Abstract: The utilisation of renewable energy sources (RES) in increasing drastically because of various issues including depletion of fossil fuels, greenhouse gas emissions, climate change and so on. As the power generated from RES is fluctuating in nature, therefore, the appropriate sizing of the hybrid model based on RES is utmost important. In this study, the grey wolf optimisation, a newly developed approach is used for the optimal sizing of the hybrid model. In this work, the optimal design of solar/biomass/biogas/battery-based hybrid system has been carried out to supply continuous electricity to various households of a cluster of villages of Haryana state of India. The results obtained from the proposed model have been compared with harmony search and particle swarm optimisation and found better.

Shahzad et al. [32] developed a grid independent SPV/biomass hybrid energy system to electrify the domestic and agricultural sector of the rural area located in Pakistan. It is concluded that the hybrid system comprising of 10 kW of SPV, 8 kW of biogas with 32 battery storage system and 12 kW converter was economical with NPC of PKR4.48M. The cost of energy (COE) of the proposed system is 5.51 PKR/kWh as compared to grid supply rate of 10.35 PKR/kWh. Asrari et al. [33] presented a case study for economic assessment of renewable energy based hybrid systems for electrification of a rural area in Iran. HOMER software was used to assess the feasibility of different hybrid DG-RES and grid-RES energy systems. Results revealed that RES based power generation in off-grid and grid-connected scenario makes more cost-effective power system. Bhattacharjee and Dey [34] carried out the techno-economic feasibility of grid-connected hybrid PV/biomass system to fulfil the electricity requirement of rice mill of Tripura state in India. The COE was computed as 0.143 $/kWh with a renewable fraction of 91%. Sensitivity analysis was also carried out to find the effects of varying solar irradiation; load demand electricity price and maximum yearly capacity shortage. Padrón et al. [35] also employed HOMER software to develop an optimal hybrid system to provide a reliable power supply to Autonomous reverse osmosis desalination system located at Lanzarote and Fuerteventura.

Balá et al. [36] employed GA to design an optimal hybrid mini-grid system comprising of SPV and DG for a fishing society in an isolated island Sandwip in Bangladesh. Results showed that the major contribution of cost through SPV panels and battery. Mostofi and Sharyeghi [37] optimised the hybrid SPV–wind–fuel cell (FC)–hydro system utilising GA. The results were compared with HOMER and found it more accurate. Kourtoulis and Kolokotsa [38], Yang et al. [39, 40], Nafeh [41], Abdullahrahman and Addoweesh [42], and Tégani et al. [43] also utilised GA for size optimisation of SPV–wind hybrids systems for various rural applications in respect of minimising cost. Further, particle swarm optimisation (PSO) technique was used by Pirhaghshenasvali and Asaei [44] to achieve optimal sizing of system components of off-grid hybrid SPV–battery–wind system while minimising cost. Maleki and Askarzadeh [45] assessed the performance of four different heuristic algorithms namely PSO, Tabu Search (TS), simulated annealing (SA) and HS for optimal sizing of hybrid systems of SPV–wind–FC and SPV–wind–battery in order to...
continuously satisfied the load with minimum total annualised cost. It has been found that PSO provides more promising results.

For remote areas of Iran, the optimal size of a hybrid system consisting of SPV, wind, battery storage was performed by Maleki et al. [46] via comparing different optimisation techniques such as PSO, modified PSO, PSO-RF, PSO-FC, PSO-W, HS, TS and SA. Results indicated that PSO-CF is the most auspicious technique compared to others. Askarzadeh [24] employed diverse harmony search (DHS) based algorithm for optimal sizing of solar arrays and wind turbines of the hybrid system. Chauhan and Saini [47] also utilised DHS algorithm for optimal sizing of SPW/biomass/biogas/micro-hydro/battery hybrid system with and without demand response (DR). Results revealed that a substantial amount of savings in system sizes and costs are attained with DR strategy instead of without DR. Additionally, the various combinations of the hybrid system were optimised in terms of power reliability at 0 and 5% unmet load.

Upadhyay and Sharma [48] performed a comparative analysis of PSO, GA and HOMER techniques for the size optimisation of a hybrid system. It has been found that PSO provides more promising results than GA and HOMER. The same authors also indicated that TLBO performs better followed by BFPSO, PSO and GA. Sensitivity analysis was also performed to inspect the power reliability at 0 and 5% unmet load.

et al. [53] applied the PSO based algorithm for the optimal design of solar arrays. It has been found that PSO provides more promising results than GA.

Based on the literature, it has been revealed that intelligent techniques inspired by natural phenomenon such as a neural network (NN), GA, differential evolution, PSO, ant colony optimisation algorithm, harmony search (HS), BBO and so on are being largely explored by the researchers for optimisation. A GWO approach is a recently developed evolutionary approach proposed by Mirjalili et al. [56]. This approach is motivated by the social behaviour of the grey wolf and its prey methodology. Grey wolves are acme predators’ means they are at the summit of the chain sequence. Grey wolves generally have a preference to live in a crowd or group. The crowd size is on average 2–12. They have a very stern social dominant hierarchy due to their particular interest. GWO approach has many advantages like good computational efficiency along with qualitative results, easy to implement with a few parameters and so on [56]. Therefore, intelligent techniques GWO has been employed for optimal sizing and design of the hybrid system in this paper.

This paper deals with the size optimisation of off-grid and grid connected hybrid system for selected study areas. Based on the availability of RES, configurations are selected to meet the load demand of the selected rural areas. Finally, the size of different generators has been calculated using a recently developed GWO algorithm. Further, the results have been compared with PSO and HS in MATLAB.

2 Description of study area

A case study of the total 533 households of the group of four villages situated at Sonipat district of Haryana state in India has been selected in this paper. The selected area is located at latitude and longitude of 28.98°N and 77.02°E, respectively [57]. The geographical location of the study area is shown in Fig. 1. Due to the variations in temperature during the year have an effect on energy consumption, three seasons; season I (April–July), season II (August–November) and season III (December–March) have been considered in this study. The average daily energy demand of the study area has been calculated as 2997.58, 2357.98, 1286.149 kWh/day during seasons I–III, respectively. Furthermore, the potential of RES such as solar radiation, biogas and biomass has been estimated based on the collected data. It has been found that mean daily radiation of this location is 5.26 kWh/m²/day. Biogas of 820.24 m³/day from cattle dung and biomass of 470.19 tons/year from crop residues have been computed in the selected area.

3 Mathematical modelling of hybrid system components

Mathematical modelling is one of the indispensable steps for designing and developing an optimal model and sizing of the hybrid system. Therefore, the mathematical modelling of each hybrid system component is described as follows.

3.1 Solar PV system

PV system composed of PV panels connected in series and parallel. The output power of the PV system (PPV(t)) is evaluated as [38]

\[ P_{PV}(t) = N_{PV} \times V_{OC}(t) \times I_{SC}(t) \times FF \]  

where \( N_{PV} \) stands for the number of PV panels, \( V_{OC}(t) \) and \( I_{SC}(t) \) represent an open-circuit voltage (V) and short-circuit current (A) of SPV panels, respectively, FF defines fill factor. \( V_{OC}(t) \) and \( I_{SC}(t) \) of an SPV panel can be calculated as [38]

\[ V_{OC}(t) = V_{OC,N} - \tau \times (T_{PV}(t) - 25^\circ) \]  

\[ I_{SC}(t) = I_{SC,N} - \zeta (T_{PV}(t) - 25^\circ) \times \frac{Q_{oc}(t)}{1000} \]  

\[ T_{PV}(t) = T_{amb}(t) + \frac{(T_{PV,amb} - 20^\circ)}{800} \times Q_{PV}(t) \]
where $V_{OCS}(t)$ represents open-circuit voltage (V) under standard test conditions (STC), $I_{SCS}(t)$ is short-circuit current (A) under STC. $\tau$ depicts an open-circuit voltage temperature coefficient (V/°C), $\varsigma$ stands short-circuit current temperature coefficient (A/°C), $Q_{PV}(t)$ is global solar irradiance (W/m²) incident on SPV panels, $T_{PV}(t)$ is solar cell operational temperature and $T_{PVnm}(t)$ is nominal temperature of solar cell in °C, respectively, $T_{amb}(t)$ is an ambient temperature (°C).

Further, the FF of the SPV panel is computed as

$$\text{Fill factor (FF)} = \frac{V_{mpp} \times I_{mpp}}{V_{OC} \times I_{SC}}$$

(5)

where $V_{mpp}$ and $I_{mpp}$ depict voltage and current at the maximum power point, respectively.

Finally, energy generated by the PV system ($E_{PV}(t)$) in kWh at hour ‘$t$’ is evaluated as

$$E_{PV}(t) = P_{PV}(t) \times \Delta t$$

(6)

where $\Delta t$ represents the time step considered as 1 h in this work.

### 3.2 Biomass generator (BMG) system

The power generated by the BMG system ($P_{M}(t)$) at hour ‘$t$’ is estimated using the following equation [59]:

$$P_{M}(t) = \frac{Q_{AM} \times F_{M} \times \eta_{M} \times 1000}{365 \times 860 \times H_{M}}$$

(7)

where $Q_{AM}$ denotes yearly available biomass (tons/yr). $F_{M}$ stands for the calorific value of biomass (4015 kcal/kg). $\eta_{M}$ stands for overall conversion efficiency from biomass to electricity of BMG system (20%). $H_{M}$ denote operating hours per day of BMG system.

Finally, energy generated by BMG system ($E_{M}(t)$) at hour ‘$t$’ has been evaluated using the following equation:

$$E_{M}(t) = P_{M}(t) \times \Delta t$$

(8)

### 3.3 Biogas generator (BG) system

The output power ($P_{G}(t)$) of the BG system is estimated using the following equation [26]:

$$P_{G}(t) = \frac{Q_{G} \times F_{G} \times \eta_{G}}{860 \times H_{G}}$$

(9)

where $Q_{G}$ represents the availability of biogas per day (m³/day), $F_{G}$ is biogas calorific value (4700 kcal/m³), $\eta_{G}$ is overall conversion efficiency from biogas to electricity production (28%). $H_{G}$ represents operating hours of BG per day.

Finally, the energy generated ($E_{G}(t)$) by BG system at hour ‘$t$’ has been evaluated as

Fig. 1 Geographical map of the study area [58]


\[ E_{c}(t) = P_c(t) \times \Delta t \]  

(10)

### 3.4 Battery system

Sometimes, the energy generated from RES (\( E_{gen}(t) \)) may or may not be capable to fulfil the hourly load demand (\( E_L(t) \)) and that needs a suitable size of the battery bank. A comprehensive study of the battery charging and discharging states is summarised as

- When hourly generated power is more than load demand, i.e. \( E_{gen}(t) > E_L(t) \), then the extra amount of energy will be stored in the battery. During charging state, the battery capacity can be obtained as follows:

\[ E_b(t) = (1 - \gamma) \times E_b(t-1) + [E_{XW}(t) + E_{XM}(t) + E_{XD}(t) + E_{XPV}(t)] \times \eta_{bh} \]  

(11)

where \( \gamma \) denotes the self-discharging rate of battery at hour \( t \); \( E_b(t) \) denotes the amount of energy stored in the battery in kWh. \( E_{XW}(t), E_{XM}(t), E_{XD}(t) \) and \( E_{XPV}(t) \) represent the amount of excess energy generated by PV, wind, BMG and BG system after meeting the load demand, respectively, (kWh) and \( \eta_{bh} \) denotes charging efficiency.

- When \( E_P(t) > E_{gen}(t) \), then the amount of deficit energy will be supplied by the battery. During discharging state, the battery capacity can be evaluated using the following equations:

\[ E_d(t) = E_b(t) - [E_{B}(t) + E_{bd}(t) + E_{Cd}(t)] - [E_{PV}(t) \times \eta_{inv}] \]  

(12)

\[ E_{Cd}(t) = E_{bd}(t) - [E_{B}(t) + E_{bd}(t) + E_{Cd}(t)] \]  

(13)

where \( \eta_{inv} \) and \( \eta_{bh} \) are discharging efficiency of battery and inverter efficiency, respectively. \( E_{Cd}(t) \) is an unmet demand that is not fulfilled by RES (kWh).

### 3.5 Utility grid

In the first state, demand is more than generation and battery available storage; the deficit energy will be purchased from the grid and can be obtained as follows:

\[ E_{DG}(t) = E_{D}(t) - [E_{B}(t) + E_{bd}(t) + E_{Cd}(t)] + [E_{PV}(t) + (E_{bd}(t) - E_{imax})] \times \eta_{inv} \]  

(14)

where \( E_{DG}(t) \) denotes deficit energy to be purchased from the grid (kWh) and \( E_{imax} \) denotes minimum values of battery storage capacity.

In the second state, demand is less than the generation and the battery bank is fully charged, the excess energy will be sold to the grid that can be computed using the following equation:

\[ E_{GS}(t) = [E_{B}(t) + E_{bd}(t) + E_{Cd}(t)] + [E_{PV}(t) - (E_{Bmax} - E_{bd}(t))] \times \eta_{inv}] \]  

(15)

where \( E_{GS}(t) \) represents excess energy to be sold to the grid (kWh) and \( E_{Bmax} \) is the maximum value of battery storage capacity.

### 4 Economical parameters of hybrid system components

In this work, the net present cost (NPC) has been considered for the economic analysis of the hybrid system. Therefore, mathematical expressions for the NPC of individual system components have been developed as.

#### 4.1 PV panels

In this work, the project lifetime has been taken equal to the lifetime of PV panels. Further, solar irradiance acts as a fuel to generate electricity, which is free of cost. Therefore, replacement and fuel costs will be zero. Thus, the NPC of PV panels (\( NPC_{PV} \)) involves capital cost (\( C_P \)), operation and maintenance (O&M) cost (\( OM_{PV} \)) and salvage values (\( SV_{PV} \)) only and are computed as

\[ NPC_{PV} = C_P + OM_{PV} - SV_{PV} \]  

(16)

The capital cost of PV panels has been calculated as

\[ C_P = N_{PV} \times \psi_{PV} \times P_{panel} \]  

(17)

where \( \psi_{PV} \) represents an initial cost of individual PV panel ($/kW). \( P_{panel} \) represents the power of one PV panel (kW/panel).

Further, O&M cost (\( OM_{PV} \)) of PV panels has been evaluated using the following equation:

\[ OM_{PV} = \eta_{PV} \times N_{PV} \times P_{panel} \times \sum_{i} \left[ \frac{1 + \kappa_{PV} \times i}{1 + R} \right] \times P_{panel} \]  

(18)

where \( \eta_{PV}, \kappa_{PV}, R \) represent O&M cost, escalation rate and interest rate of PV panels, respectively, \( \psi \) is the project lifetime in years.

The salvage value, i.e. the resale value of PV panels (\( SV_{PV} \)) after project lifetime has been determined using the following equation:

\[ SV_{PV} = \epsilon_{PV} \times N_{PV} \times \left[ \frac{1 + \lambda}{1 + R} \right] \times P_{panel} \]  

(19)

where \( \epsilon_{PV} \) is the resale price of PV panel ($/kW) after completing their life and \( \lambda \) is an inflation rate (0.05).

#### 4.2 BMG system

The NPC of BMG system (\( NPCM \)) is evaluated by considering capital cost (\( C_M \)), the net present value of O&M cost (\( OMC_M \)), salvage value (\( SV_M \)) with fuel cost (\( F_M \)) and is given as [25]

\[ NPCM = C_M + OMC_M + F_M - SV_M \]  

(20)

\[ C_M = P_M \times \psi_M \]  

(21)

where \( \psi_M \) is the initial cost of the BMG system ($/kW). \( P_M \) denotes the generated power of the BMG system (kW). Further, the net present value of O&M cost of BMG system has been calculated as follows:

\[ OM_M = \eta_{OM} \times P_M \times \sum_{i} \left[ \frac{1 + \kappa_{OM} \times i}{1 + R} \right] + \eta_{OM} \times P_{AM} \]  

\[ \times \sum_{i} \left[ \frac{1 + \zeta_{AM} \times i}{1 + R} \right] \]  

(22)

where \( \eta_{OM} \) and \( \eta_{OM} \) denote yearly fixed and variable O&M cost of BMG system, respectively. \( P_{AM} \) represents the yearly working power of BMG system in kW/year. \( \kappa_{OM} \) denote the escalation rate of BMG system (0.075).

Further, the net present value of resale of the BMG system (\( SV_M \)) has been obtained using the following equation:

\[ SV_M = \epsilon_M \times P_M \times \left[ \frac{1 + \lambda}{1 + R} \right] \]  

(23)

where \( \epsilon_M \) denotes the cost of resale of BMG system ($/kW). By considering the biomass fuel cost and yearly biomass needed, the net present value of fuel cost (\( F_M \)) has been calculated by
\[ F_M = \xi_M \times F_{MR} \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_M^i}{1 + R} \right)^{\frac{\mu}{P_{MR}}} \]  

where \( \xi_M \) denotes the biomass fuel cost ($/ton); and \( F_{MR} \) represents yearly biomass needed (ton/year).

### 4.3 BG system

Based on the same pattern of BMG system, the NPC of the BG system (NPC\(_G\)) has been computed as

\[ \text{NPC}_G = C_G + \text{OM}_G - \text{SV}_G + F_G \]  

where the capital cost of the BG system is given as

\[ C_G = P_G \times \psi_G \]  

where \( \psi_G \) denotes the initial cost of the BG system ($/kW). \( P_G \) is generated power by the BG system (kW). Further, the net present value of O&M cost of BG system is computed as follows:

\[ \text{OM}_G = \sigma_G \times P_G \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_G^i}{1 + R} \right)^{\frac{\mu}{P_{BG}}} + \sigma_G \times P_{BG} \times 5, 10, 15, 20 \]  

where \( \sigma_G \) and \( \psi_G \) are yearly fixed and variable O&M cost of BG system, respectively. \( P_{BG} \) denotes yearly working power of BG system in kWh/year. \( \zeta_G \) is an escalation rate of BG system (0.075).

Further, the net present value of resale of the BG system (SV\(_G\)) has been obtained as

\[ \text{SV}_G = \varepsilon_G \times P_G \times \left( \frac{1 + \lambda}{1 + R} \right)^{\frac{\mu}{P_{BG}}} \]  

where \( \varepsilon_G \) denotes the resale price of the BG system ($/kW). \( P_G \) represents the power of BGs (kW).

By considering the biogas fuel cost and yearly biogas needed, the net present value of fuel cost (F\(_G\)) has been calculated by

\[ F_G = \xi_G \times F_{BG} \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_G^i}{1 + R} \right)^{\frac{\mu}{P_{BG}}} \]  

where \( \xi_G \) and \( F_{BG} \) represent biogas fuel cost ($/m\(^3\)) and the annual amount of biogas required in a year, respectively.

In the case of BG, the net present value of revenue (RE\(_G\)) generated from the organic manure is obtained as

\[ \text{RE}_G = \phi_G \times d_G \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_G^i}{1 + R} \right)^{\frac{\mu}{P_{BG}}} \]  

where \( \phi_G \) and \( d_G \) are the cost of produced manure ($/ton) and the annual amount of manure produced (ton/year), respectively.

### 4.4 Battery

The NPC of the battery bank (NPC\(_B\)) includes capital cost (\( C_B \)), O&M cost (OM\(_B\)), replacement cost (RP\(_B\)), salvage value (SV\(_B\)) and can be evaluated as

\[ \text{NPC}_B = C_B + \text{OM}_B + \text{RP}_B - \text{SV}_B \]  

\[ C_B = N_B \times \psi_B \]  

\[ \text{OM}_B = \sigma_B \times N_B \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_B^i}{1 + R} \right)^{\frac{\mu}{P_{MR}}} \]  

where \( \psi_B \) is the cost of one battery ($). \( \sigma_B \) and \( \zeta_B \) denote annual O&M cost ($/year) and escalation rate (0.075) of batteries, respectively. \( \xi_B \) denotes the resale value of one battery ($).

In this study, the life of the battery (\( \mu_B \)) has been assumed as 5 years, which is less than the project lifetime of 25 years. Therefore, the battery needs to be replaced after every 5 years. The number of replacements of the battery (\( N_B \)) is calculated as

\[ N_B = \frac{\mu_B}{\mu_B} - 1 \]  

The net present value of replacement cost of the battery is evaluated as

\[ \text{RP}_B = N_B \times \psi_B \times \sum_{i=1}^{5, 10, 15, 20} \left( \frac{1 + \zeta_B^i}{1 + R} \right)^{\frac{\mu}{P_{BG}}} \]  

### 4.5 Inverter

The NPC of the inverter (NPC\(_\text{inv}\)) has been evaluated as

\[ \text{NPC}_{\text{inv}} = C_{\text{inv}} + \text{OM}_{\text{inv}} + \text{RP}_{\text{inv}} - \text{SV}_{\text{inv}} \]  

where \( C_{\text{inv}} \), \( \text{OM}_{\text{inv}} \), \( \text{RP}_{\text{inv}} \) and \( \text{SV}_{\text{inv}} \) represent a capital cost, O&M cost, replacement cost and salvage value of inverter, respectively.

\[ C_{\text{inv}} = P_{\text{inv}} \times \psi_{\text{inv}} \]  

\[ \text{OM}_{\text{inv}} = \sigma_{\text{inv}} \times P_{\text{inv}} \times \sum_{i=1}^{\eta} \left( \frac{1 + \zeta_{\text{inv}}^i}{1 + R} \right)^{\frac{\mu}{P_{\text{inv}}}} \]  

\[ \text{SV}_{\text{inv}} = \varepsilon_{\text{inv}} \times P_{\text{inv}} \times \left( \frac{1 + \lambda}{1 + R} \right)^{\frac{\mu}{P_{\text{inv}}}} \]  

where \( \psi_{\text{inv}} \) is the initial cost of the inverter ($/kW). The lifetime of inverter assumed as 10 years is less than the project lifetime (25 years). Thus, the net present value of replacement cost is

\[ \text{RP}_{\text{inv}} = P_{\text{inv}} \times \psi_{\text{inv}} \times \sum_{i=1}^{5, 10, 15, 20} \left( \frac{1 + \zeta_{\text{inv}}^i}{1 + R} \right)^{\frac{\mu}{P_{\text{inv}}}} \]

### 4.6 Grid sale and purchase capacity

In the grid-connected scenario, the net present value of selling price (\( C_{GS} \)) and purchasing (\( C_{GP} \)) of electricity from or to the grid has been determined using the following equations:

\[ C_{GS} = \theta_{GS} \times E_{GS} \times \sum_{i=1}^{\eta} \left( \frac{1 + e_G^i}{1 + R} \right)^{\frac{\mu}{P_{GS}}} \]  

\[ C_{GP} = \theta_{GP} \times E_{GP} \times \sum_{i=1}^{\eta} \left( \frac{1 + e_G^i}{1 + R} \right)^{\frac{\mu}{P_{GP}}} \]  

where \( \theta_{GS} \) and \( \theta_{GP} \) are unit cost of sale and purchase of electricity to or from the grid ($/kWh), respectively.

Finally, the COE of the proposed hybrid system has been obtained as

\[ \text{COE} = \frac{\text{NPC} \times E_{PS}}{E_{AD} + C_{GS}} \]  

where \( E_{AD} \) is an annual energy demand (kWh/year). \( C_{RS} \) is a capital recovery factor of the hybrid system and can be evaluated as

\[ SV_B = \varepsilon_B \times N_B \times \left( \frac{1 + \lambda}{1 + R} \right)^{\frac{\mu}{P_{BG}}} \]
\[ C_{RS} = \frac{R(1 + R)^\beta}{R(1 + R)^\beta - 1} \quad (45) \]

5 Objective function and constraints

This research aims to minimise the NPC of the system and is defined as

\[ \text{Min} . \ NPC \]

\[ \text{NPC} = \text{NPC}_{PV} + \text{NPC}_M + \text{NPC}_G + \text{NPC}_B + \text{NPC}_{inv} - C_{ES} + C_{GP} \quad (46) \]

This NPC is to be minimised subject to the system components’ limits and boundary constraints as described in the following sections.

5.1 Upper and lower limits on the number of system components

In the proposed system, the size of system components, i.e. \( N_{PV}, N_B, P_M \) and \( P_G \) may vary to meet the load demand. Therefore, the upper and lower limits of these components are defined as

\[ N_{PV} = \text{Integer}, \quad N_{PV}^{\text{Min}} \leq N_{PV} \leq N_{PV}^{\text{Max}} \quad (47) \]

\[ N_B = \text{Integer}, \quad N_B^{\text{Min}} \leq N_B \leq N_B^{\text{Max}} \quad (48) \]

\[ P_G = \text{Integer}, \quad P_G^{\text{Min}} \leq P_G \leq P_G^{\text{Max}} \quad (49) \]

\[ P_M = \text{Integer}, \quad P_M^{\text{Min}} \leq P_M \leq P_M^{\text{Max}} \quad (50) \]

5.2 Storage limits on battery

To operate the battery securely, the minimum and maximum capacities of battery bank storage system have been considered as one of the constraints and is expressed as

\[ E_{B\text{\text{bmin}}} \leq E_H(t) \leq E_{B\text{\text{bmax}}} \quad (51) \]

where \( E_{B\text{\text{bmin}}} \) and \( E_{B\text{\text{bmax}}} \) denote, respectively, minimum and maximum values of battery storage capacity that can be computed using the following equations [41]:

\[ E_{B\text{\text{bmax}}} = \frac{N_B \times V_B \times Q_b}{1000} \times Q_{b\text{\text{bmax}}} \quad (52) \]

\[ E_{B\text{\text{bmin}}} = \frac{N_B \times V_B \times Q_b}{1000} \times Q_{b\text{\text{bmin}}} \quad (53) \]

where \( V_B \) is a voltage of the battery (V), \( Q_b \) is the capacity of the battery (Ah), \( Q_{b\text{\text{bmin}}} \) and \( Q_{b\text{\text{bmax}}} \) define the minimum and maximum state of charge of batteries, respectively.

5.3 Power reliability constraint

Loss of power supply probability (LPSP) has been taken as power reliability constraint in the present work. When load demand exceeds the available generation, the user suffers from non-availability of electricity. Accordingly, LPSP is computed [38] by the following equation:

\[ \text{LPSP} = \sum_{t=1}^{t=n} \frac{\text{Unmet load for a year}}{\text{Total load for a year}} \quad (54) \]

5.4 Land requirement

To consider social and environmental concerns, the land needed for the development of the hybrid system (\( L_I \)) has been taken in the optimisation as

\[ L_I = \sum_{K=1}^{K=N_{ES}} L_K \times Z_K \quad (55) \]

where \( L_K \) denotes land needed for installation of 1 kW of the \( k \)th RES in \( m^2/kW \), \( Z_K \) is the optimal size of the \( k \)th RES, \( N_{ES} \) is number of RESs considered in the proposed hybrid system. The land needed for the design of 1 kW of each renewable energy based system is given in Table 1.

### Table 1 Land needed for different hybrid system components [59]

| Renewable energy based system | Land needed, m²/kW |
|------------------------------|-------------------|
| SPV system                   | 30                |
| BG system                    | 144               |
| BMG system                   | 90.20             |

6 GWO approach

In this optimisation approach, the population is categorised into four groups such as alpha (\( \alpha \)), beta (\( \beta \)), delta (\( \delta \)) and omega (\( \omega \)). \( \alpha \) wolves are known to be a leading wolf and are most accountable for making decisions about the dormant place, hunting and all other tricks. \( \beta \) wolves are next to \( \alpha \) wolves in making help in supervisory or other group activity. \( \beta \) wolves admire the \( \alpha \) wolves but give the order to other wolves, which are low in the chain of command. Basically, \( \beta \) wolves play the role of consultant to \( \alpha \) wolves and discipliner for the whole group. Further, \( \delta \) plays a character of scapegoat. It may emerge that \( \delta \) wolves are not very important in the whole group, but the whole group faces internal combat and grief in the absence of \( \delta \) wolves. \( \alpha, \beta, \delta \) and \( \omega \) wolves gives guidance to other wolves, i.e. \( \omega \) towards promising area of the search space. Further, the hierarchy of \( \alpha, \beta, \delta \) and \( \omega \) wolves is shown in Fig. 2.

To mathematical model the social behaviour of grey wolves, while designing the GWO algorithm, \( \alpha \) is considered to be the fittest solution. \( \beta \) and \( \delta \) are assumed as second and third best solutions, respectively. \( \omega \) consists of the remaining candidate solution.

To perform optimisation, three main steps of hunting, searching for prey, encircling or trapping and attacking prey are used. Encircling or trapping behaviour of grey wolves for prey during hunting is computed using the following equations [60]:

\[ G = |A \times X_P(t) - X_{GW}(t)| \quad (56) \]

\[ X_{GW}(t + 1) = X_P(t) - \epsilon G \quad (57) \]
where $G$, $A$, and $e$ indicate the coefficient vectors, $X_D$ represents the position vector of pray, $X_{IW}$ indicates the position vector of the grey wolf. $t$ denotes the current iteration.

Further, $e$ and $A$ are evaluated using the following equations:

$$e = 2q \cdot R_1 - q$$  \hspace{1cm} (58)

$$A = 2 \cdot R_2$$  \hspace{1cm} (59)

where a component of $q$ diminishes linearly in the range of 2 to 0 during iterations. $R_1$ and $R_2$ represent random vectors that permit the wolves to arrive at any position between the prescribed points.

A grey wolf can update its position based on the position of the prey. By setting the value of $e$ and $A$ vectors, the different places in the region of the best agent can be attained concerning the current position. Hence, the position of the grey wolf inside the space around the prey in any random location can be updated by using (56) and (57).

Grey wolves can figure out their prey. The hunting is generally led by $\alpha$. Sometimes, $\beta$ and $\delta$ also play a role in hunting. However, there is no idea of the location of the prey in the abstract search space. Thus to mathematical model the hunting behaviour, we assume that $\alpha$, $\beta$ and $\delta$ wolves have good estimates for the potential location of prey. Therefore, the first three best solutions are recorded to lead the other search agents ($\omega$) to update their position based on the position of the best search agent. The operation of the score and position of $\alpha$, $\beta$ and $\delta$ wolves (first three search agents) can be done using the following equations:

$$H_\alpha = [A_1 \cdot X_{\alpha} - X]$$  \hspace{1cm} (60)

$$H_\beta = [A_2 \cdot X_{\beta} - X]$$  \hspace{1cm} (61)

$$H_\delta = [A_3 \cdot X_{\delta} - X]$$  \hspace{1cm} (62)

where $A_1$, $A_2$, $A_3$ indicate the random vectors.

The position vector of prey concerning $\alpha$, $\beta$ and $\delta$ wolves can be computed as

$$X_\alpha = X_{\alpha} - e_1 \cdot (H_\alpha)$$  \hspace{1cm} (63)

$$X_\beta = X_{\beta} - e_2 \cdot (H_\beta)$$  \hspace{1cm} (64)

$$X_\delta = X_{\delta} - e_3 \cdot (H_\delta)$$  \hspace{1cm} (65)

where $X_{\alpha}$, $X_{\beta}$, $X_{\delta}$ represent the positions of $\alpha$, $\beta$ and $\delta$ wolves, respectively. $e_1$, $e_2$, $e_3$ indicate the random vectors and $t$ defines the number of iterations.

The best position can be computed by taking mean of $\alpha$, $\beta$ and $\delta$ wolves as given below:

$$X(t + 1) = \frac{X_{\alpha} + X_{\beta} + X_{\delta}}{3}$$  \hspace{1cm} (66)

Searching for prey indicates exploration capability while attacking the prey represents exploitation capability, $e$ is a random value from $- 2q$ to $+ 2q$. During optimisation, it diminishes from 2 to 0. When $|e|$ is less than one, grey wolves are enforced to attack the prey. The random values of $e$ are used to enforce the search to move away from the prey. When $|e|$ is greater than one, the members of the population are forced to deviate from the prey.

In a nutshell, the search process initiates by creating a random population of grey wolves (candidate solutions) in the GWO approach. During the iterations, $\alpha$, $\beta$ and $\delta$ wolves estimate the possible location of prey. Each candidate solution updates its distance from the prey. Parameter $e$ is condensed from 2 to 0 to put emphasis on exploration and exploitation. Candidate solutions tend to move away from the prey if $|e|$ is greater than 1 and converge to the prey if $|e|$ is less than 1. In the end, the GWO algorithm is terminated by fulfilling the final criterion. Further, the flowchart of the GWO approach is depicted in Fig. 3.

### 7 Techno-economic input parameters

The techno-economic input parameters are required for the optimal sizing of the selected hybrid system which is given as

#### 7.1 Electrical load demand (kW)

The hourly electrical load demand during seasons I–III of the selected area is demonstrated in Fig. 4 and also provided in Table 2. The maximum load demand in seasons I–III has been computed as 217.59, 217.59 and 146.59 kW, respectively.

#### 7.2 Mean solar irradiance (kWh/m²/day)

The monthly average solar irradiance for the given area is depicted in Fig. 5 and also provided in Table 3. It is evident that the highest solar irradiance of 6.74 kWh/m²/day is available in May, whereas the lowest solar irradiance of 3.53 kWh/m²/day is available in December.

#### 7.3 Average ambient temperature (°C)

The average ambient temperature of the study area is depicted in Fig. 6 and also given in Table 4. It is evident that the ambient temperature varies from 4 to 43°C during the year.

#### 7.4 Scheduling of BMG and BG

In this work, BG and BMG are scheduled for operation during peak load hours in each season and are demonstrated in Figs. 7 and 8, respectively.

#### 7.5 Parameters of GWO algorithm

To optimise the objective function, the algorithm parameters have been set as $itr_{\text{max}} = 100$, Run = 30.

#### 7.6 Cost parameters of hybrid system components

Economical parameters comprise of capital cost, O&M cost, salvage value and fuel cost of individual system components are given in Table 5. Also, the specification of different system components has been provided in Table 6.

#### 7.7 Project parameters

In this work, the life duration of the proposed system has been taken as 25 years. Annual real interest rate of 11% is considered.

### 8 Result and discussion

In this study, an attempt has been made to get the optimal design and sizing of the hybrid system considering the different types of RESs. At first, three configurations of the hybrid system in off-grid mode have been considered as

(a) Configuration I: Biomass–SPV–battery-based hybrid energy system.

(b) Configuration II: Biogas–SPV–battery-based hybrid energy system.

(c) Configuration III: Biomass–biogas–SPV–battery-based hybrid energy system.

All off-grid configurations are optimised using GWO algorithm and compared in terms of technical and economical concerns and found the most suitable. Further, the best-off grid configuration is compared with a grid-connected hybrid system and found the most optimal solution. Finally, the result has been compared with HS and PSO optimisation techniques.

#### 8.1 Optimisation results of off-grid configuration

The considered off-grid configurations are successfully simulated to meet the full hourly demand of the area for 0% unmet load by the GWO algorithm in MATLAB. After hourly simulation, the
optimisation result of off-grid configuration has been presented in Table 7.

From Table 7, it is observed that the configuration I has least NPC and COE. The most optimal off-grid configuration consists of 234.53 kW PV array, 164 kW biomass system, 513.6 kWh battery storage and 100 kW converter. The NPC and COE are computed as $807,692.30, $0.118/kWh, respectively.

Fig. 3 Flowchart of GWO approach
8.2 Optimisation results of considered grid-connected configuration

The objective function (NPC) has been optimised using the GWO algorithm in MATLAB. After hourly simulation, the optimum sizes obtained are given in Table 8.

The most optimal configuration comprised of 235 kW PV panels, 10 kW biomass system, 55 kW biogas system, 28.8 kWh battery bank storage and 100 kW converter. The total NPC and COE are estimated as $636,923.07 and 0.088 $/kWh, respectively.

8.3 Comparison between off-grid and grid connected configurations

8.3.1 NPC and COE: The grid-connected configuration has been compared with best off-grid configuration in terms of NPC and COE. From Tables 7 and 8, it is evident that the grid-connected configuration has less NPC and COE compared to off-grid. Therefore, the grid-connected configuration is better in terms of economical concerns.

8.3.2 Total land requirement: It has been found that the total land requirement for installation of grid-connected configuration and off-grid configuration is 13,451 and 21,828.7 $m^2$, respectively. Therefore, there is a saving of 8377.7 $m^2$ in land use are obtained with grid-connected configuration.

Based on the obtained results, grid-connected hybrid system consisting of SPV, wind, biomass, biogas, and battery is proposed for selected sites. Further, the schematic diagram of the proposed system is depicted in Fig. 9.

8.4 Comparison of different optimisation algorithms

Finally, a comparison of different optimisation algorithms has also been carried out to obtain the most optimised results for the best configuration.

The results of the proposed GWO algorithm are compared with HS and PSO for 0% LPSP and given in Table 9. It has been revealed that GWO provides more optimised results compared to HS and PSO.

Also, some other parameters are also compared and demonstrated in Table 10 and evident that GWO performs better.

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**Table 2** Hourly load demand for selected seasons of the study area (kW)

| Time, h | Season I | Season II | Season III |
|---------|----------|-----------|------------|
| 01:00   | 104.084  | 50.784    | 3.566      |
| 02:00   | 104.084  | 50.784    | 3.566      |
| 03:00   | 104.084  | 50.784    | 3.566      |
| 04:00   | 104.084  | 50.784    | 3.566      |
| 05:00   | 115.936  | 62.636    | 14.666     |
| 06:00   | 92.751   | 39.451    | 14.666     |
| 07:00   | 91.093   | 91.093    | 67.108     |
| 08:00   | 91.295   | 91.295    | 63.99      |
| 09:00   | 90.495   | 90.495    | 63.99      |
| 10:00   | 81.346   | 81.346    | 67.99      |
| 11:00   | 145.741  | 145.741   | 14.816     |
| 12:00   | 140.581  | 140.581   | 118.336    |
| 13:00   | 136.146  | 136.146   | 108.741    |
| 14:00   | 107.266  | 53.966    | 107.8      |
| 15:00   | 105.61   | 170.01    | 118.98     |
| 16:00   | 170.01   | 170.01    | 118.98     |
| 17:00   | 167.37   | 167.37    | 118.5      |
| 18:00   | 156.51   | 156.51    | 107.64     |
| 19:00   | 177.712  | 177.712   | 22.194     |
| 20:00   | 177.712  | 177.712   | 22.194     |
| 21:00   | 164.92   | 111.62    | 63.502     |
| 22:00   | 160.582  | 107.282   | 60.064     |
| 23:00   | 104.084  | 50.784    | 3.566      |
| 00:00   | 104.084  | 50.784    | 3.566      |

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*Fig. 4 Hourly load demand of the study area*
Further, the convergence curve of PSO, HS and GWO for NPC is shown in Fig. 10. It is revealed from Fig. 10 that GWO provides an optimal solution before ten iterations. However, HS and PSO converged to a fixed value after 90 iterations that show GWO converges faster than other optimisation approaches.

8.5 Component wise breakdown of annual energy generation

The percentage wise contribution of different renewable energy technologies in annual power generation is shown in Fig. 11. PV array produced the highest amount of electricity of 450,570 kWh/year followed by biogas with 15,830 kWh/year and biomass with 12,735 kWh/year.

8.6 Cost wise breakdown of total NPC

The share of the capital cost, O&M cost, fuel cost, salvage value, grid purchase and grid sale in total NPC of the hybrid system are illustrated in Table 11. It is found that the cost of grid purchase has the highest share of $433,692.31 among all the system components.

8.7 Component wise breakdown of total NPC

The share of different components in total NPC is depicted in Fig. 12. It has been found that biomass has a major share of 55% in total NPC followed by PV array with 21%, converter with 10%, biogas with 9% and battery with 5%.

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Table 3 Monthly hourly average solar irradiance data of study area (kWh/m²/day)

| Time, h | January | February | March | April | May | June | July | August | September | October | November | December |
|---------|---------|----------|-------|-------|-----|------|------|--------|-----------|---------|----------|----------|
| 01:00   | 0       | 0        | 0     | 0     | 0   | 0    | 0    | 0      | 0         | 0       | 0        | 0        |
| 02:00   | 0       | 0        | 0     | 0     | 0   | 0    | 0    | 0      | 0         | 0       | 0        | 0        |
| 03:00   | 0       | 0        | 0     | 0     | 0   | 0    | 0    | 0      | 0         | 0       | 0        | 0        |
| 04:00   | 0       | 0        | 0     | 0     | 0   | 0    | 0    | 0      | 0         | 0       | 0        | 0        |
| 05:00   | 0       | 0        | 0     | 0     | 0   | 0    | 0    | 0      | 0         | 0       | 0        | 0        |
| 06:00   | 0       | 0        | 0     | 0     | 0.7 | 13.7 | 18.8 | 7.9    | 0.7       | 0       | 0        | 0        |
| 07:00   | 0       | 0        | 0     | 0     | 15.5| 85.5 | 148.3| 141.9  | 101.2     | 76.4    | 48.3     | 20.2     |
| 08:00   | 0       | 0        | 0     | 0     | 166.6|281.9 |349.8 |289.4   |341.9     |241.9    |234.7     |205.2     |
| 09:00   | 0       | 0        | 0     | 0     | 222.5|372.2 |474   |509.3   |428.1     |402.8    |377.8     |392.3     |
| 10:00   | 0       | 0        | 0     | 0     | 391.1|582   |625.4 |661.9   |570.3     |510.8    |514.6     |541.4     |
| 11:00   | 0       | 0        | 0     | 0     | 536.3|716   |796.1 |785     |688.8     |630.8    |617.5     |658.2     |
| 12:00   | 0       | 0        | 0     | 0     | 645.6|773.1 |838.1 |841.9   |754.3     |682      |672.1     |698.1     |
| 13:00   | 0       | 0        | 0     | 0     | 686.3|800.1 |873.7 |867.2   |789.6     |709.2    |731.5     |734.4     |
| 14:00   | 0       | 0        | 0     | 0     | 640.8|806.8 |843.1 |801.9   |711.9     |664.3    |708.4     |685.6     |
| 15:00   | 0       | 0        | 0     | 0     | 698.1|809.6 |849.7 |854.5   |789.6     |709.2    |731.5     |734.4     |
| 16:00   | 0       | 0        | 0     | 0     | 43.1 |512.3 |585   |632.8   |526.5     |469      |499.6     |470.5     |
| 17:00   | 0       | 0        | 0     | 0     | 258  |335.2 |403.6 |417.7   |381.7     |331.6    |348.9     |308.6     |
| 18:00   | 0       | 0        | 0     | 0     | 100.8|154.3 |205.6 |232.7   |231.3     |217.3    |212.5     |134.3     |
| 19:00   | 0       | 0        | 0     | 0     | 2.7  |14.7  |37.8  |74.9    |93.6      |84.3     |64.3      |13.3      |
| 20:00   | 0       | 0        | 0     | 0     | 0    |0.5   |5.5   |5.3     |0.3       |0        |0         |0         |
| 21:00   | 0       | 0        | 0     | 0     | 0    |0     |0     |0       |0         |0        |0         |0         |
| 22:00   | 0       | 0        | 0     | 0     | 0    |0     |0     |0       |0         |0        |0         |0         |
| 23:00   | 0       | 0        | 0     | 0     | 0    |0     |0     |0       |0         |0        |0         |0         |
| 00:00   | 0       | 0        | 0     | 0     | 0    |0     |0     |0       |0         |0        |0         |0         |
### Table 4  Monthly hourly average ambient temperature data of the study area (°C)

| Time, h | January | February | March | April | May | June | July | August | September | October | November | December |
|---------|---------|----------|-------|-------|-----|------|------|--------|-----------|---------|----------|----------|
| 01:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |
| 02:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |
| 03:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |
| 04:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |
| 05:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 20      | 14       | 12       |
| 06:00   | 10      | 13       | 16    | 23    | 28  | 30   | 30   | 27     | 26        | 22      | 16       | 13       |
| 07:00   | 12      | 14       | 16    | 25    | 28  | 30   | 31   | 28     | 27        | 24      | 18       | 15       |
| 08:00   | 14      | 16       | 18    | 27    | 30  | 32   | 32   | 29     | 28        | 26      | 20       | 17       |
| 09:00   | 16      | 18       | 20    | 29    | 32  | 34   | 33   | 30     | 28        | 22      | 18       | 16       |
| 10:00   | 18      | 20       | 22    | 31    | 34  | 36   | 34   | 31     | 31        | 30      | 24       | 20       |
| 11:00   | 20      | 22       | 24    | 33    | 36  | 38   | 35   | 32     | 32        | 31      | 25       | 21       |
| 12:00   | 22      | 24       | 26    | 35    | 38  | 40   | 36   | 33     | 33        | 32      | 26       | 22       |
| 13:00   | 24      | 26       | 28    | 37    | 38  | 42   | 37   | 35     | 34        | 33      | 27       | 23       |
| 14:00   | 26      | 28       | 30    | 39    | 40  | 42   | 38   | 37     | 35        | 34      | 28       | 24       |
| 15:00   | 24      | 26       | 28    | 37    | 38  | 40   | 37   | 35     | 34        | 33      | 27       | 23       |
| 16:00   | 22      | 24       | 26    | 35    | 36  | 38   | 36   | 33     | 33        | 32      | 26       | 22       |
| 17:00   | 20      | 22       | 24    | 33    | 34  | 36   | 35   | 32     | 32        | 30      | 25       | 21       |
| 18:00   | 18      | 20       | 22    | 31    | 32  | 34   | 34   | 31     | 31        | 28      | 24       | 20       |
| 19:00   | 16      | 18       | 20    | 29    | 30  | 33   | 33   | 30     | 30        | 26      | 22       | 18       |
| 20:00   | 14      | 16       | 18    | 27    | 28  | 32   | 32   | 29     | 28        | 24      | 20       | 16       |
| 21:00   | 12      | 14       | 16    | 25    | 28  | 31   | 31   | 28     | 26        | 22      | 18       | 14       |
| 22:00   | 10      | 13       | 16    | 23    | 28  | 30   | 30   | 27     | 25        | 20      | 16       | 12       |
| 23:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |
| 00:00   | 8       | 13       | 16    | 23    | 28  | 30   | 29   | 26     | 25        | 19      | 14       | 10       |

**Fig. 6** Monthly hourly average ambient temperature of the study area

**Fig. 7** Schedule of BMG system
8.8 Grid purchase and grid sale

The total cost of grid purchase and revenue generated from grid sale in the considered configuration are calculated as $433,692.31 and $55,792.31, respectively. Further, the annual energy purchase and sold through utility grid is 330,111 and 46,006 kWh/year, respectively. Also, the season-wise energy purchased and sold to the utility grid are indicated in Table 12.

It has been observed that the hybrid system purchases more energy in the season I followed by seasons II and III. It is due to higher energy demand during season I. Further, grid sale and grid purchase are less in season III compared to seasons I and II due to less energy demand.

8.9 Season wise battery input and output power

Season-wise battery input and output power are given in Table 13. It has been observed that the battery input power is higher in season III compared to seasons I and II due to high energy demand.

9 Conclusion

In this study, the optimal sizing of grid-connected solar/biomass/biogas/battery-based hybrid system has been carried out for rural areas located in Haryana state (India). Different configurations in the off-grid and grid-connected scenario are considered and compared using the GWO algorithm. Grid-connected configuration comprising of solar/biomass/biogas/battery found as the best configuration for the study area. Based on the hourly simulation, the optimum size of the hybrid system in grid scenario for study
area has been obtained as 235 kW PV array, 10 kW biogas system, 55 kW biomass system, 28.8 kWh battery bank storage and 100 kW converter. The total NPC and COE are estimated as $636,923.07 and 0.088 $/kWh, respectively. Further, results have also been compared with PSO and HS and found more appropriate. The land use for installation of the proposed hybrid system for the study area is 13,451 m². The present study may be useful for the development of a hybrid system for the other similar areas and helpful in fulfilling the Indian Government mission of providing 24 × 7 power to all.
### Table 12: Season wise grid purchase and sold energy

| Season | Grid purchase energy, kWh | Grid sale, kWh |
|--------|--------------------------|----------------|
| season I | 123,715.30              | 34,895         |
| season II | 113,390                 | 31,230         |
| season III | 25,382                  | 11,656         |
| total, kWh/year | 330,111               | 77,441         |

### Table 13: Season wise battery input and output power

| Season | Battery input power, kWh | Battery output power, kWh |
|--------|--------------------------|---------------------------|
| season I | 25,382                   | 172,350                   |
| season II | 24,055                  | 116,220                   |
| season III | 28,209                  | 49,410                    |
| total, kWh/year | 77,646               | 337,980                   |

### Table 11: Cost wise breakdown of NPC

| S. No. | Indicator          | Value, $ |
|--------|--------------------|----------|
| 1      | capital cost       | 123,715.30 |
| 2      | O&M cost           | 103,086.15 |
| 3      | fuel cost          | 42,526.15  |
| 4      | salvage value      | 9705.54   |
| 5      | revenue from grid sale | 55,792.31 |
| 6      | cost of grid purchase | 433,692.31 |

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