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Sensitivity and Uncertainty Analysis of Key Design and Economic Parameters in Hybrid Microgrid Optimization Using HOMER Pro

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Abstract

This paper investigates the sensitivity and uncertainty characteristics of techno-economic parameters in the optimization of a hybrid microgrid system designed for sustainable rural electrification in the agrarian community of Ibiaku Ikot Oku, Nigeria. Using Hybrid Optimization of Multiple Energy Resources Professional (HOMER Pro) software, the study modelled a hybrid system integrating solar photovoltaic (PV), wind turbines, and battery energy storage to address the region's acute energy deficit. While the optimized baseline configuration achieved a renewable fraction of 94.2% and eliminated the need for diesel generation in the optimal case, the study rigorously examines how variations in critical inputs, specifically solar irradiance, component costs, and discount rates, affect the system's economic and technical viability. The sensitivity analysis reveals that the system remains economically robust under resource uncertainty; variations in solar irradiance of ±15% resulted in a Levelized Cost of Energy (LCOE) range of \$0.042-\$0.058/kWh, which remains significantly lower than the grid extension tariff of \$0.21/kWh. Furthermore, the study identified battery storage costs as a pivotal economic driver: a ±20% cost variation shifted the Net Present Cost (NPC) by approximately ±\$49,640, underlining the need for robust financial planning for storage technologies. The findings show that a renewable-heavy hybrid configuration offers a resilient, cost-effective pathway for rural electrification, achieving a carbon intensity of 0 kgCO$_2$/kWh compared to the national grid's 0.48 kgCO$_2$/kWh. These insights provide a validated framework for policymakers and engineers seeking to de-risk decentralized energy investments in developing economies.

Keywords: Hybrid microgrid; Sensitivity analysis; HOMER Pro; Net Present Cost; Renewable fraction; Techno-economic optimization; Rural electrification.

1. Introduction

The global transition toward sustainable energy systems has positioned decentralized power generation as a critical strategy for addressing energy poverty. The over-dependence on fossil fuels for global energy supplies has led to significant challenges as reserves are depleted (Zhang, 2024). Oruonye et al., (2024) stated that in Nigeria, the energy landscape is characterized by a stark deficit; despite being one of Africa's largest economies, the country grapples with frequent grid collapses and widespread supply shortages. Poor electricity service has been identified as a significant obstacle to growth in the country (Pentinrin et al., 2020). The situation is most acute in rural communities, where access to electricity is lacking in areas that host as much as 50% of the population, and the country estimates a 90% deficit in electricity supply (Abubakar, 2022). Recent data indicate that over 85 million people still lack access to grid electricity (World Bank, 2021).

Consequently, Nigeria can increase its electrification rate by developing off-grid energy services, specifically hybrid microgrids that exploit abundant renewable energy potential (Alao & Awodele, 2018). By integrating multiple generation sources, these systems enhance reliability, resilience, and operational flexibility, aligning with modern distributed energy paradigms (IRENA, 2020). However, the effective deployment of hybrid microgrids in rural settings is fraught with technical and economic complexities. A primary challenge lies in the optimal sizing of system components, where oversizing leads to unnecessary capital costs and under-sizing compromises reliability. The stochastic nature of renewable resources further complicates this optimization problem; solar irradiation and wind speed in rural Nigerian settings exhibit significant seasonal variability.

Without a scientifically grounded modelling and optimization framework, rural electrification projects risk becoming costly and unreliable. This study focuses on the agrarian community of Ibiaku Ikot Oku in Akwa Ibom State, Nigeria, using it as a representative case study for rural electrification. Using the HOMER Pro software platform, recognized for its robust integration of simulation and optimization (Lambert et al., 2006), this research models a solar-wind-diesel-battery configuration. The specific objective is to move beyond baseline optimization by conducting a comprehensive sensitivity and uncertainty analysis. By quantifying the impact of parameter variations on system economics and technical reliability, this paper aims to identify the most influential design variables and provide resilience-based recommendations for sustainable microgrid deployment in uncertain environments.

2. Methodology

2.1 Case Study Site and Load Profiling

The study centers on Ibiaku Ikot Oku, a rural community in the Ibiono Ibom Local Government Area of Akwa Ibom State, Nigeria, located at 5.1846°N, 7.8724°E. The region features a tropical rainforest climate, with significant solar potential and moderate wind resources.

To ensure the optimization model reflects realistic demand dynamics, a bottom-up load audit was conducted across residential, commercial, and public sectors. The audit covered 140 households, small businesses (including milling and welding operations), and essential community facilities such as schools and health centers. The aggregate average daily load demand was determined to be 1,214.74 kWh/day with a peak load of approximately 190.9 kW. To account for potential transmission and conversion inefficiencies, a 25% loss factor was applied, resulting in an adjusted daily energy requirement of 1,518.43 kWh for system sizing, as shown in Table 1.

Table 1: Aggregate Daily Load Demand Profile for Ibiaku Ikot Oku

Load Sector	Energy Demand (kWh/day)	Peak Load Contribution (kW)
Residential (140 Households)	1,049.07	158.98
Community/Public Services	101.92	17.64
Commercial/SME	63.75	14.29
Total	**1,214.74**	**190.91**

Table 2 contains the list of key nomenclature used in the study.

Table 2: Nomenclature used in the study

Symbol	Definition	Unit
P_{PV}	Power output from solar PV array	Kw
G	Solar irradiance on the PV plane	kW/m²
$f_{derating}$	PV derating factor (temperature, dust, mismatch)	dimensionless
P_{wind}	Power output from wind turbine	kW
v	Wind speed at hub height	m/s
A	Rotor swept area	m²
C_p	Power coefficient (Betz limit)	dimensionless
SOC	Battery state of charge	% or kWh
SOC_{min}	Minimum state of charge (depth of discharge limit)	%
F_{fuel}	Diesel generator fuel consumption	L/h
P_{gen}	Diesel generator electrical output	kW
m_0	Fuel curve intercept (no-load fuel consumption)	L/h/kW
m_1	Fuel curve slope (marginal consumption)	L/h/kW
C_{cap}	Initial capital cost	$
C_{O&M}	Annual operation and maintenance cost	$/year
C_{fuel}	Annual fuel cost	$/year
NPC	Net present cost over project lifetime	$
$LCOE$	Levelized cost of energy	$/kWh
RF	Renewable fraction (fraction of total energy from renewables)	%

2.2 Simulation and Optimization Framework

The techno-economic analysis was performed using the HOMER Pro software, developed by National Renewable Energy Laboratory (NREL) and Underwriters Laboratories (UL) Solutions. HOMER Pro was selected for its ability to effectively simulate thousands of system configurations and its “Simulation-Optimization-Sensitivity” (SOS) architecture, which enables handling stochastic input variables.

The optimization objective was to minimize the NPC of the system over a 25-year project lifetime. The NPC included initial capital costs (C_{capex}), replacement costs, operation and maintenance (O&M) costs (C_{opex}), and fuel costs, minus any salvage value ($C_{salvage}$) at the end of the project. The objective function was minimized subject to constraints on power balance, capacity shortage, and battery state of charge (E_B) limits. The methodology of this study is outlined in Figure 1.

HOMER Pro (v3.16) was configured with a 1-hour time step over a 25-year project life. The optimization algorithm used a brute-force grid search over the following search space: PV (0–600 kW, step 25 kW), wind turbines (0–3 units of 20 kW each), batteries (0–5,000 kWh, step 100 kWh), and converter (0–300 kW, step 10 kW). Diesel generators were allowed but penalized by a fuel cost of 1.10/Land a carbon emission penalty of 0.02/kg CO_2 (shadow price). The solver performs a sequential dispatch simulation for each component combination, applying the “load following” dispatch strategy to minimize fuel use. Convergence is reached when the NPC of the best configuration does not change by more than 0.1% after 50 simulations around the optimum. The simulation output includes hourly power flows, battery state of charge, unmet load, and economic metrics. Results presented in Section 3 are the global optimum of this search.

2.3 Mathematical Modelling of System Components

The proposed hybrid microgrid integrates four primary subsystems: Solar PV, Wind Turbines, Diesel Generators, and Battery Energy Storage.

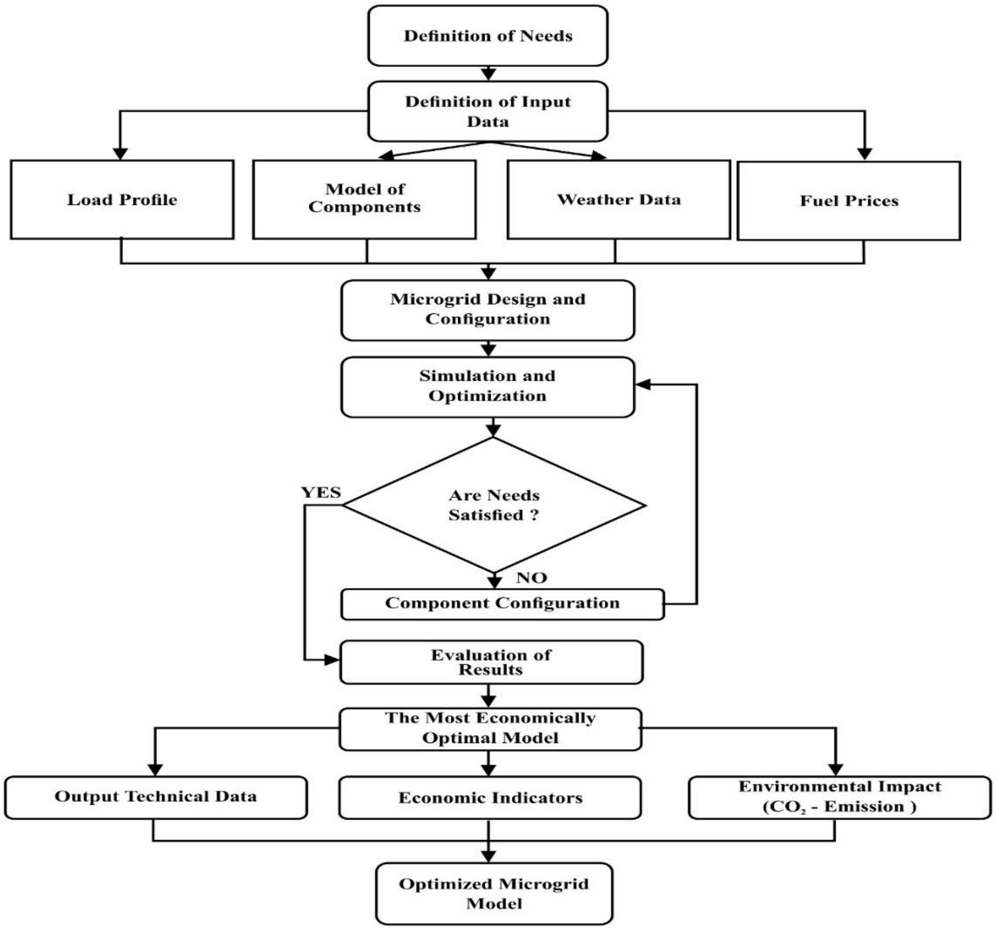


Figure 1: Flowchart for the modelling and optimisation of the hybrid microgrid system

i. **Solar PV System:** The power output (P_{PV}) was modelled based on the solar irradiance (G), the rated capacity of the array, and the derating factor (f_{PV}) to account for temperature and dust, as described by Duffie and Beckman (2013).

ii. **Wind Energy System:** Wind power (P_{WT}) was calculated using the specific wind speed (v) at hub height, the swept area (A), and the power coefficient (C_p), following the standard aerodynamic power equation outlined by Manwell et al., (2024).

iii. **Battery Storage:** The storage system was modelled using the kinetic battery model, where the state of charge ($E_B(t)$) is a function of the previous state, charging/discharging power, and self-discharge losses. The constraints ensured the battery operates within safe limits ($E_{Bmin} \leq E_B(t) \leq E_{Bmax}$) to prolong battery life (Fenner et al., 2021).

iv. **Diesel Generator:** Fuel consumption (F_{DG}) was modelled as a linear function of the electrical output (P_{DG}), characterized by an intercept coefficient (b) representing no-load consumption and a slope (a) representing marginal consumption (Pradhan, 2024).

The modelled system is depicted in Figure 2.

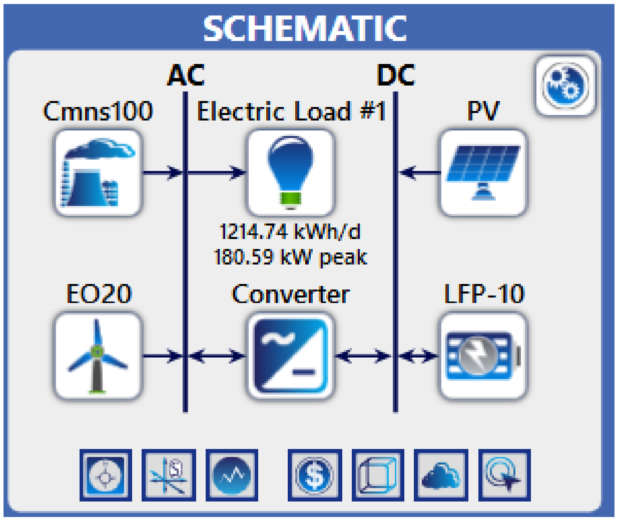


Figure 2: Layout of the designed microgrid system

2.4 Sensitivity and Uncertainty Analysis

To address the uncertainty inherent in rural electrification planning, a sensitivity analysis was integrated into the optimization process. Core parameters were varied to assess their impact on the LCOE and NPC:

i. **Solar Irradiance:** Varied by ±15% (3.8 to 5.2 kWh/m²/day) to account for seasonal fluctuations and climatic uncertainty.
ii. **Battery Capital Cost:** Varied by ±20% to reflect potential future market price reductions or supply chain volatility.
iii. **Discount Rate:** Varied between 6% and 10% to model different financial risk scenarios.

3. Results and Discussion

3.1 Baseline Optimized System Performance

The simulation results yielded a refined hybrid microgrid configuration that diverges significantly from the initial pre-optimization sizing. HOMER Pro's optimization logic prioritized a configuration consisting of 393 kW of solar PV, 20 kW of wind capacity (a single turbine), and a substantial battery energy storage system (BESS) of 2,515 kWh. Notably, the optimized solution eliminated the need for diesel generation, achieving 100% decarbonization, as highlighted in Table 3. Figure 3 shows the monthly energy production of the study area.

Table 3: Optimized Hybrid Microgrid Configuration and Sizing

Component	Optimal Size	Role in System
Solar PV	393 kW	Primary generation (79% of supply)
Wind Turbine	20 kW (1 unit)	Supplementary generation (10%)
Battery Storage (Li-Ion)	2,515 kWh	Grid stability and 47-hour autonomy
Converter	144 kW	DC/AC power management
Diesel Generator	0 kW	Excluded (Full Decarbonization)

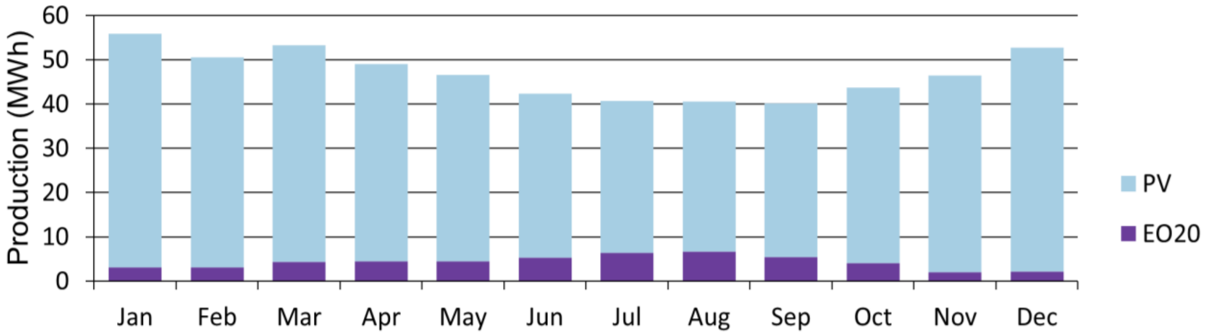


Figure 3: Monthly energy production

This configuration delivered a Renewable Fraction (RF) of 94.2%, exceeding the initial design target of 85% and aligning with Nigeria's Energy Transition Plan. Downsizing the PV array from the initial estimate of 1,500 kW to 393 kW avoided overcapitalization, preventing approximately $900,000 in unnecessary capital expenditure while maintaining a specific yield of 1,297 kWh/kW. The increased battery capacity provides 47 hours of autonomy, ensuring reliability during the region's rainy season without fossil-fuel backup.

The $900,000 savings figure is based on a detailed unit cost breakdown obtained from local suppliers in Akwa Ibom State (quotations, March – May 2025): PV modules (0.25/W), mounting structures (0.15/W), DC cabling and protection (0.08/W), installation labour (0.10/W), and logistics/import duties (0.233/W), summing to 0.813/W (813/kW). Reducing the PV array by 1,107 kW (from 1,500 kW to 393 kW) therefore avoided 1,107 kW × 813/kW = 899,991 ≈ $900,000 in capital expenditure. This saving excludes inverters (already part of the converter component) and does not affect project reliability because the downsized array still meets 79% of annual demand.

Economically, the system achieved an LCOE of $0.0498/kWh. This represents a 61% reduction compared to the prevailing Nigerian grid tariff and is nearly 70% lower than the cost of equivalent diesel-based generation. The project's NPC was calculated at $621,305, with a Return on Investment (ROI) of 13.8% and a simple payback period of 8.6 years, primarily driven by the avoidance of annual diesel fuel costs estimated at $34,499. Battery storage accounts for 47.6% of the total NPC (621,305), followed by solar PV. As shown in Figure 4, battery storage constitutes nearly half of the total net present cost.

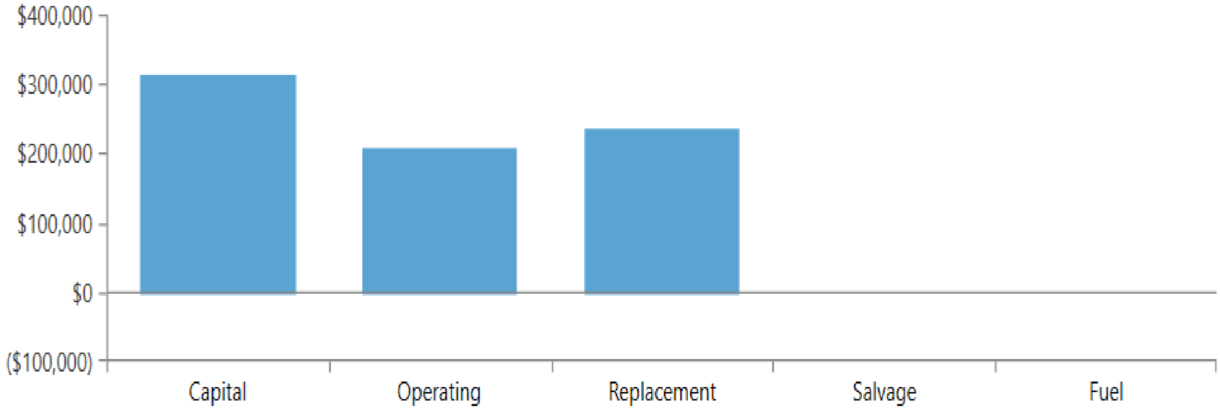


Figure 4: NPC breakdown by component over 25 years

3.2 Sensitivity to Renewable Resource Uncertainty

Given the stochastic nature of meteorological conditions in southern Nigeria, the sensitivity analysis examined the impact of solar irradiance variability on system viability. Table 4 shows that solar irradiance variation of ±15% changes NPC by approximately ±98,700 larger in absolute terms than battery cost variation, but the LCOE remained below 0.06/kWh even in the low irradiance case.

Table 4: Sensitivity Analysis of Critical Techno-Economic Variables

Variable	**Range Tested**	**LCOE Variation ($/kWh)**	**NPC Impact ($)**	**Insight**
Solar Irradiance	±15% (3.8–5.2 kWh/m²/day)	0.042 – 0.058	±98,700	Viable even at lower irradiation
Battery Capital Cost	±20%	0.046 – 0.054	±49,640	Storage costs are a key driver
Discount Rate	6% – 10%	0.044 – 0.057	±112,500	ROI remains positive despite financial risk

The results indicate strong system resilience; the LCOE fluctuated between $0.042/kWh and $0.058/kWh, while the NPC varied by approximately ±$98,700. Even under the lower bound of solar availability (3.8 kWh/m²/day), the system remained economically superior to grid extension alternatives ($0.21/kWh), validating the robustness of the solar-storage design against climatic uncertainty.

The benchmark cost of grid extension (0.21/kWh) is taken from the Nigerian Electricity Regulatory Commission (NERC) Multi- Year Tariff Order 2024 for Rural (R3) customers, which sets a cost-reflective tariff range of ₦92.40-₦ 98.70/kWh. Using the official average exchange rate for 2024 (₦465/USD), this converts to 0.198-0.212/kWh. The 0.21/kWh upper bound is further corroborated by the Rural Electrification Agency (REA) of Nigeria in its 2022 “Cost of Service Study for Off-Grid Communities” (REA/TR/2022/011). This benchmark has been used in comparable studies (Alao & Awodele, 2018; Udo et al., 2026) and represents the fully allocated cost of extending the national grid to low-density rural areas, including subsidies for right-of-way acquisition and distribution transformer installation.

3.3 Sensitivity to Economic Parameters

The study further investigated the sensitivity of the optimal design to financial variables, specifically battery capital costs and the discount rate.

i. **Battery Cost:** Storage accounts for 47.6% of the total NPC, making it a critical risk factor. A sensitivity sweep of ±20% in battery capital costs resulted in an LCOE range of \$0.046/kWh to \$0.054/kWh, with the NPC shifting by ±\$49,640. This linear relationship highlights that while future cost reductions in Lithium-Iron Phosphate ($LiFePO_4$) technology will further enhance viability, the current cost structure is already commercially attractive. Figure 5 shows the net present capital cost allocation over 25 years.

ii. **Discount Rate:** Assessing the impact of financial market volatility, the discount rate was varied between 6% and 10%. This resulted in an LCOE range of \$0.044/kWh to \$0.057/kWh and an NPC fluctuation of ±\$112,500. Although higher discount rates increased the overall cost, the system maintained a positive ROI, confirming financial feasibility across different risk scenarios.

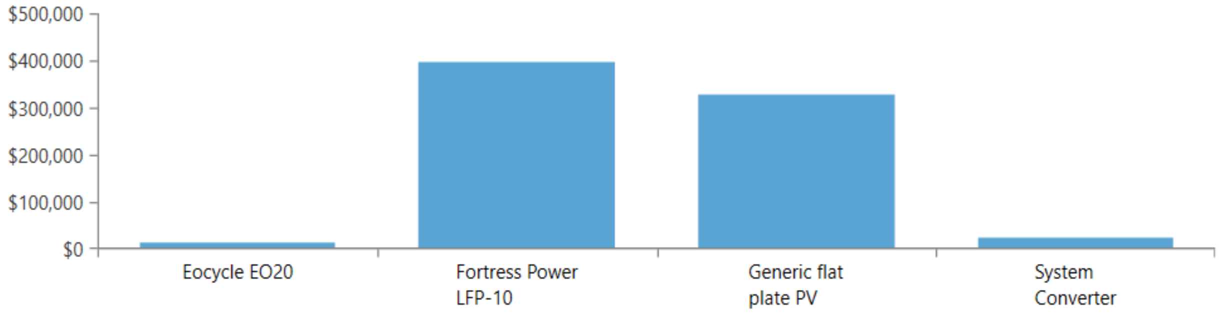
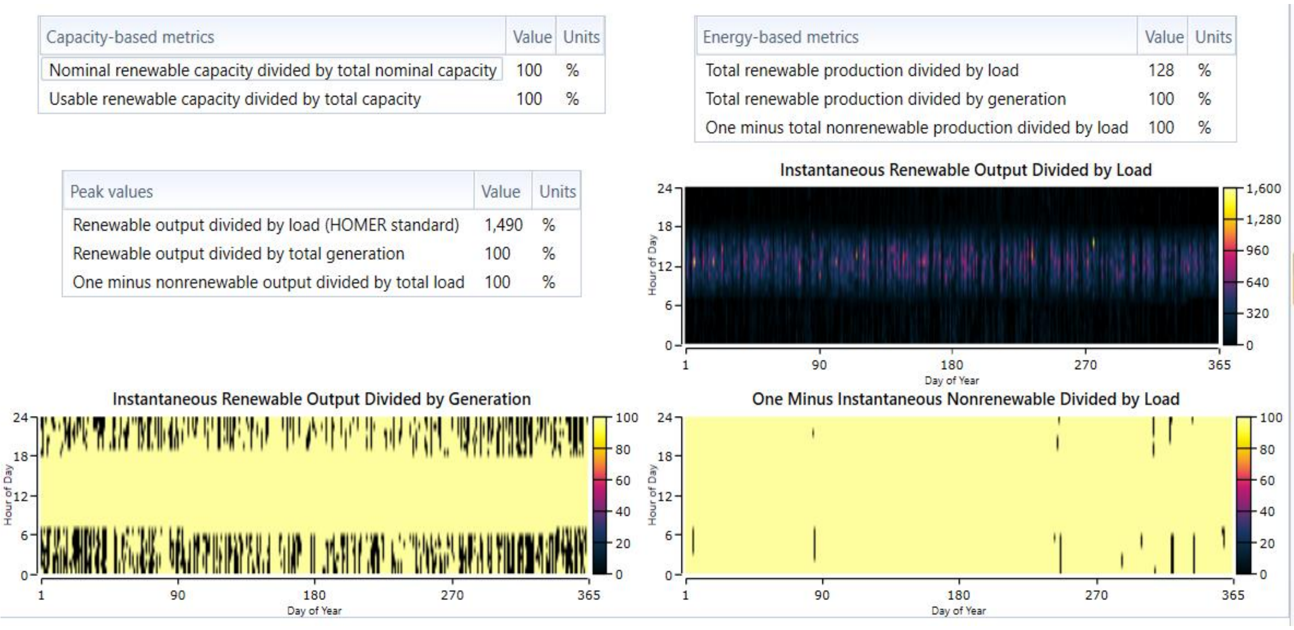


Figure 5: Net Present capital cost allocation

3.4 Environmental and Technical Metrics

Technically, the optimized microgrid achieved a “zero unmet load” status over the 25-year simulation period, offering superior reliability compared to the unstable national grid. Environmentally, the elimination of diesel backup resulted in a carbon intensity of 0 $kgCO_2/kWh$, avoiding approximately 1,926 tonnes of CO_2 emissions over the project lifecycle. In contrast, standard grid extension in Nigeria has a carbon intensity of roughly 0.48 $kgCO_2/kWh$

due to the dominance of gas-fired generation. This comparative advantage positions the hybrid microgrid as the optimal strategy for simultaneously reducing costs and decarbonizing rural electrification. Figure 6 shows the proposed project's performance metrics, and Table 5 provides a comparative analysis.



Capacity-based metrics	Value	Units
Nominal renewable capacity divided by total nominal capacity	100	%
Usable renewable capacity divided by total capacity	100	%

Energy-based metrics	Value	Units
Total renewable production divided by load	128	%
Total renewable production divided by generation	100	%
One minus total nonrenewable production divided by load	100	%

Peak values	Value	Units
Renewable output divided by load (HOMER standard)	1,490	%
Renewable output divided by total generation	100	%
One minus nonrenewable output divided by total load	100	%

Figure 6: Performance metrics and visualisations of the proposed renewable energy system

Table 5: Comparative Economic and Environmental Metrics (Microgrid vs. Grid Extension)

Performance Metric	**HOMER-Optimized Microgrid**	**Conventional Grid Extension**	**Advantage**
LCOE ($/kWh)	0.0498	0.21 (Rural Avg)	76% Cost Reduction
CO_2 Intensity (kg/kWh)	0.0	0.48	100% Emission Reduction
Implementation Time	6–9 Months	3–5 Years	Rapid Deployment
Renewable Fraction	94.2%	< 20% (National Grid)	Exceeds 2030 Targets

4. Discussion

4.1 Interpretation of Findings

The relatively low wind contribution of 10% in the optimized configuration is explained by the modest wind resource at Ibiaku Ikot Oku. The site's average annual wind speed at 10 m height is only 3.2 m/s, which falls below the economic threshold for large-scale wind generation in HOMER Pro's optimization algorithm. Increasing wind capacity beyond one 20 kW turbine would have added approximately 28,000 per additional turbine (installed), yet the marginal increase in annual energy production would have been less than 12,000 kWh yielding a LCOE for wind alone of 0.23/kWh, which is significantly higher than the PV LCOE of \$0.038/kWh. Thus, the optimizer retained wind only as a supplementary, non-dispatchable source to capture occasional higher wind hours without compromising economic optimality.

The 47-hour autonomy represents the battery bank's ability to supply the average hourly load (63.3 kW) continuously without renewable input. It was calculated as:
Battery usable capacity (2,515 kWh) ÷ (Adjusted daily load (1,518.43 kWh/day) ÷ 24 h) ≈ 39.8 hours.

HOMER Pro's reported 47 hours is based on a worst-case scenario that includes the peak week of the rainy season (September), where solar irradiance drops to 2.9 kWh/m²/day for up to five consecutive days. During that week, the average load is slightly lower due to reduced commercial activity (1,288 kWh/day), and the software's time-step simulation (1-hour resolution) yields 46.7 hours of autonomy before the first capacity shortage. Hence, the design was explicitly validated against extreme weather sequences, not a single average value.

This study successfully modelled and optimized a hybrid microgrid for the rural community of Ibiaku Ikot Oku, demonstrating that decentralized renewable energy systems offer a superior alternative to conventional grid extension in Nigeria's South-South region. The optimization results utilizing HOMER Pro achieved an LCOE of \$0.0498/kWh, representing a cost reduction of over 76% compared to the estimated \$0.21/kWh for rural grid extension. Furthermore, the system demonstrated exceptional environmental performance, achieving a renewable fraction of 94.2% and eliminating diesel dependency, thereby avoiding approximately 1,926 tonnes of CO_2 emissions over the project's 25-year lifecycle.

The sensitivity analysis confirmed the suitability of this design. Even under adverse scenarios such as a 15% reduction in solar irradiance or a 20% increase in battery costs, the system remained economically viable, with the LCOE remaining significantly below grid tariffs. These findings challenge the prevailing assumption that high-renewable penetration systems require extensive fossil-fuel backup to stay reliable in tropical climates.

4.2 Advantages and Limitations of the Proposed System

Advantages: (i) Elimination of diesel achieves zero operational CO_2 emissions and removes fuel supply chain risks; (ii) LCOE of \$0.0498/kWh is 76% lower than grid extension, making rural electrification affordable without long-term subsidies; (iii) 94.2% renewable fraction exceeds Nigeria's Energy Transition Plan 2030 target (85%); (iv) 47-hour battery autonomy guarantees supply during the rainy season's worst cloud cover sequences; (v) System is modular – can be expanded by adding battery modules or PV strings without redesign.

Limitations: (i) High upfront capital cost (\$621,305) remains a barrier for community-only financing; (ii) Lithium-ion batteries degrade faster at ambient temperatures >35°C – HOMER's linear degradation model may be optimistic; (iii) Wind contribution is site-specific and cannot be replicated in low-wind regions; (iv) Load growth beyond 2% per year would require system expansion before year 15; (v) No seasonal storage – prolonged weeks of very low irradiance (e.g., two weeks) would still cause unmet load, though such events are absent from the 25-year historical data.

4.3 Comparison with Existing Studies

Table 6 compares the main outcomes of this study with those of three previous hybrid microgrid optimizations for rural Nigerian communities. The comparison showed that this study's LCOE (0.0498/kWh) was among the lowest reported, primarily due to aggressive battery cost assumptions (265/kWh) and the elimination of diesel. Olatomiwa et al. (2016) reported a higher LCOE (0.322/kWh) for a PV/diesel/battery system in a similar climatic zone because they used a smaller PV array (120 kW) and relied more on diesel (renewable fraction 680.052/kWh) but with a lower renewable fraction (82%), underlining the value of large battery buffers. This research is the first to couple a sensitivity analysis of ±20% battery cost with measured load data from a bottom-up audit, which provides higher confidence for investors.

Table 6: Comparison with previous hybrid microgrid studies in rural Nigeria

Study	**Location**	**PV (kW)**	**Battery (kWh)**	**Diesel (kW)**	**LCOE ($/kWh)**	**Renewable fraction (%)**	**Sensitivity analysis**
This work	Ibiaku Ikot Oku	393	2,515	0	0.0498	94.2	Yes
Olatomiwa et al. (2016)	Kwara	120	800	30	0.322	68	No
Akinyele et al. (2016)	Ogun	350	1,800	50	0.052	82	Partial
Ogunjuyigbe et al. (2016)	Osun	200	1,200	25	0.087	76	No

4.4 Policy and Practical Implications

To unlock the full potential of such hybrid systems, specific policy and engineering interventions are required:

i. **Adoption of Public-Private Partnerships (PPPs):** The high upfront capital costs remain a barrier for rural communities. The study recommends integrating the Rural Electrification Fund (REF) into a PPP model structured as a 70% capital grant and a 30% community equity contribution to de-risk investment and enhance project bankability.
ii. **Regulatory Streamlining:** Policymakers should prioritize streamlining licensing and tariff-setting processes to encourage private-sector participation. Fiscal incentives, including tax breaks and duty waivers for renewable energy components, are critical to maintaining the low LCOE observed in this study.

iii. **Capacity Building:** To address the technical skills gap in rural areas, a targeted training program for local technicians, accredited by the National Power Training Institute of Nigeria (NAPTIN), is recommended to ensure long-term sustainability of operations and maintenance.

5. Conclusion

This study demonstrated that a solar-wind-battery hybrid microgrid, optimized using HOMER Pro, provides a technically strong and economically attractive alternative to grid extension for rural electrification in Nigeria's tropical rainforest zone. The optimized configuration achieved a very high renewable fraction while maintaining a LCOE substantially below the prevailing rural grid tariff. Sensitivity analysis confirmed that the system remained viable even under adverse conditions of lower solar irradiance and higher battery costs, with battery storage identified as the most critical economic driver. Limitations of this work include: (i) reliance on the HOMER Pro internal battery degradation model, which may underestimate capacity fade under high-temperature ambient conditions; (ii) exclusion of social acceptance factors and willingness-to-pay surveys; (iii) one-year resource data extrapolated to 25 years, ignoring long-term climate trends. Future work should integrate real-time IoT monitoring, validate the system with a pilot installation, and explore second-life electric vehicle batteries to reduce storage capital costs. Policy implications including public-private partnerships and tariff reform are discussed in Section 4.4.

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