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Designing of an optimal standalone hybrid renewable energy micro-grid model through different algorithms

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ABSTRACT

Electricity is regarded as a basic human requirement. Electric demand is met using either the grid (online) or the off-grid (standalone) method. The electrification of loads in remote areas requires high investment costs for extending the transmission system. A standalone Microgrid (MG) system is a low-cost method of supplying electricity to remote areas where a grid connection is not possible. This study concentrates on designing an optimal MG model for rural electrification with different renewable energy resources. The performance of the system is evaluated by considering power system reliability, economic costs, and greenhouse gas emission effects. To obtain the optimal design parameters (i.e., component sizing), different optimization techniques like Particle Swarm Optimization (PSO), Differential Evolution (DE), Manta Ray Foraging Optimization (MRFO), Shuffled Frog-Leaping Algorithm (SFLA), Reptile Search Algorithm (RSA) and RUNge Kutta Optimizer (RUN) are implemented and compared. The goal of these optimization methods is to find the most reliable and cost-effective model.

Introduction

Renewable Energy Sources (RES) such as wind, small hydro, biomass, geothermal and solar are decentralized, modular technologies, with low environmental impact, smaller in size, and have low operational costs. RES is penetrating the power system more than ever due to the above-mentioned characteristics [1,2]. HRES, which consists of Wind Turbines (WT), solar Photo-Voltaic (PV), storage systems, etc., is available and used in remote areas as an off-grid system. The installed capacity of HRES will reach 7059 GW worldwide, covering 49.21% of the total energy demand by 2040 [3].

The capital costs of RES plants will be curtailed in the future due to improved technologies in component production and storage systems. The global price of electricity generated from coal declined by 2%, while wind got 70% and solar 89% cheaper in the decade of 2010–2019 [4]. So utilizing these resources is a promising way to develop a modern power system with the benefits of being economical, reliable, and safe [5].

Based on their connection with the grid, MG operations are classified as grid-connected or standalone. The entity is not connected to the grid, is autonomous in operation, controls, and consumes the energy generated or stored in the MG, in standalone systems. Such a system is preferable for remote regions where extending the grid is not economically feasible. The main demerit of standalone systems is that the RES is stochastic in nature. This disadvantage can be mitigated by combining HRES with Energy Storage Systems (ESS). ESS is used for peak shaving or time-shifting operations, provides a spinning reserve, ancillary services, and storage, and improves power quality and reliability [6].

Economic cost, reliability, and environmental effects are all factors considered in the planning, design, and operation of HRES MG. An optimal combination of HRES components helps to realize these objectives. To find the optimal combination of HRES components, optimization techniques like PSO, DE, SFLA, MRFO, RSA, and RUN are implemented. A step-by-step solution to such optimization techniques is given in [7].

This study investigates the most cost-effective and reliable, HRES options, for supplying electricity to Jarre Village. The contribution of gas emissions from these HRES is also considered and a penalty is introduced for polluting solutions. The objective is to design a 100% reliable system, which further makes the problem, complex and infeasible. Thus it also tests the optimization techniques for their ability to obtain feasible solutions.

The paper is arranged as: section II discusses optimization algorithms, and section III, deals with performance evaluation parameters for HRES. Problem formulation is discussed in Section IV. Section V is the result and discussion part, and the conclusion is the final section of

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the paper.

Algorithms used for HRES Optimization

The algorithms presented in this section are implemented for optimally designing the MG system. The optimization techniques are selected based on the year in which they were introduced, their performance, robustness, etc.

Particle Swarm Optimization (PSO)

PSO tries to imitate the social behavior of birds flocking and was developed by R. C. Eberhart and J. Kennedy (1995) [8]. It is a robust method and has been implemented through different variations [9]. A velocity of a particle for a new iteration, V_{t+1} is modified by using Eq (1).

$$V_{t+1} + 1 = K \times [V_t + c1 \times rand(0,1) \times (pbest - X_{i(t)}) + c2 \times rand(0,1) \times (gbest - X_{i(t)})] \tag{1a}$$

$$K = \frac{2}{|2 - \phi - \sqrt{\phi^2 - 4\phi}|} \tag{1b}$$

The new position X_{t+1} for i^{th} particle are calculated as Eq. (2).

$$Xi(t+1) = Vi(t+1) + Xi(t) \tag{2}$$

where, $X_{i(t)}$, $V_{i(t)}$: current position and velocity of particle; p_{best} and g_{best}: particle and swarm best position; c1, c2: personal and social influence coefficients; $\phi = c_1 + c_2$, $\phi > 4$; K: constriction factor.

Differential Evolution (DE)

Storn and Price introduced DE in 1997 [10]. DE's basic strategy and parameter updating method include mutation, crossover, and selection as explained below: In mutation, a vector termed as mutant vector ($v_{i;G+1}$) is obtained as in Eq. 3:

$$vi;G+1 = xr1;G + F \times (xr2;G - xr3;G) \tag{3}$$

For r1; r2; r3: random indices ∈1; 2;.; NP and ir1 ≠ r2 ≠ r3; F: real and constant factor ∈ [0,2]; G: iteration number.

Crossover introduces increased diversity in perturbed parameter vectors. The trial vector $u_{i;G+1}$, for crossover update is calculated in Eqs. 4 and 5.

$$u_{i;G+1} = (u_{1i;G+1}; u_{2i;G+1};...; u_{Di;G+1}) \tag{4}$$

$$u_{i;G+1} = \begin{Bmatrix} v_{i;G+1} \text{ if } (\text{r and b}(j) \le CR) \text{or } j = \text{rnbr}(i) \\ x_{i;G+1} \text{ if } (\text{r and b}(j) > CR) \text{and } j \ne \text{rnbr}(i) \end{Bmatrix} \tag{5}$$

j = 1, 2,…,D.

A random number generated through 'randb' is used to decide the trial vector content.

In selection, the greedy criterion is used to compare the trial vector to the target vector, $x_{i;G}$. If the trial vector yields a better cost function value than the target vector, then $x_{i;G+1}$ is set to $u_{i;G+1}$; otherwise, the old value $x_{i;G}$ is retained.

Manta Ray Foraging Optimization (MRFO)

MRFO was introduced by Zhao, et al. in 2020. It imitates the behavior of the Manta rays [11]. To update the positions of variables, chain foraging, cyclone foraging, and somersault foraging are applied: The mathematical model for chain foraging can be represented through Eq. 6 and 7.

$$X^d_{i(t+1)} = \begin{Bmatrix} X^d_{i(t)} + r(X^d_{best(t)} - X^d_{i(t)}) + \alpha(X^d_{best(t)} - X^d_{i(t)}) i = 1 \\ X^d_{i(t)} + r(X^d_{i-1(t)} - X^d_{i(t)}) + \alpha(X^d_{best(t)} - X^d_{i(t)}) i = 2, ...N \end{Bmatrix} \tag{6}$$

$$\alpha = 2r\sqrt{|\log(r)|} \tag{7}$$

Where, r: random vector [0,1]; d: dimension; t: current iteration number; $X^d{}_{i\ (t)}$: the ith individual position; $X^d{}_{best(t)}$: a region with a high concentration of plankton; $X^d{}_{i-1\ (t)}$: the position update of ith manta ray; α: weight coefficient.

The mathematical model of cyclone foraging is shown through Eqs. 8 and 9 to extend.

the motion to an n-D space.

$$X^d_{i(t+1)} = \begin{Bmatrix} X^d_{best(t)} + r(X^d_{best(t)} - X^d_{i(t)}) + \beta(X^d_{best(t)} - X^d_{i(t)}) i = 1 \\ X^d_{best(t)} + r(X^d_{i-1(t)} - X^d_{i(t)}) + \beta(X^d_{best(t)} - X^d_{i(t)}) i = 2, ...N \end{Bmatrix} \tag{8}$$

$$\beta = 2e^{r1\frac{T_{\max}-t+1}{T}}\sin(2\phi r1) \tag{9}$$

Where, T_{max}: maximum iterations; β: a weight coefficient; r1: random number [0,1].

A new random position is generated considering the current best in the exploration phase, and is formulated through Eqs. 10 and 11:

$$X^d_{rand} = Lb^d + r(Ub^d - Lb^d) \tag{10}$$

$$X^d_{i(t+1)} = \begin{Bmatrix} X^d_{rand(t)} + r(X^d_{rand(t)} - X^d_{i(t)}) + \beta(X^d_{rand(t)} - X^d_{i(t)}) i = 1 \\ X^d_{rand(t)} + r(X^d_{i-1(t)} - X^d_{i(t)}) + \beta(X^d_{rand(t)} - X^d_{i(t)}) i = 2, ...N \end{Bmatrix} \tag{11}$$

Where, Lb^d and Ub^d: lower and upper boundary of dimension d, respectively; x^d_{rand}: random position in search space.

To update the positions of variables around the higher plankton concentration area, each manta ray moves around the plankton and somersaults to a new position, which is calculated as Eq. 12.

$$X^d_{i(t+1)} = X^d_{i(t)} + S(r2 \times X^d_{best(t)} - r3 \times X^d_{i(t)}),\ i = 1, ...N \tag{12}$$

Where, r_2 and r_3: random number [0,1]; S: the somersault factor, used to determine the somersault range of the manta rays, S = 2.

Shuffled Frog-Leaping Algorithm (SFLA)

SFLA was introduced by Eusuff and Lansey in 2000 and mimics the food-searching social behavior of frogs [12]. SFLA creates subdivisions within the population, which are termed memeplexes and sub-memeplexes. The frogs within the submemeplexes help each other to improve their positions. The population is again merged and the process is repeated. The step (S) and new position (XN) are computed for the frog with the worst performance in the submemeplexes using Eqs. 13 and 14.

$$S = r(X_b - X_w) \tag{13}$$

$$X_N = X_w + Sfor - S_{\max} < S < S_{\max} \tag{14}$$

Where r: random number (0,1); X_w, X_b: worst and best frog position; S_{max}: maximum step.

If the new position is better than the old position, it is replaced; otherwise, it is discarded and a new solution is randomly determined.

Reptile Search Algorithm (RSA)

RSA was proposed by Abualigah et al. Abualigah et al., [13] to mimic the hunting behavior of Crocodiles. The mathematical model of RSA is updated through encircling and hunting phases: Each solution updates its position using Eq. 15 as proposed for the encircling phase.

$$X_{i,j(t+1)} = \begin{Bmatrix} \text{Best}_{j(t)} \times -\eta_{(i,j)(t)}\beta - R_{(i,j)(t)} \times \text{rand},\ t \le \frac{T}{4} \\ \text{Best}_{j(t)} \times x_{(r1,j)} \times ES_{(t)} \times \text{rand}\ t \le 2\frac{T}{4} \text{and } t > \frac{T}{4} \end{Bmatrix} \tag{15}$$

Where, Bestj(t): best-obtained solution; rand: random number [0,1]; T: maximum iterations; t: current iteration; $\eta_{(i,j)}$: hunting operator; β:

controls exploration accuracy (0.1); $R_{(i,j)}$: reduce function; $x_{(r1,j)}$: random position of i^{th} solution; r1: random number [1 N]; $ES_{(t)}$: probability ratio takes randomly decreasing values between [− 2, 2]; $\eta_{(i,j)}$, $R_{(i,j)}$ and ES(t) are derived from other equations present in [13].

The hunting phase of the process is achieved through Eq. 16.

$$X_{i,j(t+1)} = \begin{Bmatrix} \mathrm{Best}_{j(t)} \times \mathrm{P}_{(i,j)(t)} \times \mathrm{rand},\ t \le 3\frac{T}{4} \text{and } t > 2\frac{T}{4} \\ \mathrm{Best}_{j(t)} - \eta_{(i,j)(t)} \times \mathcal{E} - \mathrm{R}_{(i,j)(t)} \times \mathrm{rand}\ t \le \frac{T}{4} \text{and } t > 3\frac{T}{4} \end{Bmatrix} \tag{16}$$

RUNge Kutta optimizer (RUN)

Proposed by Ahmadianfar et al., it is a metaphor-free population-based optimization technique based on basic mathematics [14]. Its mathematical formulation is updated using i) Root of Search Mechanism and ii) Enhanced Solution Quality.

For a position x_n it will have the worst position (x_w) and best position (x_b) as neighbors in space. The Search Mechanism (SM) in this algorithm is given by Eqs. 17 and 18.

$$SM = \frac{1}{6} X_{RK}\delta_X \tag{17}$$

$$X_{RK} = k1 + 2 \times k2 + 2 \times k3 + k4 \tag{18}$$

Where δ_x: position increment; k1, k2, k3 and k4: coefficient variables.

The use of ESQ is for improving the status of solutions and eliminating local optima. In ESQ for creating a new solution (X_{new2}), Eqs. 19–22 are used.

$$X_{new2} = X_{new1} + r.\ w\ |(X_{new1} - X_{avg}) + rn\ | \tag{19}$$

$$w = rand(0, 2)^{(c\frac{i}{T})} \tag{20}$$

$$X_{avg} = \frac{\mathrm{Xr1} + \mathrm{Xr2} + \mathrm{Xr3}}{3} \tag{21}$$

$$X_{new1} = \beta \times X_{avg} + (1 - \beta) \times X_{best} \tag{22}$$

Where, β: random number [0,1]; c: random number.

HRES Performance Evaluation

The proposed HRES system is designed as a standalone MG for rural electrification in this study and is evaluated through the commonly used performance parameters of economic cost and reliability. Reliability is fixed at 100% for all candidate solutions obtained by optimization techniques. A penalty is applied to solutions without 100% reliability. This constraint increases the problem's complexity and renders the majority of the possible solutions, infeasible. Thus, the problem at hand is more of a feasibility problem rather than optimization.

Economic Cost

The economic performance of the power system is evaluated through Cost of Energy (COE) ($/kWh) and Total Annual Cost (TAC_c) ($/yr)) as formulated in Eqs. 23 and 24. Abazari et al., [15].

$$COE = \frac{TAC_c}{E_L} \tag{23}$$

Where, E_L: yearly demand energy (kWh/yr).

$$\mathrm{TAC} = = \sum_{k=1}^{K} \mathrm{N}_{\mathrm{compk}} \left(\mathrm{C}_{\mathrm{Ck}} \frac{\mathrm{i}(1+\mathrm{i})\mathrm{n}}{(1+\mathrm{i})\ \mathrm{n}-1} + \mathrm{C}_{\mathrm{O\&Mk}} + \mathrm{C}_{\mathrm{rk}} \frac{\mathrm{i}}{(1+\mathrm{i})\mathrm{lf} - 1} \right) \tag{24}$$

Where, C_c: total capital cost of component ($/kW); $C_{O\&M}$: annual operating and maintenance cost ($/kW/yr); C_r: total replacement cost ($/kW); N_{cop}: number of components used; n: project lifetime (yr); LF: Components lifetime (yr); i: interest rate per year (%); K: components type.

Reliability

Loss of Power Supply Probability (LPSP) is all energy deficits to the total load demand within the time interval (T). LPSP is represented through Eqs. 25 and 26 [16].

$$\mathrm{LPSP} = \frac{\sum_{t=1}^{T} (P_D(t) - (P_{PV}(t) + P_{WT}(t) \pm P_{PB}(t)))}{\sum_{t=1}^{T} P_D(t)} \tag{25}$$

Where, P_{PV}, P_{WT} and P_{PB}: total generated power (W) from solar, wind and battery respectively; P_L: total load demand (W).

The constraint of 100% reliability implies that LPSP should be zero and the power supply satisfies the demand at all times. So reliability is considered the main constraint for analysis whereas system cost and environmental emissions are the main objectives.

Gas emission

Starting from production to energy generation, there is some gas emission from every RE. GHG from different HRES components influences the optimal solution. Daily Carbon-Dioxide Emission (DCE) (Kg/day) is calculated using Eq. 26 [17].

$$\mathrm{DCE} = \sum_{n=1}^{N} C_n E_{Tn} \tag{26}$$

Where, E_T: total energy produced from a unit, (kWh/day); N: number of energy generation components; C: life cycle gas emission from a unit, (kg/kWh). The amount of CO2 gas emission to produce one kWh energy in HRES by PV, WT, BS, and converter is 0.011, 0.045, 0.0402, and 0.0047 kg CO2/kWh, respectively, [18].

Total CO_2 Emission Penalty Cost (TCEP), ($/year) is calculated using Eq. 27.

$$TGE_c = DCE \times PF \tag{27}$$

Where, PF: penalty factor, (0.075$/kg) [19]; T: time period; k: number of components in the system.

Problem Formulation

The primary objective of this study is to obtain the optimal quantity of HRES components with minimal costs including GHG penalty, which is expressed as Eq. 28.

$$F = Minimize(TAC_T) \tag{28}$$

For

$$TAC_T = TACc + TCEPc \tag{29}$$

The constraints considered for analysis are formulated in Eqs. 30–34.

$$LPSP = 0 \tag{30}$$

$$N_{PV}P_{PV}(t) + N_{WT}P_{WT}(t) \pm N_{BS}P_{BS}(t) \ge P_D(t) \tag{31}$$

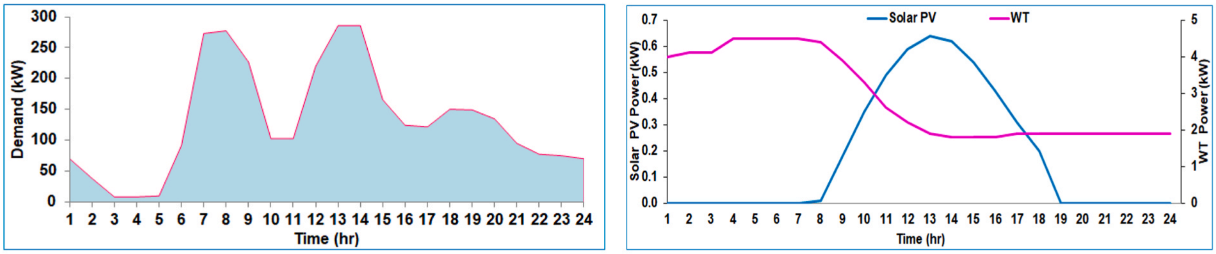
$$0 \le N_{PV}P_{PV}(t) \le PPV\ \max \tag{32}$$

$$0 \le N_{WT}P_{WT}(t) \le PWT\ \max \tag{33}$$

$$SoC_{\min} \le SoC(t) \le SoC_{\max} \tag{34}$$

Where, P_{PV}, P_{WT}, P_{BS}: power output from PV, WT, and BS, respectively; N: number of components; SoC(t): battery charge at time 't'; SoC_{min} and SoC_{max}: minimum and maximum allowable battery SoC.

The system is configured with PV and WT as energy sources and battery as ESS. The converter is considered, for configuring the generated power to the required specification. DC charge controller is



(a) Daily Load Profile **(b)** Hourly Power generated from Solar PV and WT

Fig. 1. Daily Load and RES Generation Pattern of Jarre Village.

Table 1
Component's cost for Stand-alone system.

Components	C_c ($/kW)	C_r ($/kW)	C_{OM} ($/kW/yr)	Life Span (yr)
WT, 10 kW	1500	0	10	20
Solar PV, 1 kW	1000	0	5	20
Converter, 300 kW	250	250	0	10
BESS, 100Ah	150	150	12	5

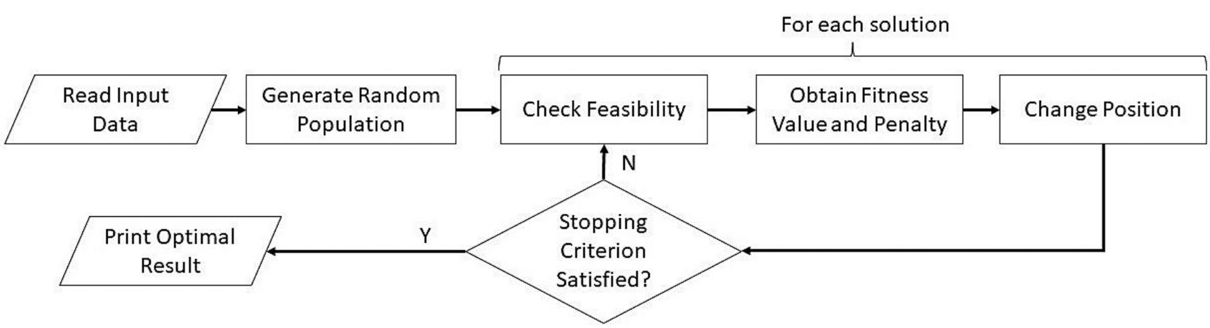


Fig. 2. Flowchart of Optimization Algorithms.

considered to regulate the charging and discharging of ESS. In the village, there are 150 households with a proposed daily load of 3173 kWh/day and a peak load of 285.5 kW. The daily load curve for the Jarre village is shown in Fig. 1a.

The hourly average RES output power is shown in Fig. 1b. The output power generated by PV and WT, is computed through equations presented in [20]. The cost of standalone hybrid power system components is listed in Table 1 and taken into account at current market prices. The considered algorithms: PSO, DE, MRFO, SFLA, RSA and RUN are executed to check the feasibility and obtain the optimal combination of system components, i.e., PV, WT, and ESS.

The process adopted by meta-heuristic methods to obtain the best solution includes the following steps: (i) required data is input and populations are generated randomly, (ii) feasibility check tests the ability of RE and BS for serving the demand during the specified time, (iii) the constraints are checked, and fitness value (with penalty) is obtained for each solution, (iv) the optimal results are printed when the stopping criterion is satisfied. The process is presented in Fig. 2.

Results and Discussion

The study is carried out for a village located at (9.690∘ N, 42.753 ∘ E), which is far away from the main grid, and extending the grid is infeasible. The analysis has the objective of supplying the load with the constraints of achieving zero LPSP and the minimum total system cost including the penalty. Each technique is coded in MATLAB. A 24-hour cycle is observed for the utilization of energy from RES and ESS. In case, the obtained combination of PV, WT, and ESS is able to supply the load for the full duration of the study, the economic evaluation is performed to derive the costs involved in installing the standalone MG.

The inverter and battery efficiency are taken as 90%, SOC_{min}, and SOC_{max} are taken as 20% and 90% respectively. The optimization techniques were executed 40 times to obtain the results. All the optimization techniques had a population size of 300 and the number of iterations was set to 500. The optimal combination of PV panels (NPV), wind turbines (NWT), and battery packs (NBAT) obtained for each technique are listed in Table 2. A single converter with a rating of 300 kW is considered in all cases to tolerate the peak load value.

The combination of RES and battery packs is conditioned to result in zero LPSP (LPSP = 0) or 100% reliable system, as a precondition. The combination of PV, WT, and BS was applied to calculate the source that shall supply the power during each hour of the day. The excess energy generated in a day from the optimized combination of the components is also evaluated. Excess energy is energy generated through renewable sources, which could not be utilized. The GHG gases emitted are obtained and converted to cost for each solution using Eqs. 27 and 28. The best solutions for different optimization techniques are shown in Table 2.

The TAC_T and excess energy results for MRFO and RUN are similar, however, MRFO performed better in run time. Similarly, the lowest COE is found with MRFO and RUN. A comparison of COE and excess energy for different optimization techniques is shown in Fig. 3.

The optimal component sizes obtained from the analysis are 247 PV panels, 46 WT, and 249 BS packs. The priorities allocated in selecting

Table 2
Optimal Solution of Multiple Optimization Techniques.

Methods	^{N}PV	^{N}WT	^{N}BT	TAC ($/yr)	Excess Energy (kWh)	Run time (sec)
PSO	242	47	249	135,293.1	719	31
DE	227	52	204	137,981.9	971	19
MRFO	247	46	249	134,275.8	677	42
SFLA	243	48	224	135,029.2	786	12
RSA	243	49	208	135,358.8	837	33
RUN	247	46	249	134,275.8	677	67

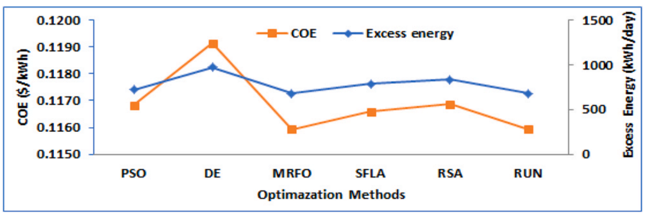


Fig. 3. COE and Excess Energy from Different Algorithms Comparison.

the best results are (i) 100% reliability, ii) minimizing COE, and iii) minimizing GHG emissions.

Conclusion

The feasibility of supplying electricity to the remote village of Jarre in Ethiopia is investigated. The village has a lower level of load, accompanied by the availability of RES. An optimal combination of RES and battery packs is found with the objectives of reliability, economics, and low GHG emissions. The comparison of different algorithms shows that MRFO is the best technique with a COE of 0.1159 $/kWh and the lowest total cost of 134,275.8 $/yr.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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