# Optimal Economic Sizing of Stand-Alone Hybrid Renewable Energy System (HRES) Suiting to the Community in Kurukshetra, India

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**Abstract:** This paper, utilizing different evolutionary optimization algorithms, investigates on optimal economic sizing of a stand-alone (HRES) for a community in Kurukshetra, India. In the process of optimization, numbers of different subsystems viz. photovoltaic (PV), wind turbine (WT), battery, and diesel engine generator (DEG) are considered as variables of interest with the net present cost, payback period, computational cost, and levelized cost of energy (LCOE) as the performance measures. From analysis of the results, it is established that the solution provided by Whale optimization algorithm (WOA) turns out to be the best in terms of LCOE, net present cost, and also the payback period compared to the solutions provided by particle swarm optimization (PSO), Gravitational search algorithm (GSA), Grey wolf optimizer (GWO) and the combined PSO-GSA algorithms. The relative performance of these algorithms is compared and contrasted qualitatively as well as quantitatively highlighting the research findings not only in respect of optimal sizing of stand-alone HRES from economic perspective, as per the problem statement, but also in terms of their other performance measures such as convergence time, computational cost, and complexity. The simulations are executed in MATLAB software.

**Keywords:** Economic sizing, HRES, LCOE, Stand-alone, Optimization algorithm

## 1. INTRODUCTION

Owing to the depleting crude oil and the associated environmental problems [1], there is tremendous growth in the renewable energy technologies, more so in recent years. Energy generated from renewable energy sources (RESs) [2] is intermittent in nature and hence the need to form a HRES by way of using conventional energy sources like DEG, and energy storage systems such as batteries [3]. In HRES, reliability of the system is better and if operated in grid connected mode it gets even better owing to flexibility of both ways power flow between HRES and grid, while if HRES is operating in stand-alone mode, energy storage systems such as battery have all important role in maintaining reliability of system [3]. Size optimization is an important factor in HRES. Both classical and evolutionary optimization algorithms have been put to use to solve the sizing problem of HRES. In classical algorithms, derivative information is required which leads to large computational time while evolutionary optimization algorithms are derivative free

and require less computational time. In recent years, the trend of using evolutionary optimization algorithms is more than classical methods because of the efficiency [3].

The contemporary research on size optimization of stand-alone HRESs is summarized in Table I giving system constituents, objective functions, methodology used, optimal indicators and decision variables. O. Nadjemi et.al. [4] proposed cuckoo-search algorithm with the objective of determining optimal sizing and for energy management of HRES where one of the important observations was that cuckoo-search gives better accuracy, less computational time than PSO. S. Sanajaoba [5] carried out the economic and technical assessments on the proposed hybrid system comprising solar, wind, and battery. Findings indicate that loss of load probability (LOLP) lies between 0 to 0.03 with the cost getting increased with increase in LOLP.

A. Abdelkader et al. [6] put to use the genetic algorithm (GA) for optimally sizing the HRES consisting of PV and wind sources. The result of the study showed that loss of power supply probability (LPSP) is minimum

with total cost of energy. C. Li et al. [7] presented a scheduling problem of hybrid system investigating the economic and environmental aspects. Analysis of the results showed that operational cost is decreased by 11.9%, pollution emission is decreased by 17.4% and renewable energy factor got increased from 50% to 100%. H. Mohammed et al. [8] optimized the power generation of hybrid system in Bretange, France by utilizing PSO to minimize the energy cost. In this study, overall cost is reduced with high accuracy and speed.

S. Moghaddam et al. [9] presented a stand-alone hybrid system for optimizing the reliability and net present cost for Zanjan city, Iran. In this, the result showed that crow search algorithm is better than other methods. M. Shivaie et al. [10] proposed an autonomous model hybrid system for reliability constrained-cost effectiveness by using a bat search algorithm wherein the total cost of the HRES was 13594.4862 $.

X. Yin et al. [11] designed a model of a hybrid system in which a hydropower station is used as a compensator

for power system. The findings in this study are that by using whale optimization technique, hydropower can very well coordinate with PV and wind power. P. Suhane, S. Rangnekar [12] put to use ant colony optimization for optimally deciding sizing of HRES consisting of solar, wind, and battery systems. The results are compared and contrasted against other methods to ensure the compatibility and efficiency of the proposed hybrid system.

As per available literature, the problem of optimum sizing and economic analysis in HRES is an important aspect of study and thus this study also focuses on optimum sizing and economic analysis in the stand-alone HRES using evolutionary optimization algorithms. The structure of this paper includes introduction in section 1 with section 2 putting forth mathematical modelling of all components in detail and section 3 describing the load and resources assessment. Section 4 explains different evolutionary optimization algorithms used in this study whereas section 5 is devoted to the discussion on results and lastly section 6 concludes the research findings.

TABLE I.          LITERATURE REVIEW SUMMARY

| Ref. | Year | Operating Mode | Energy Sources | Objective Function | Optimal Indicators | Decision variables | Method |
|------|------|----------------|----------------|--------------------|--------------------|--------------------|--------|
| [4] | 2017 | Stand-alone | PV, WT, battery | System cost minimization | Economic, technical, environmental, reliability | PV generator area, WT rated power, nominal capacity of battery | Cuckoo search |
| [5] | 2019 | Stand-alone | Battery, Solar, wind | Minimize cost of energy | reliability, economic | No of photovoltaic panel, WT and battery | Firefly algorithm |
| [6] | 2018 | Stand-alone | Supercapacitor, PV, WT, battery | Minimization of total cost of energy | Economic, reliability | No of PV panel, wind turbine, storage system, SOC | (GA) |
| [7] | 2019 | Stand-alone | Thermal generator, hydro generator, PV, wind | Minimize economic function | Economic, environment | Power balance, volume, time and capacity | Grey wolf optimization (GWO) |
| [8] | 2019 | Stand-alone | PV, wind, battery, tidal | Minimize cost of energy | Economic | State of charge, size of the system | PSO |
| [9] | 2019 | Stand-alone | PV, wind, battery | Maximize net present cost | Economic | No of PV panels, WTs, battery capacity, PV angle, wind turbine height | Crow search algorithm (CSA) |
| [10] | 2019 | Stand-alone | PV, WT, DEG, battery | Minimize total system cost | Economic, technical | No of PV panels, WTs, and battery storage | Bat search algorithm (BA) |
| [11] | 2019 | Stand-alone | PV, wind, hydro generator | Maximize the annual total power generation | Technical | Water balance, discharge flow and power | Whale optimization (WO) |
| [12] | 2015 | Stand-alone | Solar, wind, battery | Total cost minimization | Economic | No of solar panels, WTs, and batteries | Ant colony Optimization (ACO) |

## 2. MATHEMATICAL MODELING OF SYSTEM COMPONENTS

Figure 1 shows the schematic of the HRES in stand-alone mode, as used in this study. The various subsystems are explained hereunder.
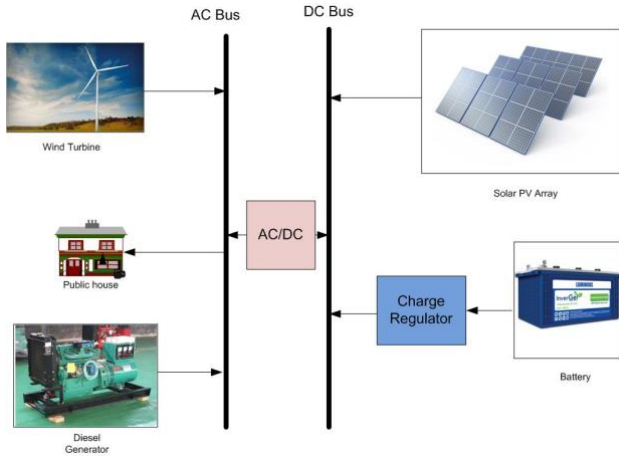


Figure 1. Schematic of the HRES

### 2.1 Solar PV

Solar PV output power, as a function of solar irradiance, can be computed as follows [13]:

$$P_{pv}(t)= P_{npv}.(G/G_{ref})[1+k_t (T_c-T_{ref})] \qquad (1)$$

$$T_c = T_a+[(NOCT-20)/800]*G \qquad (2)$$

Where, $P_{npv}$ signifies the rated output power in KW of PV module; G being the solar irradiance ($KW/m^2$) incident on PV; $G_{ref}$ represents reference incident irradiance (1000 $W/m^2$); $k_t$ represents temperature coefficient in %/$^0C$; $T_c$ indicates PV module temperature in $^0C$; $T_{ref}$ signifies the PV module temperature under standard test conditions; the nominal operating cell temperature (NOCT) being the cell temperature at ambient temperature of 20 $^0C$ and prescribed by the module manufacturer, wind speed being 1 m/s, whereas solar irradiance is 800 $W/m^2$. Here, NOCT is 45±2 $^0C$, temperature coefficient is 0.052 %/$^0C$, cell efficiency is 17%, and an area of $1m^2$.

Total net present cost ($TNPC_{pv}$) of PV module comprises capital cost ($CC_{pv}$), and operation & maintenance cost ($OM_{pv}$). Cost on account of replacement is not accounted for due to the lifetime of PV panel being 20 years. $TNPC_{pv}$ can be expressed as follows:

$$TNPC_{pv} = CC_{pv} + OM_{pv} \qquad (3)$$

$$CC_{pv} = PR_{pv}*N_{pv} \qquad (4)$$

$$OM_{pv} = OM * N_{pv} *[(1-1/(1+i)^n)/i] \qquad (5)$$

Where, $PR_{pv}$ and OM are, respectively, the price and operation & maintenance cost of each PV module, $N_{pv}$ represents No. of PV modules, i signifies interest rate and n represents lifetime of the project. Table II gives the parameters of PV module.

TABLE II.    PARAMETERS OF PV MODULE [14]

| Parameters | Value |
|---|---|
| Operating temperature in $^0C$ | 47 |
| Efficiency | 17% |
| Temperature coefficient | -38%/$^0C$ |
| $V_{oc}$ | 47.5V |
| $I_{sc}$ | 9.64A |
| Temperature coefficient | $-3.7x10^{-3}$ /$^0C$ |
| Rated output power | 1 KW |
| Life time | 25 Years |
| Capital cost* | Rs. 80,000/KW |
| Replacement cost* | Rs. 80,000/KW |
| OM cost* | Rs. 800/KW/year |

* As derived from local Indian manufacturer and distributors and expressed in Indian currency- Rupees (Rs.)

### 2.2 Wind turbine

Output power of WT is computed as under [15] –

$$P_W = \begin{cases} 0 & v < vci \\ P_r \left(\frac{v^3-vci^3}{vr^3-vci^3}\right) & vci < v < vr \\ P_r & vr < v < vco \\ 0 & v > vco \end{cases} \qquad (6)$$

Where, $P_w$ and $P_r$, respectively, represent the output and rated powers of WT in $W/m^2$; v, $v_{ci}$, $v_r$, $v_{co}$ are the instantaneous, cut-in, rated, and cut-out wind speeds, respectively in m/sec.

Electrical power output delivered by the WT is as follows

$$P_{wind\_out}= P_w*U_w \qquad (7)$$

Where,

$U_w$ is the conversion efficiency of WT

Total net present cost of WT ($TNPC_{WT}$) includes capital cost ($CC_{WT}$), operation & maintenance cost ($OM_{WT}$). Due to the lifetime of WT being 20 years, the cost on account of replacement is not required. $TNPC_{WT}$ is as follows:

$$TNPC_{WT} = CC_{WT} + OM_{WT} \qquad (8)$$

$$CC_{WT} = PR_{WT}*N_{WT} \qquad (9)$$

$$OM_{WT}= OM * N_{WT} *[(1-1/(1+i)^n)/i] \qquad (10)$$

Where, $PR_{WT}$ is the price of each WT, OM represents operation and maintenance cost of WT, $N_{WT}$ represents number of WTs, i being the interest rate, n signifies

project life period. Table III provides technical specifications of WT.

| Parameters | Value |
|---|---|
| Rated capacity | 5 KW |
| Rated wind speed | 12 m/s |
| Cut-in speed | 3 m/s |
| Cut-out speed | 25 m/s |
| Hub height | 24 m |
| Blade diameter | 6.4 m |
| Life time | 25 Years |
| Capital cost* | Rs. 1,14,000/KW |
| Replacement cost* | Rs. 1,14,000/KW |
| Operation &Maintenance cost* | Rs. 6,000/year |

* The price shown is derived from local Indian manufacturer and distributors and expressed in Indian currency- Rupees (Rs.)

### 2.3 Battery bank

Capacity of battery bank is computed as under [16]-

$$BC = (E_L*AD)/(\eta_{inv}*\eta_{batt}*DoD) \qquad (11)$$

Where, $E_L$, AD, DoD, $\eta_{inv}$, and $\eta_{batt}$, respectively, represent, in respect of battery, the average daily load energy (kWh/day), daily autonomy, depth of discharge, inverter efficiency, and battery efficiency.

Total net present cost of battery ($TNPC_{BT}$) comprises capital cost ($CC_{BT}$), OM cost ($OM_{BT}$), and replacement cost ($RC_{BT}$) because lifetime of the battery is 10 years. $TNPC_{BT}$ is as follows:

$$TNPC_{BT} = CC_{BT} + OM_{BT} + RC_{BT} \qquad (12)$$

$$CC_{BT} = PR_{BT}*N_{BT} \qquad (13)$$

$$OM_{BT}= OM * N_{BT} *[(1-1/(1+i)^n)/i] \qquad (14)$$

$$RC_{BT} = RC*N_{BT}/(1+i)^{10} \qquad (15)$$

Where, $PR_{BT}$ is the price of each battery, OM signifies operation and maintenance cost of battery, $N_{BT}$ represents number of batteries, i being interest rate while n represents project lifetime. Table IV provides the technical specifications of the battery bank.

| Parameters | Value |
|---|---|
| Standard voltage | 12 V |
| Standard capacity | 3.12 KWh |
| Maximum capacity | 260 Ah |
| DoD | 80% |
| Roundtrip efficiency | 90% |

| | |
|---|---|
| State of charge (SoC) | 20% |
| Life time | 10 Years |
| Capital cost* | Rs. 27,000/KW |
| Replacement cost* | Rs. 23,000/KW |
| OM cost* | Rs. 800/year |

* The price shown is derived from local Indian manufacturer and distributors and expressed in Indian currency- Rupees (Rs.)

### 2.4 Diesel engine generator

DEG serves as the power backup of HRES wherein fuel cost constitutes the main cost which depends upon the amount of fuel used and fuel price. Consumption of fuel per hour is calculated as follows [19]-

$$F_{DEG}(t) = \alpha_{DEG} \times P_{DEG} + \beta_{DEG} \times P_{DEG}(t) \qquad (16)$$

Where,

$\alpha_{DEG}, \beta_{DEG}$ = consumption factors in L/KWh

$P_{DEG}$ = nominal rating of DEG

$P_{DEG}(t)$ = DEG production at each hour

Fuel consumption cost ($FC_{DEG}$) can be obtained by multiplying the fuel price in that hour. Annual fuel cost ($FC_{DEG\_annual}$) can be obtained by summation of hourly fuel costs.

$$FC(t) = FP_{DEG} \times F_{DEG}(t) \qquad (17)$$

$$FC_{DEG\_annual} = \sum_{t=0}^{8760} FC(t) \qquad (18)$$

In addition to fuel cost, Total net present cost of DEG ($TNPC_{DEG}$) comprises capital cost ($CC_{DEG}$), OM cost ($OM_{DEG}$), and replacement cost ($RC_{DEG}$) because lifetime of DEG is 5 years. $TNPC_{DEG}$ is as follows:

$$TNPC_{DEG} = CC_{DEG} + OM_{DEG} + RC_{DEG} \qquad (19)$$

$$CC_{DEG} = PR_{DEG}*N_{DEG} \qquad (20)$$

$$OM_{DEG}= OM * N_{DEG} *[(1-1/(1+i)^n)/i] \qquad (21)$$

$$RC_{DEG} = RC*N_{DEG}/(1/(1+i)^5 + 1/(1+i)^{10} +1/(1+i)^{15}) \qquad (22)$$

Table V provides the technical details of DEG.

| Parameters | Value |
|---|---|
| Nominal power | 4 KW |
| Life time | 15,000 h |
| $\alpha_{DEG}$ | 0.08145 l/h/KW |
| $\beta_{DEG}$ | 0.246 l/h/KW |
| Capital cost* | Rs. 60,000 /KW |
| Replacement cost* | Rs. 60,000 /KW |
| OM cost* | Rs. 1,500 /KW |
| Fuel Cost* | Rs. 55/l |

## 3. LOAD AND RESOURCES ASSESSMENT

### 3.1 Load estimation

The energy load includes residential loads (LED, fans, TV, refrigerator) and agriculture loads (water irrigation pump, grass cutting machine). Figure 2 explains the load on hourly basis. Residential load is at its peak during morning and evening times owing to most of the domestic activities being carried out around this time because of most of the family members being at home whereas load demand is minimum during night hours because all family members are asleep. Agriculture load mainly consists of irrigation pumps that are mostly used in daytime and during evening hours, grass cutting machines are in operation. Therefore, there is no effect on the peak agriculture load demand.
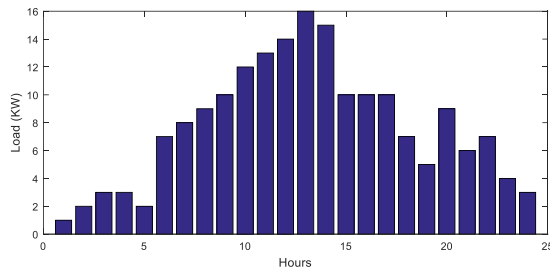


Figure 2. Hourly load profile

### 3.2 Solar and wind resources

For the selected location, solar radiation is available throughout the year with average annual value being 5.33 KWh/m$^2$/day. During summer, sun is available for 10-12 hours and during winter, sun is available for 6-8 hours. Solar radiation data is obtained from NASA website. Figure 3 depicts hourly pattern of solar radiation throughout the year at the specific location.

Hourly variation in wind speed is also obtained from NASA website with anemometer at 50-meter height. Figure 4 shows the hourly variation in wind speed over a period of one year for the specific location whereas, figure 5 depicts the hourly ambient temperature profile throughout the year.
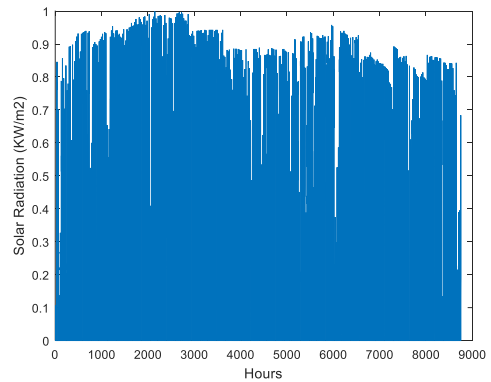


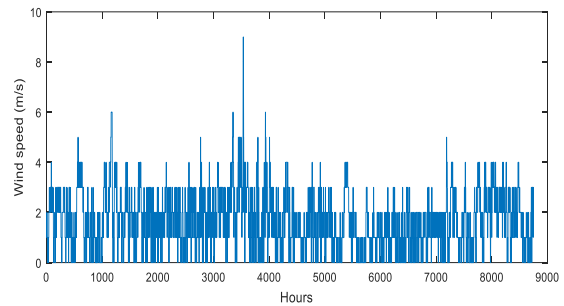Figure 3. Hourly annual solar radiation



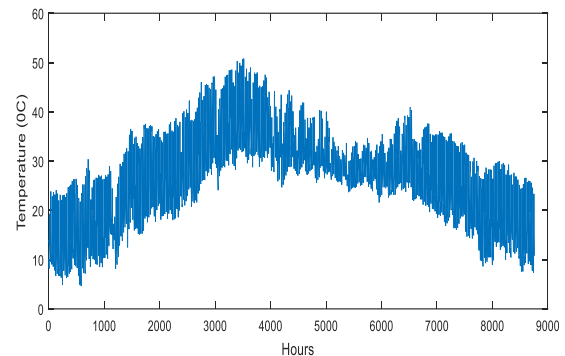Figure 4. Hourly annual wind speed at 50-meter height



Figure 5. Ambient temperature throughout the year

## Objective function

The objective function for this study is inspired by the genesis that power supply from the HRES must be reliable and to be made available at minimum possible cost. Here, the LCOE is taken as the objective function while the No. of PV modules, WTs, batteries, and DEGs are considered the decision variables. The objective function under the constraints is described as under:

$$\text{LCOE} = \text{CRF} \times (\text{TNPC}_{pv} + \text{TNPC}_{WT} + \text{TNPC}_{DEG} + \text{FC}_{DEG\_annual} + \text{TNPC}_{BT}) / \sum_{t=1}^{8760} P_L(t)$$

Where,

CRF = capital recovery factor

CRF= $i(1+i)^n / (1+i)^{n-1}$

$P_L$ (t) = load at t hour

Constraints are as follows:

$0 \leqslant N_{PV} \leqslant N_{max}$

$0 \leqslant N_{WT} \leqslant N_{max}$

$0 \leqslant N_{BT} \leqslant N_{max}$

$0 \leqslant N_{DG} \leqslant N_{max}$

Where, $N_{PV}$, $N_{WT}$, $N_{BT}$, and $N_{DG}$ represent, respectively, the numbers of PV modules, WTs, batteries, and DEGs.

**Energy Management**

Here, PV modules and WTs serve as the main power sources meaning thereby that load demand is first met by their output powers and overall energy management is exercised in three scenarios.

In first scenario: $P_{PV}$ (t) + $P_{WT}$ (t) > $P_L$ (t)/$u_{inv}$, the generation is more than demand and this excess power, computed as below, gets utilized for charging the batteries.

Pch (t) = {$P_{PV}$ (t) + $P_{WT}$ (t)}- ($P_L$ (t)/$u_{inv}$)

Where, $u_{inv}$ is the inverter efficiency

In second scenario: $P_{PV}$ (t) + $P_{WT}$ (t) < $P_L$ (t)/$u_{inv}$, the load is more than generation and consequently, the amount of deficit power is supplied by the battery and is computed as follows-

$P_{dch}$ (t) = ($P_L$ (t)/$u_{inv}$) − {$P_{PV}$ (t) + $P_{WT}$ (t)}

In third scenario: the load is more than generation and battery does not suffice in supplying the deficit power, then DEG gets started and supplies the remaining power.

Figure 6 explains the strategy of energy management pictorially.
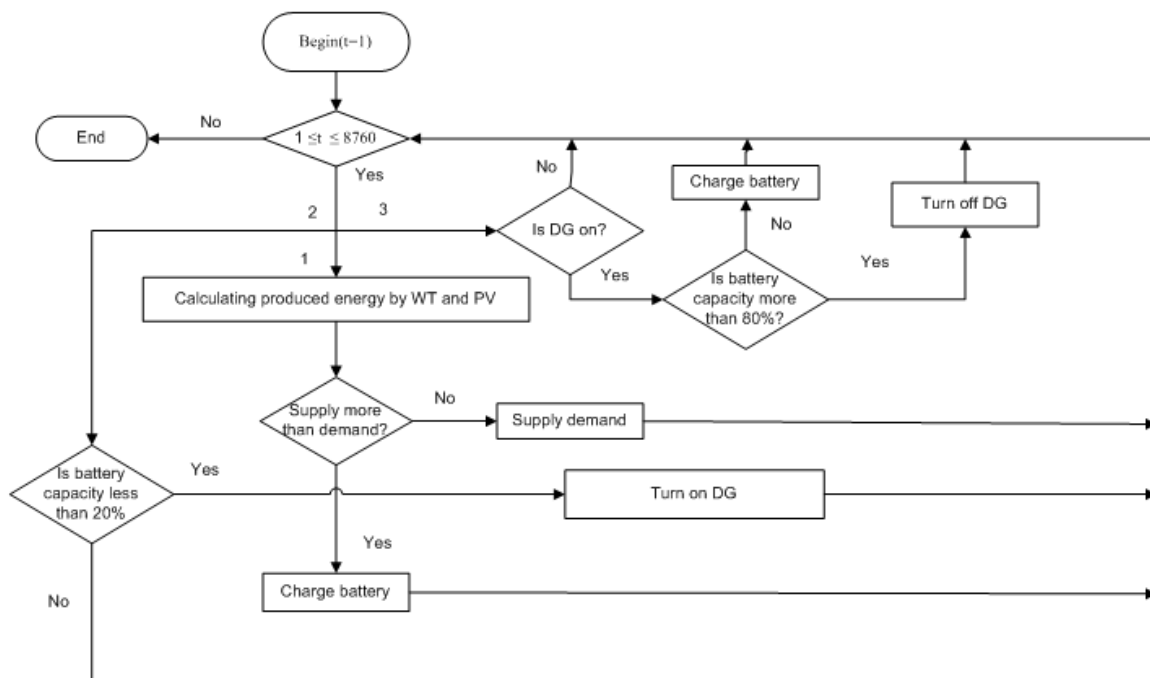


Figure 6. Energy management strategy

### 4. OPTIMIZATION ALGORITHMS

#### PSO

PSO, inspired by the swarm behavior in nature, is one of the most well-known metaheuristic algorithms put forth for the first time in 1995 by kennedy and Eberhart. Here, the location is updated for each particle by velocity which is used to find out the global best and own best. Following

are the four steps involved in execution of the algorithm [21, 22]:

1.  Generating the initial population

2.  Evaluating every particle for its fitness

3.  Updating individual and global bests

4.  Updating velocity and position of every particle

Repeating these steps till the terminating criterion is satisfied. Two inner loops are involved in PSO algorithm while iterating through population n, and one outer loop for iteration t. Consequently, the complexity of PSO for the extreme case can be expressed as [23]:

$$O\ (PSO) = O(n^2\ t) \qquad (23)$$

With n being large, even one inner loop can also suffice under certain conditions and therefore, the complexity of the PSO can be expressed as:

$$O\ (PSO) = O(n.t.log(n)) \qquad (24)$$

The flowchart depicting the execution of PSO algorithm is shown in figure 7 with the parameters used given in table VI.
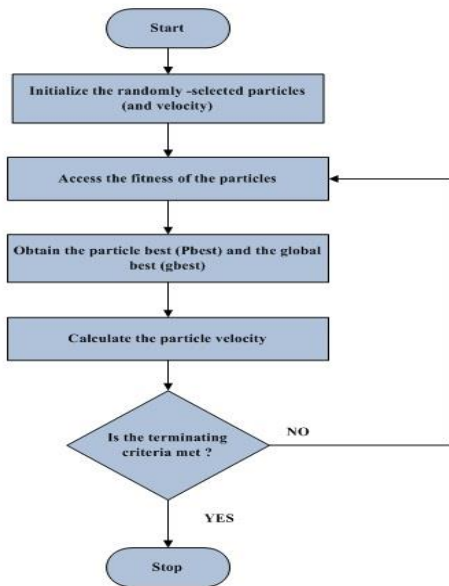


Figure 7. Flowchart of the PSO algorithm

### GSA

This algorithm, inspired by law of gravity, was put forth by Rashedi et.al. in 2009 wherein agents are considered whose performance is evaluated by their masses. Steps involved in the execution of this algorithm are as under [24]:

1. Generating initial population
2. Evaluating the fitness for each agent
3. Updating the G, best and worst of the population
4. Calculating M and a for agent
5. Updating velocity and position

### 6. Updating agent's position

These steps are repeated until stopping criterion is reached. Complexity computation of GSA involves no of solutions n and can be expressed as [25]:

$$O(GSA) = O(n^2) \qquad (25)$$

The flowchart of GSA in figure 8 explains the execution of the algorithm using the parameters as given in table VI.
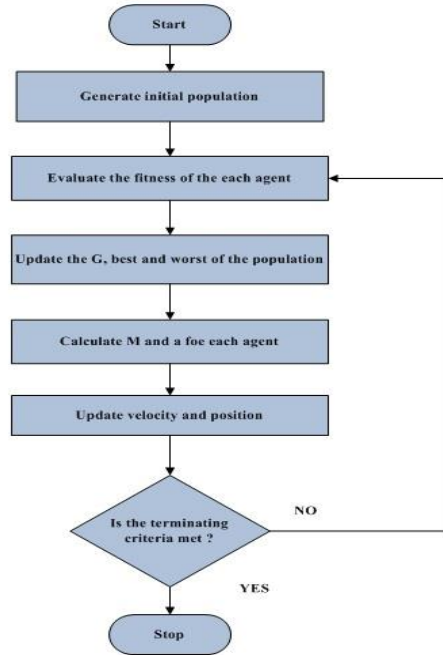


Figure 8. Flowchart of GSA algorithm

### GWO

The GWO was developed by Mirjalili, and Lewis in 2014. The main inspiration of this algorithm comes from social leadership and hunting techniques of grey wolves. In designing GWO, alpha (α) wolves are considered as the best fit solutions, beta (β) and delta (δ) wolves the second and third best solutions. Omega (ω) wolves are the remaining candidate solutions [26]. The complexity computation of the GWO involves initialization ($T_{ini}$), position updation ($T_{upd}$), and fitness evaluations ($T_{eva}$) for the population and for the standard GWO algorithm, having an N-wolf of pack, D-dimensional optimization, and MaxFEs-the maximum number of function evaluations, the complexity is computed as [27]:

$$O(GWO) = T_{ini} + T_{upd} + T_{eva}.MaxFEs = N + (N.D + N).MaxFEs$$
$$= N.(1 + (D+1).MaxFEs \qquad (26)$$

$$O(GWO) = O(N.D.MaxFEs) \qquad (27)$$

The algorithmic steps involved in execution of GWO are shown in the form of flowchart in figure 9 with the parameters used given in table VI.
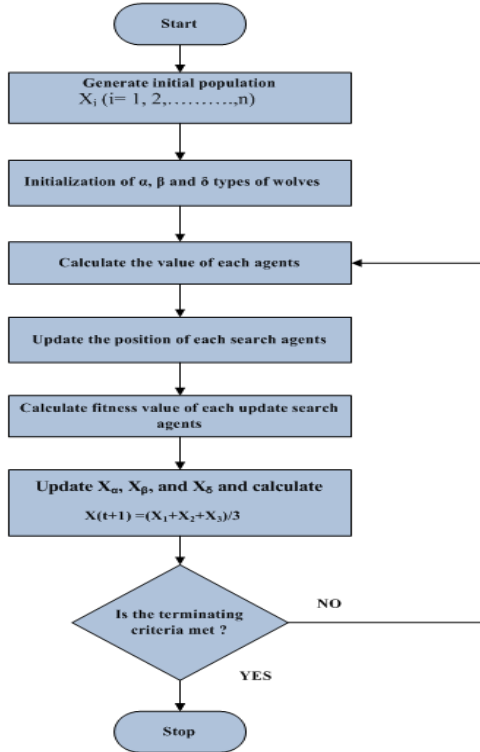


Figure 9. Flowchart of GWO algorithm

### WOA

The WOA is another swarm knowledge based optimization discovered in 2016 by Mirjalili and Lewis [28]. They observed an uncommon chasing technique in the whales' social conduct which is known as the bubble-net hunting strategy. WOA, which mimics hunting strategy of whales, is isolated into three phases: circle-hunting, bubble-net assaulting, and hunting for prey. Computational complexity of WOA [29] is governed by the numbers, respectively, of iterations and universes, and mechanisms of roulette wheel and universe sorting. Each variable in each universe requires the execution of roulette wheel selection over the iterations and is of O (n) or O (log n) depending on the implementation. The overall computational complexity can be computed as:

$$O(WOA)=O(MaxGen*NP*O(fitness)) \qquad (28)$$

Where, MaxGen represents the maximum number of generations, NP signifies the population size, and O(fitness) is application specific.

Flowchart of its execution is shown in figure 10 with the values of the parameters used given in table VI.
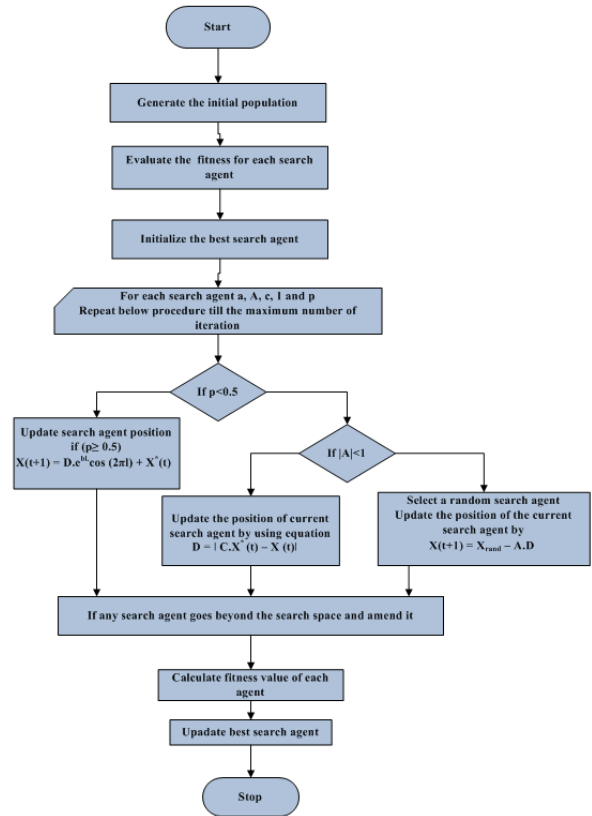


Figure 10. Flowchart of WOA

The parameters, as are used for implementation in this study, of each of these optimization algorithms are given in table VI.

TABLE VI.          PARAMETERS OF OPTIMIZATION ALGORITHMS

| | Parameters | Value |
|---|---|---|
| **PSO** | No of Population | 50 |
| | Iterations | 100 |
| | $w_{max}$ | 0.9 |
| | $w_{min}$ | 0.2 |
| | C1 | 0.5 |
| | C2 | 1.5 |
| **GSA** | No of agents | 50 |
| | Iterations | 100 |
| | ElitistCheck | 1 |
| | Rpower | 1 |
| | alfa | 20 |
| | $G_0$ | 100 |

| GWO | Search Agents | 50 |
| | Iterations | 100 |
| | a | Decrease linearly from 2 to 0 |
| PSO-GSA | No of Population | 50 |
| | Iterations | 100 |
| | C1 | .5 |
| | C2 | 1.5 |
| | alfa | 20 |
| | $G_0$ | 100 |
| WOA | Search Agents | 50 |
| | Iterations | 100 |
| | a | Decrease linearly from 2 to 0. |

## 5.   SIMULATION RESULTS AND DISCUSSION

Simulation runs are executed with the optimization algorithms for optimal sizing in respect of LCOE and also capturing other performance parameters. Figures 11 and 12 show the output powers of the solar PV and WT throughout the year. Figure 13 (a) depicts the typical scenario of a winter day load and power (of all sources and storage systems) pattern including dump load. From the figure it is evident that during the period of first 11 hours, solar PV output is almost negligible and hence the load is supplied by WT(s) and DEG(s) with the excess power going to the batteries for charging until the batteries reach up to 95% SOC and thereafter excess energy gets diverted to dump load. During the interval of 12-18 hours, output power becomes available from solar PV(s) and hence the load is supplied through solar PV(s) as well.

Likewise, Fig. 13 (b) depicts the typical scenario of a summer day load and power (of all sources and storage systems) pattern including dump load. From the figure it is evident that during the period of first 6 hours, WT(s) and DEG(s) are utilized to maintain power balance between generation and load. During the interval from 8-19 hours, solar PV also starts generating power and thus contributes in supplying the load. In the event of solar PVs and WTs not being sufficient in meeting the load demand, the deficit power is drawn from the batteries. During 2-6 hours, the excess power goes to the dump load.
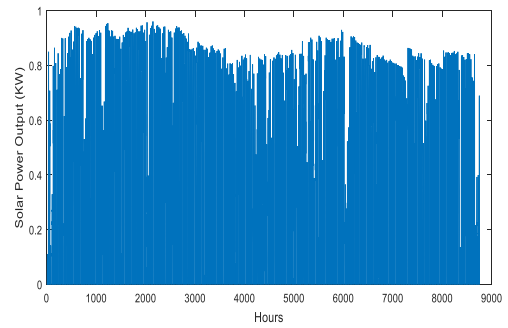


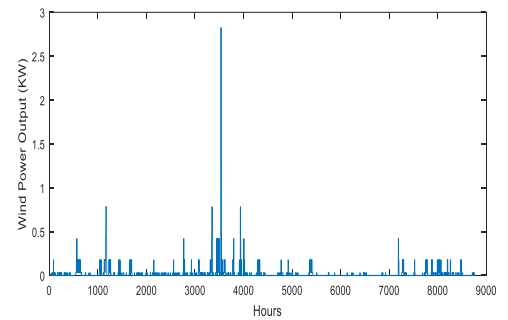Figure 11. Solar power output spread over a year
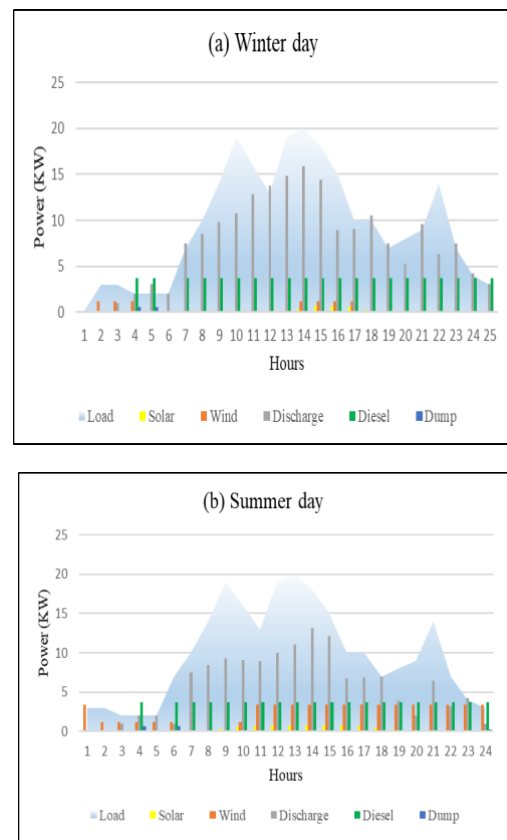


Figure 12. Wind power output spread over a year



Figure 13. Load vs. power for a typical (a) winter day (b) summer day

Figure 14 shows the convergence graphs of the different optimization algorithms with WOA converging the fastest. The quantitative relative performance of these algorithms is presented in table VII wherefrom it is clearly brought out that WOA turns out to be the best performing algorithm and provides not only the least LCOE but also the least total net present cost besides the payback period being minimum compared to other algorithms. However, the computational cost is a bit higher compared to the combined use of PSO-GSA, although it is much lower in comparison to the other two algorithms and slightly lower than GWO as well. Further, the number of components required is also the least as per the optimal solution provided by WOA as compared to all other algorithms. Table VIII shows the comparison of these algorithms in terms of their advantages and disadvantages.
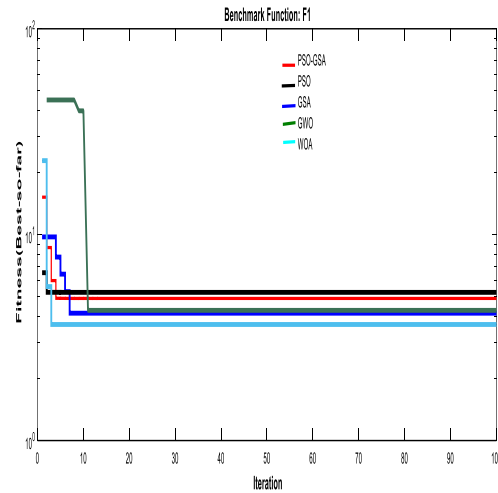


Figure 14. Convergence graph with GSA, PSO, PSO-GSA, GWO, and WOA

TABLE VII.     COMPARATIVE PERFORMANCE OF ALGORITHMS

| Optimization technique | No. of PV | No. of WT | No. of batteries | No. of DG | LCOE (Rs/KWh) | Total net present cost (Rs.) | Computational cost for 1 iteration (sec) | Payback period (years) |
|---|---|---|---|---|---|---|---|---|
| PSO | 39 | 2 | 42 | 1 | 7.78 | 58,55,200 | 91.6 | 11.10 |
| GSA | 29 | 4 | 39 | 1 | 5.50 | 41,27,500 | 76.32 | 10.95 |
| PSO-GSA | 34 | 3 | 36 | 1 | 7.76 | 58,05,400 | 24.99 | 11.10 |
| GWO | 37 | 2 | 36 | 1 | 5.76 | 43,34,450 | 43.3 | 10.98 |
| **WOA** | **32** | **2** | **32** | **1** | **4.98** | **39,98,560** | **40.2** | **10.34** |

**6. CONCLUSION**

The optimal sizing of the HRES in stand-alone mode for

TABLE VIII.     ADVANTAGES AND DISADVANTAGES OF OPTIMIZATION ALGORITHMS

| Algorithm | Advantages | Disadvantages |
|---|---|---|
| PSO | • Convergence time is less | • Computational cost is very high<br>• The performance in terms of the optimal solution is very poor |
| GSA | • The algorithm performs good in respect of LCOE, net present cost, and payback period however, inferior to WOA | • Computational cost is much higher than others however, lesser than PSO |
| PSO-GSA | • Computational cost is very less<br>• Convergence time is less | • The algorithm performs relatively poorly in respect of LCOE, net present cost, and payback period |
| GWO | • Computational cost is relatively less<br>• The algorithm performs good in respect of LCOE, net present cost, and payback period | • Convergence time is fairly large |
| WOA | • The algorithm demonstrates the best performance in respect of LCOE, net present cost, and payback period<br>• Convergence time is the least<br>• Computational cost is very competitive. | • Although very competitive, the computational cost is a little higher than PSO-GSA |

a community in Kurukshetra, India has been established by using the evolutionary optimization algorithms- PSO, GSA, PSO-GSA, GWO, and WOA and their relative performance is also brought out. The number of components, LCOE, total net present cost, payback period, and the computational cost are evaluated as the performance measures for the HRES against which the

algorithms are compared and contrasted. The WOA turns out to be the most effective and provides the best optimal results with least LCOE, total net present cost, less payback period, and the fastest convergence.

As a future scope, the proposed HRES may be investigated for the grid connected mode and also its seamless changeover from grid connected to stand-alone mode and vice-versa employing these algorithms along with suitable control strategies. The outcomes of the extended research can be utilized for possible commissioning and installation of HRES in and around the specific location.

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