compared to NSGA-II and IMOHS. Based on C-metric, Sp-metric results and the Pareto fronts, it can be concluded that MOACS has better search capability in finding evenly distributed superior Pareto front solutions.

**TABLE 5** Convergence metric (C-metric) results

| Avg C-metric | $I_C (MOACS, NSGA-II)$ | $I_C (NSGA-II, MOACS)$ | $I_C (MOACS, IMOHS)$ | $I_C (IMOHS, MOACS)$ |
|--------------|------------------------|------------------------|----------------------|----------------------|
| $S-I$        | 0.1623                 | 0.1301                 | 0.205                | 0.16047              |
| $S-II$       | 0.166667               | 0.115333               | 0.22066              | 0.15247              |

**TABLE 6** Spaced metric (Sp-metric) results

| Avg Sp-metric | MOACS | NSGA-II | IMOHS |
|---------------|-------|---------|-------|
| $S-I$         | 0.547666 | 0.553171 | 0.55935 |
| $S-II$        | 0.552253 | 0.561504 | 0.5603  |
CONCLUSION

This study presents a probabilistic approach for the design of a PV, wind, and biomass-based grid-integrated HRES with ESS for a group of houses (colony) in a small village in Andhra Pradesh (India). The time-varying nature of wind power, solar power, and load are mathematically modelled using probabilistic models and considered for analysis while designing an HRES system. MOACS, IMOHS and NSGA-II algorithms are employed for the sizing, costing, and performance analysis of grid-integrated HRES. From the analysis, it is evident that by including biomass gasifier in HRES, the system becomes more reliable and the unit cost of energy with the optimised sizing configuration is much lesser than the unit cost of energy purchased from the grid. The designed battery size can provide 30 min of backup power during peak load in the absence of grid power and HRES power. It is evident from the C-metric and Sp-metric analysis that MOACS performs better than IMOHS and NSGA-II in finding evenly distributed superior Pareto front solutions. With almost the same ALCC, the MOACS algorithm results in lesser LPSP, compared to the other two algorithms. The sizing configuration obtained in this study is able to serve the total load of a colony in a small village with low cost and low LPS.

NOMENCLATURE

- $f_{pv}$: derating factor
- $ff$: fill factor
- $V_{oc}$: open circuit voltage
- $I_{sc}$: short-circuit current
- $K_{t}, K_{v}$: temperature coefficients of current and voltage
- $C_{mp},{C}'$: shape and scale parameters
- $V_{rated}, V_{ca}, V_{co}$: rated, cut-in, and cut-out velocities
- $n_{mppt}$: mppt factor
- $CV_{wb}$: biomass calorific value
- $\mu$: expectation or mean
- $C_{b}$: total annualised cost of biomass gasifier and power inverter
- $G^{2}$: variance
- $C_{bat}$: nominal battery capacity (Ah)
- $\Delta t$: time step (equal to 1)
- $sdr$: self-discharge rate
- $n_{e}$: efficiency factor
- $SOC$: state of charge
- $P_{l}(t)$: probability of load demand of a given state during any time frame $t$
- $S_{st}$: irradiance at standard test condition (stc)
- $P_{supplied}$: power supplied to the load by the grid-integrated HRES in time frame $t$
- $C_{w}^{stc}$, $C_{v}^{stc}$: annualised salvage cost and replacement cost of a particular component
- $C_{w}$, $C_{v}$: replacement cost of a particular component
- $P_{grid}(t)$: power purchased from grid in time frame $t$
- $m$: number of objectives
- $P_{grid}(t)$: power pumped into the grid in time frame $t$
- $N_{c}$, $P_{req}$: number of units of a particular component power required by the load in time frame $t$
- $n_{rc}, n_{inv}$: rectifier and inverter efficiencies
- $N_{s}, N_{w}, N_{j}$: total number of solar irradiance states, wind speed states, and load states
- $a, b, I_{fo}$: working condition parameters of the battery
- $N_{bio}$: number of biomass gasifiers
- $N_{pv}, N_{w}$: number of PV modules and WTs
- $f_{i}$: inflation and interest rate
- $C_{er}$: unit cost price of purchased energy from the grid
- $C_{es}$: unit cost price of sold energy to the grid
- $\eta$: planning period or the total lifetime of the project
- $N_{st}$: number of series-connected batteries
- $N_{sh}$: number of shunt paths
- $t$: time segment
- $\rho_{bat, sl, max}(t)$: maximum power delivered by battery bank in time frame $t$
- $P_{bio}$: power generated by biomass gasifier
- $t_{w}$: biomass gasifier working hours per annum
- $t_{bio}$: biomass gasifier working hours per day
- $P_{w}$: rated power of WT
- $C_{g}$: total cost of energy sold to the grid
- $C_{ep}$: total cost of energy purchased from the grid
- $C_{per}, C_{act}, C_{b}$: total annualised cost of entire PV panels, WTs, and batteries
- $T_{stc}$: PV module temperature at stc
- $S_{st}, V_{st}, I_{st}$: solar irradiance, wind speed, and load demand in $st$ state for a given time frame $t$
- $C_{w}^{arg}, C_{v}^{arg}$: annualised capital cost and maintenance cost of a particular component
- $C_{w}^{st}$, $C_{v}^{st}$: present value of salvage cost of a component
- $G$: standard deviation
- $P_{dump}$: dump power
- $C_{w}^{m}$: total maintenance cost of a single unit
- $I_{ch}(t)$: charging current of battery in time frame $t$
- $V_{bat}$: terminal voltage of the battery
- $P_{bat, sl, max}(t)$: maximum power can be stored in the battery in a time frame $t$
- $d$: mean of all $d_{j}$

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