Development of a Hybrid Salp Swarm–Grey Wolf Optimization Technique for Cost Minimization and Reliability Enhancement of Off-Grid Renewable Energy Microgrids in Rural Communities

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Abstract
Reliable electrification of geographically isolated communities depends on appropriately balancing investment expenditure, renewable generation and continuity of service. This study formulates a hybrid Salp Swarm–Grey Wolf Optimization (SSA–GWO) procedure for sizing a stand-alone photovoltaic–wind–battery–diesel microgrid under explicit economic and reliability requirements. The evaluation uses a constructed 8,760-hour rural electricity-demand and renewable-resource dataset with approximately 174.9 MWh annual consumption and a 47.4 kW maximum load. Installed photovoltaic, wind, battery and diesel capacities, together with the minimum battery reserve, are treated as coupled decisions. A twenty-year financial model applies an 8% real discount rate, while admissible solutions must limit annual unserved energy to 0.5% and achieve at least 86% renewable electricity contribution. The best hybrid solution across ten independent searches comprises 64.7 kW of photovoltaics, 39.8 kW of wind generation, 175.9 kWh of storage and 15.2 kW of standby generation. The corresponding estimated net present cost is US$300,626, with a levelized electricity cost of US$0.176/kWh, an energy-shortage fraction of 0.50% and 95.97% renewable contribution. Against a specified manually sized reference, the solution reduces electricity cost by 15.4% and unserved energy by 82.0%. A tighter 0.1% reliability target raises modeled cost to roughly US$0.183/kWh. Repeated algorithm trials show that the hybrid method achieves a competitive best outcome but does not consistently outperform standalone Grey Wolf Optimization. Reduced renewable production and higher demand further weaken adequacy when capacities remain unchanged. The study therefore establishes a testable planning methodology rather than a site-validated engineering design. It demonstrates the value of integrating chronological dispatch, reliability constraints and lifetime economics, while identifying measured resource records, consumer demand surveys, battery degradation, realistic reserve margins and external optimization benchmarks as prerequisites for practical deployment in Nigerian rural communities. The approach supports

transparent examination of affordability and supply security before committing to procurement or promising service levels in remote settlements.

Keywords: *Salp Swarm Algorithm; Grey Wolf Optimizer; rural electrification; hybrid microgrid; techno-economic optimization; reliability; battery energy storage.*

1. Introduction

Electricity availability influences nearly every dimension of rural development: school facilities, health services, irrigation, food preservation, communications and productive enterprise all depend on sustained supply. International access assessments continue to identify substantial gaps, concentrated particularly in lower-income and remote communities. The 2025 assessment estimated 666 million people without basic access, and the following reporting cycle placed the figure near 655 million (IEA et al., 2025; World Bank, 2026). In sparsely populated districts, extending conventional feeders can be constrained by long distances, difficult logistics, low initial consumption and continuing maintenance burdens. Autonomous microgrids therefore deserve assessment as a permanent and potentially complementary route to electrification.

A stand-alone microgrid can coordinate photovoltaic modules, wind turbines, batteries and a dispatchable generator within a common energy balance. Daytime photovoltaic production may support homes and businesses, and wind power can diversify the resource mix where local winds justify installation. Batteries shift surplus energy across shorter time intervals, whereas controllable backup generation covers residual shortages. Selecting component sizes is nonetheless a delicate trade-off. Oversized assets increase capital requirements and curtailment; undersized assets leave consumers without power. Future changes in appliance ownership and productive-use demand complicate the choice further.

Recent economic evidence strengthens the case for scrutinizing design assumptions. IRENA (2025) reported that large-scale photovoltaic and onshore wind technologies remained cost-competitive in many markets and documented falling storage costs, while its 2026 assessment emphasized that site-specific conditions and financing still affect project economics. These global averages cannot be transferred directly to Nigerian villages: retail procurement, transport, foreign-exchange exposure, inverter replacement, local maintenance and battery operating temperatures may alter costs considerably (IRENA, 2025, 2026). Studies by Lewis et al. (2024) and Seidu et al. (2026) likewise demonstrated the importance of techno-economic evaluation for Nigerian rural settlements, but their findings depend on the particular load, technology and environmental assumptions adopted.

The central research question concerns whether a specifically implemented hybrid SSA–GWO search can identify economically attractive microgrid capacities without compromising prescribed adequacy thresholds. SSA explores the search space through leader–follower population movements, while GWO draws directional information from its three strongest candidates. Their combination could improve the exploration–exploitation balance, but hybridization alone is not evidence of a superior optimizer. Following prior optimization investigations (Belboul et al., 2024; Ren et al., 2025), the assessment uses common test data and computational settings for SSA, GWO and the proposed hybrid.

The work develops an hourly generation-and-dispatch model, links its outcomes to lifetime economic measures, enforces renewable-contribution and unserved-energy limits, and evaluates three stochastic search variants using comparable trials. It also investigates how stricter service targets and adverse resource or demand changes alter the preferred design. The study addresses preliminary capacity planning; it does not perform protection coordination, harmonic analysis or transient stability studies. All results arise from the

constructed computational case described in Section 3 rather than observations of an installed village microgrid.

2. Related Works

Hossain et al. (2023) investigated hybrid multi-objective optimization for PV–wind–battery sizing and showed that joint evaluation of energy cost and loss-of-power-supply probability is more informative than economic optimization alone. Ashetehe et al. (2024) employed the Zebra Optimization Algorithm and a stochastic load profile in an Ethiopian rural electrification study, emphasizing that both consumption uncertainty and the selected reliability target affect the preferred technology mix. These contributions demonstrate that renewable-system sizing is naturally nonlinear, constrained and sensitive to uncertainty. Their conclusions also suggest that objective-function definitions and reliability thresholds must be disclosed before results are compared across publications.

For isolated PV–wind–battery–diesel microgrids, Belboul et al. (2024) proposed an improved SSA and compared its sizing performance with alternative metaheuristic methods. Their work provides an important basis for considering SSA in off-grid planning while identifying premature convergence as a practical concern. Tukkee et al. (2024) applied GWO to stand-alone microgrid scheduling and techno-economic-environmental objectives, demonstrating the usefulness of jointly considering cost, losses and emissions. Ren et al. (2025) further improved GWO for capacity configuration of a wind–solar–battery–diesel microgrid, reporting gains under their specified benchmarks. Together, these studies support the feasibility of swarm-based searches, but they do not imply that one optimizer will always dominate another on different resource profiles.

Recent case studies also reveal a pronounced geographical dimension. Adefarati et al. (2024) investigated a PV–diesel–battery system for a Nigerian farm settlement; Lewis et al. (2024) assessed rural mini-grid options in northeast Nigeria; and Seidu et al. (2026) evaluated autonomous renewable systems for Auchi. These studies highlight the relevance of demand composition, fuel expenditure, resource quality and financing assumptions. Bouchaala et al. (2026) used SSA with rule-based energy management for rural electrification in Algeria and reported measurable economic and reliability performance, reinforcing the need to state how batteries and diesel generators are dispatched.

The unresolved issue is not merely the availability of another metaheuristic method, but whether improvements persist when algorithms share one objective, one hourly simulator and the same reliability rules. Differences in demand profiles, fuel prices, reserve settings or penalty functions can otherwise be mistaken for algorithmic advantages. This paper therefore specifies five design variables, evaluates ten independent runs per optimizer and assesses both cost and feasibility. The final design is also tested under resource and consumption disturbances to reveal how closely it operates to its reliability boundary.

3.Methodology

3.1 System architecture and synthetic case definition

Figure 1 illustrates the autonomous AC microgrid, which draws electricity from photovoltaic and wind generation, a bidirectionally connected battery bank and a diesel generator. Operating logic first allocates available renewable electricity to the load. The battery then discharges down to its selected minimum state of charge; any remaining deficiency is assigned to the generator subject to its power limit. Surplus generation charges the battery, and energy beyond the battery's acceptance capability is curtailed. Any unresolved deficit is accumulated as energy not served.

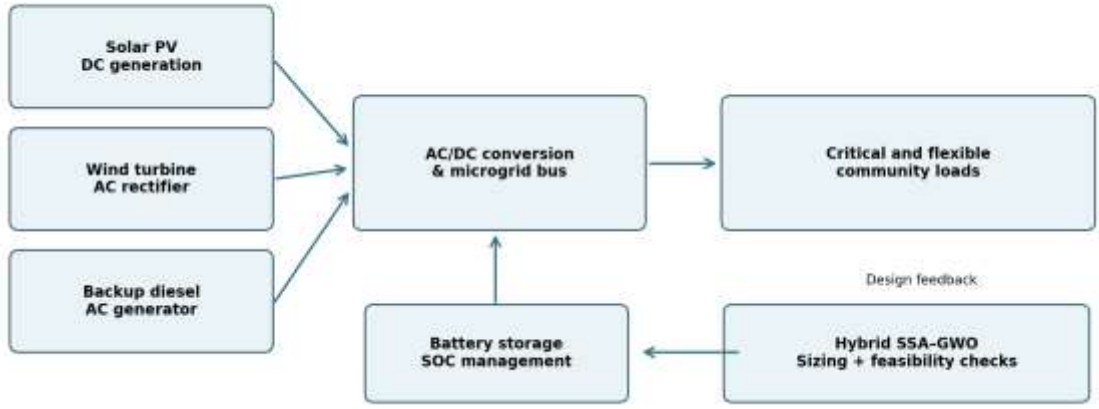


Figure 1. Proposed off-grid PV–wind–battery–diesel architecture and SSA–GWO optimization feedback (schematic).

The numerical case comprises 365 consecutive days resolved at one-hour intervals with a fixed random seed. The demand model captures evening residential peaks alongside daytime commercial and agricultural activity, yielding 174,919 kWh annually and a 47.4 kW maximum hourly load. Diurnal and seasonal patterns, weather variability and extended cloudy periods are incorporated into the generated solar sequence; the wind sequence also changes by hour and season. The assumed solar yield is 5.11 kWh per installed kilowatt per day before curtailment, with an 11% system derating, and the annual wind capacity factor is 24.7%. These conditions define a computational test case and should be replaced by site measurements for any specific community.

3.2 Solar PV and wind generation models

Photovoltaic production in each hour is approximated from the installed rating, incoming plane-of-array irradiation and the combined conversion derating factor. The simplified expression is intended for chronological planning rather than detailed semiconductor modelling; field application should incorporate measured module temperature and inverter performance. Wind production uses a piecewise turbine curve, with cubic growth between cut-in and rated wind speeds, constant rated output and a cut-out limit.

$$P_{PV}(t) = C_{PV} \times [G(t)/G_{STC}] \times \eta_{PV,system} \quad (1)$$

$$P_W(t) = C_W \times f_W(v_t); \quad f_W(v) = 0,\ v < v_{ci};\ (v^3 - v_{ci}^3)/(v_r^3 - v_{ci}^3),\ v_{ci} \le v < v_r;\ 1,\ v_r \le v < v_{co} \quad (2)$$

Here C_{PV} and C_W denote installed capacities (kW), G is plane-of-array irradiance, G_{STC} = 1 kW/m², and $\eta_{PV,system}$ = 0.89. The illustrative wind curve uses cut-in speed 3 m/s and rated speed 11 m/s; observed-speed samples remain below the assumed cut-out threshold. The power model is a screening representation instead of a substitute for a turbine manufacturer's certified power curve.

3.3 Battery dynamics and hourly supply balance

Battery operation is tracked through the energy stored at successive hourly steps. Charging and discharging efficiencies are each assumed to be 94%, corresponding to an approximate 88.4% round-trip efficiency. Charging and discharging power cannot exceed 0.5 times nominal energy capacity per hour, and the maximum permitted stored energy is 90% of rated capacity. The lower state-of-charge limit is optimized over an 8–35% interval, and the dispatch prevents charging and discharging simultaneously.

$$E_B(t+1) = E_B(t) + \eta_{ch} P_{ch}(t)\Delta t - P_{dis}(t)\Delta t/\eta_{dis} \quad (3)$$

$$SOC_{min} C_B \le E_B(t) \le 0.90\, C_B;\ 0 \le P_{ch}, P_{dis} \le 0.5\, C_B \quad (4)$$

$$P_PV(t)+P_W(t)+P_dis(t)+P_DG(t)+P_UNS(t)=P_L(t)+P_ch(t)+P_CUR(t) \quad (5)$$

The battery rating C_B is expressed in kilowatt-hours, whereas diesel contribution P_DG, unmet demand P_UNS and curtailed renewable output P_CUR is expressed in kilowatts. The simulation interval is one hour, and initial stored energy is fixed at 55% of nominal capacity. Terminal state of charge is recorded to detect any energy-boundary advantage. A more detailed multi-year model should initialize storage periodically or impose a cyclic boundary condition so that the design cannot benefit from an unrepaid initial energy stock.

3.4 Reliability, renewable fraction and economic indicators

Electricity adequacy is quantified by the proportion of annual load energy that remains unserved. This is an energy-based measure and should not be confused with customer interruption indices such as SAIFI. Renewable contribution is calculated from served energy after excluding the diesel-produced component. The financial model discounts capital replacement, annual operation and fuel expenditure to obtain net present cost; annualized net present cost is then divided by electricity actually delivered. Using served rather than requested energy avoids crediting a design for power it failed to supply.

$$LPSP_E = \Sigma_t E_UNS(t) / \Sigma_t E_L(t) \quad (6)$$

$$REF = 1 - [\Sigma_t P_DG(t)\Delta t] / [\Sigma_t E_served(t)] \quad (7)$$

$$CRF(r,n) = r(1+r)^n / [(1+r)^n - 1] \quad (8)$$

$$NPC = C_0 + \Sigma_k C_rep,k/(1+r)^k + C_O\&M,annual/CRF + C_fuel,annual/CRF \quad (9)$$

$$LCOE = NPC \times CRF / E_served,annual \quad (10)$$

A 20-year economic horizon and 8% real discount rate give CRF = 0.101852. The illustrative costs are: PV US$850/kW, wind US$1,750/kW, batteries US$300/kWh, diesel US$550/kW, converter allowance US$190 per kW of modelled conversion capacity, and fixed integration cost US$6,500. Battery replacement is estimated at 70% of original battery cost in year 10 and diesel replacement at 70% of original generator cost in year 12. Fuel is costed at US$1.05/litre. Annual O&M equals 1.2%, 2.5%, 1.0% and 4.0% of the initial PV, wind, battery and diesel asset costs, respectively, plus US$2,500 fixed service expenditure. Financing, taxes, network distribution, land, decommissioning and productive-use revenues are excluded.

Table 1. Decision variables, bounds and main planning assumptions.

Decision / condition	Illustrative value
PV rated capacity, C_PV	45–275 kW
Wind rated capacity, C_W	0–120 kW
Battery nominal energy, C_B	50–1,000 kWh
Diesel rated output, C_DG	5–85 kW
Minimum battery reserve	8–35% of nominal capacity
Battery power limit	0.5C charge and discharge
Reliability constraint	LPSP_E ≤ 0.005
Renewable-fraction constraint	REF ≥ 0.86
Project horizon / real rate	20 years / 8%
Annual load / peak demand	174,919 kWh / 47.4 kW

3.5 Hybrid SSA–GWO objective and implementation

The five-element capacity vector is X = [C_PV, C_W, C_B, C_DG, SOC_min]. The primary objective is minimum lifetime unit cost, provided that shortage and renewable-contribution targets are met. Candidate solutions violating either target incur a nonnegative penalty, while candidates inside the feasible domain incur none. Every search method evaluates the same

chronological physical model, cost assumptions and penalty expression. The formulation is nonlinear and partly nonsmooth, making heuristic search practicable without implying that its final value is the global minimum.

$$\min_X F(X) = LCOE(X) + 8a + 100a^2 + 2b + 3b^2 \quad (11)$$

$$a = \max(0, LPSP_E - 0.005), \quad b = \max(0, 0.86 - REF) \quad (12)$$

For SSA, food position F* is the best currently retained design, $c_1 = 2\exp[-(4k/K)^2]$ controls leader exploration, and follower positions are smoothed along the population chain. GWO constructs a new candidate using the three best members, commonly denoted α, β and δ, with $A = 2au - a$ and $C = 2v$. In this hybrid, the SSA phase proposes candidate positions; a scheduled subset of followers is then blended with the GWO-guided update. Each iteration retains the globally best feasible or penalized solution, thereby preventing loss of the best-so-far design.

$$X_SSA,leader = F^* \pm c_1[(U-L)u+L]; \quad X_SSA,follower,i = \tfrac{1}{2}(X_i + X_(i-1)) \quad (13)$$

$$X_GWO = (X_\alpha - A_1|C_1X_\alpha - X| + X_\beta - A_2|C_2X_\beta - X| + X_\delta - A_3|C_3X_\delta - X|)/3 \quad (14)$$

$$X_hybrid = 0.55\ X_SSA + 0.45\ X_GWO, \text{ for selected followers} \quad (15)$$

The hybrid GWO blending probability increases linearly from 0.35 to 0.80 during the run. A small, decaying Gaussian perturbation is applied to one nonelite candidate each iteration, followed by bounds projection. Each of the SSA, GWO and hybrid experiments uses 26 individuals, 140 iterations and ten fixed but independent initialization seeds (101–1012). Thus, the comparison is matched in population and iteration count; it is not a calibrated comparison of wall-clock efficiency because the hybrid performs additional mathematical updates per iteration. The reported best objective is retained after evaluating each iteration.

4. Results and Discussion.

4.1 System resource and load characteristics

Annual demand in the computational case totals 174,919 kWh, or approximately 479 kWh each day, with a 47.4 kW peak. The pronounced evening load requires stored or dispatchable energy beyond daytime photovoltaic output. A mean modeled wind capacity factor of 24.7% provides useful temporal complementarity, reducing pressure to expand solar capacity and battery storage. Wind performance of this magnitude is geographically dependent and is not assumed to characterize every inland Nigerian location.

Hourly profiles were generated numerically using controlled random inputs and prescribed seasonal patterns. Their purpose is to establish a repeatable comparison environment for the optimization methods. They are not energy-audit or meteorological measurements. Applying the method to a real settlement would require verified hourly resource histories, metered consumption, information on seasonal farming and commercial loads, and a defensible forecast of future demand growth.

4.2 Optimal capacity allocation and financial performance

Table 2 places four planning arrangements side by side: a manually chosen fixed-rule case, the least-cost hybrid SSA–GWO solution, a design meeting a tighter 0.1% shortage target and an intentionally oversized alternative. The preferred hybrid search selects 64.7 kW PV, 39.8 kW wind, 175.9 kWh of batteries and a 15.2 kW generator, with an 8.01% minimum battery reserve. The model returns approximately US$200,400 upfront investment, US$300,626 net present cost and US$0.17593/kWh levelized cost. Of the annual demand, 174,044 kWh is served and 874.6 kWh remains unmet, representing 0.50%. Renewable generation accounts for 95.97% of served electricity.

Table 2. Capacity, economic and reliability comparison (modeled planning case).

Indicator	Fixed-rule	Hybrid SSA–GWO	Reliability-first	Oversized fixed
PV capacity (kW)	110.0	64.7	61.7	130.0
Wind capacity (kW)	20.0	39.8	42.4	30.0
Battery capacity (kWh)	180.0	175.9	164.9	340.0
Diesel capacity (kW)	12.0	15.2	25.1	65.0
LCOE (US$/kWh)	0.20808	0.17593	0.18261	0.25613
NPC (US$)	347,404	300,626	313,291	439,865
LPSP_E (%)	2.783	0.500	0.100	0.000
Renewable share (%)	87.85	95.97	95.32	99.84
Diesel fuel (L/year)	6,695	2,345	2,906	129

When compared with the chosen fixed-rule reference, the hybrid solution lowers modeled unit cost by 15.45% and net present cost by 13.46%, while reducing the unmet-energy fraction by 82.03%. Generator fuel use declines from roughly 6,695 to 2,345 litres annually. With an assumed emission factor of 2.68 kg CO_2 per litre, direct diesel-related emissions fall from about 17.94 to 6.29 tonnes per year. These values exclude equipment manufacture, transportation and end-of-life emissions. Because the fixed reference breaches the 0.5% shortage constraint, the comparison describes an improvement over one manual design; it is not a like-for-like ranking of optimization algorithms.

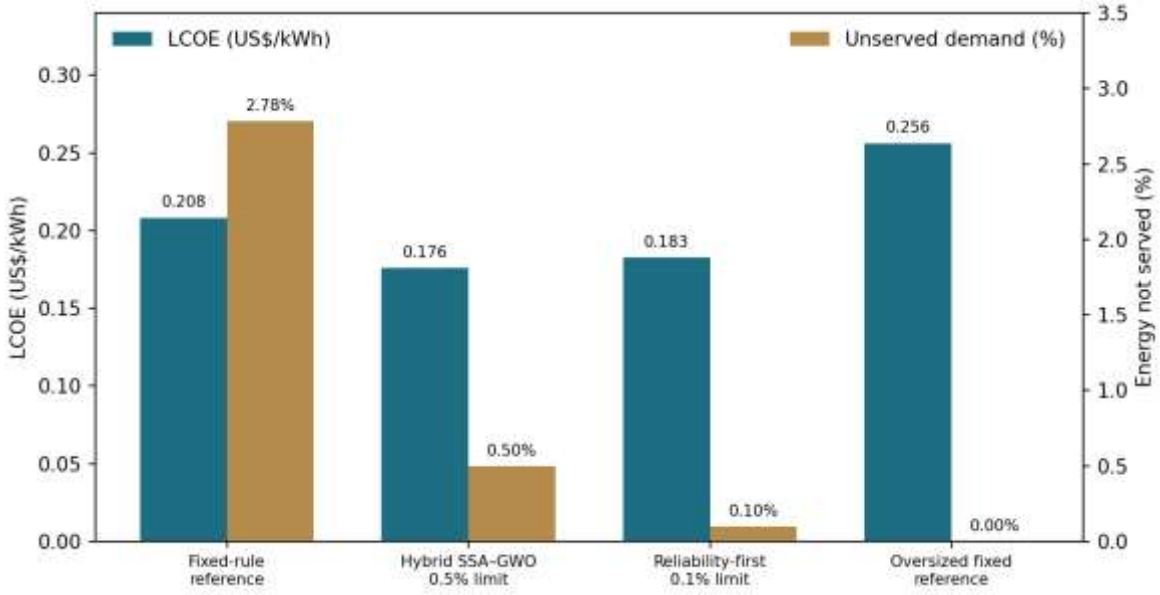


Figure 2. Cost–reliability trade-offs for four designs on the common hourly dataset.

The oversized reference achieves zero modeled unmet demand but requires more initial capital and excess renewable production. Its US$0.256/kWh LCOE is 45.6% above the hybrid candidate. This contrast reveals a familiar planning dilemma: reducing energy-not-served risk tends to require additional standby power or storage, but beyond a certain point

that extra capacity has a disproportionately high cost. The preferred service-quality level should therefore reflect the social and financial consequences of an interruption, including clinics, borehole pumps, refrigeration and local businesses.

4.3 Comparative optimization performance

Algorithm assessment requires more than the lowest cost produced by a single search, particularly when all three solvers use random initialization. The present comparison therefore draws on ten independent runs for each optimizer, matched in population size, iteration allowance and objective function. The best, mean and dispersion of feasible outcomes are considered alongside convergence behavior. This guards against treating an unusually successful seed as proof of general superiority.

Table 3. Comparison of ten optimization runs (identical hourly inputs).

Method	Best LCOE	Mean LCOE	SD across runs	Runs
Standalone SSA	0.17608	0.17914	0.00242	10
Standalone GWO	0.17594	0.17598	0.00004	10
Hybrid SSA–GWO	0.17593	0.17607	0.00030	10

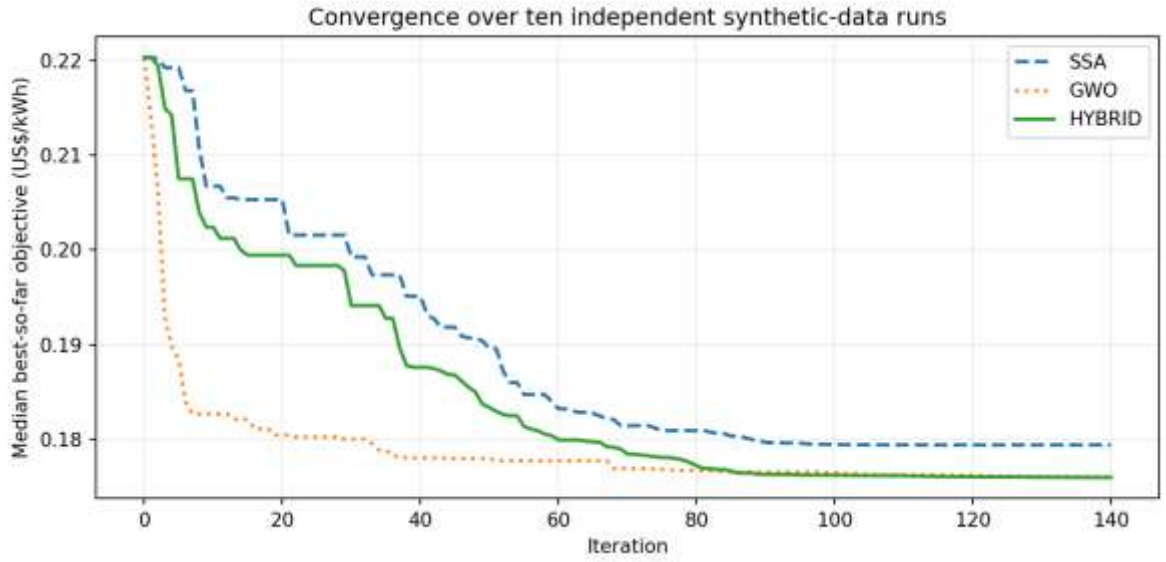


Figure 3. Median best-so-far convergence of SSA, GWO and hybrid SSA–GWO, across ten random seeds.

Figure 3 illustrates the convergence pattern instead of proving global optimality. The median GWO and hybrid curves approach similar cost levels while standalone SSA displays greater between-run variation. Since the proposed combination uses GWO guidance to supplement SSA follower movement, its principal observed benefit is search consistency relative to the less stable standalone SSA in this particular setting. Stronger claims would require more random seeds, confidence intervals, CEC-type analytical benchmarks, equal function-evaluation accounting, independent datasets and significance testing. The best configuration reported in Table 2 should therefore be treated as a candidate planning solution, not a mathematically proven global optimum.

4.4 Hourly energy management and operational interpretation

Figure 4 presents hourly electricity dispatch during a selected seven-day period of the constructed annual sequence. Photovoltaic and wind generation jointly address demand whenever available, and the battery moves energy between surplus and deficit hours. Diesel generation is dispatched when renewable supply and the permitted battery discharge are insufficient. The trace shows how storage and backup provision contribute to adequacy, although the seven-day window cannot by itself establish annual reliability.

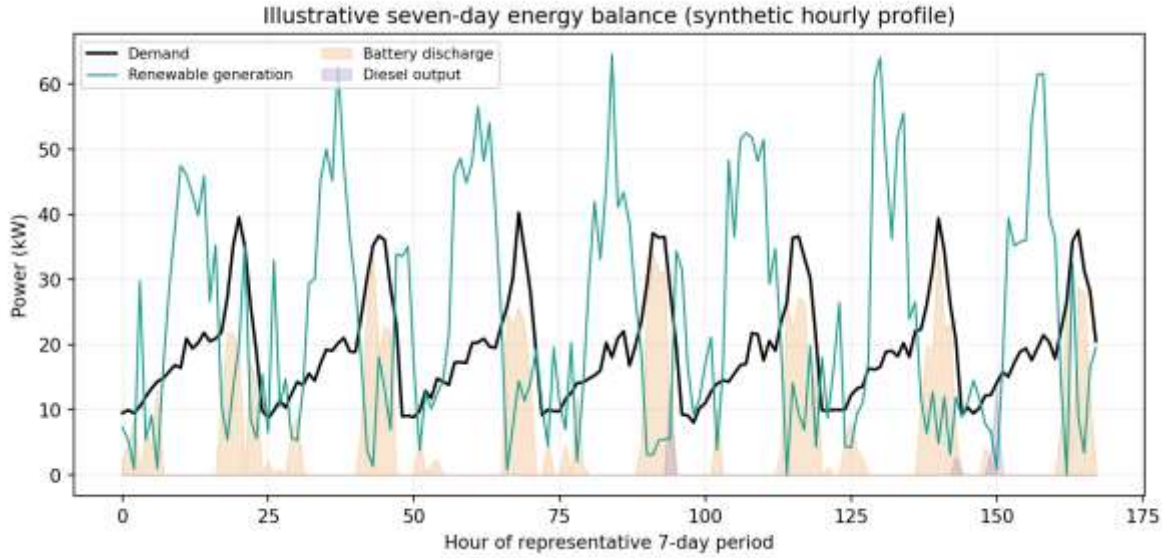


Figure 4. synthetic seven-day load, renewable generation and dispatch contributions.

The best nominal solution operates near the maximum permitted LPSP. This boundary behavior is economically intuitive: once a small energy-shortage allowance is introduced, spending more on a larger generator or battery is often not optimal until the reliability limit is tightened. However, aggregate unserved energy can conceal concentrated multi-hour interruptions. Future work should supplement LPSP with maximum outage duration, loss-of-load hours, expected energy not served by critical-load class and a monetary interruption-cost model. Network voltage stability, inverter overload capability, black-start requirements and fuel delivery reliability must also be assessed before an engineering design can be approved.

4.5 Reliability-first alternative and sensitivity analysis

Tightening the unserved-energy target from 0.50% to approximately 0.10% produces a second illustrative hybrid solution with 61.7 kW PV, 42.4 kW wind, 164.9 kWh storage and 25.1 kW diesel backup. NPC rises to about US$313,291 and LCOE to US$0.18261/kWh, only 3.8% above the least-cost base solution. The larger generator provides additional peak-deficit capacity, although the resulting renewable share decreases slightly. A rural clinic or a settlement with essential water pumping may reasonably prefer this more reliable alternative if the additional expenditure is justified by the economic and health costs of outages.

The base-case design was then exposed to four independent deterministic stress settings without resizing the equipment. A 20% reduction in solar output increases modeled energy not served to 1.78%; a 25% reduction in wind output raises it to 1.09%; and a 15% demand increase raises it to 2.28%. A combined case with solar generation 15% lower, wind generation 25% lower and demand 15% higher produces approximately 6.04% unserved energy, substantially violating the original 0.5% constraint. These findings demonstrate that satisfactory performance on one assumed typical year cannot guarantee resilience when weather and electricity consumption depart from the initial design envelope.

Table 4. Post-design stress-test performance (no re-optimization).

Scenario	Energy not served (%)	Renewable share (%)
Base	0.50	95.97
Solar −20%	1.78	93.52
Wind −25%	1.09	92.57
Demand +15%	2.28	92.45
Combined stress	6.04	85.01

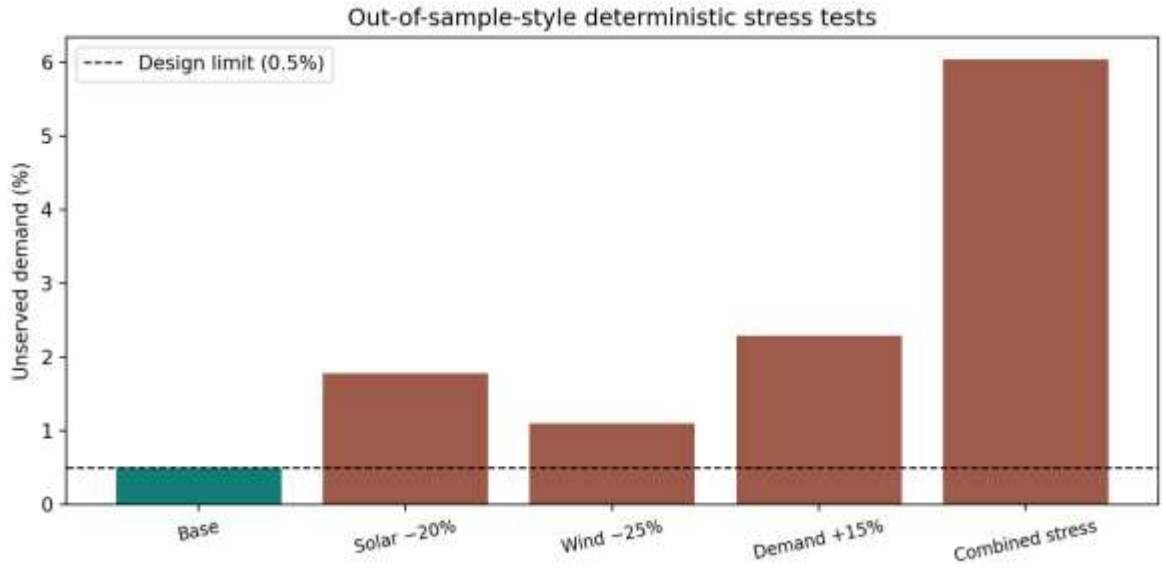


Figure 5. Sensitivity of annual energy-not-served fraction to changes in renewable output and demand.

A design selected close to the maximum allowed energy-shortage boundary offers little protection against unforeseen resource shortfalls. Even though tightening the constraint increases unit cost, a planner may prefer the additional reserve when clinics, water facilities or other critical services cannot tolerate prolonged interruption. This choice should be informed by load criticality, acceptable outage duration and community willingness to pay rather than cost minimization alone.

4.6 Financial and practical limitations

The reported LCOE reflects generation and storage costs within an illustrative islanded microgrid boundary. It does not include medium- or low-voltage distribution construction, revenue collection, theft, tariff subsidies, taxes, financing fees, community engagement or land acquisition. Such omissions may be substantial for remote community mini-grids. Moreover, the US$1.05/litre fuel price and generic dollar-denominated equipment costs may not match current Nigerian quotations. A bankable feasibility study should develop costs in local currency, test foreign exchange and borrowing rates, and estimate the affordability of the tariff to households and productive users. The 20-year horizon assumes replacements but does not explicitly model declining battery capacity, calendar aging or variation in generator efficiency with loading. The annual simulation assumes an adequately sized electrical distribution system and does not perform three-phase power flow. Therefore, the proposed optimization should be considered a generation-and-storage planning layer. Subsequent design stages should verify feeder voltage deviations, cable thermal limits, protection coordination, inverter fault current, frequency control, grounding, lightning protection and reserve margins. These limitations do not invalidate the computational exercise, but they

materially restrict the claims that can be made about real-world deployment.

5. Conclusions

The principal finding is that capacity planning, battery reserve choice and dispatch rules must be assessed together. Under the defined hourly case, the hybrid SSA–GWO procedure identifies an off-grid PV–wind–battery–diesel combination that satisfies a 0.5% unserved-energy cap and an 86% minimum renewable fraction while reducing modeled cost relative to a manual reference. The analysis supports the proposed methodology as a practical screening approach, not as a fully verified field design. The resulting capacities are 64.7 kW of PV, 39.8 kW of wind, 175.9 kWh of battery energy and 15.2 kW of diesel backup. The calculated net present cost is US$300,626, and electricity delivered by the model costs US$0.176/kWh. A renewable contribution of 95.97% is achieved, with the annual shortage fraction at 0.50%. The cost saving of approximately 15.4% against the specified fixed-rule case should be interpreted in light of the reference design's higher unserved-energy level.

Comparative trials also temper claims about optimizer performance. The hybrid gives the lowest observed best-run objective, yet standalone GWO produces a slightly more favorable mean across the available seeds. A tighter reliability requirement raises the cost of electricity, and fixed-design resource or load stress tests can violate the original adequacy target. Hence the preferred capacity mix is contingent on both the service standard and the assumed operating environment. Further work should use metered community demand, independent weather data, equipment quotations and realistic component replacement schedules. Robust or scenario-based sizing, critical-load prioritization, improved battery aging models and detailed distribution-system power-flow and protection checks should precede a deployment proposal. These steps would establish whether the relationships observed in the present constructed case are maintained in a real rural electrification project.

6. Contributions to Knowledge

The central methodological contribution is a single chronological model that links capacity selection and generator–battery dispatch to both financial cost and energy adequacy. Each candidate design is evaluated with the same hourly accounting, allowing component interactions to influence the optimizer directly rather than being assessed in separate and potentially inconsistent calculations. A further contribution is the explicit specification of a hybrid SSA–GWO update scheme and its evaluation against the two constituent methods under matched settings. The paper reports independent-run behavior, not merely a favorable convergence trace, and therefore demonstrates how an algorithmic enhancement can be tested without overstating evidence of universal superiority. The work treats renewable contribution and the fraction of unserved energy as feasibility constraints. This enables planners to distinguish designs with low financial costs but inadequate service from those that satisfy a chosen minimum standard, and to quantify the additional cost associated with stricter reliability requirements. The economic and environmental reporting connects equipment capacities with net present cost, annualized electricity cost, generator fuel use and direct operating emissions. Sensitivity experiments identify conditions under which a nominally compliant design no longer meets its shortage limit. These paired outputs make the trade-offs easier to assess in preliminary feasibility studies. Finally, the fully specified numerical inputs create a reusable starting point for independent replication. Replacing the constructed profiles with measured weather and demand, adding component aging and commercially available discrete sizes, and testing feeder voltage and protection performance would convert the framework into a stronger evidence base for rural planning.

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