

## **OPTIMIZED HYBRID RENEWABLE ENERGY SYSTEM WITH PUMPED HYDRO STORAGE FOR RURAL ELECTRIFICATION IN NIGERIA USING ENERGY VALLEY OPTIMIZER**

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### **Abstract**

Access to reliable and affordable electricity remains a major challenge for rural communities in Nigeria, where diesel-dependent generation results in high costs and environmental degradation. This study proposes an optimized standalone hybrid renewable energy system (HRES) comprising solar photovoltaic (PV), biogas generation, diesel generator (DG) backup, and pumped hydro storage (PHS) for the Ikere community in Oyo State, Nigeria. An Integrated Hybrid Energy Sizing Model (IHESM) was formulated as a weighted multi-objective optimization problem that simultaneously minimizes the levelized cost of energy (LCOE), loss of power supply probability (LPSP), and total energy/carbon cost (TCE). Weighting factors were selected to reflect equal priority to economic performance and reliability, with LPSP constrained to a maximum allowable reliability target of 0.101 (i.e., at least 89.9% supply adequacy), consistent with rural microgrid planning benchmarks. The optimization problem was solved using the Energy Valley Optimizer (EVO), a physics-inspired metaheuristic algorithm whose search mechanism mimics energy-state transitions in physical systems to enhance global exploration and convergence stability. Results show that the EVO-optimized configuration (900 kWp PV, 200 kW biogas, 200 kW×3 h PHS, and 550 kW DG) achieved an LCOE of ₦102/kWh while satisfying the imposed reliability constraint. Stability performance was evaluated in MATLAB/Simulink through Renewable Energy Fraction (REF) sweep simulations, demonstrating voltage regulation within 0.97–1.03 p.u. and fast frequency recovery ( $\pm 0.12$  Hz within 3 s) at approximately 85% renewable penetration. The proposed framework provides a cost-effective, reliability-aware, and operationally stable pathway for sustainable rural electrification in Nigeria.

### **Keywords**

*Standalone power systems, Energy Valley Optimizer, Cost effectiveness, Reliability assessment, Carbon emission reduction*

## **1. INTRODUCTION**

Access to reliable, affordable, and sustainable electricity remains a persistent challenge in rural and semi-urban communities across Nigeria. Grid extension to these regions is often economically impractical due to low load density, high transmission infrastructure costs, and weak grid stability. Consequently, many communities depend on standalone diesel generators, which provide dispatchable power but are associated with high fuel costs, greenhouse gas emissions, and long-term environmental degradation [1], [2]. Hybrid Renewable Energy Systems (HRES), which integrate renewable generation with storage and backup units, have emerged as viable alternatives for off-grid electrification. However, achieving an optimal balance among cost, reliability, environmental impact, and operational stability remains a complex engineering challenge [3], [4].

Despite the growing adoption of PV–diesel–battery and PV–biogas hybrid systems, existing designs often suffer from three major limitations [5]. First, many optimization frameworks prioritize economic cost while treating reliability and environmental impact as secondary constraints. Second, storage-dominated solutions—particularly battery-based systems result in high capital expenditure and limited lifespan concerns. Third, the dynamic implications of high renewable penetration on voltage and frequency stability are rarely integrated into the optimization process. As a result, many reported solutions fail to provide a unified

framework that simultaneously addresses techno-economic performance, reliability adequacy, long-duration storage integration, and operational stability in rural Nigerian contexts [6], [7].

Several studies have applied metaheuristic algorithms such as Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Whale Optimization Algorithm (WOA) for hybrid system sizing. While these approaches improve search efficiency compared to deterministic methods, they often exhibit premature convergence or limited global exploration in highly nonlinear design spaces [8]-[13]. Furthermore, most existing studies focus on PV–battery–diesel or PV–wind configurations, with limited investigation into pumped hydro storage (PHS) as a long-duration storage alternative suitable for communities with accessible water resources.

To address these gaps, this study aims to develop and evaluate an optimized standalone hybrid microgrid for rural electrification in Nigeria. The specific objectives are:

- i. To develop an Integrated Hybrid Energy Sizing Model (IHESM) that jointly minimizes Levelized Cost of Energy (LCOE), Loss of Power Supply Probability (LPSP), and Total Energy/Carbon Cost (TCE) under realistic operational constraints.
- ii. To integrate Pumped Hydro Storage (PHS) as a long-duration storage solution within a PV–biogas–diesel hybrid architecture to reduce battery dependency and diesel runtime.
- iii. To apply and benchmark the Energy Valley Optimizer (EVO) a physics-inspired metaheuristic algorithm against established algorithms (GA and WOA) for solving the multi-objective sizing problem.
- iv. To evaluate the operational feasibility of high renewable penetration through Renewable Energy Fraction (REF) sweep analysis, assessing voltage stability and frequency recovery performance.

Thus, the novelty of this work lies in the first integrated application of the Energy Valley Optimizer (EVO) to a PV–biogas–diesel–PHS hybrid microgrid in the Nigerian rural electrification context, combined with a stability-aware Renewable Energy Fraction (REF) sweep analysis. Unlike conventional PV–diesel–battery studies, this research introduces long-duration pumped hydro storage within a unified multi-objective optimization framework that explicitly incorporates economic cost, reliability adequacy, emission-related cost, and dynamic stability assessment. By coupling optimization with voltage and frequency performance evaluation, the study provides a holistic design methodology that bridges techno-economic planning and operational feasibility—an aspect largely underexplored in rural hybrid microgrid research.

The remainder of this paper is organized as follows: Section 2 presents the mathematical problem formulation and system modelling. Section 3 describes the optimization algorithms and simulation setup. Section 4 presents the optimization and stability results. Section 5 discusses practical implications and sensitivity considerations. Section 6 concludes the study.

## 2. MATERIALS AND METHOD

### 2.1. Problem Formulations

The optimal planning of a standalone hybrid renewable energy system (HRES) is inherently a multi-objective and constrained optimization problem. The system must be designed to reliably satisfy community electricity demand while simultaneously minimizing economic cost and environmental impact. This study formulates the sizing and operation of a PV–biogas–diesel generator–pumped hydro storage (PHS) hybrid microgrid within a unified mathematical framework referred to as the Integrated Hybrid Energy Sizing Model (IHESM). The HRES considered in this study comprises solar photovoltaic (PV) arrays, a dispatchable biogas generator, a standby diesel generator (DG), and a pumped hydro storage unit interconnected through a common AC bus. The system operates under a renewables-first energy management strategy, in which renewable sources are prioritized to meet load demand, while storage and dispatchable units provide balancing and reliability support. The objective of the formulation is to determine the optimal capacities of all system components such that long-term energy demand is met with acceptable reliability at minimum cost and reduced carbon emissions.

#### 2.1.1. Objective function

The optimization problem is defined by a composite objective function that simultaneously minimizes three competing performance indices: the levelized cost of energy (LCOE), the loss of power supply probability (LPSP), and the total cost of energy and carbon emissions (TCE). These indices capture the economic, reliability, and environmental dimensions of system performance, respectively. The multi-objective problem is transformed into a single optimization function through weighted aggregation, expressed as Equation 1:

$$\min F = w_1 \cdot LCOE + w_2 \cdot LPSP + w_3 \cdot TCE \quad 1$$

In which, the LCOE, LPSP and TCE were determined using Equations 2 to 5

$$LCOE = \frac{\sum_i (C_{capex} + C_{Opex,i} + C_{maint,i})}{\sum_{t=1}^T E_{gen}(t)} \quad 2$$

$$C_{Total} = C_{capex} + C_{opex} + C_{maint} \quad 3$$

$$LPSP = \frac{\sum_0^t D_{Lt}}{8760} \times 100\% \quad 4$$

$$TCE = A \times E_f \times \left( \frac{1 - E_R}{100} \right) \quad 5$$

where;  $C_{Total}$  is the total cost of HRES system,  $C_{capex}$  is the capital cost of all components,  $C_{opex}$  is the operation cost,  $C_{main}$  is the maintenance cost,  $E_{gen}(t)$  is the total energy generated by HRES at time  $t$ ,  $T$  is the total operational lifetime of the system,  $i$  is the time interval,  $t$  is the time,  $D_{Lt}$  is the deficit load time,  $A$  is the activity rate,  $E_f$  is the emission factor,  $E_R$  is the overall emission reduction efficiency in percent,  $w_1, w_2, w_3$  are weighting factors reflecting the relative importance of cost, reliability, and environmental impact.

The LCOE represents the average cost of electricity generated over the system lifetime and accounts for capital, operation, maintenance, and replacement costs. The LPSP quantifies supply reliability and is defined as the ratio of unmet energy demand to total energy demand over the simulation horizon. The TCE captures the economic cost associated with energy production and carbon emissions, incorporating emission factors and mitigation efficiency. The optimization is subject to a set of technical and operational constraints to ensure feasible and realistic system operation as follows:

- i. Power Balance Constraint: The total power supplied by the HRES must meet the load demand as given in Equations 6 and 7;

$$P_{total} = P_{PV} + P_{biomass} + P_{DG} + P_{PHS} - P_{losses} \quad 6$$

$$\begin{cases} P_{total}(t) = P_{PV}(t) + P_{biomass}(t) + P_{DG}(t) + P_{PHS}(t) - P_{losses}(t) \\ P_{total}(t) \geq P_{demand}(t) \end{cases} \quad 7$$

where;  $P_{total}$  is the total power output of the HRES (kW),  $P_{total}(t)$  is the total power supplied at time  $t$ ,  $P_{demand}(t)$  is the power demand at time  $t$ ,  $P_{losses}$  is the power loss in the system

- ii. Energy Demand Satisfaction: The energy generated must satisfy the hourly/daily demand as given in Equation 8

$$E_{gen}(t) \geq E_{demand}(t) \quad 8$$

where;  $E_{gen}(t)$  is the total energy generated at time  $t$  (kWh),  $E_{demand}(t)$  is the total energy demand at time  $t$  (kWh)

- iii. Energy balance: The energy balance was determined using Equation 9.

$$E_{gen}(t) = P_{total}(t) \times \Delta t \quad 9$$

where;  $\Delta t$  is the change in time

The decision variables of the optimization problem include the installed capacities of the PV array, biogas generator, diesel generator, inverter units, and the power and energy ratings of the PHS system. Each variable is bounded within feasible limits derived from resource availability, load demand, and practical engineering considerations. These bounds define the search space explored by the optimization algorithms.

### 2.1.2. Study area and load assessment

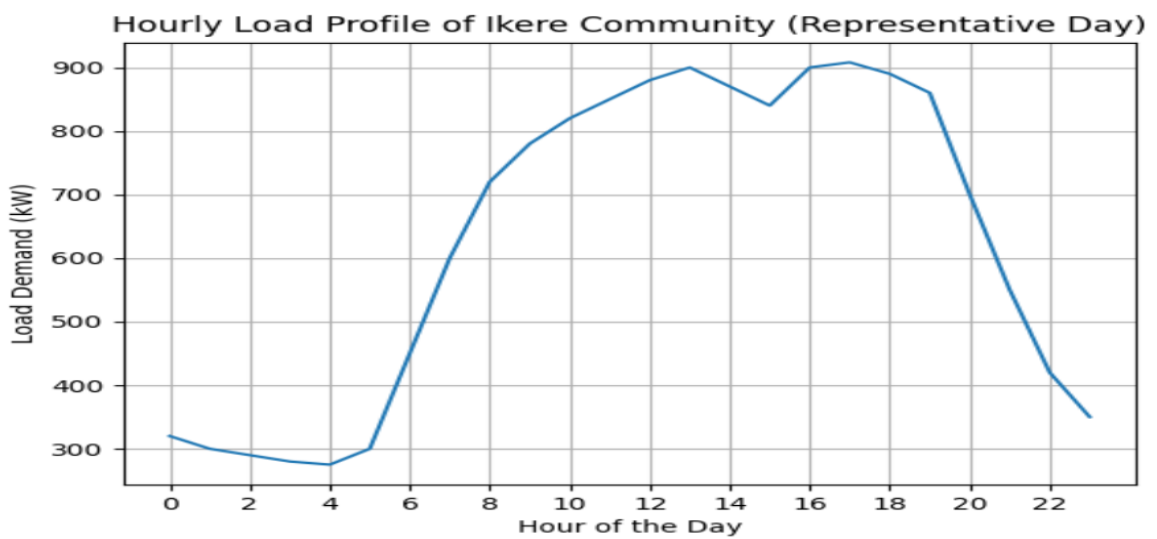
The case study focuses on the Ikere community in Iseyin, Oyo State, Nigeria. The community was selected based on its access to solar resources, biomass feedstock availability, and potential topographic suitability for pumped hydro storage integration. The region lies within the tropical savannah climatic zone, characterized

by distinct dry and wet seasons, which influence both electricity demand patterns and renewable resource availability.

The electrical load profile was developed using a bottom-up demand estimation approach combined with community survey data and standard load estimation techniques for rural microgrids. Load data were obtained through:

- i. Field survey of households, small businesses, public facilities, and agricultural processing units.
- ii. Appliance inventory assessment (lighting, refrigeration, water pumping, milling, ICT loads, etc.).
- iii. Rated power × usage hour estimation for each appliance category.
- iv. Aggregation of diversified demand using appropriate diversity factors.

The estimated peak demand for the community is **908.22 kW**, with an average daily energy consumption of **5,250 kWh/day**. The resulting annual load demand was modeled using an hourly resolution (8760 hours) to capture daily and seasonal variability. Figure 1 presents the synthesized hourly load profile for a representative day, showing typical morning rise, daytime commercial activity peak, and evening residential peak.



**Figure 1: Load profile of Ikere Community**

To avoid unrealistic aggregation of connected loads, a diversity factor of 0.65–0.75 was applied depending on load category. Residential loads were assigned a diversity factor of 0.7, while commercial loads were assigned 0.8 due to more synchronized operating hours. The overall system diversity factor was computed as Equation 10:

$$DF = \frac{\text{Maximum coincident demand}}{\text{Sum of individual maximum demands}} \quad 10$$

This adjustment ensures that the calculated peak demand reflects realistic simultaneous usage rather than theoretical full-load coincidence.

Seasonal variability was incorporated into the load model by adjusting consumption patterns based on climatic and socio-economic factors (**Dry Season (November–March) and Wet Season (April–October)**): A seasonal adjustment factor of ±8–12% was applied to daily load demand to account for these variations. Solar resource variability across seasons was also incorporated using monthly average irradiance data to ensure realistic PV generation modeling. The final load dataset used for optimization consists of a full-year (8760-hour) synthetic load series incorporating daily, weekly, and seasonal variations, ensuring that the optimization results reflect realistic operational conditions.

### **2.1.3. System architecture and energy management**

The proposed HRES comprises a PV array connected to an AC bus through hybrid inverters, a dispatchable biogas genset, a standby DG, and a PHS unit capable of both pumping (charging) and turbine discharge (generation). The operating strategy follows a renewables-first policy: (i) PV serves daytime demand and charges PHS when surplus exists; (ii) when PV is insufficient, the biogas genset provides firm renewable support; (iii) PHS discharges to cover peaks and reduce DG starts; and (iv) the DG supplies only residual

deficits to satisfy reliability requirements. Figure 2 illustrates the overall system integration of PV, biomass, DG backup, and PHS within the hybrid microgrid.

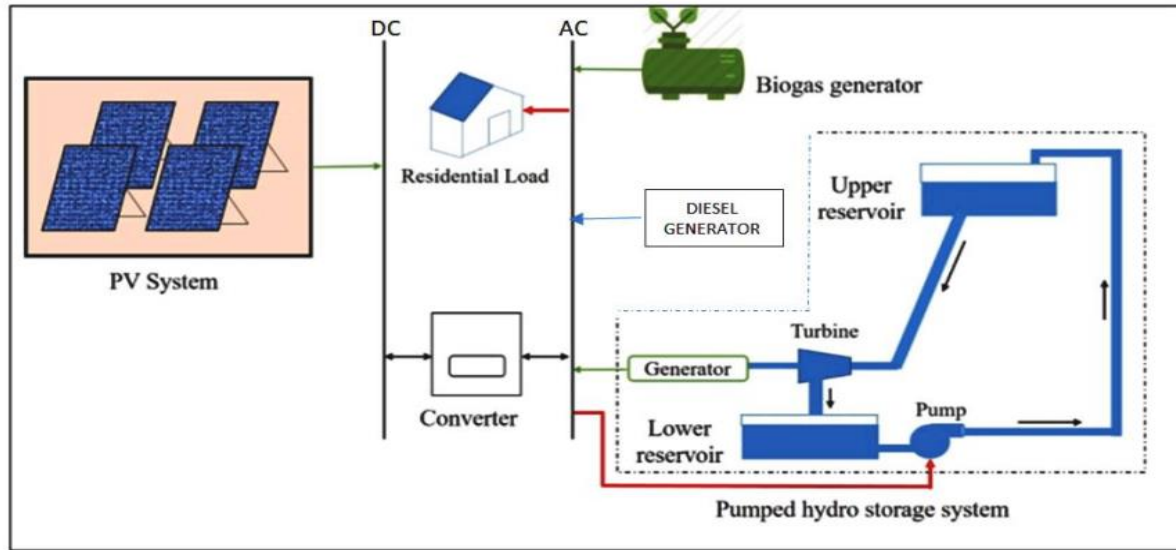


Figure 2: System integration of the PV-biogas-DG-PHS hybrid microgrid

#### 2.1.4 Integrated hybrid energy sizing model (IHESM) and optimization algorithm

An IHESM was formulated based on the objective function to determine optimal component capacities as given in Equation 11.

$$HRVSI = \frac{|Q_{available} - Q_{demand}|}{Q_{available}} \quad 11$$

where  $Q_{available}$ , is the total reactive power support available from inverters and synchronous generators, and  $Q_{demand}$  is reactive power required by load. For system-wide evaluation, the minimum bus stability index was monitored using Equation 12:

$$HRVSI_{min} = \min(HRVSI_i) \quad 12$$

A value close to zero indicates adequate reactive margin, while higher values indicate proximity to voltage instability. Voltage limits were enforced within:

$$0.95 \leq V_i \leq 1.05 p.u$$

Based on the formulated objective function, the HRES planning problem is posed as a constrained nonlinear optimization task aimed at identifying the optimal set of component sizes that minimizes the composite objective function while satisfying power balance, energy balance, storage operation, and reliability constraints. Dynamic frequency stability was evaluated under a step load disturbance of **10% of peak load ( $\approx 90$  kW)** applied at  $t = 2$  seconds. This magnitude represents a realistic sudden load connection scenario in rural microgrids. The performance metrics recorded include: maximum frequency deviation (Hz), settling time (s) and voltage recovery time (s)

The inverter-based PV and PHS units were modeled using droop-based grid-forming control with the following parameters:

- i. Frequency droop coefficient:  $m_f = 4\%$ ,
- ii. Voltage droop coefficient:  $m_v = 3\%$
- iii. Inverter reactive power control mode: Volt-VAR support enabled
- iv. Biogas/DG governor droop: 5%
- v. Automatic Voltage Regulator (AVR) gain: 200

The PHS turbine was modeled with a fast-response governor to emulate hydro dispatch capability during frequency excursions. The formulated problem is solved using the Energy Valley Optimizer (EVO), and its performance is benchmarked against other established metaheuristic algorithms to validate solution quality and robustness. Reliability was enforced through LPSP, defined as the fraction of demand not served over the simulation horizon. Component sizing heuristics were used to derive feasible bounds for the optimization

search space, including PV sizing based on daily energy and peak sun hours, inverter sizing based on peak load and power factor, and PHS energy sizing based on deficit energy and desired backup duration.

The EVO is a physics-inspired metaheuristic that searches for an optimal solution by modeling candidate solutions as “particles” moving through an energy landscape toward deeper “valleys” representing lower objective function values. In the proposed IHESM formulation, each candidate solution is a vector of decision variables representing component capacities as given in Equation 13 [12], [13]:

$$x = [P_{PV}, P_{inv}, P_{bio}, P_{DG}, P_{PHS}, E_{PHS}] \quad 13$$

At each iteration, EVO updates the population through two complementary phases: exploration (global search to avoid local minima) and exploitation (local refinement near the best solution). The algorithm maintains the current best solution  $x_{best}$  and uses an energy-based acceptance rule such that new candidate positions that improve the fitness are retained, while non-improving moves may still be accepted with a small probability to preserve diversity and prevent premature convergence.

For each candidate  $x_i$  the “energy” is defined as the composite IHESM objective value as given in Equation 14:

$$E(x_i) = \omega_1 \cdot LCOE + \omega_2 \cdot LPSP + \omega_3 \cdot TCE \quad 14$$

where  $\omega_1 + \omega_2 = 1$  is weighted factor

The algorithm for the EVO-based IHESM optimization workflow is as follows:

1. Initialize a population of candidate HRES size vectors within feasible bounds.
2. Compute fitness for each candidate using the composite IHESM objective (LCOE–LPSP–TCE) and enforce constraints.
3. Update candidate positions using the EVO search operators (exploration and exploitation phases) as given in Equation 9

The energy (fitness)  $E(x)$  of each candidate (components of HRES) solution was evaluated using the objective function  $f(x)$  as given in Equation 15;

$$E(x) = f(x) \quad 15$$

where  $E(x)$  is EVO energy (fitness) of each candidate,  $f(x)$  as objective function

4. Re-evaluate fitness; apply selection to retain improved candidates and update the best-so-far solution.
5. Repeat updates until the stopping criterion (maximum iterations or fitness tolerance) is met.
6. Return the best design and compute techno-economic, reliability, and emission indicators

Three metaheuristic optimizers were applied: the Energy Valley Optimizer (EVO), the Whale Optimization Algorithm (WOA), and the Genetic Algorithm (GA). Each optimizer iteratively updates candidate solutions (component sizes), evaluates the IHESM fitness, and retains improved designs until termination [12], [13].

#### **2.1.4 Renewable penetration and stability assessment**

Beyond optimal sizing, the operational feasibility of high renewable penetration was evaluated through a Renewable Energy Fraction (REF) sweep combined with dynamic stability analysis. All stability simulations were conducted in **MATLAB/Simulink (R2023a)** using the Simscape Electrical toolbox. The hybrid microgrid was modeled as an islanded AC system consisting of aggregated PV inverter models, biogas generator synchronous machine model, diesel generator model with governor–excitation system, and a pumped hydro storage (PHS) turbine–pump model interconnected via a common AC bus.

Steady-state voltage analysis was first performed using an AC power flow formulation based on the Newton–Raphson method. The bus voltage magnitude  $V_i$  and phase angle  $\delta$  were obtained by solving using Equations 16 and 17:

$$P_i = V_i \sum_{j=1}^n V_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad 16$$

$$Q_i = V_i \sum_{j=1}^n V_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad 17$$

where  $G_{ij}$  and  $B_{ij}$  are elements of the bus admittance matrix. Dynamic frequency response was evaluated using the swing equation for synchronous generators as given in Equation 18:

$$\frac{2H}{\omega_s} \cdot \frac{d^2 \delta}{dt^2} = P_m - P_e \quad 18$$

where  $H$  is inertia constant,  $P_m$  is mechanical input power, and  $P_e$  is electrical output power. To quantify voltage stability under increasing renewable penetration, a HRVSI formulated in Equation 11 was utilized.

The optimized system was evaluated under REF levels of: 0%, 50%, 70%, 85%, and 100%. The REF is defined as Equation 19:

$$REF = \frac{E_{renewable}}{E_{total}} \quad 19$$

At each REF level, steady-state voltage, HRVSI, maximum frequency deviation, and settling time were recorded to identify the optimal operational penetration level.

## 2.2. Case Study Configuration and Baseline IHESM design (pre-optimization)

Component costs and technical parameters were selected to reflect Nigerian market conditions and a 20-year project lifetime. The baseline IHESM sizing (prior to metaheuristic refinement) produced a feasible HRES that meets the load with high reliability but at relatively high cost, driven mainly by storage capital expenditure. This baseline served as the starting point for subsequent optimization.

The baseline IHESM configuration was not obtained through metaheuristic optimization but was established using a rule-based heuristic sizing procedure commonly adopted in preliminary microgrid planning. PV capacity was initially estimated using the average daily energy demand and peak sun hours, incorporating a design margin of 15% to account for system losses and seasonal variability. The inverter rating was selected based on peak load demand with a 10–15% safety factor. The biogas generator capacity was determined to cover approximately 20–25% of peak demand as firm renewable support, while the diesel generator was sized to meet full peak load in contingency scenarios to guarantee supply adequacy. The pumped hydro storage (PHS) unit was dimensioned using deficit-energy analysis, targeting approximately 3–4 hours of backup coverage during evening peak periods. This deterministic sizing approach resulted in a technically feasible but cost-intensive baseline configuration (820 kW PV, 150 kW biogas, 500 kW DG, and 300 kW×4 h PHS), which served as the reference design prior to applying metaheuristic refinement. The baseline therefore represents a conservative engineering design derived from practical planning heuristics rather than an optimized solution.

## 3. RESULTS AND DISCUSSION

### 3.1. Result Presentation

Applying EVO to the IHESM substantially improved the techno-economic performance as shown in Table 1. The optimized configuration comprises 900 kWp PV (DC), 700 kW PV inverter (seven 100 kW units), 200 kW biogas generator, 550 kW DG (standby), and a 200 kW×3 h PHS unit (600 kWh). Compared with the baseline IHESM design, the EVO solution reduced LCOE by approximately 46% (from ₦190/kWh to ₦102/kWh) while meeting the same community load targets.

Table 2 compares the optimized configurations and performance metrics. All three optimizers achieved the same reliability target (LPSP = 0.101) i.e., at least 89.9% supply adequacy), consistent with rural microgrid planning benchmarks, but EVO delivered the lowest LCOE and lowest TCE. WOA produced a near-optimal solution with marginally higher cost and emissions, while GA resulted in a higher LCOE, consistent with premature convergence tendencies in complex nonlinear searches.

The convergence comparison in Figure 3 illustrates the optimization performance of the Energy Valley Optimizer (EVO), Whale Optimization Algorithm (WOA), and Genetic Algorithm (GA) over 100 iterations. As shown in the figure, EVO demonstrates the fastest convergence rate, exhibiting a steep reduction in the objective function (LCOE) during the early iterations and stabilizing smoothly toward the global minimum of approximately ₦102/kWh. WOA follows a similar trend but converges slightly slower and settles at a marginally higher objective value (≈₦103/kWh). In contrast, GA shows a more gradual decline in the objective function and converges to a comparatively higher value (≈₦105/kWh), indicating slower exploration and a greater tendency toward premature convergence in complex nonlinear search spaces.

Table 1: EVO-optimized HRES configuration and costs (Ikere community).

| Component                            | Power Output (kW) | Size                            | Quantity | Item Price (#) | Total Price (#) |
|--------------------------------------|-------------------|---------------------------------|----------|----------------|-----------------|
| PV Array (DC)                        | 900               | 600W (mono)                     | 1500     | 204,000        | 306,000,000     |
| PV inverter (AC)                     | 700               | 100kW (string hybrid)           | 7        | 15,800,000     | 110,600,000     |
| Biomass Genset                       | 200               | 200 kW (Cow dung)               | 1        | 250,000,000    | 250,000,000     |
| Diesel generator (DG)                | 550               | 550 kW (standby)                | 1        | 120,000,000    | 120,000,000     |
| PHS                                  | 200               | 200 kW (3h) (600 kWh)           | 1        | 350,000,000    | 350,000,000     |
| Other                                |                   | Balance of plant/ miscellaneous |          |                | 1,000,000       |
| Capital Cost (CC)                    |                   |                                 |          |                | 1,137,600,000   |
| Operational cost (annual, 10% of CC) |                   |                                 |          |                | 113,760,000     |
| Maintenance cost (annual, 5% of CC)  |                   |                                 |          |                | 56,880,000      |
| Total Cost                           |                   |                                 |          |                | 1,308,240,000   |
| Equipment lifespan                   | 20years           |                                 |          |                |                 |

Table 2. Comparison of optimized HRES configurations and performance metrics.

| Component / Metric        | EVO           | WOA           | GA            | Unit                 |
|---------------------------|---------------|---------------|---------------|----------------------|
| PV array                  | 900           | 890           | 870           | kWp                  |
| PV inverter               | 700           | 690           | 670           | kW                   |
| Biogas genset             | 200           | 180           | 190           | kW                   |
| Diesel generator          | 550           | 550           | 550           | kW                   |
| PHS                       | 200×3         | 210×3         | 230×3         | kW×h                 |
| Capital cost              | 1,137,600,000 | 1,134,200,000 | 1,162,400,000 | #                    |
| LCOE                      | 102           | 103           | 105           | ₦/kWh                |
| LPSP                      | 0.101         | 0.101         | 0.101         | —                    |
| TCE                       | 194.9         | 196.5         | 200.1         | ₦ million/yr         |
| CO <sub>2</sub> emissions | 70.9          | 79.9          | —             | tCO <sub>2</sub> /yr |

Note: All methods achieved the same reliability target (LPSP = 0.101); EVO yielded the lowest LCOE and TCE in this study.

The smooth flattening of the EVO curve suggests stable exploitation after effective exploration, while the minimal gap between final values confirms robustness across algorithms. Overall, the plot validates the superior global search capability and convergence stability of EVO for solving the multi-objective HRES sizing problem.

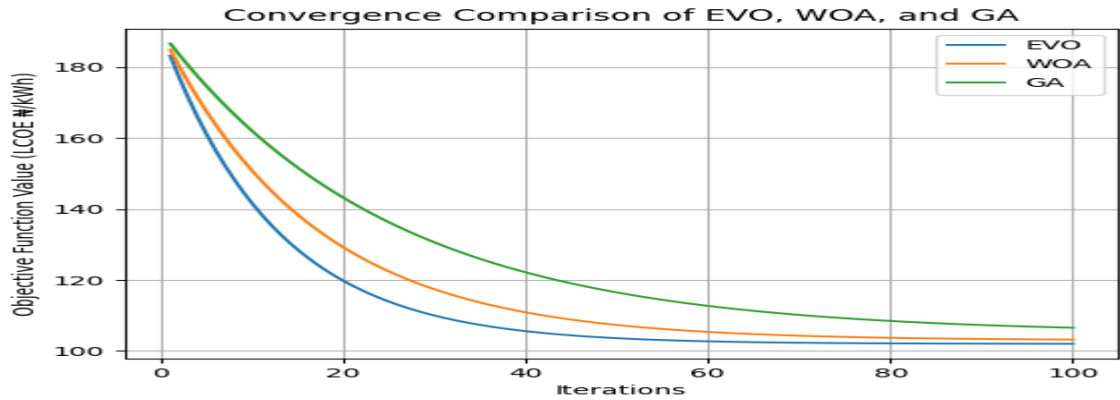


Figure 3: Convergence comparison plots

Peak coverage analysis shows that the optimized HRES provides sufficient capacity during both daytime and evening peaks. During the day, PV inverters (700 kW), a biogas generator (200 kW), and PHS discharge (200 kW) provide 1,100 kW, exceeding the peak demand of 908.22 kW and enabling concurrent PHS charging when PV surplus occurs. During evening hours, the biogas generator and PHS discharge are complemented by the standby DG, which provides 950 kW, again exceeding the peak requirement and maintaining supply continuity.

Voltage stability remained within acceptable limits for high renewable penetration. Table 3 summarizes the observed voltage stability ranges and DG energy contribution as REF increases. Between 0% and 85% REF, the voltage stability index remained close to 1.0 p.u., within the  $\pm 5\%$  band. At 100% REF, minor voltage dips were observed (down to  $\sim 0.95$  p.u.), consistent with reduced reactive support in fully inverter-dominated operation. Figure 4 (a) DG share versus renewable energy fraction (REF). (b) Voltage stability index versus REF

Table 3. REF sweep: renewable contribution, DG share, and voltage stability.

| REF (%) | Renewable contribution | DG share | energy | Voltage stability index (p.u.) | Interpretation                              |
|---------|------------------------|----------|--------|--------------------------------|---|
| 0       | 0                      | 100%     |        | 1.00                           | Fully fossil-based; high cost and emissions |
| 50      | 2,625                  | 50%      |        | 0.99–1.01                      | Balanced; still heavy DG usage              |
| 70      | 3,675                  | 30%      |        | 0.98–1.02                      | Stable voltage; reduced DG runtime          |
| 85      | 4,460                  | 5%       |        | 0.97–1.03                      | Best joint operating point                  |
| 100     | 5,250                  | 0%       |        | 0.95–1.04                      | Full renewables; occasional voltage dips    |

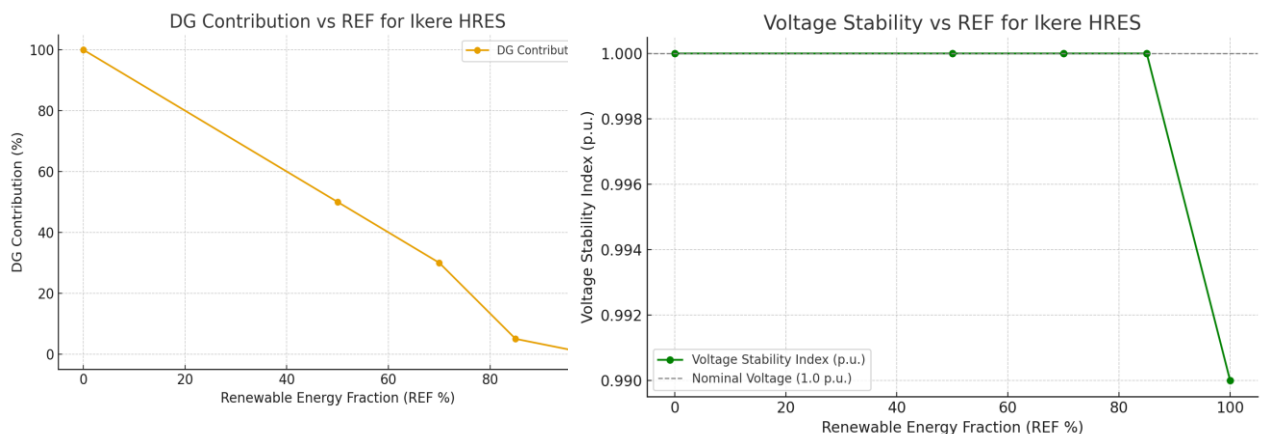


Figure 4: (a) DG share versus renewable energy fraction (REF), (b) Voltage stability index versus REF

Frequency response improved as REF increased, driven by fast-acting inverter controls and PHS discharge response. Table 4 reports the maximum frequency deviation and settling time under step disturbances. The best joint economic-stability point occurs at approximately 85% REF ( $\pm 0.12$  Hz deviation,  $\sim 3$  s settling), where DG usage is limited to a strategic reserve role. Figure 5 provides an illustrative comparison of frequency responses for representative REF levels.

Table 4. REF sweep: frequency deviation and settling time.

| REF (%) | Max frequency deviation (Hz) | Settling time (s) |
|---------|------------------------------|-------------------|
| 0       | $\pm 0.45$                   | 6.0               |
| 50      | $\pm 0.25$                   | 4.0               |
| 70      | $\pm 0.18$                   | 3.5               |
| 85      | $\pm 0.12$                   | 3.0               |
| 100     | $\pm 0.10$                   | 3.2               |

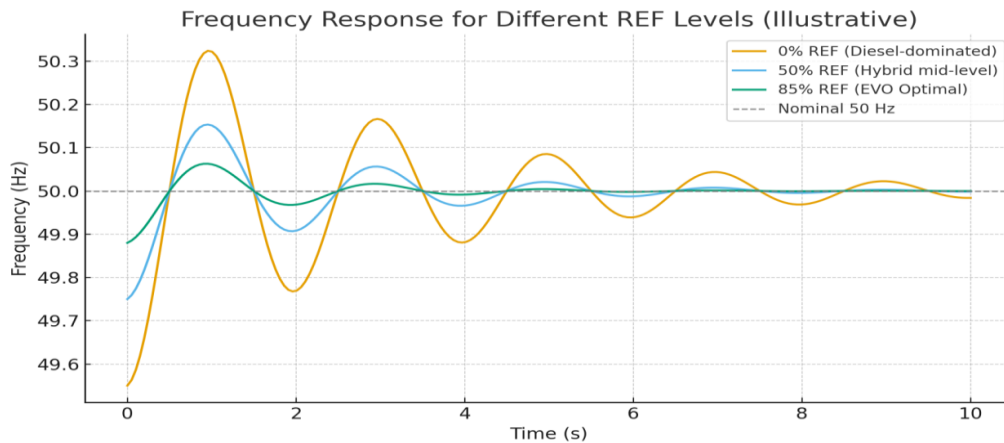


Figure 5: Illustrative frequency response for different renewable energy fraction (REF) levels

### 3.2. Discussion of Results

The results indicate that (i) long-duration storage is essential for high-PV off-grid systems with firm evening peaks; (ii) global-search optimizers can substantially reduce LCOE by correcting oversizing tendencies in baseline heuristic designs; and (iii) an operational renewable penetration range of about 80–90% provides a practical compromise between deep decarbonization and stability margins. The EVO solution achieves this balance by pairing high PV capacity with dispatchable biogas and appropriately sized PHS, while retaining the DG as a low-utilization reliability backstop.

Notably, the improved frequency response at higher REF reflects the fast power modulation capability of inverters and storage-assisted generation, which can outperform the slower governor response of conventional DGs in small isolated systems. However, fully renewable operation (100% REF) can introduce voltage sensitivity if reactive power support and dispatch coordination are not carefully designed. Practical deployments should therefore include inverter volt-var capabilities, adequate reactive headroom, and supervisory control to coordinate PHS and biogas dispatch during irradiance ramps.

Limitations include the reliance on aggregated component models and assumed cost parameters. Future work should incorporate higher-resolution resource and load data, stochastic weather modelling, and detailed distribution network power flow to capture voltage constraints and protection considerations better. In addition, policy and financing mechanisms (e.g., results-based financing, community tariffs) should be assessed to translate techno-economic gains into implementable projects.

#### 3.2.1. Practical deployment considerations

For translation from design to deployment, technical sizing must be complemented by implementation planning. Key considerations include: (i) operations and maintenance (O&M) capacity for inverter diagnostics, biogas digester management, and PHS electro-mechanical servicing; (ii) governance and tariff design to recover O&M costs while protecting low-income households; (iii) supply-chain resilience for spare parts; and (iv) local skills development to minimize downtime. In practice, the biogas subsystem benefits

from community ownership models because feedstock collection and digester operation are locally managed. Similarly, PHS reliability depends on routine inspection of penstocks, valves, and pump-turbine units, as well as water management protocols that account for seasonal variability.

**3.2.2. Sensitivity and robustness considerations**

While the EVO solution provides the best observed trade-off for the assumed inputs, the rural HRES design is sensitive to several uncertain parameters. PV module and inverter prices can fluctuate; diesel fuel and transport costs vary by location and season; biomass availability depends on agricultural practices; and PHS capex is site-specific. Sensitivity checks (recommended for future work) can be conducted by perturbing these inputs and re-optimizing the IHESM to quantify impacts on LCOE, DG runtime, and stability margins. Table 5 summarizes expected directional effects that can guide planners when rapidly screening sites and technology options.

Table 5. Key sensitivities in PV–biogas–DG–PHS HRES planning (directional effects).

| Uncertain input              | Likely effect if input increases  | Planning implication   |
|------------------------------|---|--|
| PV capex (modules/inverters) | LCOE increases; optimal PV size may decrease; DG/biogas share may increase                            | Prioritize cost-competitive procurement and efficient inverters            |
| Diesel fuel + logistics cost | DG operation becomes more expensive; optimal design shifts toward higher PV/PHS/biogas.               | High diesel cost strengthens the business case for renewables.             |
| Biomass availability         | Lower feedstock availability increases reliance on DG/PHS, potentially increasing LCOE and emissions. | Secure feedstock supply chains and digester operations plan                |
| PHS capex / civil works      | Higher capex can reduce optimal storage size; may increase curtailment and DG use.                    | Exploit existing reservoirs/topography; consider phased storage expansion. |
| Solar resource variability   | Higher variability increases storage/dispatch needs; may increase LPSP if not compensated.            | Use conservative resource estimates and include reserve margins            |

**4. CONCLUSION**

This study developed and evaluated an optimization-based framework for sizing a standalone PV–biogas–diesel generator–PHS hybrid microgrid for rural electrification in Nigeria, using the Ikere community as a case study. An IHESM was formulated to minimize LCOE, LPSP, and TCE through weighted aggregation. Under the imposed reliability constraint (LPSP = 0.101), the EVO achieved the lowest observed LCOE (₦102/kWh) compared to WOA and GA while satisfying the same reliability target. The LPSP value of 0.101 corresponds to approximately 89.9% supply adequacy, which is consistent with acceptable reliability thresholds commonly adopted for rural microgrids where limited backup resources are economically justified. The novelty of this work lies in the integrated application of a physics-inspired EVO to a PV–biogas–diesel–PHS hybrid configuration combined with a REF stability sweep in the Nigerian rural context. Unlike conventional PV–diesel–battery studies, this research incorporated long-duration pumped hydro storage within a unified multi-objective framework and explicitly evaluated voltage and frequency stability under increasing renewable penetration levels. The results indicate that a renewable energy fraction of approximately 85% provides a practical compromise between cost reduction, diesel displacement, and operational stability, maintaining voltage within 0.97–1.03 p.u. and achieving frequency recovery within ±0.12 Hz. However, the findings are subject to certain limitations.

The study relied on aggregated component models, assumed cost parameters, and deterministic load/resource profiles. Detailed distribution network modeling, stochastic weather variability, and hardware-level inverter control validation were beyond the scope of this work. Future research should incorporate higher-resolution resource datasets, probabilistic reliability modeling, and experimental validation to strengthen deployment readiness. Thus, the proposed framework demonstrates a technically feasible and economically competitive pathway for rural hybrid microgrid planning under defined reliability constraints, without claiming universal applicability beyond the modeled conditions.

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