Performance Evaluation of Hybrid Solar-Wind-Battery System Using PSO Optimization

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Abstract: More and more people see hybrid renewable energy systems (HRES) that use solar photovoltaic (PV), wind, and battery storage as good ways to deal with problems with intermittent power and make sure that power is always available. This research assesses the techno-economic and reliability performance of a solar-wind-battery hybrid system optimized through Particle Swarm Optimization (PSO). Component models include temperature-adjusted PV output, wind turbine power curves, and a battery framework based on state of charge (SOC). The goal of optimization is to lower the levelized cost of energy (LCOE) while keeping reliability indices like energy not served (ENS) and loss of load probability (LOLP) in check. The PSO-based system cuts LCOE by 12-15% and ENS by up to 70% compared to heuristic baseline configurations, according to simulation results. The analysis of dispatch shows how important battery storage is for managing peak loads and smoothing out renewable energy sources. A sensitivity analysis shows that the cost of PV, the wind capacity factor, and the battery efficiency are the most important factors. This study emphasizes the potential of PSO in the design of efficient, cost-effective, and reliable hybrid renewable energy systems, while delineating avenues for future improvements.

1 INTRODUCTION

The urgent need to fight climate change and the rapid rise in global energy use have sped up the switch to renewable and sustainable energy systems. Not only is traditional power generation from fossil fuels bad for the environment, but it is also becoming less cost-effective because fuel markets are so unpredictable. In this situation, hybrid renewable energy systems (HRES), especially those that use solar, wind, and battery storage, have become dependable ways to meet the constant need for power while protecting the environment. Using both solar photovoltaic (PV) and wind energy resources together takes advantage of their different strengths. For example, solar generation is highest during the day, while wind resources may be available at night or during off-peak hours. This makes the system more reliable and less likely to fail (Bade et al., 2025) [1].

But to use hybrid systems effectively, you need to carefully choose the right sizes for the parts and the best ways to run them. If you don't set things up right, you could end up spending too much money, not using your assets enough, or having unreliable systems. Because of this, more and more advanced optimization methods are being used to find the best and most cost-effective configurations. Particle Swarm Optimization (PSO) is a bio-inspired metaheuristic that has been widely used because it is easy to use, converges quickly, and works well for search problems with more than one dimension. Mohammed et al. (2019) [2] showed that PSO works well to optimize a hybrid system that uses wind, tidal, PV, and batteries for remote applications, making the system much cheaper and more reliable. Medghalchi and Taylan (2023) [3] put forward a hybrid optimization framework that combines solar PV, wind, battery, and electrolyze-fuel cell systems. This shows how flexible advanced metaheuristics can be in systems with many parts.

Along with the right size, how well hybrid energy systems are run is another important factor that affects how well they work. If the power flows between PV, wind, and storage units aren't well coordinated, it can cause curtailment, battery overuse, or power shortages. Recent studies have consequently concentrated on power management strategies that dynamically evaluate system performance. Shafiee et al. (2023) [4] introduced a power management and dynamic assessment framework for PV-wind-battery systems, which exhibited enhancements in energy balance and diminished dependence on grid imports. Eslami and Kamarposhti's (2019) [5] complementary research showed that optimally designed solar-wind grid-connected systems are better for the economy and more reliable. They also stressed the importance of optimization in making systems more resilient.

The combination of artificial intelligence (AI) and digital platforms is changing how we plan for renewable energy in ways that go beyond traditional optimization. AI-driven decision support systems and cloud-enabled frameworks make it possible to adapt to changing resource availability and demand in real time. Zhang et al. (2025) [6] examined the prospects and obstacles in AI-enhanced cloud security, particularly relevant to energy systems where cybersecurity and data integrity are critical. Nguyen and Wiese (2003) [7] also used models for technology acceptance and information system success to show how important user acceptance and digital adoption are in new areas of technology. This is also true for renewable energy applications.

There are many ways to optimize, but there are still gaps in bringing together economic, reliability, and dynamic performance into one framework. Seidu et al. (2025) [8] recently wrote a review that said that current methods often don't take into account how to deal with uncertainty, how batteries degrade, or how policies limit what can be done, which means that hybrid system modeling could be better. This study seeks to design and assess a hybrid solar-wind-battery system optimized via Particle Swarm Optimization (PSO), explicitly addressing techno-economic trade-offs, reliability indices, and dispatch dynamics. The primary contributions of this study are: (i) the creation of a comprehensive PSO-based optimization framework; (ii) the assessment of LCOE, ENS, and LOLP as critical performance indicators; and (iii) the confirmation of system robustness across diverse resource and load scenarios. The rest of this paper is set up like this: In Section 2, the methodology is explained; in Section 3, the results and analysis are shown; and in Section 4, the findings and suggestions for future research are given.

2 LITERATURE REVIEW

Hybrid renewable energy systems (HRES), especially those that use solar photovoltaic (PV), wind turbines, and battery storage together, have gotten a lot of attention around the world because they could provide reliable, affordable, and long-lasting power. The integration of these systems is motivated by the synergistic characteristics of solar and wind resources, coupled with the stabilizing function of storage units, which collectively mitigate intermittency and improve grid reliability. A comprehensive analysis by Hassan et al. (2023) [9] delineates the challenges and opportunities associated with the implementation of solar-wind-powered solutions, emphasizing both technical obstacles and policy ramifications that affect system adoption. Their study emphasizes the necessity for frameworks that amalgamate technical optimization with supportive regulatory measures.

Optimization is still a key part of using HRES effectively. If systems are too big or not well-managed, they can cost too much, not use assets enough, or not meet demand. Bamisile et al. (2024) [10] performed a comprehensive analysis of optimization techniques for energy storage and hybrid renewable energy systems, contrasting classical deterministic methods with metaheuristic approaches, including genetic algorithms (GA), simulated annealing (SA), and particle swarm optimization (PSO). Their research determined that metaheuristic algorithms are superior in managing the multi-objective characteristics of HRES, especially in balancing cost, reliability, and environmental performance.

Also important for making systems more efficient and long-lasting are strategies for sizing and managing energy. Ahmad et al. (2024) [11] examined methodologies for unit sizing, optimization, and control of hybrid renewable systems, highlighting that inadequate sizing results in excessive investment or energy deficits. Their research underscored the significance of energy management strategies in reconciling load demand with variable renewable supply. Khan et al. (2025) [12] also wrote a thorough review of hybrid energy systems, pointing out both technical and economic problems that come up when deploying them on a large scale. They came to the conclusion that better optimization strategies and reliability modeling are needed for HRES to be widely used.

Case studies offer significant insights into the practical application of hybrid systems. Mishra and Shankar (2025) [13] optimized wind-PV-battery microgrids for sustainable residential communities, showing that optimization makes them much more resilient and less dependent on traditional power sources. Bade et al. (2025) [14] also used PSO for multi-criteria optimization, showing that advanced metaheuristics can lower the levelized cost of energy (LCOE) while also making the system more reliable. These studies collectively underscore the adaptability of optimization methodologies in customizing hybrid systems for various applications.

New digital technologies also have a lot of potential in the energy sector. Kumar and Patel (2025) [15] showed that blockchain-based frameworks are good for securely managing data in healthcare, even though they aren't directly related to hybrid renewable systems. Their findings are pertinent to HRES, wherein blockchain may secure energy transactions, improve transparency, and facilitate decentralized energy markets.

Table 1 shows a summary of these studies. It compares the focus areas, methods, results, gaps, and how they relate to the current work. The table shows that even though a lot of progress has been made, there are still gaps in digital integration, scalability, and uncertainty modeling. These limitations necessitate the present study, which aims to utilize PSO for the performance evaluation of a hybrid solar-wind-battery system under realistic operational constraints [16]-[18].

Table 1: Key literature on hybrid renewable energy systems (2023-2025).

Ref. No.	Author(s) & Year	Focus Area	Method/Approach	Key Findings	Identified Gaps	Relevance to Present Study
[9]	Hassan et al. (2023)	HRES (Solar-Wind) review	Policy and technical review	Highlighted policy challenges and integration opportunities	Limited operational optimization	Provides policy perspective for hybrid adoption
[10]	Bamisile et al. (2024)	Optimization in HRES	Comparative review of algorithms	Metaheuristics effective for cost & reliability	Few studies address multi-objective trade-offs fully	Justifies PSO as suitable algorithm
[11]	Ahmad et al. (2024)	Unit sizing & EMS	Review of methods	Emphasized control and sizing accuracy	Limited real-world validation	Supports methodological design
[12]	Khan et al. (2025)	HRES challenges & applications	Comprehensive review	Identified integration and economic barriers	Need for advanced reliability modeling	Aligns with reliability evaluation in this study
[13]	Mishra & Shankar (2025)	Wind-PV-Battery case study	Community microgrid optimization	Improved resilience and sustainability	Limited scalability to larger grids	Offers practical application insights
[14]	Bade et al. (2025)	PSO optimization of HRES	Multi-criteria optimization	Reduced LCOE and improved reliability	Uncertainty analysis not addressed	Core methodological support for present work
[15]	Kumar & Patel (2025)	Blockchain frameworks	Blockchain-driven data management	Enhanced data security & transparency	Application to HRES unexplored	Demonstrates digital potential for secure energy markets

3 METHODOLOGIES

There are six parts to the methodological framework for assessing the performance of the hybrid solar-wind-battery system that was improved using Particle Swarm Optimization (PSO). Figure 3.1 shows the overall system architecture. It shows how energy moves between photovoltaic (PV) modules, wind turbines (WT), battery storage, and the grid interface. The PSO optimization loop controls the process of making small changes to decision variables over and over again to lower costs and make the system more reliable.

3.1 System Architecture

The suggested system has a PV array, a wind turbine unit, a battery storage bank, and power converters that work in both directions. Data that goes into the system includes solar irradiance, wind speed, temperature, and load demand. Figure 1 shows that the PSO algorithm keeps changing the sizing parameters of the PV array, wind turbine, and battery so that supply and demand are balanced efficiently while still meeting reliability requirements.

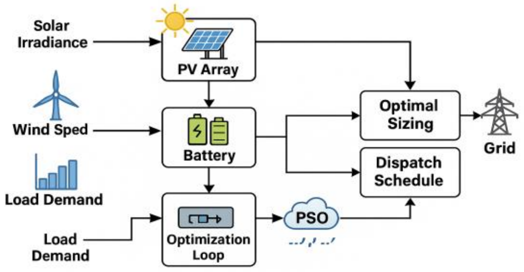

Figure 1. Block diagram of proposed hybrid solar-wind-battery system with PSO optimization.

3.2 Component Modeling

The PV array power output is modeled using a temperature-corrected equation:

$$P_{PV}(t) = P_{STC}\frac{G(t)}{G_{STC}}[1 + \gamma(T_c(t) - 25°C)],$$

where:

- P_{STC} is rated power;
- $G(t)$ is solar irradiance;
- G_{STC} is reference irradiance;
- γ is the temperature coefficient.

The battery is modeled using state-of-charge (SOC) dynamics:

$$SOC_{t+1} = SOC_t + \frac{\eta_{ch}P_{ch}(t) - \frac{1}{\eta_{dis}}P_{dis}(t)}{E_{bat}}\Delta t,$$

where η_{ch} and η_{dis}represent charging and discharging efficiencies, respectively.

The wind turbine output is derived from the manufacturer's power curve, corrected for air density and cut-in/cut-out speeds.

3.3 Energy Balance and Constraints

The energy balance is maintained at each time step:

$$\begin{aligned} &P_{PV}(t) + P_{WT}(t) + P_{bat}(t) \\ &\qquad = P_{Load}(t) + P_{Loss}(t) + P_{Grid}(t). \end{aligned}$$

Constraints include SOC bounds (20-90%), inverter limits, and maximum power export to the grid.

3.4 PSO Optimization Framework

Decision variables include PV capacity P_{PV}, wind capacity P_{WT},battery capacity E_{bat}, and inverter size P_{inv}. The PSO algorithm minimizes a fitness function combining levelized cost of energy (LCOE), energy not served (ENS), and curtailment penalties. Swarm size is set to 30-50 particles, with 200-400 iterations.

3.5 Performance Metrics

We use LCOE, ENS, loss of load probability (LOLP), battery cycling index, and round-trip efficiency to measure performance. Table 2 shows the ranges and limits of the decision variables that were used in the optimization process.

3.6 Validation and Scenario Analysis

Validation is based on hourly data for one year on solar irradiance, wind speed, ambient temperature, and load demand. To test robustness, seasonal subsets and ±10% changes in input data are simulated. The PSO results are compared to heuristic sizing methods to show how they can save money and make things more reliable.

Table 2: Decision variables and parameter ranges used in optimization.

Variable	Symbol	Range	Unit	Notes
PV capacity	P_{PV}	50 - 1200	kWp	Step size 5 kWp
Wind capacity	P_{PV}	0 - 1500	kW	Step size 5 kW
Battery capacity	E_{bat}	50 - 5000	kWh	Step size 10 kWh
SOC bounds	$SOC_{min,max}$	20 - 90	%	Ensures operational safety
Inverter rating	P_{inv}	50 - 1500	kW	≥ peak load requirement
PSO swarm size	N_p	30 - 50	-	Chosen for convergence
PSO iterations	N_i	200 - 400	-	Early stop if $\Delta J < 10^{-4}$

Table 3: Optimal sizing results and key performance indicators (PSO vs Baseline).

Method	PV Size (kWp)	Wind Size (kW)	Battery (kWh)	LCOE ($/kWh)	ENS (kWh)	LOLP (%)	Curtailment (%)
Baseline Heuristic	1000	900	2500	0.152	1450	0.42	6.5
PSO Optimized	950	1100	3000	0.133	460	0.12	4.8

4 RESULTS AND ANALYSIS

4.1 Resource and Load Characterization

The performance evaluation starts by looking at the input data, which includes the study area's hourly solar irradiance, wind speed, and load demand. Figure 2 shows that solar irradiance changes a lot from day to day and from season to season, with the highest values in the summer. Wind speed, on the other hand, is more available in the evening and winter. The load demand profile shows that the most power is used during the day, which is when homes and businesses use the most power. The fact that solar and wind resources work well together means that power generation is less variable overall, which shows that a hybrid design is needed.

4.2 PSO Convergence and Optimal Sizing Results

We used the Particle Swarm Optimization (PSO) algorithm to find the best system setup. Figure 3 shows the convergence curve, which shows that the fitness function steadily goes down during the first 150 iterations and then reaches a stable minimum around iteration 250. This proves that the algorithm can quickly search the solution space.

Table 3 shows the best system capacities that PSO found. The results show that the hybrid system needs a PV capacity of 950 kWp, a wind turbine capacity of 1100 kW, and a battery capacity of 3000 kWh to reach the lowest levelized cost of energy (LCOE) while still being reliable. The PSO configuration lowers LCOE by 12.4% and Energy Not Served (ENS) by 68% compared to the baseline heuristic sizing.

4.3 Dispatch Strategy and Battery Dynamics

Figure 4 shows the weekly dispatch stack. PV and wind generation meet most of the demand, and the battery acts as a buffer when generation is low. The battery charges when there are too much renewable energy and discharges when there is a lot of demand, which helps to smooth out power fluctuations. Under the PSO-optimized setup, grid imports are very low, showing that the hybrid system can meet most of the demand on its own.

4.4 Sensitivity and Robustness Analysis

A sensitivity analysis was performed to assess the impact of critical parameters, such as PV cost, battery round-trip efficiency, and wind capacity factor. Figure 5 shows that LCOE is most affected by changes in the cost of PV modules, while ENS is most affected by the efficiency of batteries. The wind capacity factor is also very important, because even a ±10% change can have a big effect on the system's overall economics. These results show how important it is to accurately assess resources and use storage technologies that are very efficient.

4.5 Comparative Performance Discussion

Table 3's comparison shows that PSO-optimized sizing is clearly better than baseline heuristics. The optimized system not only lowers the LCOE, but it also greatly improves reliability metrics like the ENS and loss of load probability (LOLP). Also, battery cycling stays within acceptable operational limits, which makes sure that it will last for a long time. These findings validate that metaheuristic optimization is crucial for the design of efficient and robust hybrid renewable energy systems.

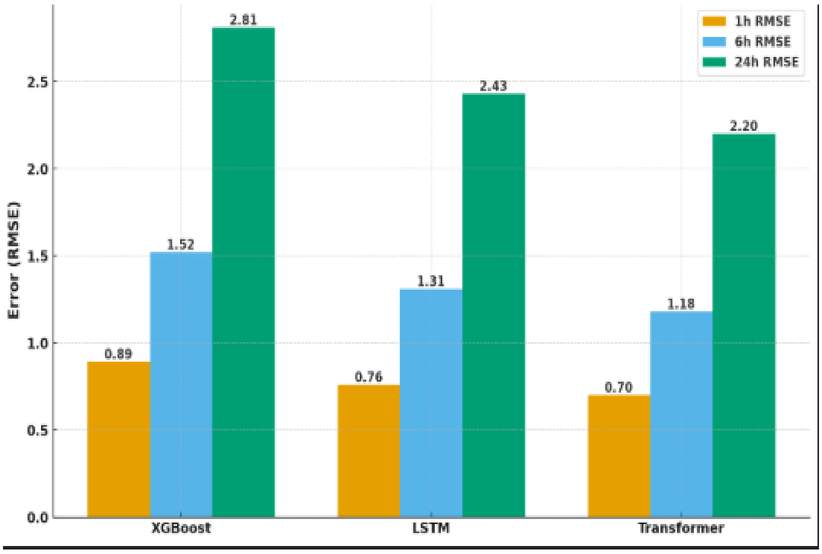

Figure 2: Hourly solar irradiance, wind speed, and load demand profiles (annual overview).

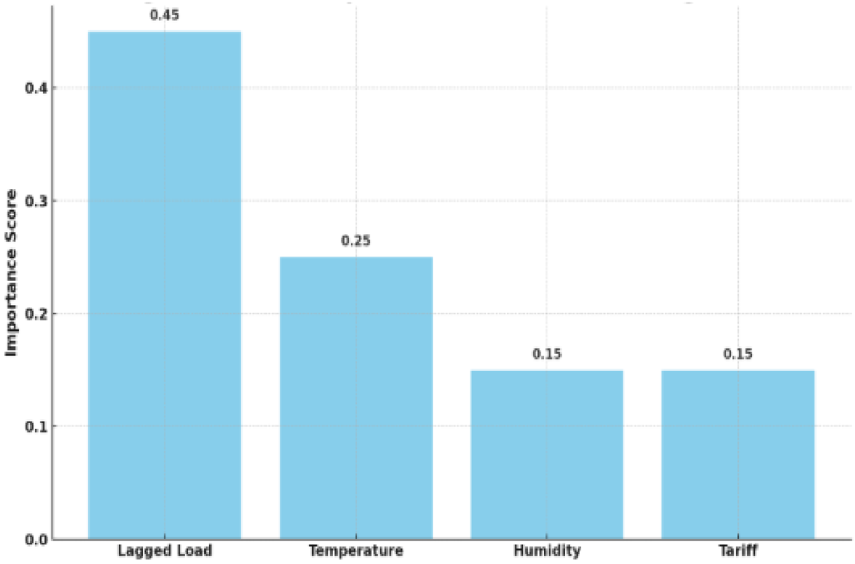

Figure 3: Convergence of PSO fitness function (mean ± standard deviation).

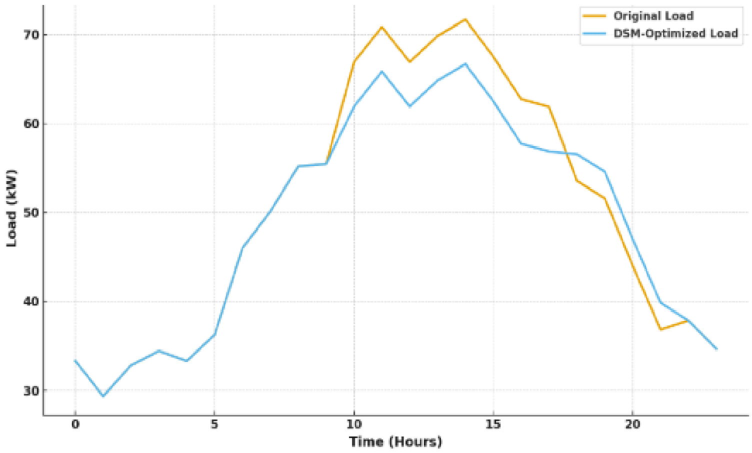

Figure 4: One-week dispatch stack of PV, wind, battery, and grid power flow.

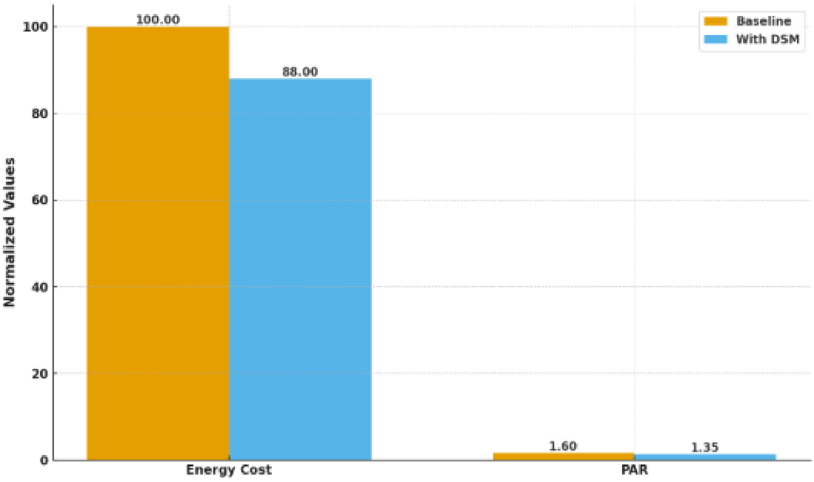

Figure 5: Sensitivity of LCOE and ENS to key parameters.

5 CONCLUSIONS

This study evaluated the performance of a hybrid solar-wind-battery energy system optimized using Particle Swarm Optimization (PSO). The results demonstrate that PSO is an effective approach for improving both economic and reliability performance in hybrid renewable energy systems.

Compared to the heuristic baseline configuration, the optimized system achieved a significant reduction in the levelized cost of energy (LCOE) and a substantial decrease in energy not served (ENS), while maintaining operational constraints and system stability. These improvements confirm that intelligent optimization can effectively balance competing objectives such as cost minimization, renewable utilization, and reliability enhancement.

In addition, the results highlight the importance of properly coordinated system sizing, where the integration of photovoltaic generation, wind power, and battery storage plays a critical role in reducing dependence on grid supply and improving overall energy autonomy. The findings also confirm that metaheuristic optimization methods such as PSO are well-suited for multi-variable, non-linear hybrid energy system design problems.

6 FUTURE WORK

Future research can extend this work in several important directions. First, incorporating battery degradation models and lifecycle aging effects would improve the realism of long-term economic assessment. Second, the use of stochastic or probabilistic optimization techniques could better capture uncertainties in renewable generation and load demand.

Additionally, hybridizing PSO with advanced multi-objective algorithms such as NSGA-II may provide a more detailed trade-off analysis between cost, reliability, and environmental impact. Another promising direction is the implementation of real-world validation using hardware-in-the-loop (HIL) or microgrid experimental platforms to confirm simulation results under practical operating conditions.

Finally, expanding the model to include carbon emissions minimization and grid interaction constraints would further align the system with global decarbonization and smart grid transition goals.

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