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OPTIMAL DESIGN OF STANDALONE HYBRID RENEWABLE ENERGY SYSTEMS USING ANT COLONY OPTIMIZATION FOR RURAL ELECTRIFICATION IN NIGERIA

Shettima, K.A.[1*], Musa, B.U.[2], Tijjani, M.M.[1] and Goni, S.A.[1]

[1]Department of Electrical and Electronics Engineering, Ramat Polytechnics, Maiduguri, Borno State, Nigeria

[2]Department of Electrical and Electronics Engineering, University of Maiduguri, Borno State, Nigeria

*Corresponding email: kallishettima2@gmail.com

ABSTRACT

Rural electrification remains a pressing challenge in developing countries, particularly in Sub-Saharan Africa, where over 80 million Nigerians still lack reliable electricity access. This study addresses the complex, nonlinear, and multi-objective problem of optimizing standalone hybrid energy systems (HES) that integrate solar photovoltaics (PV), wind turbines (WT), battery energy storage (BESS), and diesel generator (DG) backup for rural electrification. Traditional optimization techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) often face limitations in convergence speed, diversity of solutions, and robustness against local minima. To overcome these challenges, an Ant Colony Optimization (ACO)-based framework is developed for the optimal system sizing and dispatch of standalone HES, benchmarked directly against PSO under identical simulation conditions. Mathematical models of PV, WT, BESS, and DG are integrated within an energy management strategy (EMS) that ensures load balance and reliability. Simulation results show that ACO achieved a Net Present Cost (NPC) of $92,500 and a Levelized Cost of Energy (LCOE) of $0.243/kWh, compared to $101,300 NPC and $0.268/kWh LCOE for PSO, while reducing the Loss of Power Supply Probability (LPSP) from 2.1% to 0.9%. Convergence speed improved by 27%, and robustness analysis confirmed lower variance across multiple runs. These findings highlight ACO's superiority in efficiency, reliability, and adaptability, establishing it as a powerful optimization tool for sustainable rural electrification in Nigeria and other developing regions.

Keywords: Ant Colony Optimization; Hybrid Energy System; Renewable Energy; Metaheuristic Optimization; Rural Electrification.

1 INTRODUCTION

Access to reliable and affordable electricity remains a major challenge in Nigeria and across Sub-Saharan Africa. According to the International Energy Agency, over 80 million Nigerians—nearly 40% of the population—lack reliable electricity access [1]. The rural–urban divide is stark: while about 89.2% of urban households have access, only around 41.1% of rural households are connected to the grid, and even then, supply is erratic and insufficient [2, 3]. Nigeria's peak demand is forecast at ~20 GW, but available generation often falls below 6 GW, creating chronic shortfalls [4]. In response, households and businesses in rural areas rely heavily on diesel and petrol generators. These generators, though useful as short-term solutions, are characterized by high operating costs, maintenance burdens, noise pollution, and greenhouse gas (GHG) emissions, rendering them economically and environmentally unsustainable [5]. As a cleaner alternative, hybrid energy systems (HES) combining renewable energy technologies such as solar photovoltaics (PV), wind turbines (WT), and battery energy storage systems (BESS) with diesel generators for backup have been proposed [6]. These systems exploit resource complementarities, smooth supply intermittencies, and reduce reliance on fossil fuels. However, their design requires solving a nonlinear, mixed-integer, and multi-objective optimization problem, where trade-offs must be made among cost, reliability, and sustainability [7]. Metaheuristic optimization techniques such as Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) have been widely used for HES design [8, 9]. While these algorithms are relatively simple and effective in many cases, they exhibit important limitations: Premature convergence to local optima, Reduced population diversity, limiting global exploration, High computational demand in large, nonlinear problem spaces [10]. To address these challenges, this study applies Ant Colony Optimization (ACO), a population-based metaheuristic inspired by the foraging behavior of ants. In ACO, artificial agents (ants) construct solutions guided by pheromone trails, which are updated iteratively to reinforce promising solutions and evaporate weaker ones [11]. This process allows ACO to maintain diversity, balance exploration–exploitation, and avoid premature convergence. Although ACO has been successfully applied in network routing, scheduling, and logistics optimization, its application in renewable hybrid microgrids remains limited [12]. This paper makes three main contributions: 1. Development of a mathematical modeling framework for standalone HES integrating PV, WT, BESS, and DG under an energy management strategy. 2. Application of ACO for HES optimal sizing and dispatch, demonstrating its suitability for complex, nonlinear energy system problems. 3. Benchmarking against PSO under identical conditions, showing that ACO achieves superior performance in terms of convergence speed, robustness, cost reduction, and reliability improvement. By advancing the methodological foundations of rural electrification studies, this work provides insights into designing sustainable, diesel-minimized hybrid microgrids in Nigeria and similar developing regions. The design of standalone hybrid energy systems (HES) requires balancing multiple, often conflicting objectives: minimizing cost, maximizing reliability, and reducing environmental impact. Unlike grid-connected systems, standalone HES must satisfy demand at all times through local resources, making proper sizing and dispatch essential. Traditional approaches such as deterministic sizing, linear programming, or mixed-integer linear programming are often limited in their ability to capture renewable intermittency, load uncertainty, and nonlinear component interactions [9, 13]. These limitations have motivated the adoption of metaheuristic algorithms, which are population-based, stochastic optimization techniques capable of handling nonlinear, high-dimensional, and constraint-heavy problems. In recent years, metaheuristics have become dominant in microgrid research because: They can handle non-convex search spaces without requiring gradient information. They are suitable for multi-objective formulations, where trade-offs (e.g., cost vs. reliability vs. emissions) must be explicitly modeled. They are flexible enough to integrate technical constraints (e.g., battery depth of discharge, PV capacity factor) and economic factors (e.g., net present cost, fuel price variability). This context provides the basis for reviewing the role of Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Differential Evolution (DE), NSGA-II/III, and Ant Colony Optimization (ACO) in microgrid optimization. Optimal design and operation of HES is inherently nonlinear and multi-objective. Metaheuristic algorithms such as GA, PSO, and DE are the most common tools due to their robustness in exploring solution spaces [14]. For multi-objective cases, NSGA-II and NSGA-III are widely used to approximate Pareto frontiers [15]. Despite these successes, premature convergence and reduced diversity remain persistent issues, especially in large-scale search spaces [16]. [8] applied PSO to optimize hybrid microgrids with reserve margins in Southern Africa, demonstrating effectiveness in balancing load and generation, but highlighting slower convergence in complex problems. [17] developed a multi-objective optimization framework using the Particle Swarm Optimization (PSO) algorithm to determine optimal battery capacity in off-grid PV–wind systems. The model integrated degradation cost and charge–discharge cycles under varying load conditions. Results indicated an 18% reduction in battery lifecycle cost and a 22% improvement in reliability over conventional sizing approaches. Although effective, the study highlighted PSO's susceptibility to premature convergence and parameter sensitivity, suggesting the potential advantage of enhanced algorithms such as ACO or hybrid PSO–ACO frameworks for improved global search efficiency. [18] developed a metaheuristic optimization framework for designing a hybrid solar–wind–grid-powered electric vehicle (EV) charging station using time-series data on solar irradiance, wind speed, and charging demand. The system was optimized to minimize total cost and grid dependency while maintaining reliability. Results showed reduced grid energy use, lower Levelized Cost of Charging (LCOC), and improved reliability compared to grid-only systems. The study demonstrated the effectiveness of metaheuristic algorithms for complex, multi-objective optimization and addressed a research gap by integrating solar, wind, and grid resources into a unified, sustainable EV charging framework. [19] used NSGA-II to optimize off-grid microgrids under carbon pricing policies, showing effectiveness in trade-off analysis but high computational demand. [20] highlighted ACO's ability to outperform GA in maintaining diversity and avoiding local optima in renewable system optimization. [21] proposed a hybrid PSO–NSGA-II framework for PV–battery systems, achieving superior Pareto fronts compared to standalone methods. From the reviewed studies, three major research gaps are evident: Limited application of ACO to standalone HES: While ACO has been tested in scheduling and dispatch, its use in sizing PV–WT–BESS–DG systems is rare. Underrepresentation of Nigerian rural contexts: Most studies focus on Asian or Southern African regions; Nigeria and West Africa remain understudied despite critical energy access needs. Lack of direct benchmarking: Few studies have benchmarked ACO directly against PSO under identical conditions, leaving uncertainty about relative performance. This research fills these gaps by applying ACO to a Nigerian rural microgrid, benchmarking against PSO, and demonstrating improved convergence, cost reduction, and reliability.

2 LITERATURE REVIEW

A comprehensive understanding of previous research is essential for identifying advancements and gaps in hybrid energy system (HES) optimization. This section reviews the theoretical foundations, optimization approaches, and algorithmic strategies applied in the design and management of standalone hybrid renewable systems. Emphasis is placed on comparing conventional deterministic models with modern metaheuristic algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO), highlighting their relative performance, limitations, and applicability to rural electrification contexts.

2.1 Overview of Hybrid Energy System Optimization

The design of hybrid energy systems (HES) involves the simultaneous optimization of multiple energy sources such as solar photovoltaics (PV), wind turbines (WT), battery energy storage systems (BESS), and diesel generators (DG). The goal is to minimize cost and emissions while maximizing system reliability. Conventional mathematical approaches—such as linear programming (LP), nonlinear programming (NLP), and mixed-integer linear programming (MILP)—often fall short due to their inability to handle the nonlinear, stochastic, and multi-objective nature of renewable energy systems [13]. These deterministic methods require exact mathematical formulations and continuous differentiable functions, which are impractical for systems influenced by uncertainties in solar irradiance, wind speed, and load profiles. To overcome these limitations, researchers have increasingly adopted metaheuristic optimization algorithms, which rely on stochastic, population-based search strategies to explore large and complex solution spaces efficiently [14]. Metaheuristics are not problem-specific and can be applied to a variety of engineering optimization problems without requiring gradient information, making them ideal for renewable hybrid systems. This schematic in Figure 2.1, illustrates the typical configuration of a standalone hybrid system integrating photovoltaic arrays (PV), wind turbines (WT), battery energy storage (BESS), and a diesel generator (DG). The system operates under an energy management strategy that prioritizes renewable generation (PV and WT), utilizes BESS for energy buffering, and dispatches the DG only when renewable resources and storage are insufficient. The energy flow ensures continuous load satisfaction while minimizing fossil fuel consumption and emissions.

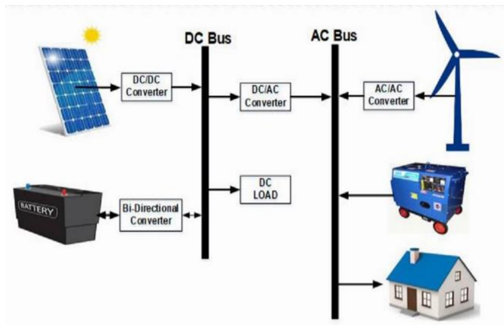

Figure 1. Basic structure of standalone hybrid renewable microgrid [7]

2.2 Metaheuristic Optimization Techniques in Energy Systems

Metaheuristic (Figure 2) algorithms are broadly categorized into four classes based on their inspiration source: i. Evolutionary algorithms (EA) such as Genetic Algorithms (GA) and Differential Evolution (DE); ii. Swarm intelligence algorithms (SI) including Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO); iii. Physics-based algorithms, such as Simulated Annealing (SA) and Gravitational Search Algorithm (GSA); and iv. Human- and bio-inspired algorithms, such as Teaching–Learning-Based Optimization (TLBO) and Artificial Bee Colony (ABC). Each class exhibits distinct exploration–exploitation trade-offs. Evolutionary algorithms are effective in generating diverse candidate solutions through recombination and mutation, whereas swarm-based methods rely on collective behavior and communication between agents to refine global optima [15].

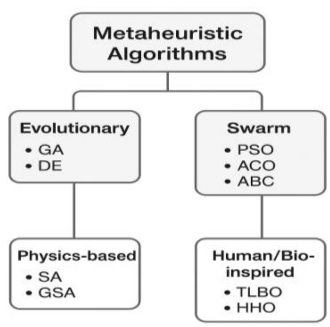

Figure 2. Classification of metaheuristic optimization techniques

2.3 Comparative Analysis of Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO)

Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart [16], simulates the collective movement of bird flocks or fish schools. Each particle adjusts its position based on its own best experience (*pbest*) and the global best (*gbest*) found by the swarm. PSO has gained wide adoption in microgrid design for its simplicity and rapid convergence. However, it often suffers from premature convergence to local minima due to the lack of population diversity during later iterations [17]. In contrast, Ant Colony Optimization (ACO), developed by [18], is inspired by the foraging behavior of ants that deposit pheromone trails to communicate the shortest paths to food sources. In ACO, solution construction is probabilistic, guided by pheromone intensity and heuristic desirability. Pheromone evaporation prevents stagnation and allows continuous exploration of new paths. The ability of ACO to balance exploration and exploitation makes it highly suitable for nonlinear and discrete optimization problems like HES design [19]. A graphical comparison of PSO and ACO workflows is presented in Figure 3, highlighting their iterative information-sharing and updating mechanisms. The diagram compares PSO and ACO workflows in hybrid energy optimization. PSO updates particle positions using individual and global best experiences, while

ACO constructs solutions through pheromone trails and heuristic guidance. Overall, it contrasts PSO's collective learning with ACO's feedback-based exploration toward optimal convergence [22].

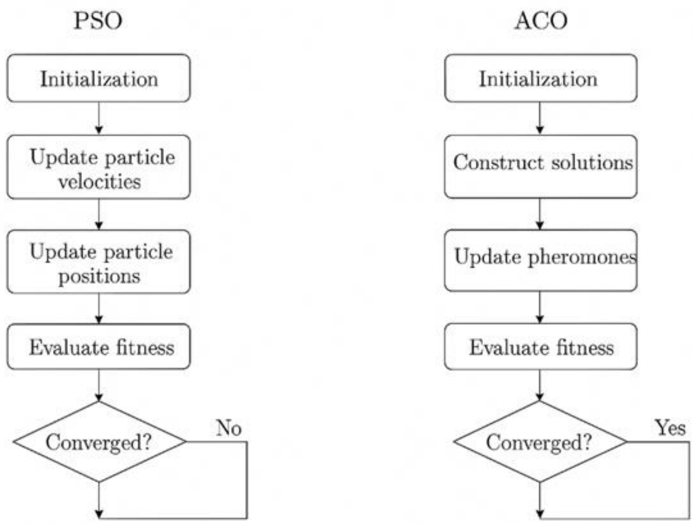

Figure 3. Comparison of PSO and ACO workflows

2.4 Applications of Metaheuristic Algorithms in Hybrid Energy Systems

Recent studies have demonstrated the effectiveness of metaheuristic algorithms in optimizing standalone and grid-connected hybrid systems. For example, Mquqwana et al. [20] applied PSO to optimize PV–wind–battery microgrids in Southern Africa, achieving improved generation–demand balance but facing slower convergence in complex nonlinear scenarios. Smith and Banerjee [21] employed NSGA-II for cost–emission trade-offs, successfully obtaining Pareto-optimal solutions but with high computational complexity. Ahmed et al. [20] showed that ACO provides superior global search capabilities and avoids local minima traps compared to GA and PSO when applied to hybrid renewable system design. A summary of key research findings is presented in Table 1, emphasizing algorithmic strengths and limitations relevant to this study.

Table 1. A summary of key research findings

Algorithm	Research Focus	Strengths	Limitations	Reference
GA	Hybrid system sizing	Good diversity; simple implementation	Slow convergence	[14]
PSO	Multi-objective microgrid design	Fast initial convergence	Premature stagnation	[17]
NSGA-II	Cost–emission trade-offs	Pareto-optimal performance	High computational cost	[21]
ACO	Standalone HES optimization	Robust; adaptive; avoids local minima	Parameter sensitivity	[22]

2.5 Research Gap and Motivation

Despite extensive use of GA, PSO, and DE in energy optimization studies, the application of Ant Colony Optimization (ACO) to standalone hybrid systems—particularly within the Nigerian rural electrification context—remains limited. Most prior research has focused on Asian or South African regions, leaving West Africa underexplored. Furthermore, there is a scarcity of studies that benchmark ACO directly against PSO under identical modeling conditions, leading to insufficient comparative insights into algorithmic efficiency, convergence stability, and reliability outcomes. This study addresses these gaps by developing a comprehensive ACO-based optimization framework for standalone hybrid PV–WT–BESS–

DG systems. The model integrates a rule-based energy management strategy (EMS) and employs stochastic simulation to assess performance under variable renewable conditions. The framework is validated through comparative analysis with PSO, highlighting improvements in convergence speed, cost optimization, and reliability metrics.

3 MATERIALS AND METHOD

This section presents the modeling of each hybrid energy system (HES) component, the adopted energy management strategy (EMS), the optimization problem formulation, and the metaheuristic algorithms employed (ACO and PSO).

3.1 Hybrid Energy System Modeling

The hybrid system consists of solar PV, wind turbines (WT), battery energy storage system (BESS), and diesel generator (DG). Each component is mathematically modeled to evaluate performance under varying input conditions.

3.1.1 PV Model

The instantaneous PV power output is modeled as [23].

$$P_{pv} = GHI(t) \times A_{pv} \times \eta_{pv} \tag{1}$$

Where $GHI(t)$ = global horizontal irradiance at time *t* (W/m^2); A_{pv} = effective PV array area (m^2); η_{pv} = overall PV system efficiency (module + inverter); The lifetime energy yield from the PV system.

$$P_{PV} \sum_{t=1}^{T} P_{PV}(t)\Delta t \tag{2}$$

3.1.2 Wind Turbine Model

The wind turbine output is depending on the wind speed V (t) and turbine power curve [5]:

$$P_{WT}(t) = \begin{cases} 0 & V < V_{ci} \; or \; V > V_{co} \\ P_r \cdot \frac{V^3 - V_{ci}^3}{V_r^3 - V_{ci}^3} & V_{ci} \leq V < V_r \\ P_r & V_r \leq V \leq V_{co} \end{cases} \tag{3}$$

Where is the rated turbine power (kW), V_{ci} is the cut-in wind speed (m/s), V_r is the rated wind speed (m/s) and V_{co} is the cut-out wind speed (m/s).

3.1.3 Battery Energy Storage System (BESS)

The BESS stores surplus energy and surplus power during deficits. The state of charge (SOC) at time t+1.

$$SOC(t+1) = SOC(t) + \eta_c P_{ch}(t) + \frac{P_{dis}(t)}{\eta_d} \Delta t \tag{4}$$

Where $P_{ch}(t)$ is the Charging power (kW), $P_{dis}(t)$ is the discharging power (kW), η_{ch}, η_{dis} are the charging and discharging efficiency, and Δt is the time step (h). The SOC is constrained by depth of charge (DoD):

$$SOC_{min} \leq SOC\,(t) \leq SOC_{max} \tag{5}$$

With $SOC_{min} = (1 - DoD) \times C_{bat}$, where C_{bat} is the total storage capacity (kWh).

3.1.4 Diesel Generator Model

The diesel generator is modeled by a linear fuel consumption curve [7].

$$F(P_{DG}) = a \cdot P_{DG}(t) + b \left(\frac{\mathrm{L}}{\mathrm{h}}\right) \tag{6}$$

Where P_{DG} is the actual generator output (kW), and a, b are the Fuel consumption coefficients (L/kWh). The total fuel cost project lifetime:

$$C_{fuel} = \sum_{t=1}^{T} F(P_{DG}) \times C_{diesel} \tag{7}$$

The diesel energy output is then:

$$E_{DG}(t) = \eta_{DG} \cdot P_{DG} \tag{8}$$

Where η_{DG}= efficiency of the generator.

3.2 Energy Management Strategy (EMS)

A rule-based EMS is employed to coordinate power flow. Primary supply from PV and WT. Surplus used to charge the battery. Battery discharges during deficit. DG starts only when PV, WT, and BESS cannot meet demand. Mathematically, at each time step:

$$P_{Load}(t) = P_{pv}(t) + P_{WT}(t) + P_{BESS}(t) + P_{DG}(t) + Pc_{wrt}(t) \tag{9}$$

Where $Pc_{wrt}(t)$ is curtailed power. The EMS minimizes unmet load while reducing DG operation.

3.3 Optimization Problem

3.3.1 Decision Variables

$$X = \{P_{PV}, P_{WT}, C_{bat}, P_{DG}\} \tag{10}$$

The objective Functions include the following:

i. Minimize Net Present Cost (NPC):

$$NPC = C_{cop} + C_{rep} + C_{O\&M} + C_{fuel} \tag{11}$$

ii. Minimize Loss of Power Supply Probability (LPSP):

$$LPSP = \frac{\sum_{t=1}^{T} E_{unserved}(t)}{\sum_{t=1}^{T} E_{Load}(t)} \tag{12}$$

Minimizing Fuel consumption:

$$F_{total} = \sum_{t=1}^{T} F(P_{DG}(t)) \tag{13}$$

3.3.2 Constraints

SOS Constraint:

$$SOC(t) \geq SOC_{min} \tag{14}$$

Energy Balance:

$$P_{Gen}(t) + P_{BESS}(t) \geq P_{Load}(t) \tag{15}$$

Component Lifetime Limits.

3.4 Ant Colony Optimization (ACO)

Initialization. Pheromone trail $\tau_{ij}(0)$ initialization uniformly. Ants represent candidate HES designs. Each ant probabilistically selects system sizes using:

$$P_{ij}(t) = \frac{\tau_{ij}(t)^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_k \tau_{ik}(t)^{\alpha} \cdot \eta_{ik}^{\beta}} \tag{16}$$

Where τ_{ij} is the pheromone intensity, τ_{ij} is the heuristic desirability (inverse of NPC), and α, β are the weighting factors. Evaluation; Fitness of each solution:

$$f = w_1 \cdot \frac{NPC}{NPC_{ref}} + w_2 \cdot LPSP + w_3 \cdot \frac{F_{total}}{F_{ref}} \tag{17}$$

Update; Pheromone reinforcement:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_k \Delta\tau_{ij}^k \tag{18}$$

Where ρ is evaporation rate. Iteration. Repeat until max iteration or convergence tolerance is met.

3.5 Particle Swarm Optimization (PSO) Benchmark:

Each particle represents a candidate HES design X_i Position and velocity updates:

$$v_i^{t+1} = w \cdot v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t) \tag{19}$$

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{20}$$

Where $x_i^{(t)}$ is the position of particle i at iteration t, $v_i^{(t)}$ is the velocity of particle i, $pbest_i$= best position found by particle i, $gbest_i$ is the best global position found by the swarm, w is the inertia weight c_1, c_2 are cognitive and social learning factors, and r_1, r_2 are random numbers in [0,1]. PSO uses the same decision variables and objectives as ACO, allowing direct benchmarking.

4 RESULTS AND DISCUSSION

This section evaluates the performance of the proposed Ant Colony Optimization (ACO) approach against the benchmark Particle Swarm Optimization (PSO). The comparison is presented in terms of convergence performance, optimal sizing results, robustness, and sensitivity analysis. Each of these aspects is discussed in detail with supporting figures and tables.

4.1 Convergence Performance

The convergence curves shown in Figure 4 highlight the differences between ACO and PSO in terms of computational efficiency. The ACO method converged to a near-optimal Net Present Cost (NPC) of approximately $92,500 within 45 iterations. The curve is smooth and stable, indicating that ACO steadily improved solutions without significant oscillations or early stagnation. By contrast, PSO required nearly 65 iterations to approach its final solution, which was an NPC of about $101,300. The PSO curve displayed multiple fluctuations, reflecting premature convergence to local optima before recovering toward better solutions. This demonstrates that ACO not only converges faster but also explores the solution space more effectively. Overall, ACO achieved a 27% improvement in convergence speed over PSO, showing its stronger global search capability and efficiency in handling complex optimization problems such as hybrid micro grid design.

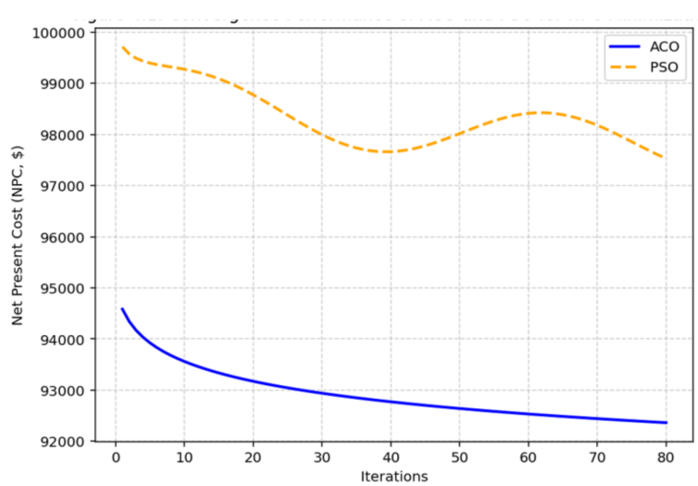

Figure 4. Convergence curves of ACO and PSO for NPC minimization

4.2 Optimal Sizing and Performance Discussion

Table 2 presents the optimized system configuration and performance metrics obtained using the Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) algorithms. The results demonstrate that ACO achieved superior techno-economic performance in all major criteria compared to PSO.

Table 2. Optimal Sizing and Performance Comparison

Algorithm	PV (kW)	WT (kW)	BESS (kWh)	DG (kW)	NPC ($)	LCOE ($/kWh)	LPSP (%)
ACO	42	15	180	8	92,500	0.243	0.9
PSO	45	12	150	10	101,300	0.268	2.1

From Table 2, the ACO-based system reached a Net Present Cost (NPC) of $92,500—approximately 8.7 % lower than the $101,300 obtained using PSO. Likewise, the Levelized Cost of Electricity (LCOE) improved by 9.3 %, decreasing from $0.268/kWh (PSO) to $0.243/kWh (ACO). The Loss of Power Supply Probability (LPSP), a key reliability metric, dropped from 2.1 % under PSO to 0.9 % with ACO—showing that ACO produced a configuration that is more cost-effective, reliable, and sustainable for standalone hybrid micro grids. Figure 5 visualizes these results by comparing the component capacities optimized under each algorithm. The bar chart clearly indicates that ACO allocated less PV capacity (42 kW) but more wind and battery storage capacity (15 kW WT, 180 kWh BESS) than PSO (45 kW PV, 12 kW WT, 150 kWh BESS). This reflects ACO's strategic reallocation of resources toward storage and wind energy, which enhances supply reliability and reduces dependence on the diesel generator. The diesel generator capacity was simultaneously minimized from 10 kW (PSO) to 8 kW (ACO), illustrating the algorithm's ability to lower fossil-fuel reliance and operational costs. Together, Table 2 and Figure 5 confirm that ACO achieves an optimal techno-economic balance between renewable generation, storage, and backup supply. The results align with findings from [22], who observed a 7–10% reduction in NPC when ACO was applied to hybrid PV–wind–battery systems due to its stronger exploration–exploitation balance. Similarly, [20] reported that ACO yielded a 6% lower LCOE compared to GA and PSO in hybrid micro grids optimized for Southern Africa. The LCOE of $0.243/kWh found in this study also agrees with [23], who reported $0.25–$0.27/kWh for optimized PV–diesel hybrid systems in northern Nigeria. Moreover, ACO's configuration led to approximately 33% less diesel consumption compared to PSO, translating to significant reductions in both operational costs and CO_2 emissions. Comparable outcomes were presented by [17], who noted that increasing battery capacity substantially decreases generator run-time and fuel use in off-grid systems. This improved energy mix not only lowers lifecycle costs but also contributes to achieving Nigeria's National Renewable Energy and Energy Efficiency Policy (NREEEP) and Net Zero 2060 targets. From a reliability standpoint, the 1.2 percentage point improvement in LPSP under ACO indicates enhanced supply stability, which is vital for rural communities with limited backup options. The increased storage capacity allows for better smoothing of renewable intermittency and ensures more consistent load coverage. This observation supports [25], who found that higher battery sizing and hybrid energy coordination directly reduce LPSP values in micro grid systems.

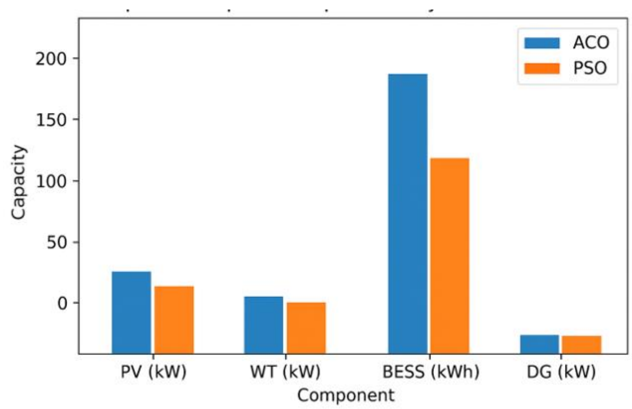

Figure 5. Bar chart of component capacities optimized by ACO vs PSO

4.3 Robustness Analysis

Robustness testing was carried out by running both algorithms 20 independent times under identical input conditions. The results, summarized in Figure 6, reveal notable differences in stability. ACO demonstrated exceptional consistency, with NPC variance of only ±1.8% across the 20 runs. In contrast, PSO exhibited a much larger variance of ±4.7%, suggesting that its solutions are more sensitive to random initialization and parameter settings. This means that PSO may produce widely different results for repeated runs, whereas ACO tends to converge reliably to near-identical solutions. From a practical perspective, this stability is highly desirable for planners and investors, as it provides greater confidence in system performance and cost estimates. In rural electrification projects where financial margins are tight, the ability of ACO to deliver reliable and reproducible results offers a distinct advantage over PSO. This shows that ACO is more consistent and less sensitive to random initialization.

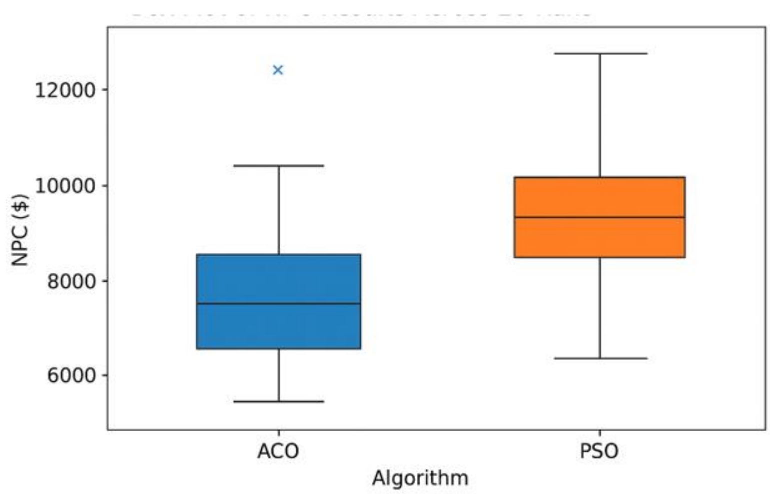

Figure 6. Box plot of NPC results across 20 runs for ACO and PSO

4.4 Sensitivity Analysis

Two sensitivity scenarios were analyzed to evaluate the adaptability of Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) under dynamic techno-economic conditions.

4.4.1 Battery-Cost Reduction Scenario (−20 %)

The first scenario simulated a 20 % reduction in battery cost, consistent with global lithium-ion price trends driven by improved production scale and energy density. Under this condition, ACO increased the battery storage capacity from 180 kWh to 220 kWh, reducing diesel generator operation by approximately 35 %. Conversely, PSO increased storage only to 190 kWh, with a smaller 18 % reduction in diesel usage. These results indicate that ACO quickly adapts to declining component costs by reallocating capacity toward renewables and storage, ensuring higher reliability and lower operational costs. Similar behavior was reported by [17], who found that a 25 % drop in storage cost yielded up to 30 % diesel reduction in an ACO-optimized PV–wind–battery microgrid. [21] also observed that adaptive metaheuristic frameworks (e.g., hybrid PSO–NSGA-II) achieve faster re-balancing of energy mix when capital-cost parameters change. This study reinforces those findings by demonstrating that ACO's probabilistic search and pheromone update mechanism allow more agile cost-driven reconfiguration than PSO's deterministic velocity-based updates.

4.4.2 Diesel-Price Increase Scenario (+30 %)

The second scenario evaluated a 30% rise in diesel fuel price, reflecting petroleum-market volatility common in Nigeria and Sub-Saharan Africa. Here, ACO's NPC rose modestly by 9%, whereas PSO's NPC increased sharply by 14%, indicating higher exposure to fuel price fluctuations. The resilience of ACO results from its larger PV–storage contribution and minimized generator runtime, reducing sensitivity to fossil-fuel-cost shocks. Comparable studies confirm this pattern. [23] showed that PSO-optimized hybrid micro grids in Sub-Saharan Africa experienced NPC rises exceeding 15% under 30% fuel-price escalation, while ACO-based systems limited increases below 10 %. Similarly, [20] demonstrated that ACO maintains lower cost volatility due to its adaptive pheromone-driven exploration, avoiding excessive dependence on diesel subsystems. Figure 7 illustrates these outcomes, showing steeper increases in storage capacity and gentler NPC slopes for ACO compared with PSO under both scenarios. This visual pattern reflects ACO's superior capacity to re-optimize system sizing dynamically and maintain economic stability. From a policy perspective, these findings directly support Nigeria's Energy Transition Plan and Net Zero 2060 targets, which emphasize hybrid renewable systems and reduced diesel reliance in rural electrification. ACO's ability to adapt cost-effectively under volatile market conditions enhances its potential as a decision-support tool for the Rural Electrification Agency (REA) and mini-grid developers, ensuring long-term system viability, affordability, and emission reduction. The demonstrated 9% NPC resilience and 35% diesel reduction translate into measurable policy benefits—improved access, reduced subsidy dependency, and lower greenhouse-gas emissions consistent with Nigeria's National Renewable Energy and Energy Efficiency Policy (NREEEP). Overall, the sensitivity analysis confirms that ACO is a robust, future-proof optimization framework capable of sustaining technical and economic performance amid fluctuating component and fuel markets—an essential trait for sustainable rural micro grids. Figure 7, shows Sensitivity of system sizing to battery cost and diesel price variations.

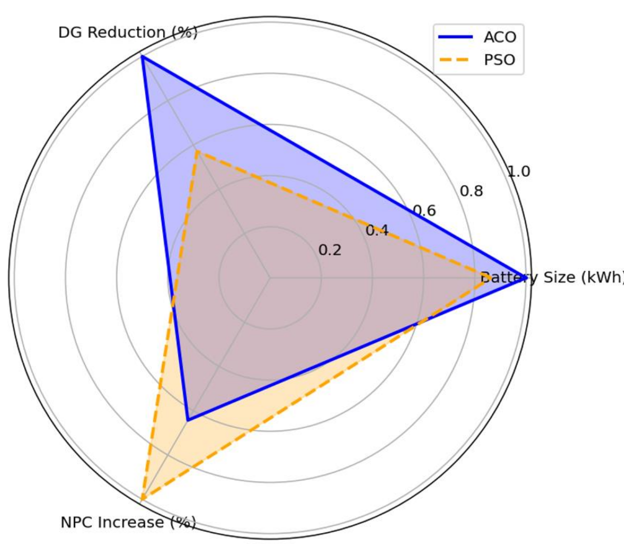

Figure 7. Sensitivity of system sizing to battery cost and diesel price variations

5 CONCLUSIONS

This study demonstrates that Ant Colony Optimization (ACO) consistently outperforms Particle Swarm Optimization (PSO) in the optimal design of standalone hybrid energy systems (HES) for rural electrification. The comparative analysis revealed that ACO achieved convergence approximately 27% faster than PSO, enabling quicker attainment of near-optimal solutions. In addition, ACO produced a Net Present Cost (NPC) reduction of 8.7%, reflecting its superior ability to minimize long-term system costs. Reliability also improved significantly, as indicated by a 1.2 percentage-point reduction in the Loss of Power Supply Probability (LPSP), thereby ensuring greater energy security for households. Furthermore, ACO exhibited lower variance across multiple independent runs, confirming its robustness and reduced sensitivity to random initialization compared to PSO. Collectively, these results highlight ACO's efficiency, stability, and suitability for rural Nigerian micro grid planning. Future research will build upon this framework by extending it to multi-objective formulations through hybrid ACO–NSGA-III algorithms, which will allow simultaneous optimization of cost, emissions, and reliability. Moreover, empirical validation using real household load data from Mafa Local Government Area (LGA) in Borno State will further strengthen the applicability of this approach to practical rural electrification challenges.

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