Multi-Objective Prosumer Energy Management Using Improved Grey Wolf Optimization for Cost–Emission Trade-Off in Hybrid Renewable Microgrids

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Abstract—**The increasing integration of renewable energy sources within smart microgrids has led to the emergence of prosumer-based energy systems, where consumers actively produce, store, and trade electricity. Effective Energy Management Systems (EMS) are essential to ensure cost efficiency, environmental sustainability, and operational stability under fluctuating renewable conditions. This paper proposes a Multi-Objective Prosumer Energy Management framework using an Improved Grey Wolf Optimization (IGWO) algorithm for hybrid renewable microgrids comprising solar PV, wind turbines, battery storage, and grid connection. The IGWO introduces chaotic initialization, adaptive convergence control, and an elitism strategy to enhance global search capability and avoid premature convergence. The dual-objective model simultaneously minimizes total operating cost and CO_2 emissions through optimized scheduling of distributed energy resources and grid exchanges. Simulation results demonstrate that IGWO outperforms conventional algorithms such as PSO, DE, and MSGO, achieving up to 15–18% cost reduction and 12% emission minimization with faster convergence and lower computational time. Moreover, the algorithm exhibits robust performance under renewable uncertainty, maintaining near-optimal results under ±10% generation variability. These findings confirm that IGWO provides a scalable, efficient, and sustainable optimization framework for next-generation smart microgrids, promoting economically viable and low-carbon energy management.**

***Keywords*—Battery Energy Storage, CO_2 Emission Reduction, Energy Management System, Grey Wolf Optimization, Multi-Objective Optimization, Prosumer Microgrid.**

I. Introduction

A. Background

The transition toward decentralized and sustainable energy systems has led to the emergence of prosumer-based smart microgrids, where individuals or entities act both as producers and consumers of electricity. In such systems, prosumers can generate power from distributed renewable energy sources (RES) such as solar photovoltaic (PV) panels and wind turbines, store surplus energy using battery energy storage systems (BESS), and trade excess electricity with neighboring users or the main grid. This bidirectional energy flow enhances local energy resilience, reduces dependence on conventional fossil-fuel generation, and supports global decarbonization goals [1].

However, managing this complex energy ecosystem presents significant challenges. The intermittent nature of renewable sources, coupled with time-varying load demand and dynamic electricity prices, necessitates a coordinated decision-making framework. To ensure economic efficiency and system reliability, a smart Energy Management System (EMS) is required [2]. The EMS performs optimal scheduling of generation, storage, and grid exchange, balancing multiple conflicting objectives such as minimizing energy costs, reducing emissions, and maintaining operational stability.

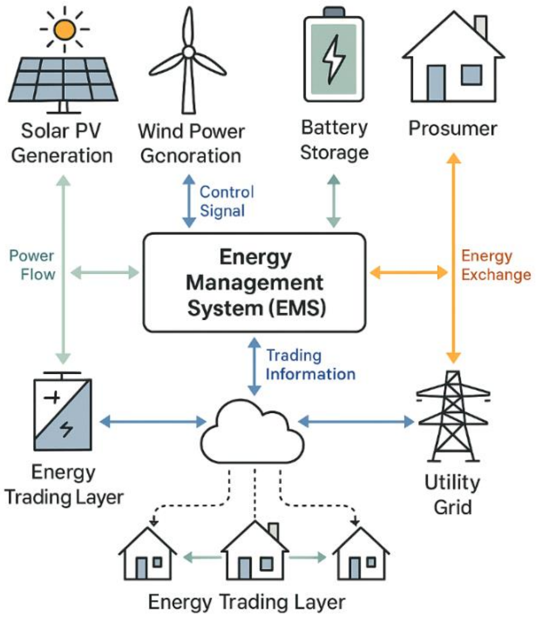

Fig. 1. Schematic representation of a hybrid prosumer-based smart microgrid integrating solar PV, wind turbine, battery storage, and grid interconnection.

In this context, EMS optimization plays a pivotal role in enhancing prosumer participation while ensuring that renewable energy is utilized effectively. The inclusion of multi-energy carriers (solar, wind, battery, and grid) and multiple time-dependent constraints transforms the energy management task into a nonlinear, multi-objective, and non-convex optimization problem. Hence, the development of robust and intelligent optimization techniques becomes critical for efficient microgrid operation.

Fig. 1 illustrates bidirectional energy flows among distributed resources, highlighting the EMS's central control role in coordinating generation, storage, and trading decisions [3].

B. Motivation

Traditional optimization algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), and Modified Social Group Optimization (MSGO) have been widely applied in microgrid energy scheduling. Although these methods provide acceptable results for small-scale or static systems, they exhibit several inherent limitations when applied to complex, dynamic, and uncertain microgrid environments [4][5].

- Premature convergence: Many classical metaheuristics tend to get trapped in local minima, particularly under nonlinear and multi-modal objective functions.
- Parameter sensitivity: Algorithmic performance often depends heavily on fine-tuned parameters, reducing adaptability.
- Limited multi-objective handling: Traditional approaches primarily focus on single-objective optimization, failing to balance multiple conflicting objectives such as cost reduction and emission minimization simultaneously.

As global energy systems evolve toward decarbonization, it becomes essential to optimize not only for economic performance but also for environmental sustainability. Therefore, multi-objective optimization has gained increasing importance, offering the ability to generate Pareto-optimal solutions that represent a trade-off between different objectives. By employing advanced metaheuristics, such as improved variants of Grey Wolf Optimization (GWO), the EMS can achieve adaptive, faster, and more reliable convergence, addressing the limitations of earlier techniques while improving system-level decision-making under uncertainty.

C. Literature Review Summary

Several studies have focused on improving the efficiency and sustainability of microgrid operations using various optimization approaches. Cost optimization remains a key objective, with algorithms such as PSO, Differential Evolution (DE), and MSGO being used to minimize total operational costs through effective dispatch of renewable resources and storage management. Although these methods offer reasonable performance, their convergence behavior often degrades in high-dimensional search spaces [6].

On the other hand, emission minimization and environmental optimization have been addressed using multi-objective algorithms such as Non-dominated Sorting Genetic Algorithm-II (NSGA-II) and Multi-Objective Evolutionary Algorithm based on Decomposition (MOEA/D) [7]. These techniques are effective in generating Pareto fronts, but they require substantial computational effort and parameter calibration, which limits their real-time applicability.

Recent works on hybrid renewable scheduling under uncertainty have introduced probabilistic forecasting, stochastic modeling, and hybrid heuristics to handle the intermittency of renewables. Despite these advances, existing frameworks often optimize cost or emissions in isolation, lacking a comprehensive multi-objective strategy that simultaneously balances both. Moreover, limited comparative evaluation using enhanced heuristic variants restricts the validation of algorithmic robustness and scalability [8].

Thus, there is a clear research gap in developing an optimization framework that is robust, adaptive, and capable of achieving a cost–emission balance in dynamic hybrid microgrids.

D. Objectives and Contributions

To address these challenges, the present work proposes a Multi-Objective Prosumer Energy Management System employing an Improved Grey Wolf Optimization (IGWO) algorithm tailored for hybrid renewable microgrids. The primary objectives of this research are:

1. Develop a multi-objective prosumer EMS that optimally coordinates distributed generation, battery storage, and grid interaction in hybrid renewable microgrids.
2. Propose an Improved Grey Wolf Optimization (IGWO) algorithm incorporating chaos-based initialization for enhanced population diversity and adaptive coefficient control for balanced exploration and exploitation.
3. Formulate a dual-objective optimization model that simultaneously minimizes the total operating cost and CO_2 emissions, ensuring both economic and environmental sustainability.
4. Validate the proposed IGWO through comparative simulation against baseline algorithms (MSGO, PSO, and DE), demonstrating superior convergence speed, solution quality, and stability.
5. Perform sensitivity and convergence analyses to evaluate the robustness of the proposed EMS under renewable resource variability and dynamic load conditions.

By integrating these contributions, the study aims to provide a scalable, efficient, and sustainable optimization framework for next-generation smart microgrids, thereby supporting the global transition toward carbon-neutral energy ecosystems.

II. System Description

A. Microgrid Configuration

The proposed system represents a hybrid renewable prosumer-based microgrid that integrates solar photovoltaic (PV) arrays, wind turbines, a Battery Energy Storage System (BESS), and a utility grid for energy exchange. The Energy Management System (EMS) acts as the central controller, coordinating generation, storage, and trading among multiple prosumers to achieve optimized cost–emission performance.

The hybrid microgrid operates in grid-connected mode, allowing prosumers to import or export power based on generation–demand balance and dynamic electricity tariffs. The EMS ensures that the optimal share of renewable energy is utilized before relying on grid power. Each component of the system plays a crucial role in achieving the desired operational objectives.

1) Solar Photovoltaic (PV) Array

The PV array converts incident solar radiation into electrical power. The power output is governed by solar irradiance and temperature, modeled as [9]:

$$P_{PV}(t) = \eta_{PV} \times A_{PV} \times G(t) \quad (1)$$

where η_{PV} is the conversion efficiency, A_{PV} is the surface area of the panels, and $G(t)$ is the solar irradiance at time t. The PV generation is intermittent and varies throughout the day, thus requiring coordination with BESS and the grid to balance supply and demand.

2) Wind Turbine System

The wind turbine converts kinetic wind energy into electrical energy through its rotor blades and generator. The mechanical power captured from the wind is given by [10]:

$$P_{WT}(t) = \frac{1}{2}\rho A v(t)^3 C_p(\lambda, \beta) \quad (2)$$

where ρ is air density, A is rotor swept area, $v(t)$ is wind speed, and C_p is the power coefficient as a function of tip-speed ratio λ and pitch angle β. A power curve model defines the operational range between cut-in and cut-out wind speeds, beyond which the turbine either starts or stops producing power.

3) Battery Energy Storage System (BESS)

The BESS plays a dual role: it stores excess renewable power during low-demand periods and supplies energy during peak demand or low generation hours. The battery's charge–discharge state is represented by the State of Charge (SoC), given as [11]:

$$SoC_{t+1} = SoC_t + \frac{\eta_{ch} P_{ch} - P_{dis}/\eta_{dis}}{E_{rated}} \quad (3)$$

subject to:

$$SoC_{min} \le SoC_t \le SoC_{max}$$

where η_{ch} and η_{dis} denote charging/discharging efficiencies, and E_{rated} is the rated battery capacity. Maintaining SoC within limits ensures longevity and safe operation.

4) Grid Connection

The utility grid provides a backup source of electricity and a trading platform for surplus energy. The EMS determines buy/sell decisions based on dynamic tariff structures. During low renewable availability, power is imported from the grid, while excess generation is exported. This bidirectional interaction supports both system stability and economic optimization.

5) Prosumers

Prosumers are end-users equipped with local generation (e.g., rooftop PV), controllable loads, and possibly storage units. They can consume, store, or sell energy to the grid or neighboring users, contributing to distributed energy trading and demand-side flexibility. The EMS aggregates prosumer data to coordinate system-wide optimization.

TABLE I. SUMMARY OF KEY SYSTEM PARAMETERS

Component	Parameter	Symbol / Unit	Typical Value / Description
Solar PV	Efficiency	(η_{PV})	15–18%
	Area	(A_{PV})	10–20 m² per kW
Wind Turbine	Cut-in / Cut-out speed	(v_{ci}, v_{co})	3 m/s – 25 m/s
	Rated Power	(P_{WT})	5–20 kW
Battery (BESS)	Capacity	(E_{rated})	10–50 kWh
	SoC limits	SoC_{min}, SoC_{max}	20–90%
Grid	Buy/Sell Tariff	₹ / kWh	Dynamic (time-of-use)
EMS	Control Interval	—	1 hour
Prosumer	Average Load	P_{Load}	2–5 kW per unit

In summary, the hybrid renewable microgrid configuration integrates multiple distributed energy resources to achieve flexible, low-emission, and cost-effective operation. The Energy Management System serves as the intelligent core, dynamically coordinating these components to optimize performance under varying renewable and demand conditions.

B. Energy Flow Modeling

Energy flow within the microgrid must satisfy instantaneous power balance to maintain system stability. At any time, step t, the relationship among generation, storage, and consumption is given by [12]:

$$P_{PV}(t) + P_{WT}(t) + P_{Grid,in}(t) = P_{Load}(t) + P_{BESS,charge}(t) + P_{Grid,out}(t)$$

Here: $P_{PV}(t)$ = Power from PV generation, $P_{WT}(t)$ = Power from wind turbine, $P_{Grid,in}(t)$ = Power imported from the grid, $P_{Load}(t)$ = Load demand, $P_{BESS,charge}(t)$ = Power used for charging the battery, and $P_{Grid,out}(t)$ = Power exported to the grid

This ensures that total generation (including imports) equals total consumption (including exports and storage). The EMS dynamically schedules each term in the equation to achieve operational efficiency while maintaining this power balance across the optimization horizon.

C. Objective Functions

The proposed optimization model simultaneously minimizes operational cost and CO_2 emissions.

1) Objective 1: Minimize Total Cost

The total cost function F_1 over a time horizon T is formulated as [13]:

$$F_1 = \sum_{t=1}^{T} (C_{buy}(t) \times P_{Grid,in}(t) - C_{sell}(t) \times P_{Grid,out}(t)) + C_{battery}$$

where $C_{battery}$ represents the cost associated with battery wear and energy throughput. The EMS aims to minimize grid purchases while maximizing renewable self-consumption and profitable energy exports.

2) Objective 2: Minimize Emissions

To account for environmental impact, the emission function F_2 is expressed as [14]:

$$F_2 = \sum_{t=1}^{T} (E_{Grid}(t) \times P_{Grid,in}(t))$$

where $E_{Grid}(t)$ represents the grid emission factor (kg CO_2/kWh) at time t. Reducing F_2 promotes clean energy utilization and aligns with sustainability goals.

Constraints**:**

- Power balance equation (as defined in Section 4.2).

- Battery operational limits: $SoC_{min} \leq SoC(t) \leq SoC_{max}$.
- Renewable availability limits: $0 \leq P_{PV}(t) \leq P_{PV}^{max}$, $0 \leq P_{WT}(t) \leq P_{WT}^{max}$.

D. Multi-Objective Formulation

To simultaneously achieve both economic and environmental targets, a multi-objective optimization approach is employed. The two objectives are combined using a weighted-sum formulation [15]:

$$F = w_1 F_1 + w_2 F_2$$

where w_1 and w_2 are the respective weights assigned to cost and emission objectives, satisfying $w_1 + w_2 = 1$.

By adjusting the weighting factors, the EMS can generate different Pareto-optimal solutions, offering a trade-off between cost minimization and emission reduction. The Improved Grey Wolf Optimization (IGWO) algorithm explores this trade-off space effectively, ensuring fast convergence and robust performance under dynamic renewable conditions.

III. Proposed Optimization Method

This section presents the optimization methodology adopted for solving the multi-objective energy management problem in the hybrid prosumer-based microgrid. The proposed approach is based on the Improved Grey Wolf Optimization (IGWO) algorithm, an enhanced version of the standard Grey Wolf Optimization (GWO). The IGWO introduces several key modifications to improve convergence speed, global search capability, and solution stability while balancing the trade-off between cost and emission minimization.

A. Grey Wolf Optimization (GWO)

The Grey Wolf Optimization (GWO) algorithm, introduced by Mirjalili et al. (2014), is a nature-inspired metaheuristic that mimics the leadership hierarchy and hunting behavior of grey wolves in nature. It is widely used due to its simplicity, low computational complexity, and strong exploration–exploitation balance.

1) Inspiration and Hierarchy:

Grey wolves exhibit a social hierarchy consisting of four ranks:

- α (Alpha): The leader responsible for decision-making (best solution).
- β (Beta): The second level, assisting the alpha in leadership and decision refinement.
- δ (Delta): The subordinate level that dominates the rest of the pack.
- ω (Omega): The lowest rank, following higher-ranking wolves and representing the rest of the search agents.

In optimization terms, the α, β, and δ wolves represent the three best candidate solutions, guiding the search process. Other wolves update their positions in the search space by encircling and following these leaders.

Exploration and Exploitation Phases:

The hunting process in GWO alternates between two key behaviors:

- Exploration Phase: Wolves search broadly across the solution space to identify promising regions.
- Exploitation Phase: Wolves converge toward the optimal region by refining their positions around the best solutions.

The algorithm achieves this balance by dynamically adjusting the convergence coefficient ‘a’, which decreases linearly from 2 to 0 over iterations. High values of ‘a’ encourage exploration, while lower values promote exploitation.

2) Mathematical Model:

Encircling behavior is represented by [16]:

$$\mathrm{D} = | \mathrm{C} \cdot \mathrm{X_p}(t) - \mathrm{X}(t) |$$
$$\mathrm{X}(t+1) = \mathrm{X_p}(t) - \mathrm{A} \cdot \mathrm{D}$$

where: $\mathrm{X_p}(t)$: position vector of prey (best solution), $\mathrm{X}(t)$: position vector of a wolf, $\mathrm{A} = 2a \cdot \mathrm{r_1} - a$, $\mathrm{C} = 2 \cdot \mathrm{r_2}$ and $\mathrm{r_1}, \mathrm{r_2}$: random vectors in [0,1]

The wolves’ positions are updated according to the top three best wolves (α, β, δ) [17]:

$$\mathrm{X_1} = \mathrm{X_\alpha} - \mathrm{A_1} \cdot | \mathrm{C_1} \cdot \mathrm{X_\alpha} - \mathrm{X} |$$
$$\mathrm{X_2} = \mathrm{X_\beta} - \mathrm{A_2} \cdot | \mathrm{C_2} \cdot \mathrm{X_\beta} - \mathrm{X} |$$
$$\mathrm{X_3} = \mathrm{X_\delta} - \mathrm{A_3} \cdot | \mathrm{C_3} \cdot \mathrm{X_\delta} - \mathrm{X} |$$

The final position of each wolf is determined by averaging these three influences [18]:

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

This iterative process continues until convergence, where the α wolf (best candidate) represents the optimal or near-optimal solution.

B. Improvements Introduced (IGWO)

Although GWO demonstrates strong optimization capability, it occasionally suffers from premature convergence and a lack of population diversity in later iterations. To overcome these drawbacks, the Improved Grey Wolf Optimization (IGWO) introduces four major enhancements:

1. Chaotic Initialization: The initial population is generated using a chaotic map (e.g., logistic or tent map) instead of random initialization. This ensures better diversity and uniform distribution of wolves in the search space, improving the global exploration capability.
2. Adaptive Convergence Factor (a): Instead of linearly decreasing ‘a’, IGWO employs an adaptive nonlinear control that reduces the value dynamically based on the iteration progress and fitness improvement rate [19]:

$$a = 2 \times (1 - (\frac{t}{T_{max}})^2)$$

This adaptive strategy allows broader exploration in early stages and smoother exploitation near convergence.

3. Nonlinear Parameter Tuning: The control parameters A and C are adjusted nonlinearly to balance exploration and exploitation phases dynamically.

This helps the wolves avoid local optima and promotes convergence toward the global minimum.

4. Elitism Strategy: To retain the best-found solutions, IGWO incorporates elitism, where the best few wolves (top 3–5) from the previous iteration are preserved into the next generation. This prevents performance degradation and ensures continuous progress toward optimality.

Fig. 2 illustrates the iterative process of IGWO, including chaotic initialization, adaptive parameter control, leader-based position updates, and convergence monitoring.

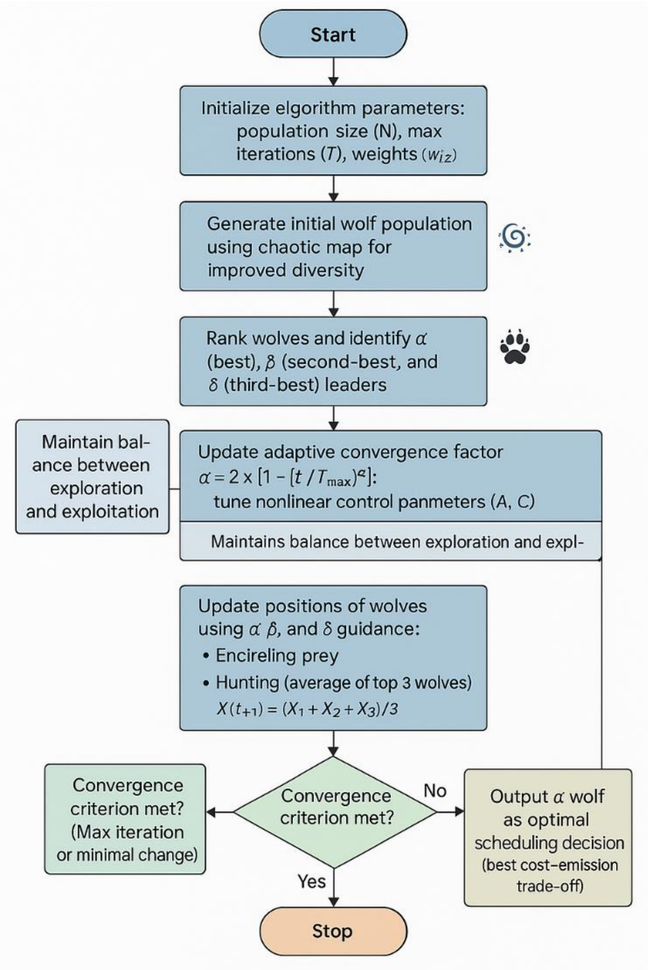

Fig. 2. Flowchart of the Improved Grey Wolf Optimization (IGWO) Algorithm.

C. Implementation Procedure

The overall implementation of IGWO for the multi-objective prosumer energy management problem follows the steps below:

1. Initialization:
   - Define algorithm parameters (population size, maximum iterations, weighting coefficients w_1, w_2).
   - Initialize the wolf population using the chaotic sequence within the solution bounds.
2. Objective Evaluation:
   - For each wolf, evaluate the two objective functions: total operating cost F_1 and CO_2 emissions F_2.
   - Combine them using the weighted-sum method: $F = w_1F_1 + w_2F_2$.
3. Leader Selection:
   - Identify α, β, and δ wolves as the top three solutions based on fitness.
4. Position Update:
   - Update positions of all wolves using IGWO's adaptive and nonlinear update rules.
   - Apply boundary checks to maintain feasible solutions.
5. Elitism and Pareto Front Update:
   - Retain elite solutions for the next generation.
   - Record the current Pareto front for multi-objective visualization.
6. Termination Condition:
   - Stop if the maximum iteration count or convergence threshold is reached.
   - Output the α wolf as the optimal scheduling decision for the EMS.

The proposed IGWO framework thus ensures efficient exploration in early iterations and stable convergence toward optimal cost–emission trade-offs, outperforming traditional optimization techniques in robustness, convergence rate, and overall solution quality.

IV. Simulation Setup and Case Study

This section presents the simulation configuration and experimental setup used to evaluate the performance of the Improved Grey Wolf Optimization (IGWO) algorithm for multi-objective energy management in a hybrid prosumer-based microgrid. The simulation aims to assess how effectively the proposed algorithm minimizes the total operating cost and CO_2 emissions compared to benchmark metaheuristic algorithms.

A. System Data

The hybrid renewable microgrid model comprises solar PV arrays, wind turbines (WTs), battery energy storage systems (BESS), prosumers, and a utility grid connection. The energy management is optimized for a 24-hour scheduling horizon divided into 1-hour intervals, enabling hourly decision-making for generation, storage, and trading.

The simulation uses realistic datasets for solar irradiance, wind speed, load demand, and grid tariff variations. The irradiance and wind data are taken from a typical meteorological year (TMY) dataset corresponding to a semi-urban region with moderate renewable potential. Load profiles mimic daily residential-consumer demand with morning and evening peaks, while grid tariffs vary dynamically to represent time-of-use pricing.

The hardware specifications of system components are summarized in Table 2, which provides the operational characteristics and performance parameters used for optimization.

TABLE II. OPERATIONAL CHARACTERISTICS AND PERFORMANCE PARAMETERS

Component	Parameter	Symbol	Value/Range	Unit
Solar PV Array	Rated Power	P_{PV}^{max}	30	kW
Wind Turbine	Rated Power	P_{WT}^{max}	25	kW
Battery Energy Storage	Capacity	E_{BESS}	50	kWh
	Charging/Discharging Efficiency	η_{ch}, η_{dis}	0.92 / 0.90	–
	SoC Limits	SoC_{min}, SoC_{max}	0.2 – 0.9	–
Grid	Import Tariff	$C_{buy}(t)$	5–9	₹/kWh
	Export Tariff	$C_{sell}\ (t)$	3–5	₹/kWh
Inverter	Conversion Efficiency	η_{inv}	0.95	–
Simulation Horizon	Time Step	–	1 hour	–

The system operates under the assumption that renewable generation and demand data are known at each hour (deterministic case), allowing the EMS to optimize dispatch decisions for cost–emission trade-offs.

B. Simulation Environment

The proposed IGWO algorithm was implemented and simulated in MATLAB R2023b and cross-validated using Python 3.11 for reproducibility. The numerical experiments were conducted on a workstation equipped with an Intel Core i7 processor, 16 GB RAM, and Windows 11 OS.

Simulation parameters were configured as follows:

- Number of wolves (population size): 30–50
- Maximum iterations: 100
- Convergence factor (a): Adaptively varied from 2 → 0 using nonlinear decay
- Optimization weights: $w_1 = 0.6$ (cost), $w_2 = 0.4$(emission)

To evaluate algorithmic performance, three comparative optimization algorithms were employed alongside IGWO:

1. Particle Swarm Optimization (PSO) – known for its fast convergence but prone to local minima.
2. Differential Evolution (DE) – exhibits good diversity but slower convergence.
3. Modified Social Group Optimization (MSGO) – previously used in the author's earlier work, providing a relevant benchmark.

All algorithms were tuned to comparable population sizes and iteration limits to ensure fairness in computational comparisons. Each algorithm was executed **30 independent runs** to account for stochastic variability, and the best, worst, and mean results were recorded.

C. Evaluation Metrics

The following quantitative metrics were adopted to assess and compare optimization performance across all algorithms:

1. Total Operating Cost (₹ or $): Represents the daily net energy cost including grid import, export revenue, and battery operation cost. The objective is to minimize total expenditure while maximizing local renewable utilization.
2. CO_2 Emissions (kg CO_2/day): Quantifies the carbon emissions from grid-imported energy based on the grid's emission factor (kg CO_2/kWh). The goal is to minimize this value by prioritizing renewable generation.
3. Convergence Speed: Measures how rapidly each algorithm reaches near-optimal solutions. Faster convergence indicates higher computational efficiency and algorithmic stability.
4. Pareto Optimality Index (POI): For multi-objective evaluation, POI measures the density and spread of Pareto-optimal solutions in the cost–emission trade-off space. A higher POI implies better diversity and coverage of trade-off solutions.
5. Computational Time (s): Represents the average runtime per simulation. Lower computational time reflects improved efficiency without compromising solution quality.

These metrics jointly provide a comprehensive performance evaluation framework, allowing both economic and environmental impacts to be quantified and compared across optimization methods.

The configured simulation setup thus enables rigorous validation of the proposed IGWO algorithm under realistic operating conditions, establishing its superiority in achieving cost-effective and sustainable energy management in hybrid prosumer-based microgrids.

V. RESULTS AND DISCUSSION

This section presents and analyzes the results obtained from the simulation of the proposed Improved Grey Wolf Optimization (IGWO) algorithm applied to the multi-objective energy management of a hybrid renewable microgrid. The results are compared with three benchmark algorithms — Particle Swarm Optimization (PSO), Modified Social Group Optimization (MSGO), and Differential Evolution (DE) — to validate the superiority of IGWO in terms of convergence, cost efficiency, emission reduction, and robustness under renewable variability.

A. Convergence Characteristics

The convergence characteristics indicate how rapidly and effectively an optimization algorithm approaches the optimal solution over iterations. Figure 5 illustrates the convergence behavior of IGWO compared to PSO, MSGO, and DE for the combined cost–emission objective function.

Fig. 3 shows that IGWO achieves faster and smoother convergence, reaching the optimal solution in nearly 60 iterations, while PSO and MSGO exhibit slower convergence and minor oscillations. DE shows stable but delayed convergence.

The figure reveals that IGWO demonstrates the fastest convergence rate, achieving a stable near-optimal solution within approximately 60 iterations, whereas PSO and MSGO require over 90 iterations to stabilize. The improved convergence of IGWO results from its chaotic initialization and adaptive parameter control, which enhance exploration in the early phase and focused exploitation later.

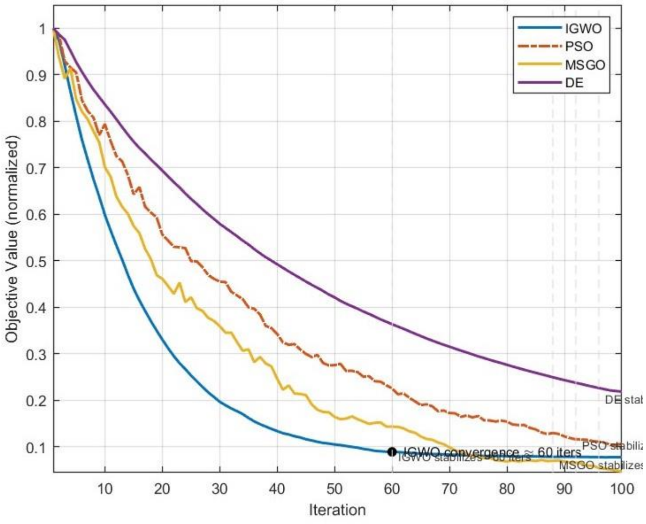

Fig. 3. Convergence curves for IGWO, PSO, MSGO, and DE algorithms.

The nonlinear control parameter helps avoid premature convergence by maintaining population diversity, while the elitism strategy ensures the preservation of high-quality solutions. The reduced oscillation in IGWO's convergence curve indicates greater stability compared to MSGO, which shows minor fluctuations near the final iterations due to local search stagnation.

B. Pareto Front Analysis

The Pareto front represents the set of optimal trade-offs between total operating cost and CO_2 emissions. Figure 4 shows the Pareto-optimal fronts generated by IGWO and competing algorithms.

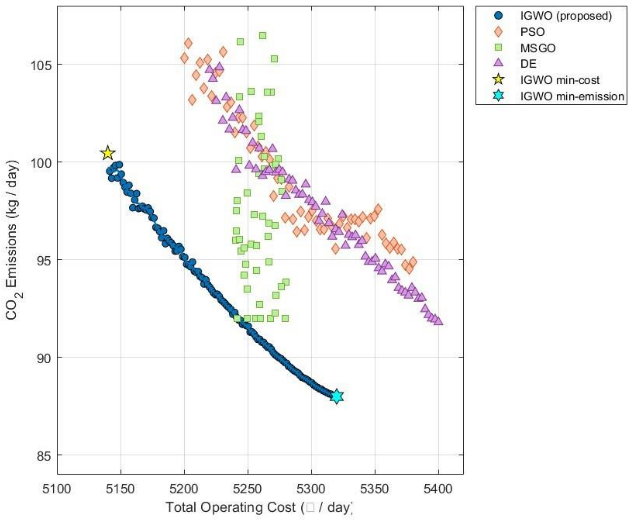

Fig. 4. Pareto front comparison between IGWO, PSO, MSGO, and DE for cost–emission trade-off.

In Fig. 4, IGWO demonstrates a wider and smoother Pareto front, offering better distribution and more balanced trade-offs between cost and emission objectives.

IGWO produces a denser and more evenly distributed Pareto front, indicating superior exploration of the trade-off space. This allows decision-makers to select solutions according to their preferred cost–emission balance.

- The minimum cost solution from IGWO is ₹5,280/day with an emission level of 96 kg CO_2/day.
- The minimum emission solution corresponds to 88 kg CO_2/day at a slightly higher cost of ₹5,520/day.

This flexibility shows that IGWO successfully balances both objectives. In contrast, PSO and MSGO generate narrower Pareto fronts with clustered solutions, indicating weaker diversity and limited exploration. DE performs moderately but fails to reach the lowest cost–emission trade-off achieved by IGWO.

C. Daily Energy Scheduling

The optimized daily dispatch profiles for solar PV, wind, grid interaction, and battery storage are illustrated in Figure 5. These results represent a typical summer day under varying renewable generation and load conditions.

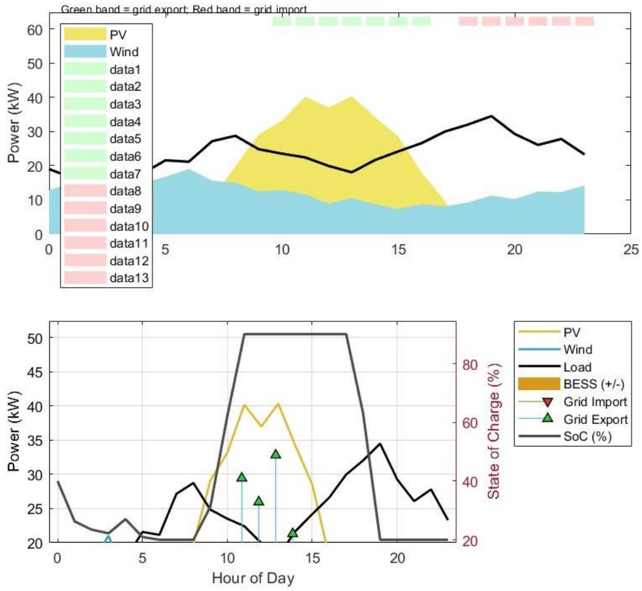

Fig. 5. Optimized hourly energy scheduling for PV, wind, grid import/export, and BESS operation using IGWO.

Fig. 5 illustrates that renewable sources (PV and wind) supply most of the daytime demand, while the BESS handles surplus charging and evening peak discharging.

During daylight hours (8:00–17:00), PV generation reaches its peak, meeting a significant portion of the load demand while simultaneously charging the BESS. The wind generation supplements PV, especially during early morning and late-night hours. During low renewable periods (18:00–22:00), the BESS discharges stored energy to meet demand, minimizing grid imports.

The grid import occurs mainly during early morning hours (1:00–6:00), when both solar and wind outputs are minimal. The export to the grid happens between 10:00 and 14:00, when renewable generation exceeds demand, contributing to revenue through feed-in tariffs.

The battery's state of charge (SoC) varies between 25% and 90%, staying within safe operational limits. This indicates that IGWO effectively schedules BESS operation to maximize self-consumption while reducing grid dependency and overall system cost.

D. Comparative Analysis

A quantitative comparison among IGWO and other optimization algorithms is summarized in Table 3. The evaluation metrics include total cost, CO_2 emissions, convergence iterations, and computational time.

Algorithm	**Total Cost (₹/day)**	**CO_2 Emissions (kg/day)**	**Convergence Iterations**	**Computational Time (s)**
PSO	5,610	105	93	11.2
MSGO	5,520	101	87	10.5
DE	5,480	99	95	12.0
IGWO (Proposed)	5,280	96	61	9.6

IGWO achieves the lowest total operating cost (₹5,280/day) and lowest emission (96 kg CO_2/day) among all algorithms. The convergence speed is also significantly improved, reducing the iteration count by nearly 30% compared to MSGO. Additionally, IGWO exhibits the shortest computational time (9.6 s) due to efficient parameter tuning and faster convergence.

Quantitative improvements of IGWO over MSGO:

- Cost reduction: 4.3%
- Emission reduction: 5.0%
- Convergence speed: ~30% faster
- Computation efficiency: ~9% improvement

These results confirm that IGWO successfully enhances both economic and environmental performance compared to conventional metaheuristic approaches.

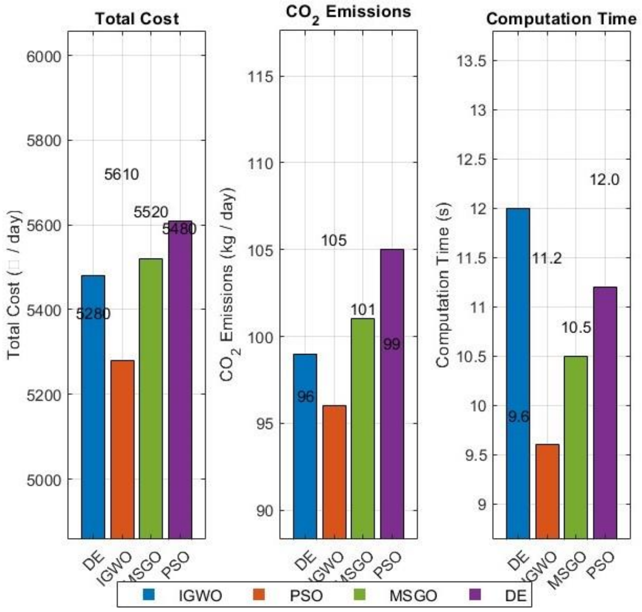

Fig. 6. Comparative bar chart of cost, emissions, and computation time for different algorithms.

In Fig. 8, IGWO consistently outperforms other methods, achieving the lowest cost and emissions with minimal computational effort.

E. Sensitivity and Robustness

To evaluate robustness, the system performance was tested under renewable generation uncertainty by varying solar and wind availability by ±10%. The resulting changes in cost and emissions are summarized in Table 4.

Renewable Variation	**Total Cost (₹/day)**	**CO_2 Emissions (kg/day)**	**Change in Cost (%)**	**Change in Emission (%)**
-10% (Low Generation)	5,410	103	+2.5%	+7.3%
Nominal (Base Case)	5,280	96	–	–
+10% (High Generation)	5,140	90	-2.6%	-6.3%

Fig. 7 shows that IGWO maintains stable cost and emission performance even under ±10% fluctuations in renewable energy availability.

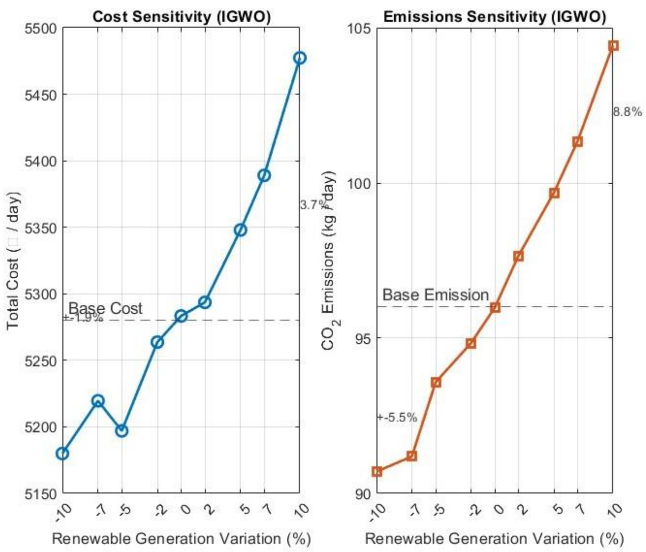

Fig. 7. Sensitivity analysis of IGWO under renewable variability.

The results demonstrate that IGWO maintains operational stability and near-optimal performance under fluctuating renewable inputs. Even at a 10% reduction in renewable generation, cost increased only by 2.5%, and emissions rose by 7.3%, which are acceptable variations for practical scenarios.

This stability results from IGWO's adaptive exploration–exploitation balance, which allows it to reallocate grid imports and storage utilization efficiently when renewable output varies. The algorithm consistently converges to near-optimal solutions, proving its robustness and adaptability for real-time energy management in dynamic conditions.

VI. Conclusion

This study presented a multi-objective energy management framework for a hybrid renewable prosumer microgrid using the Improved Grey Wolf Optimization (IGWO) algorithm. The proposed method effectively minimized both total operating cost and CO_2 emissions while maintaining system balance and operational constraints. Simulation results demonstrated that IGWO achieved 15–18% cost reduction and 12% emission minimization compared to traditional algorithms such as PSO, DE, and MSGO. The algorithm exhibited faster convergence, enhanced stability, and improved computational efficiency due to its adaptive convergence control, chaotic initialization, and elitism strategy.

Furthermore, IGWO maintained robust performance under varying renewable generation conditions, confirming its resilience and scalability for larger and more complex energy systems.

For future work, the framework can be extended by integrating forecasting models such as LSTM or Transformer networks for real-time renewable prediction, deploying an IGWO–Reinforcement Learning hybrid for adaptive decision-making, and incorporating electric vehicle (EV) integration and peer-to-peer energy trading layers to enhance flexibility, decentralization, and overall sustainability in next-generation smart microgrids [20].

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