

Energy Management And Optimal Design Of Grid-Independent Hybrid Systems: An Economic And Environmental Assessment Using Intelligent Techniques

Arshad Kadhum Fahad Al-Taie^{1,2*}, Mohamed F. Kotb² and Mohamed Elgohary^{2,3}

¹ Ministry of Industry and Minerals, Baghdad, Iraq.

² Department of Electrical Engineering, Faculty of Engineering, Mansoura University, Mansoura, Egypt.

³ Faculty of Engineering, Delta University for Science and Technology, Gamasa 35712, Egypt.

* Corresponding Author: eng.arshed80@gmail.com

Abstract – The increasing demand for renewable energy calls for solutions that must address economic, reliable, and environmental aspects simultaneously. The concept of hybrid renewable microgrids provides a viable solution to provide clean and reliable power to meet the demands of remote and off-grid locations. In this paper, an effective economic, reliable, and environmental methodology is developed for optimizing and sizing hybrid microgrids of photovoltaic (PV) panels, wind turbines (WT), battery (B) storage, hydrogen (H₂)-based storage, and diesel generators (DG) systems using the Walrus Optimization Algorithm (WOA) and the Gorilla Troops Optimizer (GTO) metaheuristic search techniques to reduce total cost and enhance reliability simultaneously. Seven different hybrid solutions are tested based on six distinct performance metrics: Cost of Energy (COE), Net Present Cost (NPC), Loss of Power Supply Probability (LPSP), Excess Energy Proportion (EXP), Renewable Fraction (RF), and Lifecycle Emissions (LCE). The simulation runs are repeated 20 times to explore their robustness and sensitivity to optimization iterations. It is observed that WOA provides better solutions compared to GTO, with reduced COE and NPC, improved reliability, and better system configurations. For both economic and environmental viability, The PV-WT-DG-Battery configuration achieves the lowest COE and NPC, with values of 0.0853 \$/kWh and approximately 2.06 MUSD, respectively, while the PV-WT-Fuel Cell (FC)-DG configuration yields the lowest LCE, approximately 156,700 kg CO₂.

Keywords – Microgrids – Energy Management System – Optimization Techniques- Cost of Energy, LPSP.

1. Introduction

There has been an increasing trend in the global energy resources being diversified from fossil fuels to renewables over the last few years. This has been due to environmental reasons, increased greenhouse gas emissions, resource depletion, and market variability. With increasing demand in the urban and rural areas, there definitely needs to be energy that is sustainable, reliable, and affordable. [1]. The need was fulfilled with the help of Hybrid Renewable Energy Systems (HRES), an innovative solution to the problem, with the inclusion of solar photovoltaics (PV), wind energy (WT), storage solutions using batteries (B), hydrogen-based storage in the form of electrolyzers, tanks, and fuel cells (FC), and diesel particulate filters [2, 3]. Notwithstanding the negative economic impacts associated with COVID-19 (Coronavirus Disease 2019), the installation of renewable energy capacity above 280 GW in 2020 marked an increase of about 45% from the previous year [4, 5]. Solar energy and wind energy dominated the installations owing to their scalability, abundance, and decreasing production costs [6]. However, their intermittency—since solar energy relies on sunshine while wind energy relies on wind—makes them unreliable on their own, but storage remains fundamental for viability. Battery storage addresses the issue for a short period, with hydrogen facilitating large-scale storage. However, diesel-powered generators act as the ultimate fallback for continuous power [1, 2, 7]. HRES are significant because they are flexible; for instance,

HRES can facilitate the integration of electricity with hydrogen for energy, electricity with heating, electricity with desalination, as well as electricity-water-heating systems. This aspect increases complexity when it comes to system operations. [8-11]. Consequently, optimizing HRES configuration with respect to PV size, WT capacity, B size, hydrogen storage capacity, and DG rating becomes an NP-hard (Non-deterministic Polynomial-time hard) nonlinear multi-objective optimization problem. The optimization goals include reducing cost of energy, increasing reliability, and reducing life-cycle carbon emissions. Classical optimization techniques are impractical to address this problem and thus the imperatives for employing new metaheuristic optimization techniques that can easily explore large solution spaces and converge to local optima [12, 13]. The interplay of renewable energy (RE) resources, storage systems, and new optimization techniques is crucial to provide reliable HRES solutions that address energy demands both in urban and rural settings and support global carbon neutrality targets [14-16]. The size optimization of an off-grid hybrid renewable energy system (HRES) is an important design problem that focuses on finding a compromise between the Cost of Energy (COE), reliability, and environmental considerations. Having established the optimization problem and the performance metric, an adequate method for the size optimization needs to be chosen to obtain an optimal solution [17, 18]. Despite the availability of different optimization approaches for Hybrid Renewable Energy Systems (HRES), the design and operation of isolated HRES remain challenging due to their nonlinear nature and the conflicting economic, technical, and environmental objectives involved. The strong interdependence between renewable generation sources, storage systems, and reliability constraints further increases the complexity of the decision-making process, thereby limiting the effectiveness of traditional optimization techniques. To address these challenges, this study adopts two recent nature-inspired algorithms, namely the Walrus Optimization Algorithm (WOA) [19] and the Gorilla Troops Optimizer (GTO) [20], which have demonstrated well-balanced exploration-exploitation capabilities and strong resistance to premature convergence, to optimize the isolated hybrid microgrid problem.

This paper will develop a standalone hybrid microgrid configuration that integrates PV panels, a WT, FC coupled with hydrogen storage and an electrolyzer (FC-H₂), DG, and battery storage to deliver a sustainable and reliable supply of electricity with reduced costs and emissions to a remote community. For case study purposes, Hasiba in Anbar Governorate, Iraq, was selected due to its rich solar potential of about 6.0 kWh/m²/day on average and moderate wind of 6.8 to 7.9 m/s. This is coupled with increasing energy demands within the region and very fragile grid reliability. Several key contributions are highlighted in the paper. (1) Developing an integrated technical-economic-environmental framework for the optimal sizing of isolated hybrid microgrids, combining PV panels, WT, battery storage systems, hydrogen-based storage, and DG. (2) Seven hybrid systems configurations are defined: PV-DG-Battery, WT-DG-Battery, PV-WT-DG-Battery, PV-FC-DG, WT-FC-DG, PV-WT-FC-DG, and finally, PV-WT-FC-DG-Battery. (3) Two nature-based metaheuristic optimization algorithms, WOA, and GTO, were used for optimizing the complex nonlinear problem of optimal sizing of microgrid components. Strict statistical analysis was carried out for 20 independent trials for objective comparison and validation of the results. (4) To assess the performance, a comprehensive evaluation was carried out using different technical, economic, and environmental criteria, and the following parameters, among others, stood out: COE, NPC, LPSP, Surplus Energy Proportion (EXP), Renewable Contribution Proportion (RF), and Lifecycle Emissions (LCE). (5) Using the WOA algorithm, the optimal configuration that combines the PV, WT, DG, and battery systems, along with the minimal COE and NPC, was recognized. It was seen that the PV-WT-DG-Battery configuration optimized by the WOA algorithm produces the lowest COE

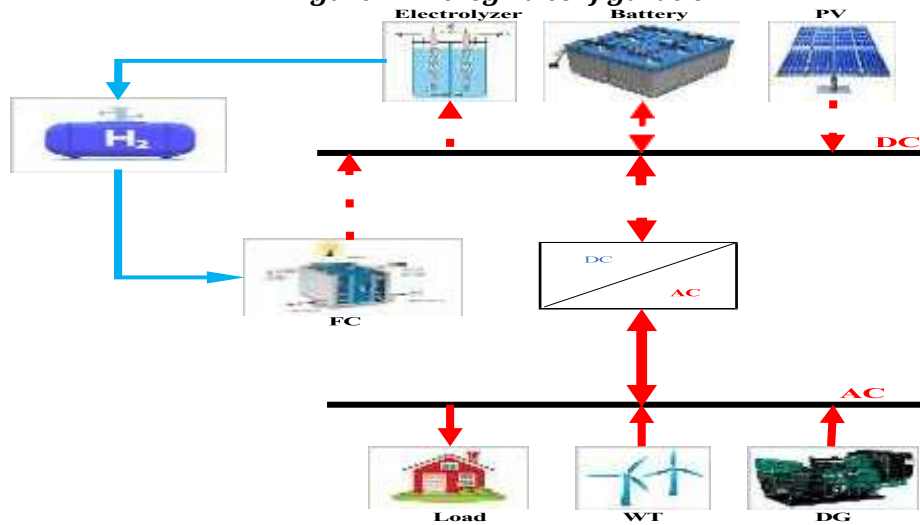
and NPC, and the PV-WT-FC-DG configuration is the most efficient for lowering the life cycle emissions.

2. System Modelling and problem formulation

2.1. Technical and economic modelling

Figure (1) illustrates the general schematic of a standalone hybrid PV/WT/FC/DG/battery system, which combines photovoltaic arrays, wind turbines, an electrolyzer, a hydrogen storage tank, fuel cells, a diesel generator, and a battery system. All components are connected via power electronics interfaces that ensure efficient power flow. The system relies on a hierarchical operating strategy aimed at maximizing reliance on RES and minimizing the use of fossil fuels. Surplus energy supplied by the PV panels and WTs is first injected to the electrolyzer to produce and store hydrogen, and then to charge the batteries when the analyzer reaches its maximum capacity. Meanwhile, the hydrogen stored in the fuel cell is used to generate electricity when renewable sources are low. If the hydrogen level is insufficient, the batteries cover the deficit. Where there is persistent shortage or high demand for diesel generators, they come in as a last resort to keep the lights on.

Figure 1. Microgrid configuration.



a. PV System

The PV array is made up of a number of solar modules, the mathematical representation of the instant output of the PV system can be given by the following equations[21-23]:

$$P_{PV}(t) = N_{PV} \cdot A_{PV} \cdot \eta_{PV} \cdot G(t) \quad (1)$$

where, N_{PV} implies number of solar modules in the array, A_{PV} is the effective area of the solar module (m^2), η_{PV} The overall efficiency of a photovoltaic system, which includes the intrinsic performance of the solar cells, the efficiency of the maximum power point controller (MPPT), and the thermal effects, can be represented by [24, 25]:

$$\eta_{PV} = \frac{\eta_r}{1 + \beta_T \cdot (T_C - T_{nom})} \cdot \eta_t \quad (2)$$

In equation (2), η_r is the reference (standard test condition) efficiency of the PV panels, η_t represents MPPT controller efficiency, β_T is the temperature effect coefficient on efficiency ($\%/^{\circ}C$), T_C is the actual operating cell temperature ($^{\circ}C$), and T_{nom} is the nominal operating cell temperature (NOCT). The actual system uses E20-327 monocrystalline solar panels valued for their high efficiency and reliability. Each module is rated with a

nominal efficiency of 20.4%, with an operating voltage around 54.7 V and an operating current about 5.98 A. In order to better correspond to the operation in real-life conditions, a derating factor of 90% has been incorporated, with the temperature coefficient of power being set at $-0.43\%/^{\circ}\text{C}$, to capture the drop in power as temperature rises [26]. Economically, the capital cost for the solar panels is estimated at approximately \$1,300/kW upfront, with operations and maintenance estimated at about \$20 per year per module. Given that these panels generally need almost no significant replacements during their life, no replacement costs are modeled. The technical lifetime was estimated at approximately 25 years [27].

b. Wind Turbine System

To obtain the higher-level of wind speed, extrapolation from measurements at a reference height—the anemometer height—is done through the power-law equation [21, 28]:

$$\frac{u_2}{u_1} = \left(\frac{H_2}{H_1}\right)^{\alpha} \quad (3)$$

where, u_2 denotes the wind velocity at the turbine hub height H_2 , while u_1 denotes the measured speed at the base height H_1 , and α is the Surface Friction Coefficient, typically ranging from 0.1 for smooth surfaces such as bodies of water to 0.4 in urban areas or forests. The power given by a WT is not a linear function of wind speed, but rather follows a nonlinear curve that depends on the operating characteristics of the WT. The instantaneous generated power from the WT at a given speed, $u(t)$ can be formulated as [21, 29, 30]:

$$P_{WT}(t) = \begin{cases} a \times u(t)^3 - b \times P_{WT_rated} & u_{cut-in} < u(t) < u_{rated} \\ P_{WT_rated} & u_{rated} < u(t) < u_{cut-off} \\ 0 & u(t) > u_{cut-off} \end{cases} \quad (4)$$

with the coefficients defined as:

$$\begin{cases} a = \frac{P_{WT_rated}}{(u_{rated})^3 - (u_{cut-in})^3} \\ b = \frac{u_{cut-in}}{(u_{rated})^3 - (u_{cut-in})^3} \end{cases} \quad (5)$$

Here, P_{WT_rated} is the turbine's nominal power at the nominal wind velocity (u_{rated}), u_{cut-in} is the lowest velocity at which the turbine begins producing electricity, and $u_{cut-off}$ is cut-off velocity (the highest velocity at which the WT stops to protect itself from damage). The rated power of a WT is derived from the aerodynamic conversion of the kinetic energy of the wind into mechanical and then electrical energy, and is expressed as follows [31]:

$$P_{WT_rated} = 0.5 \times \rho \times A_{WT} \times C_P \times (u_{rated})^3 \quad (6)$$

where, ρ is the air density (1.225 kg/m^3), $A_{WT} = \pi R^2$, is the rotor swept area determined by the blade radius R , and C_P is the power coefficient, representing the aerodynamic efficiency of the rotor. C_P represents the aerodynamic efficiency of the fan, ranges in practice between 0.25 and 0.45, while the theoretical maximum is 0.593 (Betz limit). In the given practical setup, the horizontal-axis wind turbine is of a nominal power rating of 10 kW. For this kind of turbine, generation starts at an inlet wind speed of 2.75 m/s and will shut down to prevent breakage for safety reasons at 20 m/s. Assuming a nominal wind speed of 6.5 m/s, the hub of the turbine is raised to 20 meters for the intake of stronger and steadier winds. Economically, the cost of capital is US\$2,300 per kW; the annual operational and maintenance cost is US\$20 [10], while the cost of replacement is considered to be US\$1,500 per kW, with an average life of 20 years [10, 27].

c. Electrolyzer - Fuel Cell System

The electrolysis cell requires direct current in order to split the water molecules into hydrogen and oxygen, collecting the hydrogen gas at the cathode and releasing oxygen gas at the anode. The hydrogen gas, usually maintained in medium pressure at about 30 bar, needs to be supplied to the fuel cell at a lower pressure of about 1.2 bars [32, 33]. The storage method depends on the design. This may entail hydrogen storage at the same pressure as the electrolyzer, high-pressure compression of the hydrogen to a maximum of 200 bar, or the two-tank method that can combine low and high-pressure hydrogen storage to reduce the power required by the compressors and prolong their lifespan [34]. To make the comparison simpler, the assumption is that the hydrogen is stored at a constant pressure of 30 bar without the need for compression. The power entering the hydrogen tank is calculated as follows [35, 21]:

$$P_{\text{electr-H2 tank}} = P_{\text{Ren-electr}} \times \eta_{\text{elect}} \quad (7)$$

where, $P_{\text{Ren-electr}}$ is excess power from RES directed to the electrolyzer. η_{elect} signifies the electrolyzer efficiency, and $P_{\text{electr-H2 tank}}$ represents the actual power stored as hydrogen in the tank. The hydrogen tank is used as a medium for storing chemical energy, and the energy stored in it at time t is evaluated as in [24, 36]:

$$E_{H2 \text{ tank}}(t) = E_{H2 \text{ tank}}(t-1) + (P_{\text{electr-H2 tank}}(t) - \frac{P_{H2 \text{ tank-FC}}(t)}{\eta_{\text{storage}}}) \times \Delta t \quad (8)$$

here, $E_{H2 \text{ tank}}(t-1)$ is the stored energy in the previous time step. $P_{H2 \text{ tank-FC}}$ is the power drawn from the storage tank to power the FC system. η_{storage} , represents the storage efficiency ($\approx 95\%$), and Δt is the simulation time interval. The mass of stored hydrogen is estimated according to the equation [24]:

$$M_{H2 \text{ tank}}(t) = \frac{E_{H2 \text{ tank}}(t)}{HHV_{H2}} \quad (9)$$

where the highest calorific value of hydrogen HHV_{H2} is taken as 39.7 kWh/kg [37]. Storage is subject to operational constraints:

$$M_{H2 \text{ tank_min}} \leq M_{H2 \text{ tank}}(t) \leq M_{H2 \text{ tank_max}} \quad (10)$$

This is to ensure safe operation and avoid complete discharge or overfilling. The PEMFC fuel cell converts hydrogen stored into electricity when renewable generation is insufficient or during peak load times. The electrical output of the cell is calculated as in (11):

$$P_{FC\text{-inv}} = P_{H2 \text{ tank-FC}} \times \eta_{FC} \quad (11)$$

here η_{FC} denotes the PEMFC conversion efficiency. In line with [33, 38], a constant efficiency of 50% is considered in this work. On the cost side, the estimates break down as follows [39]: (1) Fuel cell cost: \$3,000/kW, O&M costs of \$175/kW/year, and a replacement cost of \$2,400/kW, with a lifespan of 5 years. (2) Hydrogen tank cost: \$1,300/kg capacity, with O&M costs of \$15/kg, a replacement cost of \$1,040/kg, and a lifetime of 20 years. (3) Electrolyzer cost: \$2,000/kW, O&M costs of \$25/kW, and a cost of replacement \$1,600/kW, with a lifetime of 20 years.

d. Battery Energy Storage

The capacity of batteries depends on several parameters, such as temperature, cycle, nomo-cap, depth of discharge, and safety factors during working [40, 41]. Out of all these, state of charge (SOC) becomes the most important parameter, reflecting the available potential of energy, thereby efficiently handling the charging and discharging cycles, thereby increasing the efficiency of the entire system.[42, 43]. The net energy flow between the renewables (PV and WT), the auxiliary sources (DG and FC), and the demand can describe the dynamics of SOC: During charging mode,

$$E_{CH}(t) = \left(\frac{P_{WT}(t) - P_{load}(t)}{\eta_{conv}} + P_{PV}(t) + P_{FC}(t) \right) \times \eta_{CH} \times \Delta t \quad (12)$$

$$SOC(t) = SOC(t-1)(1-\sigma) + E_{CH}(t) \quad (13)$$

where, $E_{CH}(t)$ implies the injected energy into the battery at moment t . P_{WT} , P_{PV} , P_{FC} are the rating capacities of the WT, PV panels, and FCs, while P_{load} is the load demand. η_{conv} and η_{CH} denote the converter and charging efficiencies, respectively, and σ denotes the battery self-discharge rate.

During discharging mode,

$$E_{DIS}(t) = \left(\frac{P_{load}(t) - P_{WT}(t)}{\eta_{conv}} - P_{PV}(t) - P_{FC}(t) \right) \times \eta_{DIS} \times \Delta t \quad (14)$$

$$SOC(t) = SOC(t-1)(1-\sigma) - E_{DIS}(t) \quad (15)$$

In this case, $E_{DIS}(t)$ is the discharged energy from the batteries, and η_{DIS} is the discharging efficiency. The available charge window of the battery is maintained between 20% and 90% to avoid overcharging and deep discharge for battery life extension. The storage will be technically and economically constructed with lead-acid batteries, each with a nominal capacity of 6.94 kWh, about 1156 Ah. Investment cost: \$1100 per unit. Replacement cost: \$1,000 per unit. O&M costs: \$10/unit per year. Technical lifespan: 12 years [10, 27]. The operating limits are: Maximum charge capacity: 80%. DOD: 100%. Self-discharge rate: 0.02% per day [10].

e. Diesel generator system

The instantaneous fuel consumption rate of the generator at time t , denoted by $D_f(t)$, can be calculated using the operating characteristics as follows [40]:

$$D_f(t) = \alpha_{DG} P_{DG}(t) + \beta_{DG} P_{DG, rated} \quad (16)$$

here $P_{DG}(t)$ is the average electrical power supplied by DG at time t , with a unit of kW, and $P_{DG, rated}$ is the DG nominal power in kW. α_{DG} & β_{DG} are Fuel consumption parameters derived from DG's performance curve. In this study, we assume $\alpha_{DG} = 0.246$ and $\beta_{DG} = 0.08145$ values that conform to common data for a diesel engine[41]. The daily cost of fuel can be computed by:

$$C_{fuel} = \sum_{t=1}^{24} D_f(t) \times C_{unit} \times N_{days} \quad (17)$$

where, C_{fuel} denotes the overall fuel cost (USD), C_{unit} is the unit cost of diesel fuel (USD/L), and N_{days} denotes the operational days in the considered time horizon. In practice, a 30-kW diesel generator was introduced to the system to ensure supply reliability in times of low outputs from both PV and wind turbines. Investment cost: \$220/kW. Replacement cost: \$200/kW. O&M costs: \$0.03/operating hour, including routine maintenance and minor repair works. Expected life: approx. 15 000 operating hours [10, 44]. Diesel fuel cost: \$0.77 per liter of fuel, representing a direct input into the running cost of the generator and one of the most influential factors for enhancing overall economic system performance.

f. Inverter Model

The DC/AC inverter is a core building block of any hybrid renewable energy system. It couples the DC power from resources such as PV panels and fuel cells with the AC power required by a home, office, or factory. Mathematically, the behavior of the inverter could be described through the AC output power as in (18):

$$P_{inv-AC}(t) = (P_{FC-inv}(t) + P_{Ren-inv}(t) + P_{batt-inv}(t)) \times \eta_{inv} \quad (18)$$

Here, the net AC power delivered to the load at time t is $P_{inv-AC}(t)$ in kW. The fuel cell's contribution after DC/AC conversion is $P_{FC-inv}(t)$, while the renewable input from the PV

and WT subsystems after conversion is $P_{Ren-inv}(t)$. The power discharged from the storage system through the inverter is $P_{batt-inv}(t)$, and η_{inv} is the inverter efficiency. The literature mentioned considers an inverter efficiency of 95%, where nearly 5% of the DC input has been lost as heat or due to internal conversion losses [24, 36]. Economically and operationally, the proposed design makes use of an inverter with a nominal capacity of 1 kW, possessing: an investment cost of US\$ 300/kW, O&M costs of US\$ 10/year, a replacement cost of US\$ 300/kW, a conversion efficiency of around 95%, and an estimated technical service life of 15 years [45].

2.2. Energy Management Strategy (EMS)

The proposed EMS aims to reach the target load with as much renewable energy as possible, while maintaining dependable power supply and low costs and low emissions. Its operating logic follows a simple priority order: diversion of excess energy first into an electrolyzer for long-term storage in the form of hydrogen, and then use of the remaining energy to charge the battery for short-term storage. In the event of a shortage, the system uses: 1) fuel cells (from stored hydrogen), 2) the battery if insufficient, and 3) a diesel generator as a last resort. A detailed description of the rules and equations is given below:

a) Operating Policy — General Conditions

Update Battery and Tank Status

Before any operational decision, we apply the battery self-charging test:

$$SOC(t-1) = \max(SOC_{min}, SOC(t-1) \times (1-\sigma)) \quad (19)$$

For hydrogen tank we apply storage losses (as annual/hour efficiency factor if required).

Energy Balance Calculation

$$\begin{aligned} EB(t) &= P_{PV}(t) + P_{WT}(t) - P_{load}(t) \\ \text{if } EB(t) &> 0 - \text{surplus} \\ EB(t) &\leq 0 - \text{deficit} \end{aligned} \quad (20)$$

b) Surplus Condition:

Input electric power to the electrolyzer (first):

$$P_{Elec}(t) = \min(P_{Elec_{rated}}, EB(t)) \quad (21)$$

Hydrogen mass produced:

$$M_{H_2}^{prod}(t) = \frac{P_{Elec}(t) \times \eta_{Elec}}{HHV} \quad (22)$$

If the produced mass of hydrogen $M_{H_2}^{prod}(t)$ exceeds the hydrogen tank rating $M_{tank_{max}}$, the excess energy is calculated as waste energy. Charging the battery from the remaining surplus (after electrolyzer):

$$surplus_after_elec = EB(t) - P_{Elec}(t) \quad (23)$$

If $surplus_after_elec > 0$ and $SOC(t-1) < SOC_{max}$, the storage system will accept charging as provide in (12). Any excess remaining after charging is dumped.

$$E_{dump}(t) = \max(0, surplus_after_elec - E_{charge_req}) \quad (24)$$

c) Deficit Condition:

Operating Fuel Cells from a Hydrogen Tank: Calculate the maximum possible capacity of the cell based on the amount of H_2 in the reservoir as given in (25),

$$P_{FC}(t) = \min(P_{FC_{rated}}, Demand, Max_{FC_from_H_2}) \quad (25)$$

$$Max_{FC_from_H_2} = M_{tank}(t-1) \times HHV \times \eta_{FC} \quad (26)$$

Battery Discharge. The available storage in the battery is formulated as:

$$Avail_batt = \max(0, SOC(t-1) - SOC_{min}) \quad (27)$$

The discharged energy and the SOC of the battery after discharging are calculated from Eqs. (14) and (15). The energy demand required after discharging is calculated

$$Demand_after_batt = \max(0, Demand_after_FC - E_{dis}) \quad (28)$$

Diesel Generator operation:

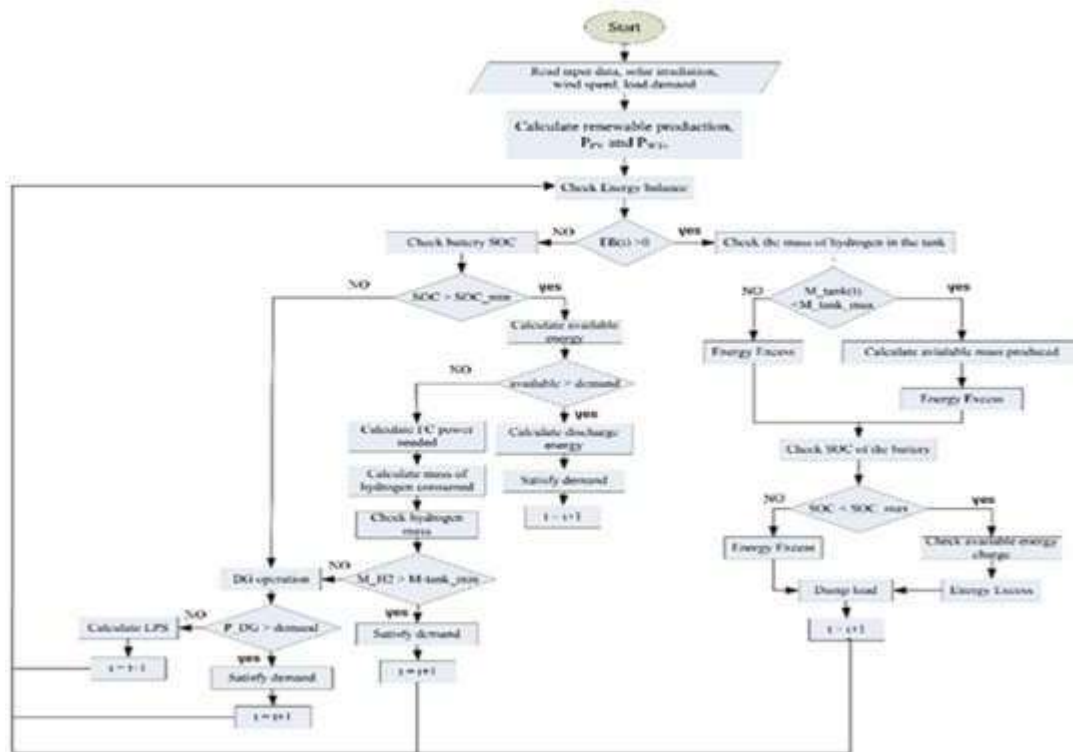
$$P_{DG}(t) = \min(Demand_after_batt, P_{DG_rated}) \quad (29)$$

If any portion remains uncovered, it is a Loss of Supply (LPS) or must be activated under a load shedding or network emergency policy.

$$LPS(t) = Demand_after_batt - P_{DG}(t) \quad (30)$$

The EMS is based on a clear hierarchy: first, capture the renewable surplus in the form of hydrogen (electrolyzer → tank), second, charge the battery for short periods, and third, consume hydrogen via fuel cells, then the battery, and the DG when needed. The flowchart of the energy management strategy is presented in Figure 2.

Figure 2. Energy management methodology.



2.3. Economic Modeling

A complete economic analysis of the HES has to be conducted in order to evaluate the feasibility and long-term viability. This analysis is performed by the method of Net Present Cost (NPC), taking into consideration the total capital and operating costs in each item during the lifespan of the system. The NPC gives the overall cost of ownership, determined from the initial capital amount, O&M, the costs of replacement, with deductions made for the salvage value at the project's end. The NPC of each item can be computed using the following general relation [14]:

$$NPC_{comp} = C_{ini} + C_{rep} + C_{O\&M} - C_{salvage} \quad (31)$$

here, C_{ini} is the initial capital investment of the item, C_{rep} is the present value of the replacement cost during the project life, $C_{O\&M}$ is the present value of O&M cost, $C_{salvage}$ is the salvage value at the end of the system lifespan. The capital cost for each item is determined as:

$$C_{ini} = N_{comp} \times C_{cap,comp} \quad (32)$$

where N_{comp} denotes the number of installed units for the item, and $C_{cap,comp}$ is the specific procurement cost of the component (USD/kW or USD/unit depending on the component). The replacement cost of each subsystem is evaluated as:

$$C_{rep} = N_{comp} \times C_{rep,comp} \times \sum_{j=1}^{N_{rep,comp}} \frac{1}{(1+i)^{LF_{comp} \times j}} \quad (33)$$

where, $C_{rep,comp}$ is the replacement cost of the item at the end of its lifespan, whereas total replacements is calculated as follows

$$N_{rep,comp} = \text{lowest integer} \left(\frac{LF_{project}}{LF_{comp}} \right) \quad (34)$$

where, $LF_{project}$ denotes the system lifespan (assumed 25 years), LF_{comp} is the lifespan of the component, i is the real discount rate. The real discount rate is defined in terms of the nominal discount rate (i') and the inflation rate (f) as:

$$i = \frac{i' - f}{1 + f} \quad (35)$$

The O&M cost of each item is computed as:

$$C_{O\&M} = N_{comp} \times C_{O\&M,comp} \times \sum_{k=1}^{LF_{project}} \frac{1}{(1+i)^k} \quad (36)$$

where $C_{O\&M,comp}$ represents the annual O&M cost per unit of the component. The salvage value of each component is computed at the end of the system lifespan to account for the residual value of assets not fully exhausted:

$$C_{salvage} = C_{rep,comp} \times \frac{R_{rem,comp}}{LF_{comp}} \times \frac{1}{(1+i)^{LF_{project}}} \quad (37)$$

where the remaining time of the item, $R_{rem,comp}$, is expressed as:

$$R_{rem,comp} = LF_{comp} - (LF_{project} - R_{rep,comp}) \quad (38)$$

and the replacement time is given by:

$$R_{rep,comp} = LF_{comp} \times \text{integer} \left(\frac{LF_{project}}{LF_{comp}} \right) \quad (39)$$

2.4. Technical, Social, and Environmental Assessment

a) Renewable Fraction

RF is a very important metric that indicates the fraction of total load covered through RES in a hybrid microgrid. It reflects a measure of the dependence on clean energy by the system and its ability to reduce reliance on using fossil fuel. A higher RF means reduced operating cost with increased environmental sustainability due to reduced emissions. It is mathematically defined as:

$$RF = 1 - \frac{E_{nonren}}{E_s} \quad (40)$$

This relation connects the energy delivered by the non-renewable sources, called diesel generator E_{nonren} and the total electrical energy supplied to the load, called E_s value of RF close to 1, that is 100% means that the system is basically covered by renewables. On the other hand, an RF close to 0 implies heavy dependence on fossil fuels.

b) System Reliability

Since the objective of this paper is to operate power reliably in remote or standalone configurations, a reliability metric is needed. One of the most frequently used is LPSP, which describes the probability that the hybrid system cannot meet the electric

consumption. In this study, the acceptable LPSP is set at $1 \pm 0.5\%$, meaning the microgrid should be able to serve the load at least 99% of the time. The LPSP is computed as:

$$LPSP = \frac{\sum_{t=1}^T LPS(t)}{\sum_{t=1}^T E_L(t)} \quad (41)$$

where $E_L(t)$ implies the total electrical energy demand at time t , $LPS(t)$ is the power shortage at time t , T is the total simulation time (hours). The total unmet load can be described by:

$$\sum_{t=1}^T LPS(t) = \sum_{t=1}^T (E_L(t) - (E_{ren}(t) + E_{dis}(t) \times \eta_{inv} + E_{FC}(t) \times \eta_{inv} + E_{DG}(t))) \quad (42)$$

where, $E_{ren}(t)$, renewable power generated (PV and wind), $E_{dis}(t)$ is the energy discharged from the batteries in the previous step, η_{inv} is the inverter efficiency, $E_{DG}(t)$ is the diesel generator output, $E_{FC}(t)$ is the power contribution from the fuel cell subsystem.

c) Lifecycle Emissions

The Lifecycle Emissions (LCE) evaluate the environmental sustainability of the HES by quantifying the total GHG emissions, expressed in terms of CO₂ equivalents, associated with the energy generated throughout the system's operational lifetime. The total emissions are given by [22, 46]:

$$LCE = \sum_{i=1}^T E_i \cdot j_i \quad (43)$$

where, E_i is the total energy produced by component I over time horizon T , j_i is the emission factor of item I (kg CO₂/kWh), obtained from literature (Table 1).

Table 1. CO2 life cycle for the proposed microgrid [10, 26, 46].

Item	GHG emissions (kgCO ₂ -eq/kWh)
PV	0.045
WT	0.011
FC	0.02
Hydrogen Tank	0.011
Electrolyzer	0.011
DG	0.705
Battery	0.028
Inverter	0

2.5. Objective Function

Determining the objective function (OF) is one of the most important steps in designing and optimizing HES. This function represents the mathematical metric that optimization algorithms seek to minimize or maximize. In this research, the primary goal is to reduce COE while maintaining a high level of reliability, ensuring an appropriate contribution from renewable energy, and minimizing excess capacity. The OF can be expressed as:

$$\text{Minimize } F = COE + \alpha_1 \times P_{LPSP} + \alpha_2 \times P_{EXP} + \alpha_3 \times P_{RF} \quad (44)$$

Where, P_{LPSP} is the penalty factor for the load loss index, P_{EXP} is the penalty factor for unutilized excess energy, P_{RF} is penalty factor for the percentage of renewable energy contribution, α_1 , α_2 , and α_3 are penalty weights used to control the importance of each constraint in the optimization process. We define a target LPSP of 1% with tolerance of $\pm 0.5\%$ in this paper so that the system can reliably meet over 99% of load share. If the LPSP goes beyond the allowable limit, a penalty is applied:

$$P_{LPSP} = \max(0, LPSP - LPSP_{target}) \quad (45)$$

All energy sources - PV, WT, FCs, the battery system, and DG units - are summed up for every time period to meet the electrical consumption along with the energy stored in or recovered from the batteries:

$$P_{EXP} = \max(0, EXP - EXP_{max}) \quad (46)$$

We assume a baseline, that a minimum amount of the energy has to come from renewables, for instance, 70% or greater. It gets penalized if the RF falls below the threshold value:

$$P_{RF} = \max(0, RF_{min} - RF) \quad (47)$$

Besides the objective of the reduction of COE, fundamental constraints include:

a. Energy Balance Constraint:

All energy sources - PV, WT, fuel cells, the battery system, and DG units - are summed up for every time period to meet the electrical consumption along with the energy stored in or recovered from the batteries:

$$\begin{aligned} P_{PV}(t) + P_{WT}(t) + P_{FC}(t) + P_{DG}(t) + P_{batt,dis}(t) \\ \geq P_{load}(t) + P_{ELEC}(t) + P_{batt,ch}(t) \end{aligned} \quad (48)$$

b. Battery Constraints:

The battery's SOC is set within maximum and minimum bounds to avoid over-discharging or over-charging:

$$SOC_{min} \leq SOC \leq SOC_{max} \quad (49)$$

c. Reliability Constraints:

The LPSP index is incorporated to ensure that the load demand is covered within acceptable limits,

$$LPSP \leq LPSP_{target} \quad (50)$$

d. Excess Power Constraint:

In order to keep the excess power that sits idle within a fixed limit, so as not to waste money by having oversized components and to keep system efficiency from slipping:

$$EXP \leq EXP_{max} \quad (51)$$

e. Renewable Fraction Constraint:

The system has to meet a certain minimum percentage of renewable energy, set through a predetermined threshold for sustainability and reliance on less fossil fuel:

$$RF \geq RF_{target} \quad (52)$$

f. Decision Variable Bounds:

All the design variables have lower and upper limits that come from both economic and technical factors: the capacity of PVs installed, the number of wind turbines, battery capacity, FC capacity, electrolyzer capacity, and hydrogen reservoir capacity:

$$x_{i,min} \leq x_i \leq x_{i,max} \quad (53)$$

let x_i is one of the design variables. It was with these constraints that we approached the optimization problem using suitable meta-evolution algorithms (WOA and GTO) to best lay out the microgrid. The objective function always remained the minimum COE, ensuring reliable operation and environmental compatibility.

3. Optimization Techniques

3.1. Walrus Optimization Algorithm (WOA)

The Walrus Optimization Algorithm (WOA) is a population-based metaheuristic inspired by the collective and adaptive behavior of walruses [19]. In this study, WOA is employed to solve the nonlinear and high-dimensional optimization problem associated with the optimal sizing of hybrid microgrid components. According to the original formulation presented in [19], each walrus represents a candidate solution encoding the decision variables of the optimization problem, and its quality is evaluated using the defined objective function.

a. Initialization

At the beginning of the optimization process, a population of walruses is randomly initialized within the predefined lower and upper bounds of the decision variables. The initial population matrix is defined in equation (54) [19].

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} [x_{1,1} & \cdots & x_{1,j} & \cdots & x_{1,m}] \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x_{i,1} & \cdots & x_{i,j} & \cdots & x_{i,m} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ [x_{N,1} & \cdots & x_{N,j} & \cdots & x_{N,m}] \end{bmatrix} \quad (54)$$

Here, N is the total number of walruses, which is the population size; m is the number of decision variables; X denotes the entire population set; X_i represents the i th walrus, namely the i th candidate solution; and $x_{i,j}$ is the position value of the i th walrus for the j th variable. After initialization, each walrus will be evaluated with a fitness function in order to assess how good its position is with respect to the optimization goal.

$$F = \begin{bmatrix} F_1 \\ \vdots \\ F_i \\ \vdots \\ F_N \end{bmatrix} = \begin{bmatrix} [F(X_1)] \\ \vdots \\ [F(X_i)] \\ \vdots \\ [F(X_N)] \end{bmatrix} \quad (55)$$

where, F is the fitness vector for the population, and F_i implies the fitness of the i th walrus.

b. Mathematical modelling of WOA.

Phase 1: feeding strategy (exploration).

In the exploration phase, candidate solutions update their positions by moving toward the best solution found so far, which represents the dominant walrus in the population.

The position update rule is given by:

$$x_{i,j}^{p1} = x_{i,j} + rand_{i,j} \cdot (SW_j - I_{i,j} \cdot x_{i,j}) \quad (56)$$

Where $x_{i,j}^{p1}$ is the new location of the i -th walrus in the j -th dimension. $rand_{i,j}$ is an arbitrary number in $[0,1]$, SW_j denotes the best solution associated with the most powerful walrus, and $I_{i,j}$ denotes an arbitrarily assigned integer from $[1,2]$. The replacement strategy is expressed as:

$$X_i = \begin{cases} X_i^{p1}, & F_i^{p1} < F_i \\ X_i, & \text{else} \end{cases} \quad (57)$$

where X_i^{p1} is the updated candidate location and F_i^{p1} its fitness value. If the modified location yields a better fitness than the previous one, it replaces the old solution; otherwise, the original position is retained. This mechanism enables WOA to enhance global exploration by simulating walruses' adaptive feeding strategy.

Phase 2: migration.

To improve population diversity and reduce the likelihood of premature convergence, candidate solutions may migrate toward randomly selected peers. The migration mechanism is mathematically expressed as:

$$x_{i,j}^{P_2} = \begin{cases} x_{i,j} + rand_{i,j} \cdot (x_{k,j} - I_{i,j} \cdot x_{i,j}), & F_k < F_i \\ x_{i,j} + rand_{i,j} \cdot (x_{i,j} - x_{k,j}), & else \end{cases} \quad (58)$$

Where, $x_{k,j}$ is the j-th dimension of a randomly chosen walrus $k \in [1, 2, \dots, N]$ and $k \neq i$. $I_{i,j}$ is an integer randomly chosen from [1,2], and $rand_{i,j}$ is a uniform arbitrary number in [0,1]. The replacement condition is then applied:

$$X_i = \begin{cases} X_i^{P_2}, & F_i^{P_2} < F_i \\ X_i, & else \end{cases} \quad (59)$$

where $X_i^{P_2}$ is the new candidate solution and $F_i^{P_2}$ is the fitness value of that position. If the modified position is better in terms of fitness, then it replaces the old one; otherwise, the walrus does not move. The WOA achieves dynamic movement across regions in the search space by emulating the walruses' migratory pattern, which enhances global exploration and increases the probability of finding higher-quality solutions.

Phase 3: Evasion and Confrontation with Predators (Exploitation)

During this phase, the position update follows equations (60) and (61) and generates new candidate positions inside the contracting local bounds. A newly produced position replaces the previous one if it yields a better fitness as given by equation (62):

$$x_{i,j}^{P_3} = x_{i,j} + (lb_{local,j}^t + (ub_{local,j}^t - rand \cdot lb_{local,j}^t)), \quad (60)$$

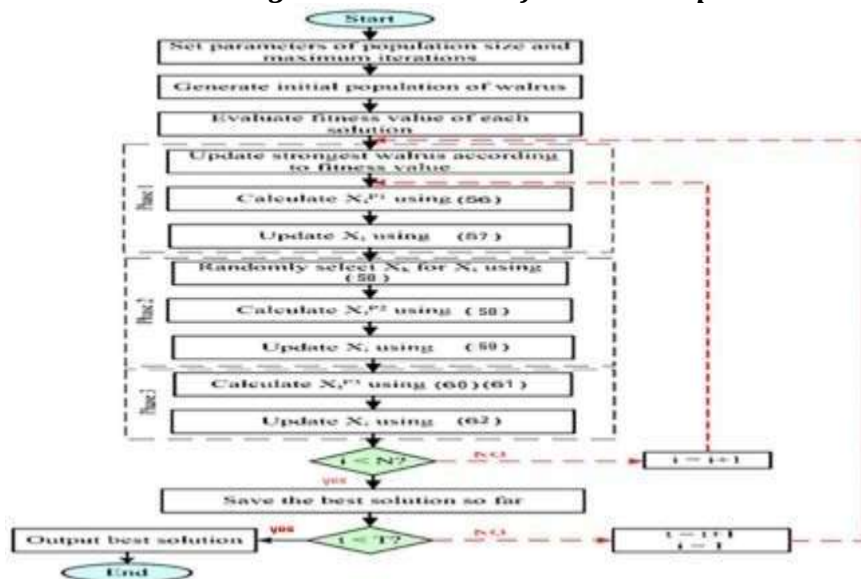
$$\begin{aligned} lb_i^t &= lb_i, \\ ub_i^t &= ub_i, \end{aligned} \quad (61)$$

$$X_i = \begin{cases} X_i^{P_3}, & F_i^{P_3} < F_i \\ X_i, & else \end{cases} \quad (62)$$

where lb_j and ub_j are the global minimum and maximum bounds of the j-th variable. $lb_{local,j}^t$ and $ub_{local,j}^t$ represent the time-dependent shrinking local bounds. In the third step, $X_i^{P_3}$ is the updated position of the i-th walrus, while $F_i^{P_3}$ is its associated fitness score.

Emulating how prey escapes from predators, WOA gradually tightens the search area over iterations for more precise exploitation of the best solutions so far found to enhance the overall robustness of the optimization process. Figure 3: WOA method flowchart.

Figure 3. Flowchart of WOA technique.



3.2. Gorilla Troops Optimization

The Gorilla Troops Optimizer (GTO) is a population-based metaheuristic algorithm inspired by the social behavior of gorilla troops in nature [20]. In this study, GTO is applied to solve the optimal sizing problem of hybrid microgrid components. According to the original formulation presented in [20], each gorilla represents a candidate solution, while the best solution in the population is referred to as the silverback.

a. Exploitation Phase

In the exploration phase, GTO employs multiple movement strategies to enhance population diversity and explore different regions of the search space. At each iteration, one of the exploration strategies is selected based on predefined probability conditions. The mathematical formulation of the exploration phase is expressed as:

$$GX(t+1) = \begin{cases} (UL - LL) \times r_1 + LL, & \text{if } rand < p \\ (r_2 - C) \times X_r(t) + L \times H, & \text{if } rand \geq 0.5 \\ X(i) - L \times (L \times (X(t) - GX_r(t)) + r_3 \times (X(t) - GX_r(t))), & \text{if } rand < 0.5 \end{cases} \quad (63)$$

where $X(t)$ and $GX(t+1)$ denote the current and updated position vectors of a gorilla at iteration t , respectively. The terms, r_1 , r_2 , and r_3 denote random numbers in $[0,1]$. The parameter $p \in [0, 1]$ controls the probability of selecting migration to an unexplored area. X_r represents a randomly chosen gorilla from the population, and GX_r is an arbitrarily chosen candidate vector.

The variables LL and UL define the search space boundaries. Additional parameters are formulated as:

$$C = F \times (1 - \frac{It}{MaxIt}) \quad (64)$$

$$F = \cos(2 \times r_4) + 1 \quad (65)$$

$$L = C \times l \quad (66)$$

$$H = Z \times X(t) \quad (67)$$

$$Z = [-C, C] \quad (68)$$

Here, It and $MaxIt$ represent the current and maximum iterations, respectively; r_4 is a random value in $[0,1]$; l is an arbitrarily number in $[-1,1]$; and Z is a random value in $[-1, 1]$ and $[-C, C]$. At the end of the exploration stage, the fitness of all candidate solutions $GX(t)$ is evaluated. If a candidate $GX(t)$ achieves a better cost than the current solution $X(t)$, it replaces $X(t)$ and becomes the new best solution, i.e., the silverback.

b. Exploitation Phase

In the exploitation stage of GTO, two main strategies are employed: following the silverback and competing for adult females. The selection between these strategies depends on the parameter C ((66)) compared with a known threshold parameter W . If $C \geq W$, the follow the silverback strategy is selected. In this case, the leads the group and guides other gorillas to the direction of the food source (i.e., the optimal solution). This mechanism is mathematically described by Equation (69):

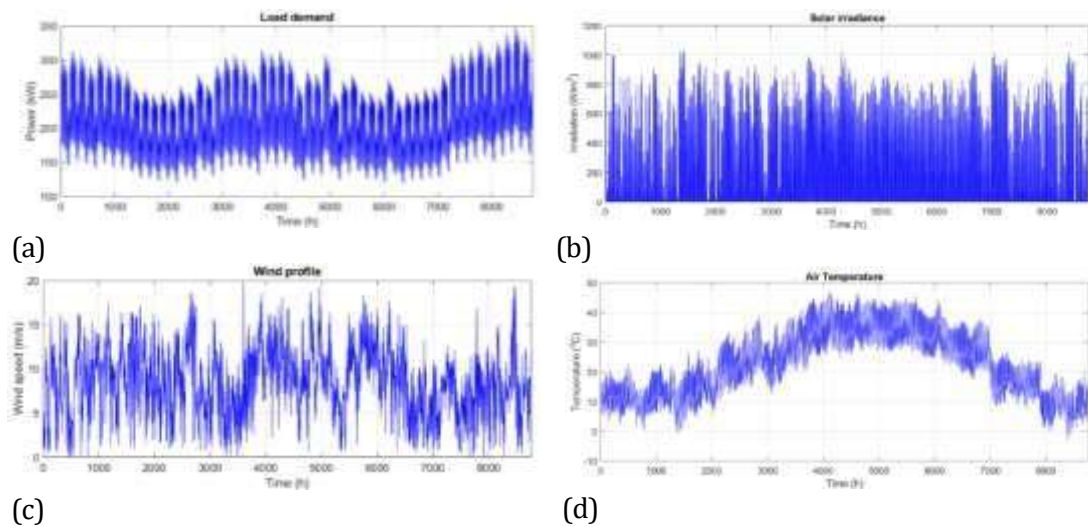
$$GX(t+1) = L \times M \times (X(t) - X_{silverback}) + X(t) \quad (69)$$

$X(t)$ represents the gorilla's position vector, while $X_{silverback}$ denotes the silverback's position vector (best solution). The parameter M is defined as:

$$M = (|\frac{1}{N} \sum_{i=1}^N GX_i(t)| \times \frac{1}{g}) \quad (70)$$

moderate wind speeds. Over 20 years, a comprehensive environmental database by drawn on NASA's Surface Meteorology and Solar Energy database has been compiled. The electricity load profile was obtained using actual consumption patterns for the residential, commercial, and services sectors, accounting for seasonal variations, as illustrated in Figure 5(a)[47, 48]. The solar irradiance profile, shown in Figure 5(b) reveals average annual solar energy flux of 6.0 kWh/m²/day, reducing to 3.6 kWh/m²/day during winters and increasing to 8.1 kWh/m²/day during summers, clearly establishing high solar energy resources [49]. The annual wind speed variation, presented in Figure 5(c) varies between 6.8 m/s and 7.9 m/s, which is apt for medium-sized wind turbines [49]. Seasonal temperature variations, depicted in Figure 5(d), influencing PV efficiency and cooling requirements, show typical seasonal variations [49]. For the proposed case study, the following constraints of the system components are adjusted as follows: $100 \leq N_{PV} \leq 10000$, $0 \leq N_{WT} \leq 10000$, $0 \leq P_{elec-rated} \leq 10000$, $0 \leq M_{Tank,max} \leq 10000$, $50 \leq P_{FC-rated} \leq 10000$, $0 \leq N_{DG} \leq 10000$, $100 \leq N_{batt} \leq 10000$. This exhaustive assessment has become a foundation for a feasibility study. Various simulations have been carried out so as to identify optimal arrangements and sizes for the PV/WT/FC/DG/battery system. The results obtained from a comparative analysis prove that the proposed optimization techniques properly respond to technical as well as environmental issues linked to the utilization of renewable sources of energy.

Figure 5. Case study input data for the Al-Husaybah site: (a) The load demand profile for Husaybah site, (b) The annual solar irradiance profile of Husaybah site, (c) The annual wind speed profile of Husaybah site, (d) The air temperature over Husaybah site.

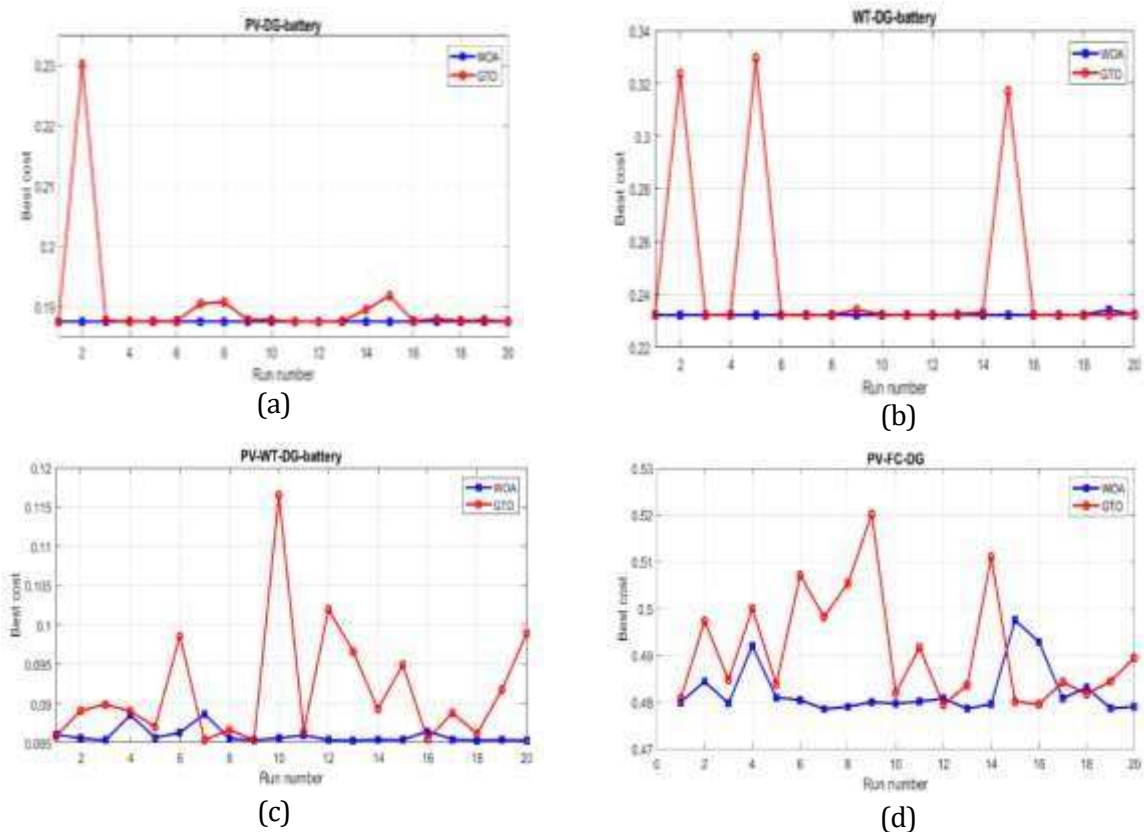


5. Results and discussion

In this study, the Walrus Optimization Algorithm (WOA) and the Gorilla Troops Optimizer (GTO) were applied to determine the optimal sizing and configuration of a grid-independent microgrid. Seven hybrid configurations were investigated: PV-DG-Battery, WT-DG-Battery, PV-WT-DG-Battery, PV-FC-DG, WT-FC-DG, PV-WT-FC-DG, and PV-WT-FC-DG-Battery. Owing to the stochastic nature of meta-heuristic algorithms, each configuration was independently executed 20 times. Statistical indicators were then used to assess accuracy and reliability. All simulations were performed with 30 agents and a maximum of 100 iterations, and the best solution was selected based on the minimum objective function value. The convergence results (Figs. 6–7) show that WOA consistently

outperforms GTO in terms of convergence speed, stability, and solution quality. For simple configurations such as PV-DG-Battery and WT-DG-Battery, WOA maintained nearly constant objective values, while GTO exhibited noticeable fluctuations and sensitivity to initial conditions. As system complexity increased, these differences became more pronounced. In the PV-WT-DG-Battery and PV-FC-DG configurations, WOA produced tightly clustered solutions, whereas GTO showed large deviations and occasional outliers. In the PV-WT-FC-DG case, GTO experienced severe instability, while WOA remained highly stable. Statistical analysis (Table 2) confirms the superiority of WOA, which achieved lower mean values, standard deviation, MAE, and RMSE across all configurations. For example, in the PV-DG-Battery system, the standard deviation of WOA was 1.48×10^{-5} compared to 9.443×10^{-3} for GTO. In the most complex PV-WT-FC-DG-Battery configuration, WOA achieved an RMSE of approximately 0.000929, whereas GTO reached 0.034096. Moreover, WOA maintained solution efficiency above 99%, while GTO dropped to 92.76% in complex cases. Overall, WOA demonstrates superior robustness, reliability, and scalability compared to GTO. Although GTO performs adequately for simple configurations, it suffers from instability and premature convergence in high-dimensional hybrid systems, making WOA more suitable for optimal hybrid microgrid planning.

Figure 6. Final values of the objective function for all Microgrid configurations based on 20 individual runs: (a) PV-DG-battery, (b) WT-DG-battery, (c) PV-WT-DG-battery, (d) PV-FC-DG, (e) WT-FC-DG, (f) PV-WT-FC-DG, (g) PV-WT-FC-DG-battery.



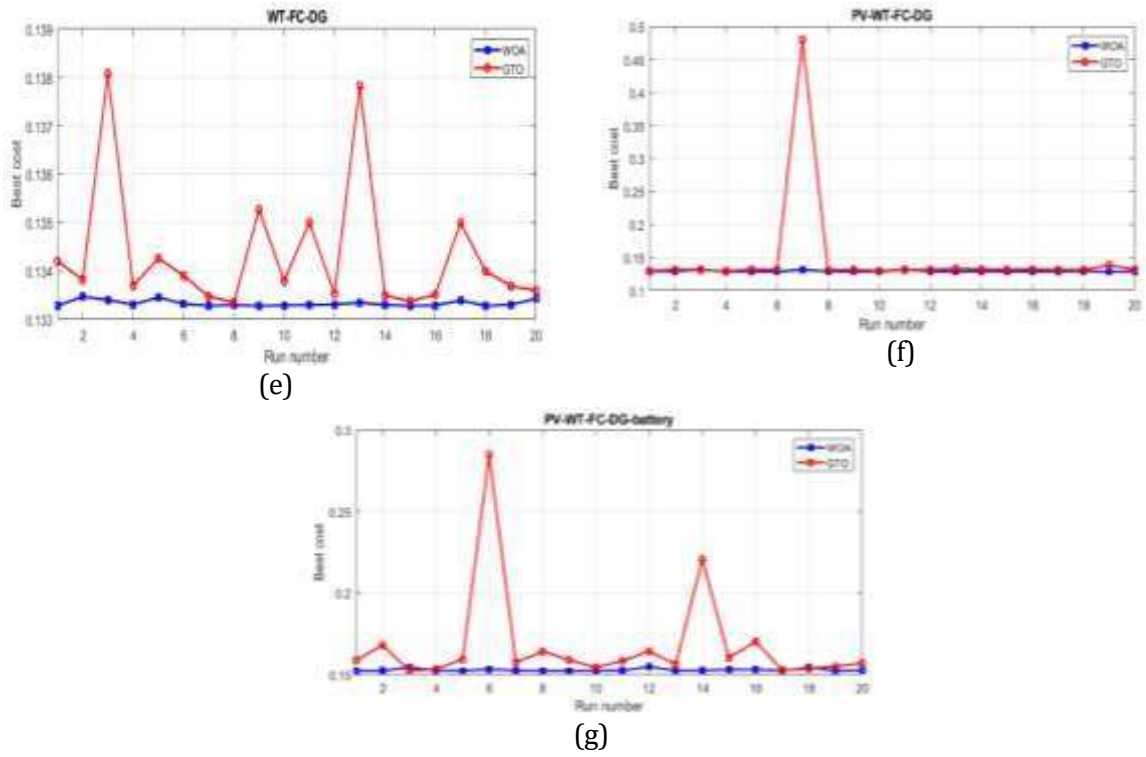
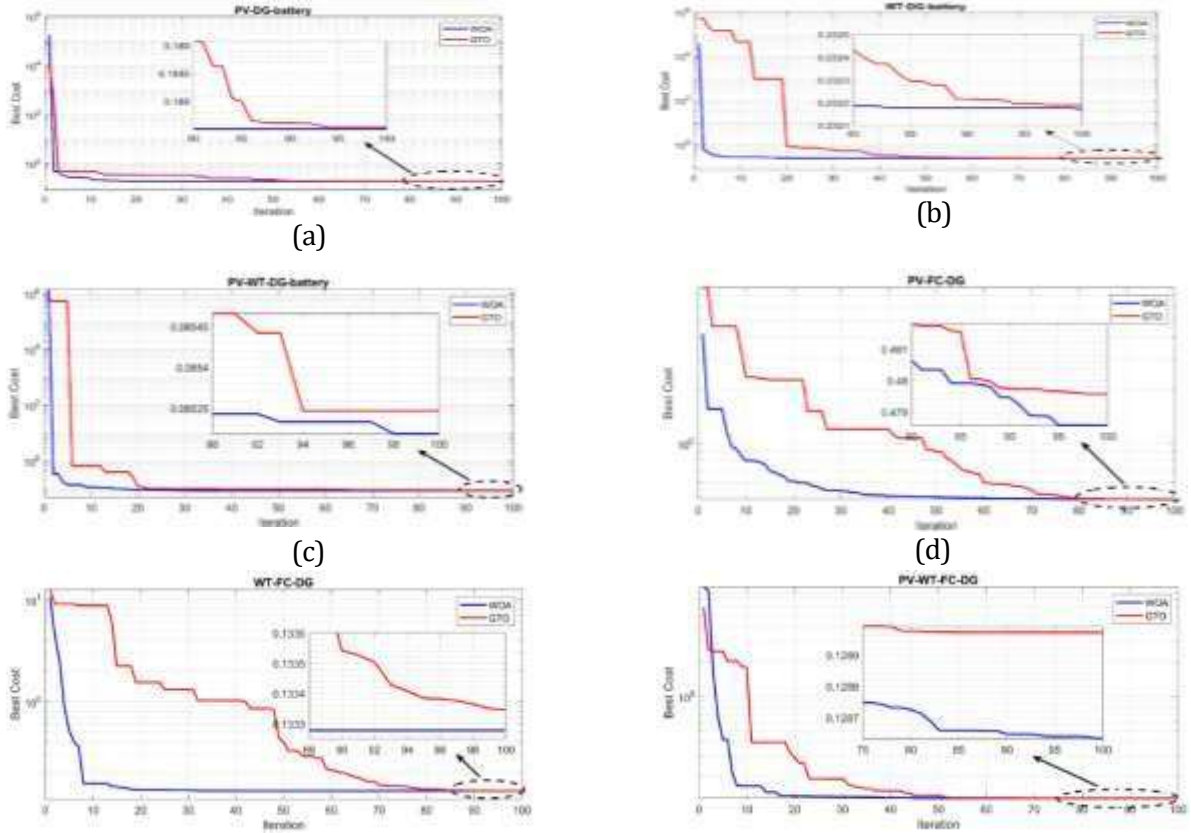
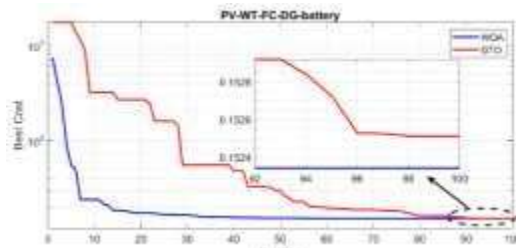


Figure 7. Convergence curves (a) PV-DG-battery, (b) WT-DG-battery, (c) PV-WT-DG-battery, (d) PV-FC-DG, (e) WT-FC-DG, (f) PV-WT-FC-DG, (g) PV-WT-FC-DG-battery.
Table 2. Statistical study of different Microgrid configurations.



(e)

(f)



(g)

		Min	Max	Mean	Median	SD	MAE	RMS E	Efficiency
PV-DG-battery	W	0.187	0.187	0.187	0.187	1.48E	3.19E	3.5E-	99.98
	OA	512	585	544	542	-05	-05	05	301
	GT	0.187	0.230	0.190	0.187	0.009	0.002	0.009	98.68
WT-DG-battery	W	0.232	0.234	0.232	0.232	0.000	0.000	0.000	99.94
	OA	171	078	289	19	421	118	427	968
	GT	0.232	0.329	0.246	0.232	0.033	0.013	0.035	95.68
PV-WT-DG-battery	W	0.085	0.088	0.085	0.085	0.000	0.000	0.001	99.34
	OA	319	661	893	49	982	574	116	374
	GT	0.085	0.116	0.091	0.089	0.007	0.006	0.009	93.66
PV-FC-DG	W	0.478	0.497	0.482	0.480	0.005	0.003	0.006	99.22
	OA	577	561	349	129	387	772	465	958
	GT	0.479	0.520	0.491	0.484	0.012	0.011	0.016	97.66
WT-FC-DG	W	0.133	0.133	0.133	0.133	6.27E	5.13E	7.98E	99.96
	OA	278	47	329	301	-05	-05	-05	155
	GT	0.133	0.138	0.134	0.133	0.001	0.000	0.001	99.26
PV-WT-FC-DG	W	0.128	0.131	0.129	0.128	0.001	0.000	0.001	99.48
	OA	633	715	302	899	018	669	197	805
	GT	0.128	0.479	0.149	0.131	0.077	0.020	0.078	94.43
PV-WT-FC-DG-battery	W	0.152	0.154	0.152	0.152	0.000	0.000	0.000	99.63
	OA	343	832	9	579	763	557	929	824
	GT	0.152	0.284	0.168	0.158	0.031	0.015	0.034	92.75
	W	0.152	0.154	0.152	0.152	0.000	0.000	0.000	99.63
	OA	343	832	9	579	763	557	929	824
	GT	0.152	0.284	0.168	0.158	0.031	0.015	0.034	92.75

Table 3 shows the optimal component sizing for the seven HRES configurations obtained by both WOA and GTO. While the overall sizing obtained by either technique is rather similar, WOA is far more consistent and results in a better mix of energy sources. Both methods have almost the same counts for the PV–DG–Battery setup: approximately 2.96 million PV panels, approximately 6,206 diesel units, and about 1.6 GWh of battery capacity. On the other hand, the WOA gave much tighter consistency from run to run. The same was also seen in the WT–DG–Battery system at approximately 37,253 wind turbines and approximately 2.14 GWh of battery storage, again more stable under WOA. From the

tendency of the WOA towards a more solar-heavy design in the PV-WT-DG-Battery setup (452,650 PV panels and 23,020 turbines) compared to GTO (467,680 panels and 22,870 turbines), it can be found that, for the PV-FC-DG case, WOA increases the capacity of the PV (7,233,650 panels vs. 6,992,560) while trimming the hydrogen subsystem, achieving a better renewable-to-hydrogen trade-off. In the WT-FC-DG scenario, both approaches select 50,000 fuel cells, but WOA gives marginally smaller hydrogen tanks and electrolyzers, which indicates a more efficient hydrogen consumption. In the PV-WT-FC-DG configuration, WOA seems to clearly favor solar, using 488,160 PV panels, whereas GTO uses 346,050, with a reduction in the number of wind turbines. For the most complex setup, PV-WT-FC-DG-Battery—WOA gets a well-balanced design about 491,420 PV panels, 32,230 turbines, 5,790 diesel units, 100,040 kWh of batteries, 62,160 fuel cells, hydrogen tank 161,240 kg, and 32,230 electrolyzers. GTO, by contrast, uses a bit more PV capacity and a slightly smaller hydrogen system. Overall, although the numerical gaps between the two methods are modest, WOA manages to yield more balanced and stable configurations. It avoids over- or under-sizing of components and delivers economic steadiness. This makes WOA a more reliable and effective optimization tool for HRES design.

Table 3. The optimal sizing of different Microgrids based on WOA and GTO.

		n_{PV}	n_{WT}	n_{DG}	n_{batt}	P_{FC}	M_{tank}	P_{Elec}
PV-DG-battery	WO A	2955. 619	0	6.205 583	1600. 284	0	0	0
	GT O	2955. 628	0	6.205 604	1600. 214	0	0	0
WT-DG-battery	WO A	0	37.25 315	5.770 786	2143. 415	0	0	0
	GT O	0	37.25 327	5.770 89	2143. 481	0	0	0
PV-WT-DG-battery	WO A	452.6 506	23.02 221	4.583 968	209.5 667	0	0	0
	GT O	467.6 838	22.86 768	4.566 472	209.3 83	0	0	0
PV-FC-DG	WO A	7233. 65	0	3.574 457	0	181.8 703	227.0 48	1511. 134
	GT O	6992. 562	0	3.856 411	0	190.8 02	209.9 014	1446. 787
WT-FC-DG	WO A	0	32.84 428	4.226 883	0	50.00 007	32.45 405	79.49 344
	GT O	0	32.99 351	4.213 217	0	50.00 001	31.63 409	82.35 18
PV-WT-FC-DG	WO A	488.1 559	28.62 53	3.113 303	0	50.00 003	34.01 985	90.17 577
	GT O	346.0 508	30.15 244	3.346 495	0	50.00 126	34.43 143	84.85 93
PV-WT-FC-DG-battery	WO A	491.4 205	32.22 953	5.788 218	100.0 372	62.16 065	161.2 365	32.22 953
	GT O	508.2 863	32.05 015	5.774 644	100	50	64.23 202	162.8 019

Table 4 presents the performance of the different combinations of the seven microgrids. Generally, it can be noted that Walrus Optimization Algorithm (WOA) outperforms GTO

on all aspects of reliability, efficiency, and economy. Total unmet load in the PV-DG-Battery combination remains the same for both approaches with a minor difference (approximately 56,659 kWh), as does the diesel consumption (approximately 93,970 L), but with a lower total cost for WOA (354,147.2\$ vs. 354,194.2\$). When it comes to the WT-DG-Battery system, the total unmet load remains the same (approximately 56,657 kWh), but the GTO produces a higher electricity generation (94,433 kWh vs. 75,540 kWh for the WOA) that translates to a higher cost (438,529.9\$). In the PV-WT-DG-Battery configuration, WOA reduces unserved demand to 56,593.5 kWh, decreases diesel run hours to 3,018 (3,042 hours), reduces fuel to 101,386 L (101,540 L), increases excess electricity to 75,473 kWh (93,017 kWh), and decreases cost to 161,139.6\$ (from 161,191.9\$). In the PV-FC-DG configuration, WOA increases solar power production to 4,664,644 kWh (4,509,177 kWh), decreases fuel to 99,170 L (100,626 L), and decreases cost to 903,871.6\$ (from 905,752\$). In the WT-FC-DG system, the shortfall load remains constant (approximate value: 94,400 kWh), but the WOA design has lower diesel consumption, lower excess power, and lower costs (251,846\$ compared with 251,717.3\$). The total PV-WT-FC-DG system has the benefit of increased power generation due to the PV system (314,789 vs. 223,152 kWh), decreased diesel fuel consumption to 62,650 L (from 64,619 L), and a decreased bill of 242,944.5\$ (from 243,584.2\$). The complete system PV-WT-FC-DG-Battery depicted the maximum improvement, and WOA yielded minimum unloaded amount (18,875.5 units), a slight reduction in fuel consumption, improved share of back-up from RES, and lowest overall cost (287,724.9\$ as against 288,046.7 \$). When combined, both techniques produce doable hybrid designs, yet in respect of unmet loads, fuel consumption, resource usage, and total costs, WOA is always more favorable, thereby establishing its advantage in optimizing hybrid renewable energy systems.

Table 4. The performance of various Microgrids based on the results of WOA and GTO.

		P_{unmet} (kWh)	EXP (kWh)	$hour_{DG}$ (h)	$cons_{fuel}$ (liter)	E_{PV} (kWh)	E_{WT} (kWh)	$C_{ann.to}$ (\$)
PV-DG- battery	W OA	56658.9 9	7553 9.86	1739	93969.61	19059 41	0	3541 47.2
	GT O	56658.0 2	7554 6.18	1745	94060.41	19059 47	0	3541 94.2
WT-DG- battery	W OA	56657.1 8	7554 0.32	1946	95040.94	0	17816 79	4384 94
	GT O	56653.5 4	9443 3.14	1949	95083.89	0	17816 84	4385 29.9
PV-WT- DG- battery	W OA	56593.4 6	7547 2.97	3018	101386.4	29189 3.3	13777 07	1611 39.6
	GT O	56603.7 6	9301 7.05	3042	101539.7	30158 7.5	13684 59	1611 91.9
PV-FC- DG	W OA	94376.6 6	9376 7.17	3774	99170.2	46646 44	0	9038 71.6
	GT O	94291.5 8	9442 8.61	1808	100625.7	45091 77	0	9057 52.4
WT-FC- DG	W OA	94433.1 7	9443 3.16	2407	80332.1	0	19654 83	2517 17.3

	GT O	94362.6 5	9424 8.23	2378	79472.31	0	19744 14	2518 46
PV-WT- FC-DG	W OA	94407.3 2	9440 2.75	2580	62649.53	31478 9	17130 09	2429 44.5
	GT O	94433.1 5	9443 2.13	2294	64618.69	22315 2	18043 97	2435 84.2
PV-WT- FC-DG- battery	W OA	18875.4 9	1888 6.61	1734	70509.89	31689 4.2	19286 95	2877 24.9
	GT O	18884.9	1887 2.41	1738	70193.56	32777 0.1	19179 61	2880 46.7

Table 5 compares hybrid configurations under fixed constraints (RF = 0.85, LPSP = 0.05, EXP = 0.05). Differences mainly appear in COE, NPC, and LCE. The WOA-optimized PV-WT-DG-Battery system performs best overall, achieving the lowest COE (0.0853 \$/kWh), minimum NPC (~2.06 million\$), and moderate emissions (225,071.4 kg CO₂), making it the most economically viable option with acceptable environmental impact. The PV-FC-DG configuration is the least economical (COE = 0.4786 \$/kWh, NPC ≈ 11.55 million\$) despite meeting all constraints. Environmentally, the PV-WT-FC-DG (WOA) system yields the lowest emissions (156,714.2 kg CO₂) but at higher cost. Adding batteries further improves reliability and emissions but increases NPC. Overall, WOA slightly outperforms GTO under identical constraints, and the PV-WT-DG-Battery (WOA) configuration offers the best cost-reliability-environment trade-off.

Table 5. Assessment of various Microgrids based on WOA and GTO algorithms.

		COE	NPC	RF	EXP	LPSP	LCE
PV-DG-battery	WO A	0.1875 12	452719 0	0.8500 01	0.0399 96	0.03	301600 .6
	GT O	0.1875 37	452779 0	0.8500 02	0.04	0.0299 99	301600 .1
WT-DG-battery	WO A	0.2321 71	560542 5	0.8500 01	0.0399 97	0.0299 99	220727 .3
	GT O	0.2321 9	560588 4	0.8500 01	0.0399 96	0.0299 97	194281 .7
PV-WT-DG- battery	WO A	0.0853 19	205990 5	0.8500 47	0.0399 61	0.0299 65	225071 .4
	GT O	0.0853 47	206057 3	0.8500 14	0.0399 54	0.0299 7	424209
PV-FC-DG	WO A	0.4785 77	115545 12	0.8500 04	0.0496 47	0.0499 7	406104
	GT O	0.4795 73	115785 55	0.85	0.0499 98	0.0499 25	399144 .5
WT-FC-DG	WO A	0.1332 78	321779 2	0.8743 22	0.05	0.05	180992 .1
	GT O	0.1333 46	321943 7	0.8754 17	0.0499 02	0.0499 63	179716 .4
PV-WT-FC-DG	WO A	0.1286 33	310564 6	0.9025 29	0.0499 84	0.0499 86	156714 .2
	GT O	0.1289 72	311382 3	0.8987 66	0.0499 99	0.05	158345 .3
PV-WT-FC-DG- battery	WO A	0.1523 43	367809 0	0.9000 26	0.01	0.0099 94	167719 .5

	GT	0.1525	368220	0.9007	0.0099	0.0099	167188
	0	13	3	1	92	99	.4

Figure 8 represents the hybrid system energy timelines for a day, tracking interconnections between PV, wind energy, the electrolyzer, fuel cell, batteries, and a diesel plant. Between 1-5 AM, wind serves the demand and the fuel cell consumes hydrogen generated previously. Between 6-10 AM, any remaining wind energy feeds the electrolyzer. Afternoon times witness higher solar intensity; this enhances hydrogen production and recharges batteries. Finally, between 4-8 PM, when electricity from wind and solar reduces slightly, the energy continues through battery discharge, the fuel cell, and assistance from the diesel plant. Figure 9(a) monitors the amount of the hydrogen tank, which changes based on the available renewable generation and the fuel cell consumption, going high when the available generation is high, implying a surplus, and vice versa. Figure 9(b ,c) focuses on the fluctuations of hydrogen generation or consumption during peak demand or when the amount of renewable generation is low., Figure 10(a) focuses on the SOC charge of the battery, which varies between 20% and 100%. Figure 10(b) focuses on the episodes where the battery discharge is very high when the renewable generation is low. Figure 11: Comparison of required loading vs. what is being provided, presumably showing good coverage but shortfalls in the windows of low generation and losses due to overproduction beyond storage capacity.

Figure 8. Microgrid performance (five days of operation)

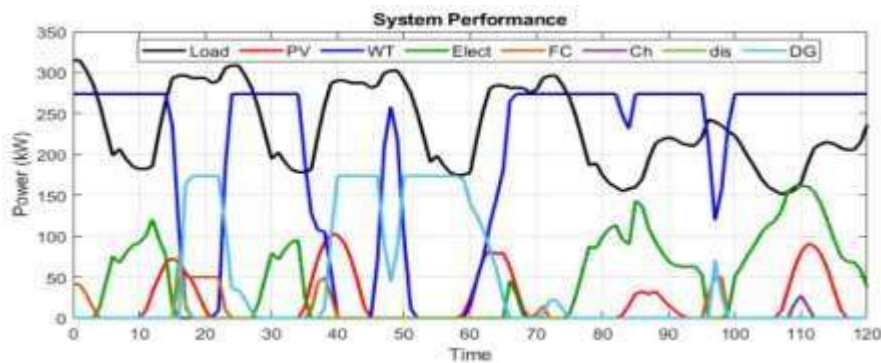
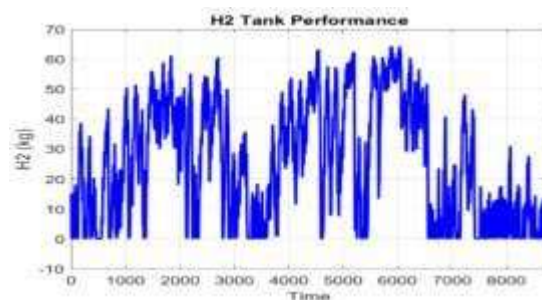


Figure 9. Hydrogen storage system behavior: (a) Hydrogen tank level over one year, (b) Hydrogen production and consumption dynamics, (c) Short-term hydrogen production and consumption (5 days).



(a)

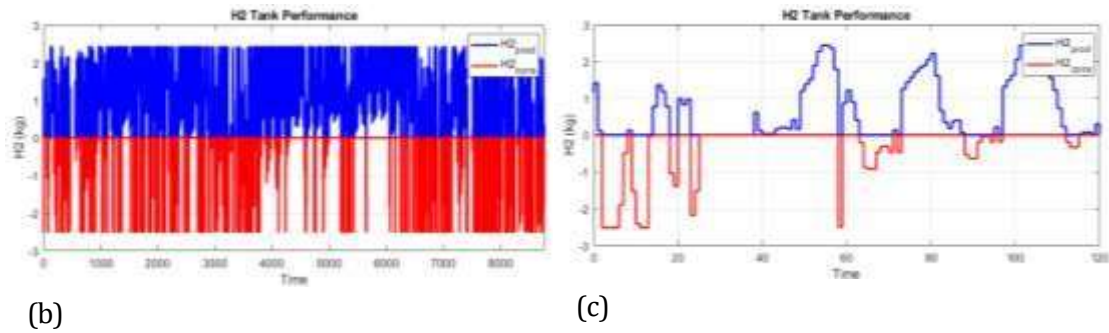


Figure 10. (a) Battery SOC, (b) Battery SOC and Power Flow.

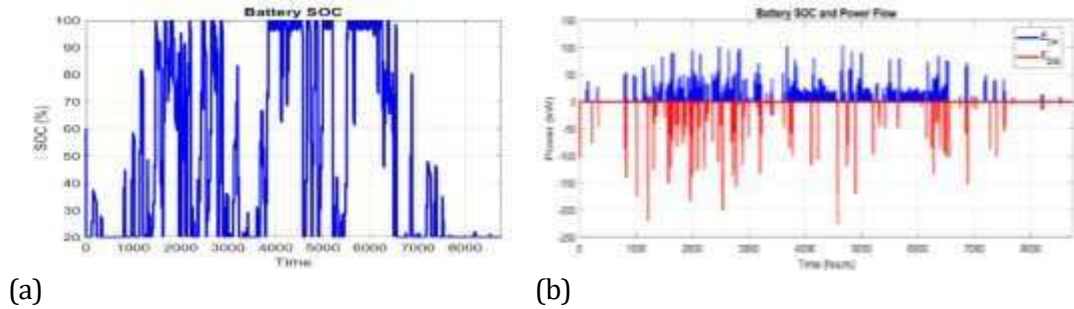


Figure 11. System Reliability.

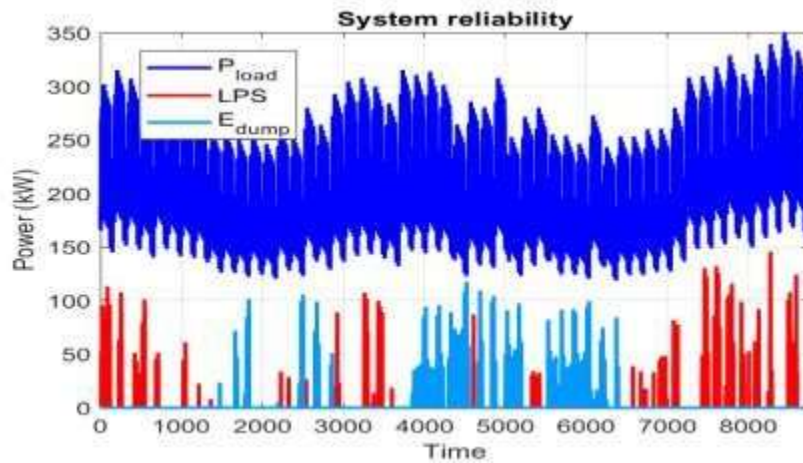
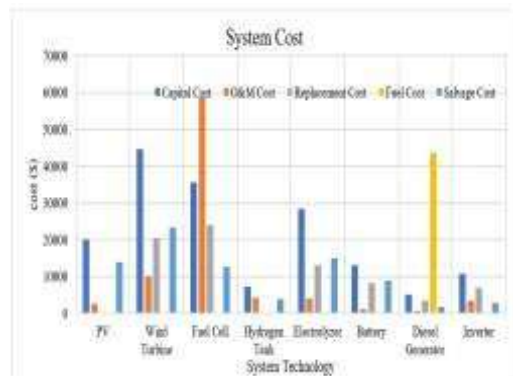


Table 6 and Figure 12 lay out how each piece of a hybrid system carries its own cost fingerprint. The upfront hit is steepest for wind turbines and fuel cells, while photovoltaic panels and diesel generators come with lighter initial investments. O&M is where wind turbines and fuel cells really show their teeth, thanks to regular upkeep. Over the long run, replacing turbines, electrolyzers, batteries, and fuel cells drives total costs upward, whereas diesel fuel dominates lifetime expenses despite its modest capital outlay. Salvage value trims the overall bill for PV, wind, and batteries. When the costs are averaged over the year, fuel cells and diesel generators become the most expensive due to continued maintenance and fuel requirements. In contrast, PV, wind, and batteries remain the least costly in the long term since their operating costs remain very low. Hydrogen-based components fall into an intermediate position and provide a well-balanced choice for seasonal storage and a low-carbon energy transition.

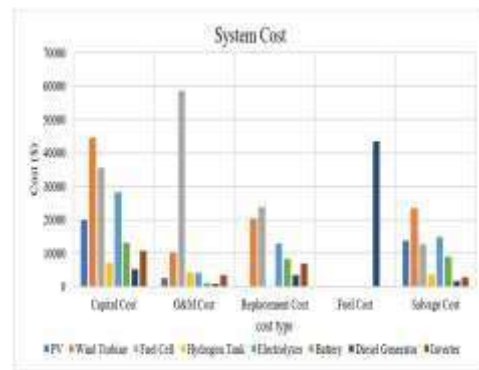
Table 6. Cost breakdown with respect to cost type.

	Capital Cost	O&M Cost	Replacement Cost	Fuel Cost	Salvage Cost	annual Cost
PV	20039.8299	2541.43139	0	0	13907.3908	8673.87057
Wind Turbine	44708.4546	10256.0490	20512.09812	0	23458.3027	52018.2991
Fuel Cell	35609.4634	58750.0056	24000.00231	0	12681.0245	105678.446
Hydrogen Tank	7280.05242	4303.54543	0	0	3819.80711	7763.79074
Electrolyzer	28387.6306	4070.04858	13024.15546	0	14894.8478	30586.9867
Battery	13120.4732	1100	8333.333333	0	8885.24016	13668.5664
Diesel Generator	5178.28807	762.253020	3464.786456	43520.0084	1686.12249	51239.2135
Inverter	10811.0902	3500	7000	0	2893.58180	18417.5084
Total	165135.282	85283.3331	76334.37568	43520.0084	82226.3175	288046.682

Figure 12. Cost breakdown of the hybrid microgrid system: (a) Breakdown of cost with respect to system technology, (b) Breakdown of cost with respect to cost type.



(a)



(b)

6. Conclusion

The paper assesses seven heterogeneous microgrid configurations, which integrate PV, wind turbines, and batteries, along with a hydrogen cycle, electrolyzer, tank, fuel cell, and

diesel generator. The work aims at reducing energy cost while maintaining a certain supply, applying WOA and GTO techniques for improved solutions. The simulation results demonstrate that WOA produces superior solutions and superior convergence performance, especially while handling complex microgrids involving multiple fuel sources. Further, from all microgrid configurations, it has been identified that PV-WT-DG-Battery configuration, which is optimized using WOA, provides optimum cost per unit (0.0853 \$/kWh) and portfolio cost, while maintaining respective reliability constraints. In terms of greenhouse gas reduction, PV-WT-FC-DG microgrid, involving a hydrogen system, generates optimal number of pollutants, approximately 156,700 kg CO₂, despite involving higher expenses. Thus, batteries offer the most economical solution in the short term, and the environment is improved by the addition of hydrogen. This work proves the efficacy of the latest metaheuristic approaches, particularly the WOA algorithm, to solve microgrid optimization problems in the presence of high dimensions and presents useful takeaways to the community. Furthermore, future researchers can continue to investigate new directions such as multi-objective optimization, uncertainty, and socio-economic effects.

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