Bi-Objective Optimization of Hybrid Renewable Energy Systems Using Modified Gray Wolf Optimization Algorithm: A Reliability-Constrained Case Study of Rural Nigeria.

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Abstract

Reliable and affordable electricity access remains a major challenge in rural regions of developing countries, particularly in sub-Saharan Africa. Hybrid renewable energy systems (HRES), integrating photovoltaic (PV), wind turbine (WT), and battery energy storage systems (BESS), offer a viable decentralized solution. This study presents a reliability-constrained bi-objective optimization framework for the optimal sizing of a PV-wind-battery system for the Dirin Gari rural community in Nigeria using a Modified Gray Wolf optimization (MGWO) algorithm. The proposed MGWO incorporates a regression-based learning mechanism that utilizes historical best solutions, along with a diversity adjustment strategy to enhance search capability and convergence stability. The optimization problem is formulated to minimize system cost while satisfying reliability constraints defined by Loss of Power Supply probability (LPSP). A parametric approach is adopted to evaluate system performance across a wide range of reliability levels (20.9%-97.8%), enabling a comprehensive assessment of cost-reliability trade-offs. Results show that lower LPSP values improve system reliability but significantly increase cost due to higher storage requirements, while higher LPSP levels reduce cost at the expense of supply quality. The optimal configuration at 20.9% LPSP yields component capacities of 395.4 kWh (PV), 606.5 kWh (WT), and 142.5 kWh (BESS), with an estimated lifecycle cost of 1.62 million USD. Comparative analysis proves that MGWO achieves improved cost efficiency and faster convergence than the conventional GWO, confirming its suitability for complex HRES design and rural electrification planning. These findings provide

insights for policymakers and energy planners seeking cost-effective electrification strategies for off-grid communities across developing countries.

Keywords: hybrid renewable energy systems, modified gray wolf optimization, loss of power supply probability, optimal sizing, rural electrification.

1. INTRODUCTION

Access to reliable and affordable electricity remains a persistent challenge in many rural regions of sub-Saharan Africa, where grid extension is often constrained by high capital cost, technical losses, and difficult terrain (Tyagi & Singhal, 2024). In Nigeria, a significant proportion of rural communities continue to rely on diesel generators and traditional energy sources, which are both economically and environmentally unsustainable (Babalola et al., 2022). As a result, decentralized energy solutions based on renewable resources have gained increasing attention (Sun et al., 2023).

Hybrid Renewable Energy Systems (HRES), which integrate solar photovoltaic (PV), wind turbines (WT), and battery energy storage systems (BESS), offer a viable pathway for improving energy access in off-grid locations (Taghizad-Tavana et al., 2025). The complementary nature of solar and wind enhances supply continuity, while energy storage mitigates intermittency and stabilizes system operation (Shafiei et al., 2025). However, the optimal design of HRES is inherently complex due to conflicting objectives of minimizing system cost and maximizing reliability under variable environmental and load conditions (Khan et al., 2025).

Optimization techniques play a critical role in addressing this challenge (Arteaga-Cabrera et al., 2025). Conventional deterministic methods often struggle with nonlinear and multi-dimensional search spaces, prompting the adoption of metaheuristic algorithms (Selvarajan, 2024). Among these, the Gray Wolf optimization (GWO) algorithm has demonstrated strong global search capability and ease of implementation (Liu et al., 2024). Despite its advantages, standard GWO suffers from premature convergence and limited adaptability in complex optimization scenarios (Liu et al., 2024).

To address these limitations, this study proposes a modified Gray Wolf optimization (MGWO) algorithm incorporating a regression-based learning mechanism and diversity adjustment strategy. The problem is formulated as a bi-objective optimization task, where system cost is minimized under reliability constraints defined by the loss of power supply probability (LPSP). A parametric approach is further adopted to evaluate system performance across a range of LPSP values, enabling a comprehensive assessment of cost-reliability trade-offs.

This study aims to determine the optimal sizing of a PV-wind-battery hybrid system for the rural Dirin-Gari community in Nigeria using the proposed MGWO framework. The contribution lies in integrating reliability constraints with sensitivity analysis, thereby providing practical insights for cost-effective and sustainable rural electrification planning.

2. LITERATURE REVIEW

The optimal design of HRES has been widely investigated using various optimization techniques, with particular emphasis on balancing economic and reliability objectives. Recent studies highlight the growing importance of metaheuristic algorithms in addressing the nonlinear and multi-objective nature of HRES design problems (Giedraityte et al., 2025; Hadj Slama et al., 2025; Kapen, 2025).

Several researchers have applied the GWO algorithm for hybrid system sizing due to its simplicity and effective global search capability. For instance, Liu et al., (2024) demonstrated the applicability of GWO in optimizing PV-wind systems, achieving improved cost performance compared to other techniques. Similarly, Sesan et al., (2023) applied an improved GWO variant for microgrid design in Nigeria, reporting enhanced reliability and reduced operational cost.

Beyond single-objective optimization, recent works have explored multi-objective frameworks to capture the trade-off between cost and reliability. Riaño-Enciso et al., (2025) developed a bi-objective GWO-based approach that simultaneously minimizes cost and emission while maintaining system reliability. Sun et al., (2024) further extended this approach by incorporating uncertainty modeling, demonstrating the importance of variability in renewable resources.

Reliability assessment in HRES is commonly quantified using indices such as Loss of Power Supply Probability (LPSP), which measures the fraction of unmet load demand. Studies by Gholami et al., (2024), and Kumar et al., (2022), emphasize the importance of integrating LPSP into optimization models to ensure realistic system performance. However, many existing studies focus on single-point optimization, often neglecting the broader relationship between cost and reliability across different operating conditions.

Recent advancements have also focused on improving the performance of metaheuristic algorithms through hybridization and adaptive mechanisms. Kumar et al., (2022) highlight that incorporating learning strategies and dynamic parameter adjustment can significantly improve convergence speed and accuracy. Despite these improvements, there remains a need for approaches that explicitly integrate historical learning and diversity preservation within the optimization process.

In addition, most existing studies provide limited insight into how system configurations evolve under varying reliability constraints. A parametric analysis of LPSP can offer a more comprehensive understanding of system behavior, particularly for practical deployment in rural environments where cost constraints are critical.

In view of these gaps, this study contributes to the existing body of knowledge by developing a regression-enhanced MGWO algorithm, formulating the HRES design problem as a reliability-constrained bi-objective task, and performing a parametric analysis across multiple LPSP levels to reveal cost-reliability trade-offs.

3. METHODOLOGY

Study Area and Data Acquisition

The study focuses on the Dirin Gari community located in northern Nigeria (latitude: 11.3377° N, longitude: 5.4025° E). The region is characterized by high solar potential and moderate wind potential, making it suitable for HRE deployment.

The electrical load profile of the community was developed through a field-based assessment covering residential, commercial, and public service sectors. The estimated average daily energy demand is 1103.6 kWh/day, reflecting typical rural consumption patterns, with a peak occurring during evening hours.

Meteorological data required for system modeling were obtained from the NASA database, covering a period of 22 years (2000-2022). The dataset includes solar irradiance, wind speed, and ambient temperature. The average solar radiation ranges between 6.3 and 6.7 kWh/m²/day, indicating strong solar resource availability, while wind speeds vary between 4.7 and 5.5 m/s, providing complementary energy potential. These datasets form the basis for modeling the photovoltaic, wind, and battery subsystems and are used as inputs to the optimization framework for evaluating system performance under varying reliability conditions.

System Modeling

The HRES considered in this study comprises a photovoltaic (PV) array, a wind turbine (WT), and battery energy storage (BESS). The mathematical representations of these components are formulated to evaluate energy generation, storage dynamics, and system reliability under varying operating conditions.

Photovoltaic (PV) Model

The output power of the PV array is modeled as a function of solar irradiance and cell temperature, as expressed in Equation 1 (Wang et al., 2021).

$$P_{PV} = A_{PV}.\eta_{PV}.G_t.[1 - \beta(T_C - T_{ref})] \quad 1$$

Where P_{PV} is the PV output power (kW), A_{PV} is the panel area (m^2), η_{PV} is the conversion efficiency (%), G_t is the incident solar irradiance on the (kW/m²),β is the temperature coefficient $(°C^{-1})$, T_C is the cell temperature (°C), and T_{ref} is the temperature under standard test conditions (25°C).

Wind Turbine (WT) Model

The mechanical power extracted from wind is modeled using aerodynamic principles as presented in Equation 2 (Wang et al., 2021).

$$P_{WT} = \frac{1}{2}\rho A C_p V^3 \quad 2$$

Where P_{WT} is the wind power output(kW), ρ is the air density (kg/m^3), typically $1.225\ kg/m^3$, C_p is the power coefficient of the turbine (dimensionless), A is the rotor swept area (m^2) and V(t) is the wind speed (m/s).

Battery Energy Storage System (BESS) Model

The battery state of charge (SOC) is modeled using the energy balance Equation expressed in Equation 3 (Bassey, 2023).

$$SOC(t+1) = SOC(t) + \left(\frac{P_{ch} - P_{dis}}{C_{BESS}}\right)\Delta t \quad 3$$

Where SOC(t) represents the state of charge, $P_{ch}(t)$ and $P_{dis}(t)$ denotes charging and discharging power in (kW), C_{BESS} is battery capacity (kWh), and Δt is the time.

Reliability Index (LPSP)

The reliability of the hybrid system is quantified using LPSP as expressed in Equation 4 (Kumar et al., 2022).

$$LPSP = \frac{\sum_{t=1}^{T} P_{unserved}(t)}{\sum_{t=1}^{T} P_{load}(t)} \quad 4$$

Where $P_{unserved}(t)$ is the power deficit at time (kWh), $P_{load}(t)$ represents total demand (kWh), T denotes the total simulation period.

Problem Formulation

The optimal design of HRES is formulated as a reliability- constrained bi-objective optimization problem. The objective is to minimize the total system cost while maintaining an acceptable level of power supply reliability. The bi-objective optimization problem is formulated and expressed in Equation 5.

$$\min \mathrm{F}(\mathrm{X}) = [\mathrm{Z}(\mathrm{X}), \mathrm{LPSP}(\mathrm{X})] \quad 5$$

Where $\mathrm{Z}(\mathrm{X})$ is the total system cost, and $\mathrm{LPSP}(\mathrm{X})$ represents the reliability index. The decision vector $\mathrm{X} = [\mathrm{X}_{\mathrm{PV}}, \mathrm{X}_{\mathrm{WT}}, \mathrm{X}_{\mathrm{BESS}}]$ represents HRES capacities.

Cost Function

The total system cost is evaluated as the sum of the component and operational costs.

$$\mathrm{Z}(X) = \mathrm{C}_{\mathrm{PV}}\mathrm{X}_{\mathrm{PV}} + \mathrm{C}_{\mathrm{WT}}\mathrm{X}_{\mathrm{WT}} + \mathrm{C}_{\mathrm{BESS}}\mathrm{X}_{\mathrm{BESS}} + \mathrm{C}_{\mathrm{O\&M}} \quad 6$$

Where C_{PV}, $\mathrm{C}_{\mathrm{WT}}, \mathrm{C}_{\mathrm{BESS}}$ are unit costs of PV, wind, and battery components, respectively, and $\mathrm{C}_{\mathrm{O\&M}}$ represents the operation and maintenance cost.

Parametric Reliability-Constrained Approach

To capture the trade-off between cost and reliability, the optimization is solved using a parametric constraint strategy. Instead of employing a full Pareto front, cost minimization is performed under predefined reliability levels:

$$\mathrm{mi\,n}\, \mathrm{Z}(\mathrm{X}) \text{ subject to } \mathrm{LPSP}(X) \leq \mathrm{LPSP}_{\mathrm{target}} \quad 7$$

The reliability constraint is varied systematically as expressed in Equation 3.9

$$\mathrm{LPSP}_{\mathrm{target}} = \mathrm{LPSP}_{\mathrm{base}} + \mathrm{n} \times 0.10, \quad \mathrm{n} = 0, 1, 2, \ldots \quad 8$$

Where $\mathrm{LPSP}_{\mathrm{base}}$ is the minimum achievable reliability level, and n defines incremental steps of 10%.

This approach enables the evaluation of system performance across a wide range of operating conditions, allowing identification of cost-reliability trade-offs reflected in sensitivity analysis. This formulation provides a practical alternative to Pareto-based optimization by enabling direct control of reliability levels during the sizing process.

Decision Variables and Constraints

The optimization problem is defined by a set of decision variables representing the capacities of the system components, subject to operational and reliability constraints that ensure feasible and realistic system performance.

Decision Variables

The primary decision variables correspond to the installed capacities of the hybrid system components (Korovushkin et al., 2025).

$$X = [X_{PV}, X_{WT}, X_{BESS}] \quad (9)$$

These variables are optimized to minimize system cost while satisfying reliability requirements.

System Constraints

To ensure technical feasibility and operational stability, the following constraints are imposed:

Power Balance Constraint: Power Balance Constraint: The system must generate sufficient power to meet the load demand at each time step. This can be expressed as:

$$P_{generated}(t) \geq P_{demand}(t) \text{ for all time steps t} \quad (10)$$

Battery State of Charge (SOC) Constraint: The battery must operate within safe and efficient limits to prevent deep discharging and overcharging:

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \text{ for all time steps t} \quad (11)$$

Component Capacity Constraints: Each component's capacity must fall within specified limits, reflecting practical considerations:

$$\text{Component Capacity Constraints} \equiv \begin{cases} X_{PV_{min}} \leq X_{PV} \leq X_{PV_{max}} \\ X_{WT_{min}} \leq X_{WT} \leq X_{WT_{max}} \\ X_{BT_{min}} \leq X_{BT} \leq X_{BT_{max}} \end{cases} \quad (12)$$

Reliability Constraint

$$LPSP \leq LPSP_{target} \quad (13)$$

These constraints collectively ensure that the optimized system configuration remains technically feasible, economically viable, and consistent with reliability requirements.

Optimization Algorithm

This study employs the GWO algorithm and its modified variant, MGWO, to solve the reliability-constrained sizing problem of the HRES.

Conventional GWO

The GWO algorithm is a population-based metaheuristic inspired by the social hierarchy and hunting behavior of gray wolves. The search process is guided by three leading agents: Alpha (X_α), Beta (X_β), and Delta (X_δ) which represent the best candidate solutions (Sesan et al., 2023).

The position of each search agent is updated based on its relative distance to these leaders.

$$X(t+1) = \frac{(X_1 + X_2 + X_3)}{3} \quad (15)$$

Where X_1, X_2, and X_3 are candidate positions derived from alpha, beta, and delta wolves, respectively. The algorithm balances exploration and exploitation through a control parameter that decreases over iterations, enabling convergence toward the optimal (Dagal et al., 2025).

Modified Gray Wolf Optimization (MGWO)

To enhance convergence performance and solution quality, the conventional GWO is modified by incorporating a regression- based learning mechanism and a diversity adjustment strategy.

Regression-Based Position Update

A regression term is introduced to incorporate historical best solutions into the search process.

$$X_{regression} = \eta . P + (1 - \eta) . H^{\dagger} \quad 16$$

Where η is the weighting factor controlling the influence of current and past positions, P denotes the current solution vector, and $H^{\dagger}$ represents historical best positions.

Diversity Adjustment

To prevent premature convergence and maintain population diversity, a perturbation term based on successive position difference is applied:

$$X_i(t+1) = X(t+1) + \epsilon . \left(X(t) - X(t-1)\right) \quad 17$$

Where ϵ is the diversity control Parameter. This adjustment enhances global search capability, particularly in complex solution spaces.

Combined Position

The final position update integrates both the regression-based and conventional GWO updates:

$$X(t+1) = \lambda X_{reg} + (1 - \lambda) . X_{classic} \quad 18$$

Where λ is a weighting parameter for balancing the influence of regression and conventional updates, and $X_{classic}$ represents the position updated.

4. RESULTS

This section presents the outcomes of the optimization process, including the load characteristics, optimal system configuration, sensitivity analysis across varying reliability levels, and convergence performance of the optimization.

Load Profile and Resource Characteristics

The estimated daily load demand for the Dirin-Gari community is approximately 1103.6 kWh/day. The load profile exhibits a peak during evening hours, primarily driven by residential consumption.

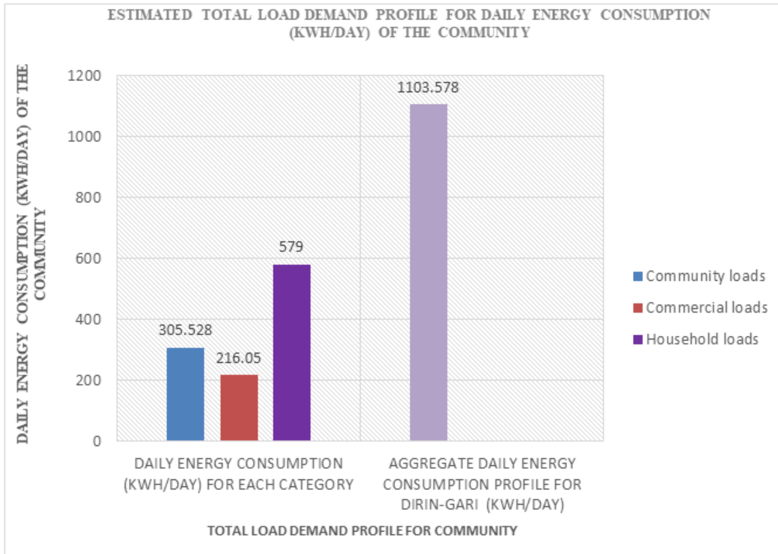

Figure 1. Daily load profile consumption pattern for Dirin-Gari community

Solar and wind resource assessments indicate average solar irradiance between 6.3 and 6.7 kWh/m^2/day and wind speeds ranging from 4.7 to 5.5 m/s, confirming the suitability of a hybrid PV-wind configuration.

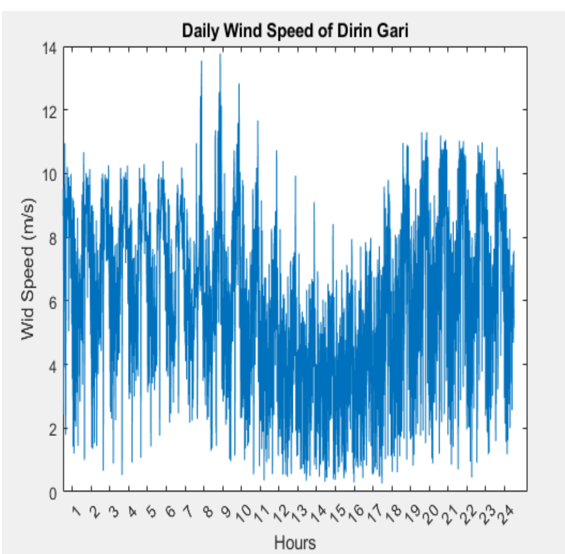

Figure 2. Daily wind speed of Dirin Gari

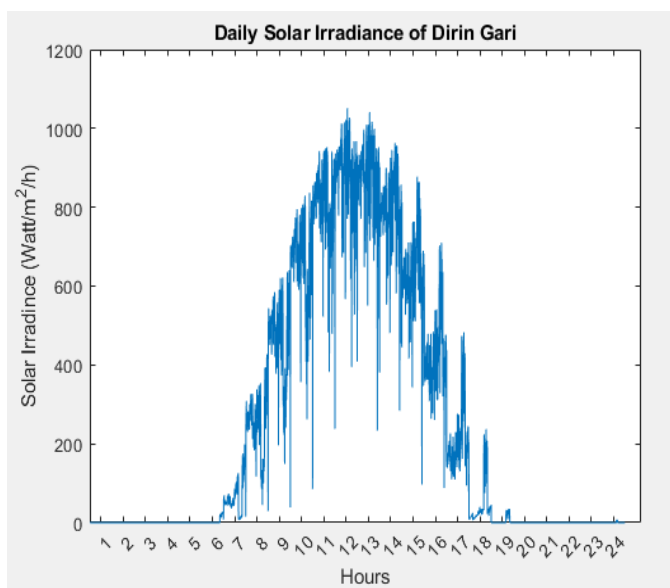

Figure 3. Daily Solar Irradiance of Dirin Gari

Optimal System Configuration

The optimization results obtained using the MGWO algorithm identify an optimal configuration at a reliability level of 20.9% LPSP. The corresponding system component sizes are summarized in Table 1.

Table 1. Component capacity distribution of HRES

Component	Capacity	Percentage Contribution
Photovoltaic System	395.4 kWh	35%
Wind Turbine System	606.5 kWh	53%
Battery Storage System	142.5 kWh	12%

The total estimated cost associated with this configuration is approximately USD 1.62 million. While the configuration at 20.9% LPSP represents the baseline optimal design, it is important to note that this solution corresponds to a specific reliability level. A broader assessment across varying LPSP values is necessary to fully understand the trade-offs between system cost and reliability, as explored in the subsequent sensitivity analysis.

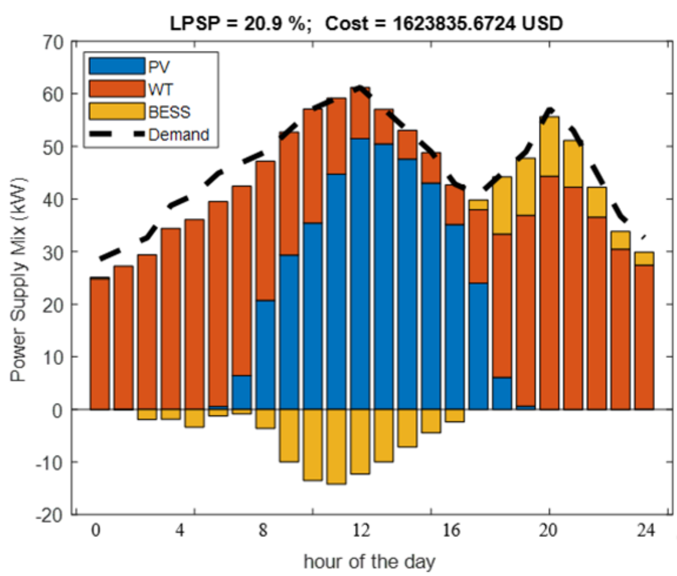

Figure 4. Power supply mix

Sensitivity Analysis under Varying LPSP

To evaluate system performance across different reliability levels, the optimization process was repeated for varying LPSP targets ranging from 20.9% to 97.8%. The resulting configurations and corresponding costs for both MGWO and GWO are presented in Table 2.

The results show a progressive change in component sizing as the allowable LPSP increases. Lower LPSP values correspond to higher storage requirements, while higher LPSP values result in reduced system capacity and cost.

Table 2. Comparative results of varying LPSP between MGWO and GWO

Algorithm	LPSP Value (%)	Installed PV Capacity (kWh)	PV Capacity (%)	Installed WT Capacity (kWh)	WT Capacity (%)	Installed BESS Capacity (kWh)	BESS Capacity (%)	System Components Cost (USD)
MGWO	20.9	395.418	35	606.471	53	142.5	12	1,623,835.67
GWO	24.2	392.634	34	503.069	52	162.6	14	1,708,383.064
MGWO	21	396.383	35	605.729	53	142.881	12	1,599,861.588
GWO	24.2	391.936	34	593.597	52	162.047	14	1,715,379.733
MGWO	21.1	395.231	35	606.614	53	142.411	12	1,708,930.01
GWO	23.7	393.375	34	592.313	52	163.241	14	1,715,529.891
MGWO	30	455.256	36	451.3	35	368.707	29	854,335.9785
GWO	30	421.309	36	522.114	44	240.507	20	1160246.0654
MGWO	40	482.673	36	330.472	25	530.374	39	582,241.152
GWO	40	452.381	36	416.686	33	376.874	30	783,693.2254
MGWO	50	483.26	39	283.597	23	484.973	39	460,755.3191
GWO	50	467.993	38	342.71	28	429.348	35	594,784.9175
MGWO	60	456.066	41	324.499	29	342.803	31	436,381.1328
GWO	60	482.583	40	214.652	18	508.849	42	423,452.3386
MGWO	70	464.771	44	225.835	22	356.162	34	323,674.8878
GWO	70	470.893	45	213.817	20	371.735	35	364,449.8096
MGWO	80	422.235	49	232.55	26	227.41	25	285,428.5484
GWO	80	150.306	21	461.153	64	107.654	15	540,049.8629
MGWO	90	416.595	58	200.869	28	99.934	14	248,062.8808
GWO	90	429.742	59	173.068	24	123.745	17	249,032.4152
MGWO	97.8	124.506	30	282.466	67	13.03	3	220,537.7924
GWO	97	370.295	66	175.085	31	15.322	3	216,785.2035

Convergence Performance

The convergence behavior of the MGWO and GWO algorithms was evaluated over a maximum of 200 iterations. The convergence points obtained for different LPSP levels are presented in Table 3.

Table 3. Algorithm convergence

LPSP Value (%)	Convergence Points	
	MGWO	GWO
20.9/24.2	**6**	**8**
21.0/24.2	11	13
21.1/23.7	12	12
30.0	15	16
40.0	13	15
50.0	**16**	17
60.0	11	**22**
70.0	6	9
80.0	11	14
90.0	12	13
97.8/97.0	12	9

Statistical Convergence Metrics

A statistical summary of convergence performance is provided in Table 4, including mean convergence, standard deviation, and best and worst-case scenarios.

Table 4. Statistical summary of convergence performance

Metric	MGWO	GWO	Improvement
Mean Convergence	11.36	13.45	15.54%
Standard Deviation	3.26	3.93	17.05%
Convergence Range	10	14	28.57%
Best case	6	8	25.00%
Worst case	16	22	27.27%

The results indicate variation in convergence behavior across different reliability conditions for both algorithms.

5. DISCUSSION

The results demonstrate a clear trade-off between system cost and reliability across varying LPSP levels. Lower LPSP values (e.g., 20.9%) ensure higher reliability but require increased system cost, largely due to higher storage capacity. In contrast, higher LPSP values significantly reduce cost at the expense of reliability. This confirms that BESS sizing is the driver of reliability, and optimal LPSP selection should reflect the economic and service requirements of rural communities.

The proposed MGWO algorithm consistently outperforms the conventional GWO in both cost efficiency and convergence behavior. This improvement is attributed to the integration of regression-based learning, which utilizes historical best solutions, and a diversity adjustment mechanism that enhances global search capability and prevents premature convergence. As a result, MGWO achieves more stable and economically efficient solutions across all LPSP levels.

The convergence analysis further indicates that MGWO reaches near-optimal solutions within 40-60 iterations (out of 200), demonstrating strong computational efficiency. Faster convergence, particularly at higher LPSP levels, highlights its suitability for complex optimization problems with large search spaces.

From a practical perspective, the findings confirm that hybrid PV-wind-battery systems are viable for electrification in regions with complementary renewable sources. The use of LPSP as a flexible reliability metric enables adaptive system design based on cont-reliability trade-offs. Compared to existing studies, this work extends beyond single-point optimization by providing a parametric reliability-based assessment, offering more practical insights for energy planning.

6. CONCLUSION

This study presented a reliability-constrained bi-objective optimization framework for the optimal sizing of a hybrid PV-wind-battery energy system using an MGWO algorithm. The proposed modification integrates a regression-based learning mechanism with a diversity adjustment strategy to enhance solution quality and convergence performance.

The results demonstrate that system design is highly sensitive to reliability requirements. Lower LPSP values improve supply reliability but significantly increase system cost due to higher storage requirements, while higher LPSP values reduce cost at the expense of quality. The analysis across the varying LPSP levels (20.9%-97.8) clearly establishes the trade-off between cost and reliability, confirming the necessity of a bi-objective optimization approach.

Comparative evaluation shows that MGWO consistently achieves better cost performance and faster convergence than the conventional GWO. The algorithm converges within 40-60 iterations, indicating strong computational efficiency and stability. These improvements validate the effectiveness of incorporating historical regression and diversity mechanisms in solving complex optimization problems.

Generally, the developed framework provides a practical and scalable solution for designing cost-effective, reliable HRES for rural electrification.

7. RECOMMENDATION

Based on the findings of this study, it is recommended that energy system designers adopt flexible reliability targets by selecting appropriate LPSP levels that balance cost and service quality, rather than enforcing overly strict reliability requirements that significantly increase system cost. The proposed MGWO algorithm should be considered for hybrid system design due to its improved convergence performance and cost efficiency. In addition, hybrid PV-wind-battery configurations are suitable for rural electrification in regions with complementary renewable sources and should be actively promoted. Policymakers and stakeholders are encouraged to support the deployment of decentralized energy systems through enabling policies and financial incentives. Future research should focus on incorporating real-time control strategies and additional renewable energy sources to further enhance performance and adaptability.

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