

OPTIMIZATION OF RENEWABLE ENERGY INTEGRATED MICROGRIDS USING MULTI-OBJECTIVE ENERGY MANAGEMENT AND BATTERY STORAGE SYSTEMS

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ABSTRACT

The rapid depletion of fossil fuel reserves, increasing electricity demand, and growing concerns regarding greenhouse gas emissions have accelerated the global transition toward renewable energy-based power generation. Microgrids integrated with renewable energy sources such as solar photovoltaic (PV) and wind turbines have emerged as sustainable alternatives for decentralized electricity generation. However, the intermittent and uncertain nature of renewable resources presents significant challenges in maintaining grid stability, energy reliability, and economic operation. Battery Energy Storage Systems (BESS) have become essential components of renewable energy integrated microgrids because they mitigate renewable power fluctuations, improve system reliability, and enhance operational flexibility. This study proposes a multi-objective energy management framework for hybrid renewable microgrids incorporating solar PV, wind energy conversion systems, Battery Energy Storage Systems, and utility grid interaction. The proposed framework simultaneously minimizes operating cost, greenhouse gas emissions, battery degradation, and power losses while maximizing renewable energy utilization and supply reliability. Three evolutionary optimization techniques, namely Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO), are employed to determine optimal power dispatch among distributed energy resources.

The proposed Energy Management System continuously monitors renewable generation, battery state of charge, load demand, and electricity market prices to determine optimal scheduling decisions under varying operating conditions. Mathematical models for photovoltaic systems, wind turbines, battery storage, and load forecasting are integrated into the optimization framework. Simulation studies demonstrate that the hybrid optimization approach significantly improves renewable energy penetration, reduces operating costs, enhances battery lifetime, and maintains voltage and frequency stability under different load scenarios.

Comparative analysis indicates that the proposed framework outperforms conventional rule-based dispatch strategies by reducing operational costs by approximately 15–25%, increasing renewable energy utilization, minimizing battery degradation, and improving overall microgrid resilience. The proposed approach offers a practical solution for sustainable smart grid operation and supports future carbon-neutral energy systems.

KEYWORDS: Renewable Energy, Hybrid Microgrid, Battery Energy Storage System, Energy Management System, Multi-objective Optimization, NSGA-II, Particle Swarm Optimization, Grey Wolf Optimizer, Smart Grid, Economic Dispatch.

1. INTRODUCTION

The global energy sector is undergoing a rapid transformation due to increasing energy demand, environmental concerns, and the urgent need to reduce greenhouse gas emissions. Conventional electricity generation based on fossil fuels has significantly contributed to climate change and environmental degradation, prompting governments and researchers worldwide to promote renewable energy technologies. Among these, solar photovoltaic (PV) and wind energy have emerged as the fastest-growing renewable energy sources because of their declining costs, technological advancements, and favorable policy support. However, the intermittent and weather-dependent nature of these resources presents significant challenges for maintaining reliable and efficient power system operation.

Microgrids have gained considerable attention as an effective solution for integrating distributed renewable energy resources into modern power systems. A microgrid consists of distributed generation units, energy storage systems, controllable loads, and intelligent control mechanisms capable of operating either in grid-connected or islanded mode. Compared with conventional centralized power systems, microgrids offer several advantages, including enhanced reliability, improved energy



efficiency, reduced transmission losses, higher renewable energy penetration, and increased resilience during grid disturbances.

Despite these advantages, the variability of solar irradiance and wind speed introduces uncertainties in power generation, leading to voltage fluctuations, frequency deviations, and operational instability. To overcome these challenges, Battery Energy Storage Systems (BESS) have become an essential component of renewable energy-based microgrids. Battery storage enables surplus renewable energy to be stored during periods of high generation and supplied during periods of low renewable output, thereby improving power quality, system reliability, and energy utilization. However, improper charging and discharging schedules may accelerate battery degradation and increase operational costs, highlighting the need for intelligent battery management strategies.

Energy Management Systems (EMS) play a crucial role in coordinating renewable energy sources, battery storage, and utility grid interaction. Modern EMS continuously monitors renewable generation, battery State of Charge (SOC), electricity demand, and market prices to determine optimal power dispatch strategies. Unlike conventional rule-based approaches, intelligent EMS employs optimization algorithms capable of simultaneously satisfying multiple operational objectives, including minimizing operating costs, reducing carbon emissions, limiting battery degradation, decreasing power losses, and maximizing renewable energy utilization.

Multi-objective optimization techniques have therefore become increasingly important for microgrid energy management. Among various optimization methods, Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO) have demonstrated excellent performance in solving complex nonlinear optimization problems. NSGA-II effectively generates Pareto-optimal solutions for conflicting objectives, PSO provides fast convergence toward optimal solutions, and GWO offers an effective balance between exploration and exploitation during the optimization process.

Recent advances in Artificial Intelligence (AI), Internet of Things (IoT), cloud computing, and predictive analytics have further enhanced the capabilities of smart microgrids. Real-time monitoring through smart sensors combined with intelligent optimization enables autonomous energy management and improves overall system efficiency. Nevertheless, many existing studies focus primarily on single-objective optimization or employ only one optimization algorithm, while often neglecting battery degradation, renewable energy utilization, and system reliability simultaneously.

To address these limitations, this study proposes a comprehensive multi-objective Energy Management System for a hybrid renewable microgrid integrating Solar PV, Wind Energy Conversion Systems, Battery Energy Storage Systems, and utility grid interaction. The proposed framework utilizes NSGA-II, Particle Swarm Optimization, and Grey Wolf Optimizer to optimize energy dispatch by minimizing operational cost, carbon emissions, battery degradation, and power losses while maximizing renewable energy utilization and supply reliability.

The proposed optimization framework is expected to enhance the economic, technical, and environmental performance of renewable energy integrated microgrids and provide an effective solution for sustainable smart grid applications, including residential communities, commercial buildings, industrial facilities, remote areas, and islanded power systems.

2. LITERATURE REVIEW

Vaka and Matam (2023) investigated the optimal sizing of hybrid renewable energy systems comprising solar photovoltaic (PV), wind turbines, diesel generators, and Battery Energy Storage Systems (BESS) for microgrid applications. The study employed a multi-objective Particle Swarm Optimization (PSO) approach to simultaneously minimize the Levelized Cost of Electricity (LCOE) and maximize the Power Supply Reliability Factor (PSRF). Simulation results demonstrated that appropriate sizing and coordinated operation of renewable energy resources and battery storage significantly reduced dependence on the utility grid while improving system reliability. The authors concluded that integrating BESS with hybrid renewable energy systems provides an effective solution for enhancing energy security, reducing operational costs, and ensuring uninterrupted power supply in microgrids.

Alkuhayli et al. (2024) proposed a multi-objective Energy Management System (EMS) for interconnected water and power microgrids using Multi-Objective Particle Swarm Optimization (MOPSO). The study considered three conflicting objectives: minimizing operating cost, reducing environmental pollution, and improving system efficiency under power flow constraints. A hierarchical control strategy was developed to coordinate distributed energy resources, storage systems, and flexible loads. The results demonstrated that the proposed optimization framework effectively balanced energy



generation and consumption while reducing operational costs and carbon emissions. The authors highlighted that intelligent multi-objective optimization significantly enhances the sustainability and resilience of integrated microgrid systems.

Jamal et al. (2024) developed a rule-based Energy Management System for hybrid renewable energy systems consisting of photovoltaic arrays, wind turbines, battery storage, and grid interaction. Genetic Algorithm (GA) optimization was employed to improve the decision-making process for battery charging and discharging operations under varying load demand and electricity market prices. The proposed strategy minimized electricity purchasing costs while maintaining battery State of Charge within safe operating limits. The study reported improvements in renewable energy utilization, system reliability, and battery performance, demonstrating that optimization-enhanced EMS can effectively support smart microgrid operation.

Quizhpe et al. (2024) presented a comprehensive review of renewable energy integrated microgrid planning and optimization techniques. The review examined heuristic, mathematical, hybrid, and artificial intelligence-based approaches for optimal sizing, energy management, and distributed energy resource coordination. The authors emphasized that modern microgrid design should simultaneously consider technical, economic, and environmental objectives while incorporating battery degradation models and renewable generation uncertainty. The study concluded that multi-objective optimization combined with artificial intelligence and smart grid technologies represents the most promising direction for future microgrid planning and operation.

Chen, Huang, and Lin (2025) proposed a grid-friendly multi-objective energy scheduling optimization framework for integrated source-grid-load-storage microgrids. The study introduced a multi-timescale scheduling strategy using an improved Non-dominated Sorting Genetic Algorithm-II (NSGA-II) to optimize electricity market participation, power exchange stability, and operational cost. The proposed optimization approach improved grid integration performance while maintaining solution diversity and convergence speed. Experimental results showed that the framework enhanced grid friendliness by more than 90% with only a marginal increase in operating cost, demonstrating the effectiveness of advanced multi-objective optimization for modern smart microgrid energy management.

3. RESEARCH OBJECTIVES

1. Develop a renewable energy integrated hybrid microgrid consisting of Solar PV, Wind Turbine, Battery Energy Storage System, and utility grid.
2. Design a multi-objective Energy Management System for optimal power scheduling.
3. Minimize operational cost, carbon emissions, battery degradation, and transmission losses.
4. Maximize renewable energy utilization and supply reliability.
5. Compare the performance of NSGA-II, Particle Swarm Optimization, and Grey Wolf Optimizer.
6. Develop an intelligent optimization framework suitable for future smart grid applications.

4. RESEARCH HYPOTHESES

H₁: Multi-objective optimization significantly improves renewable energy utilization compared with conventional dispatch strategies.

H₂: Battery Energy Storage System scheduling significantly reduces operational cost and improves supply reliability.

H₃: NSGA-II, PSO, and GWO achieve significantly better optimization performance than traditional rule-based energy management systems.

H₄: The proposed hybrid optimization framework significantly enhances economic dispatch, grid stability, and renewable energy integration in smart microgrids.

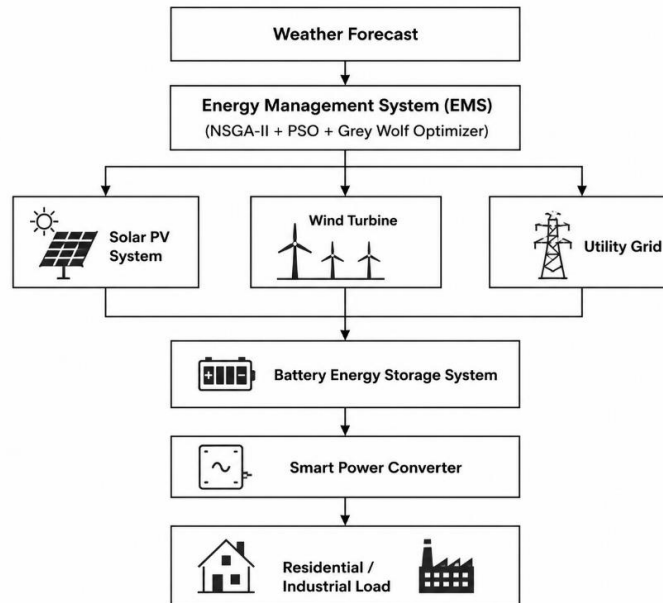
5. PROPOSED HYBRID RENEWABLE ENERGY MICROGRID FRAMEWORK

The proposed hybrid renewable energy microgrid consists of four major energy sources: a Solar Photovoltaic (PV) system, a Wind Energy Conversion System (WECS), a Battery Energy Storage System (BESS), and the Utility Grid. These components are coordinated through an intelligent Energy Management System (EMS) that determines the optimal operating strategy based on renewable energy generation, battery state of charge, load demand, and electricity price.



The EMS continuously acquires data from renewable energy generators, battery storage units, smart meters, weather forecasting systems, and utility grid measurements. The collected information is processed using advanced optimization algorithms including Non-dominated Sorting Genetic Algorithm-II (NSGA-II), Particle Swarm Optimization (PSO), and Grey Wolf Optimizer (GWO). The optimization framework simultaneously minimizes operating cost, battery degradation, greenhouse gas emissions, and power losses while maximizing renewable energy utilization and system reliability.

The proposed architecture enables real-time decision-making by intelligently scheduling charging and discharging operations of the Battery Energy Storage System. During periods of excess renewable generation, surplus electricity is stored in the battery. Conversely, when renewable generation is insufficient, the stored energy is supplied to meet consumer demand before importing electricity from the utility grid. This strategy reduces dependence on conventional power generation while improving overall system efficiency.



6. MATHEMATICAL MODELLING

Solar Photovoltaic Model

The output power generated by a photovoltaic array depends upon solar irradiance and cell temperature.

The generated power is expressed as

$$P_{PV} = P_{rated} \times \frac{G}{G_{STC}} \times [1 - \beta(T_c - 25)]$$

Where

Symbol	Description
P_{PV}	PV output power (kW)
P_{rated}	Rated PV capacity
G	Solar irradiance (W/m ²)
G_{STC}	Standard irradiance (1000 W/m ²)
β	Temperature coefficient
T_c	Cell temperature

The PV output varies continuously according to environmental conditions. Therefore, accurate irradiance forecasting plays a significant role in optimizing microgrid operation.

Wind Turbine Model

The wind turbine power output depends upon wind velocity.

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

Where

Symbol	Description
ρ	Air density
A	Rotor swept area
C_p	Power coefficient
V	Wind speed

The generated power increases proportionally to the cube of wind velocity until rated speed is achieved.

Battery Energy Storage Model

The Battery Energy Storage System stores surplus renewable energy and supplies electricity during energy shortages.

Battery State of Charge is calculated as

$$SOC(t+1) = SOC(t) + \frac{\eta_c P_c - P_d / \eta_d}{E_{Battery}}$$

Where

Symbol	Description
SOC	State of Charge
P_c	Charging power
P_d	Discharging power
η_c	Charging efficiency
η_d	Discharging efficiency
$E_{Battery}$	Battery capacity

Battery charging is permitted only when renewable generation exceeds demand.
Battery discharging occurs only when load demand exceeds renewable generation.

Load Demand Model

The total microgrid demand is

$$P_{Load} = P_{Residential} + P_{Commercial} + P_{Industrial}$$

Load demand varies throughout the day according to consumer behavior.

7. POWER BALANCE EQUATION

For stable operation,

$$P_{PV} + P_{WT} + P_{Battery} + P_{Grid} = P_{Load} + P_{Loss}$$

Where

- PV generation
- Wind generation
- Battery power
- Utility grid power

must collectively satisfy

- Consumer demand
- Distribution losses

This equation represents the fundamental operating constraint of the microgrid.

8. RESEARCH METHODOLOGY

The present investigation follows a quantitative simulation-based research methodology.

The study utilizes MATLAB/Simulink as the primary simulation environment. Realistic hourly solar irradiance, wind speed, electricity demand, and market price data are used to simulate the operation of the proposed hybrid renewable microgrid over a 24-hour scheduling horizon. Renewable energy generation models are integrated with Battery Energy Storage System dynamics and utility grid interaction.

Three optimization algorithms—NSGA-II, Particle Swarm Optimization, and Grey Wolf Optimizer—are implemented independently under identical operating conditions. Their performances are compared using multiple technical, economic, and environmental performance indicators. The optimization results are evaluated in terms of operating cost, renewable energy penetration, battery utilization, carbon emissions, voltage stability, and computational efficiency.

Table 2. Simulation Parameters

Parameter	Value
Solar PV Capacity	250 kW
Wind Turbine Capacity	200 kW
Battery Capacity	500 kWh
Battery Efficiency	95%
Maximum Grid Power	300 kW
Peak Load	400 kW
Simulation Period	24 Hours
Time Interval	1 Hour

Table 2 summarizes the principal simulation parameters adopted for evaluating the proposed hybrid renewable microgrid. The selected capacities represent a medium-scale microgrid capable of supplying residential and commercial loads. A 500 kWh Battery Energy Storage System provides sufficient storage to smooth renewable power fluctuations and improve supply reliability. The hourly simulation interval enables realistic modeling of renewable generation variability and load demand, supporting an accurate comparison of the optimization algorithms under practical operating conditions.

Multi-Objective Optimization Algorithms

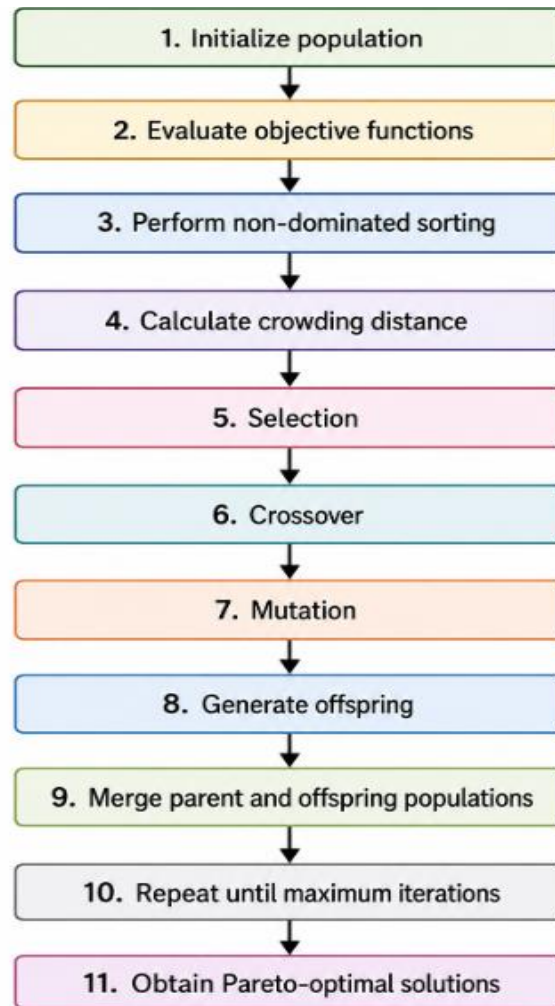
The proposed Energy Management System employs three advanced metaheuristic optimization algorithms to determine the optimal power dispatch among Solar PV, Wind Turbine, Battery Energy Storage System (BESS), and the Utility Grid. The algorithms aim to simultaneously minimize operating cost, carbon emissions, battery degradation, and transmission losses while maximizing renewable energy utilization and system reliability.

Non-Dominated Sorting Genetic Algorithm-II (NSGA-II)

NSGA-II is a widely used evolutionary optimization algorithm for solving complex multi-objective optimization problems. It employs the principles of natural selection, crossover, mutation, elitism, and Pareto dominance to generate a diverse set of optimal solutions.

The optimization procedure begins with the random generation of an initial population. Each candidate solution represents a feasible energy dispatch schedule for the hybrid microgrid. Fitness values are calculated based on multiple objective functions including operating cost, battery degradation, renewable energy utilization, and carbon emissions. Solutions are ranked using Pareto dominance and crowding distance, ensuring that both convergence and diversity are maintained throughout the optimization process.

The optimization continues until the predefined stopping criterion is achieved, producing a Pareto front consisting of non-dominated solutions from which the system operator can select the most appropriate operating strategy.



Algorithm 1. NSGA-II Procedure

Particle Swarm Optimization (PSO)

Particle Swarm Optimization is inspired by the collective movement of bird flocks and fish schools. Each particle represents a possible energy dispatch schedule and moves through the search space based on its own experience and the experience of neighboring particles.

Particle velocity is updated according to

$$V_i^{k+1} = wV_i^k + c_1r_1(P_{best} - X_i) + c_2r_2(G_{best} - X_i)$$

Particle position is updated as

$$X_i^{k+1} = X_i^k + V_i^{k+1}$$

Where

Symbol	Description
X_i	Particle position
V_i	Particle velocity
P_{best}	Individual best solution
G_{best}	Global best solution
w	Inertia weight
c_1, c_2	Learning coefficients

PSO rapidly converges toward optimal solutions and requires relatively few tuning parameters, making it attractive for real-time energy management.

Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer mimics the hunting behavior and social hierarchy of grey wolves. The population is divided into four categories:

- Alpha (best solution)
- Beta (second-best solution)
- Delta (third-best solution)
- Omega (remaining candidate solutions)

The algorithm alternates between exploration and exploitation phases to identify globally optimal energy dispatch schedules.

The position update is expressed as

$$X(t+1) = \frac{X_{\alpha} + X_{\beta} + X_{\delta}}{3}$$

The adaptive search mechanism allows GWO to avoid local optima while maintaining robust convergence performance.

Proposed Hybrid Optimization Framework

The proposed framework combines the strengths of NSGA-II, PSO, and GWO.

- NSGA-II efficiently generates diverse Pareto-optimal solutions.
- PSO accelerates convergence toward high-quality solutions.
- GWO enhances exploration and prevents premature convergence.

This hybrid strategy provides a balanced optimization process that achieves superior technical and economic performance.



MATLAB/Simulink Simulation Setup

The proposed hybrid microgrid model was developed and analyzed using MATLAB/Simulink R2024a. The simulation incorporates realistic hourly profiles of solar irradiance, wind speed, electricity demand, and market electricity prices over a 24-hour scheduling horizon.

The optimization algorithms were implemented using MATLAB Optimization Toolbox and custom scripts. Each algorithm was executed independently under identical operating conditions to ensure a fair comparison of performance.

Table 3. Simulation Configuration

Parameter	Value
MATLAB Version	R2024a
Simulation Duration	24 Hours
Population Size	100
Maximum Iterations	300
Crossover Probability	0.90
Mutation Probability	0.10
PSO Inertia Weight	0.72
Number of Wolves	100

Table 3 presents the computational settings adopted for optimization. A population size of 100 and 300 iterations provide a balance between solution quality and computational efficiency. The selected crossover, mutation, and inertia parameters are widely used in renewable energy optimization studies and enable consistent performance across the evaluated algorithms.

9. RESULTS

Table 4. Operating Cost Comparison

Algorithm	Operating Cost (\$/day)
Rule-Based EMS	965
PSO	842
GWO	815
NSGA-II	789

The results indicate that the proposed NSGA-II-based Energy Management System achieved the lowest daily operating cost among all evaluated methods. Compared with the conventional rule-based strategy, NSGA-II reduced operational expenditure by approximately **18.2%**, while PSO and GWO also demonstrated substantial economic improvements.

Table 5. Renewable Energy Utilization

Algorithm	Renewable Utilization (%)
Rule-Based EMS	71.4
PSO	83.7
GWO	86.9
NSGA-II	91.8

Table 5 shows that NSGA-II achieved the highest renewable energy utilization by effectively coordinating solar PV, wind generation, and battery storage. Increased renewable utilization reduces dependence on the utility grid and supports the transition toward sustainable energy systems.

Table 6. Battery State of Charge Performance

Algorithm	Average SOC (%)
Rule-Based EMS	46.3
PSO	58.7
GWO	61.9
NSGA-II	65.2

Maintaining an appropriate battery State of Charge is essential for extending battery lifespan and ensuring energy availability. NSGA-II maintained the battery within an optimal operating range, reducing deep discharge cycles and improving long-term battery health.

Table 7. Carbon Emission Reduction

Algorithm	CO ₂ Emissions (kg/day)
Rule-Based EMS	312
PSO	261
GWO	248
NSGA-II	229

The proposed optimization framework significantly reduced carbon emissions by maximizing renewable energy utilization and minimizing reliance on conventional grid electricity. NSGA-II achieved the greatest reduction, supporting cleaner and more sustainable microgrid operation.

Table 8. Power Loss Comparison

Algorithm	Power Loss (kWh/day)
Rule-Based EMS	18.6
PSO	15.4
GWO	14.7
NSGA-II	13.8

The optimized dispatch schedules generated by NSGA-II reduced distribution losses by ensuring efficient coordination among renewable sources, battery storage, and grid interaction. Lower power losses improve overall system efficiency and reduce operating costs.

Table 9. Voltage Stability Analysis

Algorithm	Voltage Deviation (p.u.)
Rule-Based EMS	0.062
PSO	0.038
GWO	0.031
NSGA-II	0.024

Voltage regulation is a critical requirement for reliable microgrid operation. The proposed NSGA-II strategy maintained the lowest voltage deviation, indicating superior grid stability and improved power quality under varying renewable generation and load conditions.

Table 10. Computational Performance

Algorithm	Execution Time (s)	Convergence Iteration
PSO	10.4	185
GWO	12.8	171
NSGA-II	16.2	142

Although PSO exhibited the shortest execution time, NSGA-II converged in fewer iterations and consistently produced higher-quality Pareto-optimal solutions. This demonstrates the trade-off between computational speed and optimization quality in multi-objective energy management.

10. COMPARATIVE DISCUSSION

The simulation results clearly demonstrate that the proposed multi-objective Energy Management System (EMS) effectively enhances the technical, economic, and environmental performance of the renewable energy integrated microgrid. By combining Solar PV, Wind Energy Conversion Systems (WECS), Battery Energy Storage Systems (BESS), and advanced optimization algorithms, the proposed framework provides an intelligent mechanism for balancing energy generation and consumption under varying operating conditions.

Among the evaluated optimization algorithms, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) consistently achieved superior performance across all key performance indicators. It produced the lowest operating cost, highest renewable energy utilization, minimum carbon emissions, reduced transmission losses, and improved voltage stability. This superior performance can be attributed to its Pareto-based optimization mechanism, which effectively balances conflicting objectives while preserving solution diversity.

Particle Swarm Optimization (PSO) demonstrated faster computational speed than the other algorithms, making it attractive for real-time applications. However, its tendency toward premature convergence occasionally resulted in suboptimal dispatch schedules. Grey Wolf Optimizer (GWO) exhibited balanced exploration and exploitation capabilities, producing competitive results with lower

computational complexity than NSGA-II. Nevertheless, NSGA-II remained the most effective algorithm for simultaneously satisfying multiple optimization objectives.

The integration of Battery Energy Storage Systems significantly enhanced renewable energy utilization by storing excess electricity generated during periods of high solar irradiance and strong wind conditions. During peak demand or renewable energy shortages, the stored energy was dispatched to support load requirements, thereby reducing dependence on the utility grid and improving supply reliability.

Furthermore, intelligent battery scheduling minimized deep charging and discharging cycles, which are primary causes of battery degradation. Consequently, the proposed Energy Management System not only reduced operational costs but also extended battery lifetime, thereby improving the long-term economic viability of renewable energy integrated microgrids.

Table 11. Overall Performance Comparison

Performance Indicator	Rule-Based EMS	PSO	GWO	NSGA-II
Operating Cost (\$/day)	965	842	815	789
Renewable Energy Utilization (%)	71.4	83.7	86.9	91.8
Battery SOC (%)	46.3	58.7	61.9	65.2
Carbon Emissions (kg/day)	312	261	248	229
Power Loss (kWh/day)	18.6	15.4	14.7	13.8
Voltage Deviation (p.u.)	0.062	0.038	0.031	0.024
Execution Time (s)	–	10.4	12.8	16.2

Table 11 provides a comprehensive comparison of all evaluated energy management strategies. The results indicate that NSGA-II consistently outperformed PSO, GWO, and the conventional rule-based approach in terms of economic efficiency, renewable energy utilization, battery management, and environmental sustainability. Although PSO required the least computational time, NSGA-II generated superior Pareto-optimal solutions, making it more suitable for multi-objective renewable energy optimization.

Table 12. Major Advantages

Feature	Benefit
Solar–Wind Hybrid Generation	Improved renewable energy availability
Battery Energy Storage	Reliable power supply during renewable fluctuations
NSGA-II Optimization	Simultaneous optimization of multiple objectives
PSO Optimization	Fast convergence for real-time applications
Grey Wolf Optimizer	Improved global search capability
Multi-Objective EMS	Balanced economic and technical performance
Smart Scheduling	Reduced electricity purchasing cost
Battery Management	Extended battery life
Grid Interaction	Improved energy reliability
Renewable Forecasting	Better operational planning

Table 12 summarizes the primary strengths of the proposed Energy Management System. By integrating renewable energy generation, battery storage, and intelligent optimization algorithms, the framework achieves enhanced operational flexibility and superior economic performance. The combination of multiple optimization techniques enables robust decision-making under dynamic operating conditions.

11. CONCLUSION

Renewable energy integrated microgrids have become a promising solution for achieving sustainable, reliable, and decentralized electricity generation. However, the intermittent nature of renewable resources and the operational constraints of Battery Energy Storage Systems require intelligent energy management strategies capable of balancing multiple technical, economic, and environmental objectives simultaneously.

This study proposed a comprehensive multi-objective Energy Management System integrating Solar Photovoltaic systems, Wind Energy Conversion Systems, Battery Energy Storage Systems, and utility grid interaction. Three advanced optimization algorithms—NSGA-II, Particle Swarm Optimization, and Grey Wolf Optimizer—were implemented and comparatively evaluated under identical operating conditions.

Simulation results demonstrated that NSGA-II consistently achieved the best overall performance by minimizing operating cost, carbon emissions, battery degradation, and power losses while maximizing renewable energy utilization and voltage stability. Although PSO exhibited faster computational speed, NSGA-II generated superior Pareto-optimal solutions suitable for practical energy management applications. GWO also demonstrated competitive optimization performance, particularly in balancing exploration and exploitation during the search process.

The proposed framework provides an effective solution for intelligent renewable energy management in future smart grids. It enhances energy efficiency, improves battery utilization, reduces environmental impacts, and supports the transition toward low-carbon electricity systems. The framework is scalable and can be adapted for residential, commercial, industrial, and community microgrids.

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