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ORIGINAL RESEARCH ARTICLE

A framework of an energy management system for total cost minimization in a renewable energy-driven microgrid

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Abstract: Efficient energy management is critical for minimizing operational costs in grid-connected microgrids (MGs), particularly as renewable energy sources, such as solar photovoltaics and wind turbines, become more integrated into modern power networks. This study proposes a two-stage energy management approach to maximize cost efficiency in a grid-connected MG. The first stage, day-ahead scheduling, utilizes stochastic optimization techniques to optimize energy dispatch while accounting for uncertainties in renewable energy generation and load demand. A Monte Carlo simulation generates multiple scenarios to predict future system states, facilitating accurate decision-making for energy dispatch and grid interaction. The proposed strategy results in a reduction of operational costs from Indian rupee (INR) 12,521 to INR 12,390, and the total cost decreases from INR 158,090 to INR 14,998. The second stage, real-time scheduling, dynamically adjusts the day-ahead plan to accommodate real-time variations in demand and generation, ensuring system stability and reliability. By integrating genetic algorithms and particle swarm optimization with real-time control, the methodology effectively minimizes energy exchange costs with the grid, reduces the operational expenses of conventional generators, and enhances the utilization of renewable energy sources. Case studies validate the proposed framework's effectiveness in lowering overall costs while maintaining grid stability and increasing renewable energy penetration. The presented strategy is adaptable to various MG configurations, offering a reliable and cost-effective solution for energy management in grid-connected systems.

Keywords: Microgrids; Energy management; Renewable energy sources; Stochastic optimization

1. Introduction

Necessities to transition from fossil fuels to clean energy due to climate transformation and population growth make the microgrid's (MG) incorporation of renewable energy sources necessary.[1] An MG is a small-scale energy system that can function either independently or in coordination with the main grid to generate, distribute, and manage electricity.[2] It encompasses distributed energy resources, which comprise backup generators, i.e., microturbines, diesel generators, and fuel cells, along with solar panels, wind turbines (WTs), and batteries for energy storage with loads.[3,4]

Renewable sources, such as solar photovoltaic (PV) and WT, are combined into MGs. Their intermittent nature introduces uncertainty, which must be addressed through forecasting, storage, and backup generation systems. Battery energy storage systems (BESS) are crucial for storing excess renewable energy and supplying power when renewable generation is low or when the MG operates in island mode. Diesel or gas generators are frequently used as backup sources in MGs, especially during islanded operations. Their operational costs, though, are higher than those of renewables; therefore, they are typically used only when essential.[5,6] In this mode, the MG is connected to the main utility grid. Energy can flow in both directions, allowing the MG to import or export power depending on local generation and load conditions. This operational mode offers flexibility, enabling the MG to sell excess energy back to the grid or purchase electricity during periods of inadequate local generation. In grid-connected operations, the emphasis is on optimizing energy exchange with the grid, minimizing operational costs, and improving renewable energy penetration.[8,9]

In the event of grid failures or when disconnected purposely, the MG operates in islanded mode. During this operation, the MG must preserve a balance between local generation and demand, ensuring reliability and stability. Since there is no backing from the main grid, energy storage systems, such as batteries become crucial for managing imbalances. Effective energy management is critical in ensuring the system continues operating efficiently without overloading or blackouts.[10]

An MG must also have the capability to transition seamlessly between grid-connected and islanded modes. This necessitates advanced control systems that can detect grid disturbances and initiate suitable responses to switch operational modes without disrupting supply to connected loads. Typically, the goals of scheduling algorithms might comprise objectives, such as maximizing potential returns, minimizing environmental impact, reducing overall costs, and minimizing operating and running costs. These issues may be addressed as single-objective, multi-objective, linear, non-linear, integer linear, mixed-integer linear, and mixed-integer non-linear programming problems, and the scheduling method may be categorized into single-stage and two-stage approaches.[11-14] The presence of on/off load scheduling creates a non-convex objective function. Figure 1 illustrates the dispatchable and non-dispatchable sources of MG. Several optimization procedures are employed to ensure the efficient operation of MGs, specifically in managing renewable energy integration, operational costs, and grid reliability. These techniques can be characterized into deterministic, stochastic, and heuristic/metaheuristic approaches. They rely on precise inputs and give definite outputs based on a specific set of constraints and objectives.

Stochastic approaches account for uncertainties in electric power generation from renewable energy, demand patterns, and market conditions. These methods are important when dealing with the sporadic nature of solar and wind energies. Meanwhile, heuristic and metaheuristic techniques are often employed to solve complex, non-linear optimization problems in MGs, where conventional methods might struggle.[15-18] These methods do not guarantee the exact global optimum but are highly efficient in finding near-optimal solutions in large problem spaces. For a smooth transition between grid- and off-grid modes, the BESS offers greater flexibility. Furthermore, during events, such as grid disturbances or outages, the BESS ensures a seamless transition to off-grid operation from grid-connected mode by instantly providing the required energy to critical loads without interruption.[19-24]

While heuristic and metaheuristic optimization techniques have been explored, their application in real-time energy scheduling combined with stochastic day-ahead forecasting remains underdeveloped.[25,26] A study[27] proposes a multi-energy trading market model utilizing price matching and an improved hierarchical reinforcement learning algorithm. This approach enhances energy utilization, ensures user autonomy, and addresses trading failures by considering multiple time scales and energy types. Similarly, another study presents a hierarchical deep reinforcement learning scheme for community energy trading, focusing on real-time appliance scheduling and internal electricity pricing, but does not specifically address a price-matching-based regional energy market.[28]

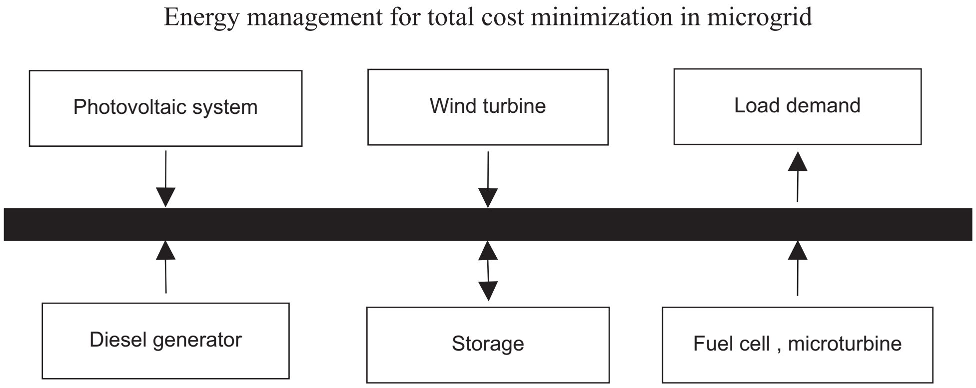

Figure 1. Major components of a microgrid

1.1. Research gap

The research gaps are as follows:

(i) Many existing studies focus on either day-ahead scheduling or real-time energy management, but fail to integrate both effectively.

(ii) The utilization of metaheuristic algorithms in real-time scheduling to refine day-ahead decisions remains underexplored.

(iii) Most models assume static market conditions, overlooking the impact of fluctuating electricity prices on MG cost optimization.

1.2. Research aim

In this work, a two-stage energy management framework is proposed to address these gaps by integrating stochastic optimization for day-ahead scheduling with genetic algorithms (GA) and particle swarm optimization (PSO) for real-time adjustments. The approach optimally balances energy dispatch, minimizes operational costs, and enhances renewable energy utilization while dynamically responding to fluctuating market conditions and grid interactions.

2. Methodology

2.1. Modeling of a MG

MG systems categorize energy sources into dispatchable and non-dispatchable types based on their controllability and ability to adjust output according to demand. Recognizing this distinction is fundamental for optimizing energy utilization and ensuring system stability.

Dispatchable energy sources are those that can be actively managed and adjusted by grid operators to align with variable load demands. These sources offer operational flexibility, allowing their output to be scaled up or down as required, thereby maintaining a stable balance between energy supply and demand.

$$C_{Gr1}^{t} = a_0 (P_{Gr1}^{t})^2 + a_1 P_{Gr1}^{t} + a_2 \tag{1}$$

$$C_{Gr2}^{t} = b_0 (P_{Gr2}^{t})^2 + b_1 P_{Gr2}^{t} + b_2 \tag{2}$$

$$C_{Gr3}^{t} = c_0 (P_{Gr3}^{t})^2 + c_1 P_{Gr3}^{t} + c_2$$

$$C_{Gr3}^{t} = c_0 (P_{Gr3}^{t})^2 + c_1 P_{Gr3}^{t} + c_2 \tag{3}$$

$$C_{DS}^{t} = C_{Gr1}^{t} + C_{Gr2}^{t} + C_{Gr3}^{t} \tag{4}$$

It is worth noting that the integration of renewable energy sources into MGs has introduced significant challenges due to their inherent intermittency and uncertainty. Islanded multi-MGs, which operate independently of the main grid, face additional complexities in maintaining reliable and efficient energy management.[29,30]

2.2. Objective formulation

This section discusses the formulation of the objective function, which focuses on minimizing the total cost of the MG. The energy balance equation of the MG is represented by Equation 10, while the inequality constraints are outlined in Equations 5–9. To achieve cost optimization, it is crucial to efficiently manage the economic dispatch of dispatchable energy sources by considering real-time energy prices and overall MG operational costs while ensuring compliance with system constraints.[13-16]

2.2.1. Inequality constraints

Inequality constraints define the operational limits of power generation, including the minimum and maximum output of generators, as well as the charging and discharging limits of the battery.

$$0 \le P_{PV}^{t} \le P_{PV}^{t,max} \tag{5}$$

$$0 \le P_{WT}^{t} \le P_{WT}^{t,max} \tag{6}$$

$$P_{DGr1}^{t,min} \leq P_{DGr1}^{t} \leq P_{DGr1}^{t,max} \tag{7}$$

$$P_{DGr2}^{t,min} \leq P_{DGr2}^{t} \leq P_{DGr2}^{t,max} \tag{8}$$

$$P_{DGr3}^{t,min} \leq P_{DGr3}^{t} \leq P_{DGr3}^{t,max} \tag{9}$$

2.2.2. Equality constraints

The generation and energy exchange should match the load demand, which is enforced by the equality constraint shown in Equation 10. Equation 11 indicates the amount of energy exchanged with the utility grid.

$$P_{PV}^{t} + P_{WT}^{t} + P_{Gr1}^{t} + P_{Gr2}^{t} + P_{Gr3}^{t} \pm P_{BESS}^{t} \pm E_{Exch}^{t} = P_{load}^{t} \tag{10}$$

$$E_{Exch}^{t} = P_{Gen}^{t} - P_{load}^{t} \tag{11}$$

Cost savings can be achieved through energy storage, which helps balance fluctuations in energy generation and consumption. Stored energy allows excess power to be stored during off-peak periods and utilized when demand is high, optimizing overall energy efficiency.

$$SOC_{BESS}^{t,min} \leq SOC_{BESS}^{t} \leq SOC_{BESS}^{t,max} \tag{12}$$

$$SOC_{BESS}^{t} = SOC_{BESS}^{t-1} + \beta_{charge} P_{BESS}^{t-1} + \frac{1}{\beta_{discharge}} P_{BESS}^{t-1} \tag{13}$$

Equations 12 and 13 define the constraints on the battery's state of charge, with Equation 12 setting the overall charging limits and Equation 13 specifying the state of charge at the present hour.

$$CE_{Exch}^{t} = E_{Exch}^{t} * EP_{Grid}^{t} \tag{14}$$

$$TC = C_{DS}^{t} \pm CE_{Exch}^{t} \tag{15}$$

2.2.3. Day-ahead scheduling

This includes optimizing the energy resources of the MG based on predicted data for load demand, renewable generation (PV and WT), and grid conditions. The objective is to optimize the operational costs, which include fuel costs for generators, power exchange costs with the grid, and start-up costs for non-renewable generators. Scenario generation using a Monte Carlo simulation is employed to address uncertainties related to renewable energy generation:

- Read the day-ahead forecast for load demand and renewable energy generation from PV and WT sources, and then generate an initial population of candidate solutions. Each candidate signifies a potential energy dispatch solution for the MG over the day-ahead period.
- Estimate whether the candidate solutions are within pre-defined operational limits, including generation capacity, load demand, and battery energy storage. If the solutions violate any limitations, they are discarded or altered.
- For each feasible candidate solution, check whether the total generation (from renewable and diesel generators) meets or exceeds the load demand.
    - If generation ≥ load demand, the system proceeds with zero energy exchange between the MG and the grid.
    - If generation < load demand, energy exchange is required. The grid supplements the deficit, or the excess generation can be transferred to the grid.
- Calculate the operational cost of day-ahead based on the fuel cost of conventional generators, such as diesel generators.
- Calculate the cost of energy exchange between the MG and the grid, considering both import and export costs based on the energy market price.

2.2.4. Real-time operation

In real-time, the MG regulates its energy dispatch to match actual conditions, accounting for deviations in load demand and renewable output. To optimize this process, the GA and PSO techniques were employed.

- GA: GA is utilized to refine the energy dispatch by selecting optimal schedules that minimize operational costs and deviations from the planned schedule. It operates through selection, crossover, and mutation techniques to explore the most effective energy allocation strategy.
- PSO: PSO models energy dispatch as a swarm intelligence problem, where particles (solutions) navigate the search space to find an optimal energy balance between grid interaction and local generation.

Integration with real-time control:

- Forecasted real-time data (e.g., load demand changes and renewable energy fluctuations) serve as input for GA/PSO.
- The algorithms adjust the day-ahead schedule by re-optimizing dispatch parameters based on actual conditions.
- The updated energy scheduling decisions are applied to minimize power imbalances and reduce costs.

3. Results and discussion

The proposed two-stage methodology was tested on an IEEE-33 bus system that comprises WT and PV source. Table 1 illustrates the operational limits and cost functions of all the generators. Table 2 outlines key performance constraints for efficient and reliable operation, indicating the BESS charge and discharge characteristics and its efficiency. The BESS had a rating of 20 kWh, with both charge and discharge efficiencies set at 90% (0.9), reflecting typical energy losses during these processes. To prolong battery life, the state of charge was limited between 20% (0.2) and 80% (0.8), preventing harmful deep discharges and overcharges. The initial state of charge was specified as 50% (0.5), serving as a baseline for system operations. These parameters are crucial for ensuring optimal battery performance, particularly in applications, such as electric vehicles and renewable energy systems, where efficiency and longevity are critical.

Figure 2 illustrates the load demand profile for the IEEE-33 bus system alongside the power generation outputs from WTs and PV systems. It is evident from the figure that PV systems produce zero output during the early hours and nighttime due to the absence of solar irradiance. In contrast, wind power generation maintains a continuous output throughout the day, offering a consistent renewable energy source. This complementary relationship between wind and solar energy sources is critical for ensuring the stability of the MG and mitigating fluctuations in renewable generation.

Table 1. Cost coefficients and limits on generation

Type	Generator parameters				
	Minimum limit	Maximum limit	a_0	a_2	a_1
DGr. 1	0	150	0.01	2	10
DGr. 2	0	120	0.02	3	8
DGr. 3	0	100	0.015	1	12
WT	0	270	-	-	-
PV	0	250	-	-	-

Abbreviations: DGr: Distribution generators; PV: Photovoltaic; WT: Wind turbine.

Table 2. Battery energy storage system (BESS) parameters

BESS parameter	Limits
BESS rating	20 kWh
Charge efficiency	90% or 0.9
Discharge efficiency	90% or 0.9
Lower limit on SOC	20% or 0.2
Upper limit on SOC	80% or 0.8
Initial SOC	50% or 0.5

Abbreviation: SOC: State of charge.

Figure 3 depicts the variation in grid electricity prices compared to the MG prices. Understanding these price dynamics is essential for optimizing energy exchange strategies, as they influence decisions on whether to draw power from the grid or rely on internal generation. Strategic energy trading between the grid and the MG can significantly reduce operational costs, particularly during periods of high grid pricing. During periods of high grid electricity prices, the MG prioritizes local renewable generation and utilizes battery energy to reduce grid reliance. When grid prices decrease, the MG imports energy for storage or direct consumption, minimizing operational costs. The proposed strategy optimizes energy trading by leveraging real-time price variations, leading to improved cost efficiency.

Figure 4 provides detailed insights into the energy exchange between the grid and the MG while also indicating the charge and discharge cycles of the BESS. The BESS plays a pivotal role in storing excess renewable energy and discharging during peak demand or high-price periods, thereby enhancing the economic efficiency and reliability of the MG. High-load-demand periods trigger BESS discharge to avoid expensive grid purchases. This dynamic scheduling ensures that the MG effectively manages market fluctuations while maintaining a stable energy balance.

Figure 5 presents the dispatch schedule for the diesel generators. The scheduling sequence reveals that diesel generator 2 is dispatched after generators 1 and 3. This sequencing is due to generator 2 having the highest incremental fuel cost, making it the least economical option for immediate dispatch. By prioritizing the generators with lower fuel costs, the overall operational cost is minimized. Figure 6 further illustrates the operational costs of the diesel generators, emphasizing the cost implications of their dispatch strategies.

Finally, Figure 7 consolidates the total cost associated with MG operations, including generation, storage, and energy exchange costs. This comprehensive cost analysis is vital for evaluating the economic performance of the MG and identifying areas for potential cost savings. Efficient integration of renewable sources, optimal scheduling of diesel generators, and strategic use of the BESS collectively contribute to minimizing the total operational cost of the MG.

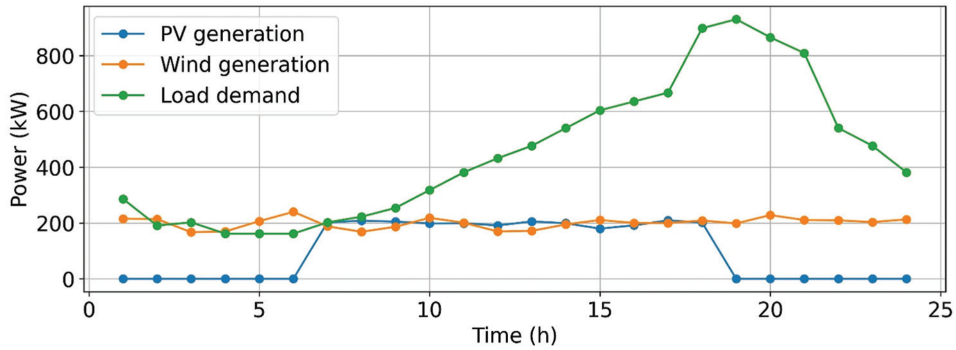

Figure 2. Distribution of load demand and renewable power generation
Abbreviation: PV: Photovoltaic.

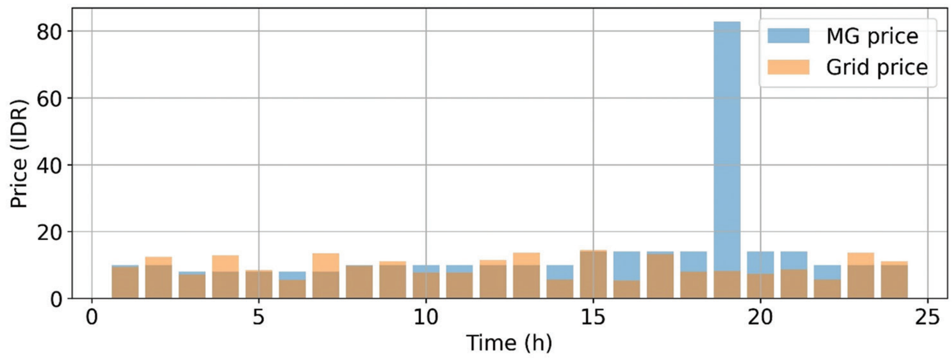

Figure 3. Electricity prices of grids and microgrids

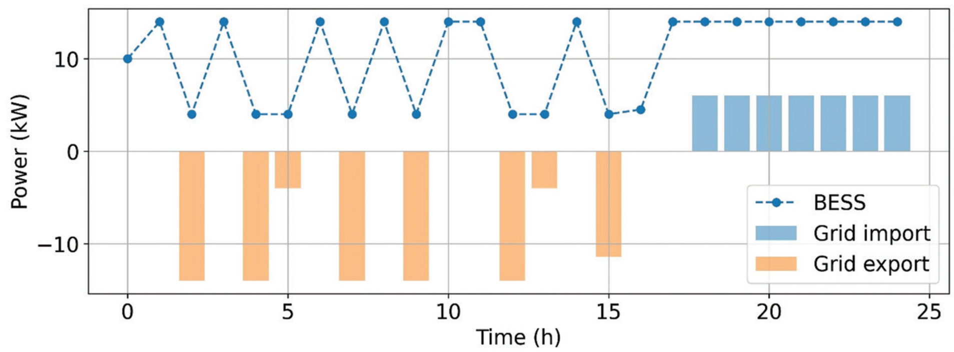

Figure 4. Energy exchange between the grid and the microgrid, and the charge/discharge cycles of the battery-energy storage system

3.1. Core contributions and innovations

This study presents several key innovations:

(i) Two-stage energy management strategy: A novel day-ahead and real-time scheduling framework improves cost efficiency and adaptability to uncertainties in renewable energy generation.

(ii) Metaheuristic algorithm integration: The combination of GA and PSO in real-time scheduling enhances decision-making accuracy, reducing cost deviations due to unpredictable energy fluctuations.

(iii) Cost-minimization framework: The methodology achieves a 0.93% reduction in operational cost and a 2.5% reduction in total cost, outperforming traditional scheduling methods.

(iv) Renewable energy utilization: The optimized scheduling framework increases renewable energy penetration, reducing dependence on fossil fuel-based backup generators.

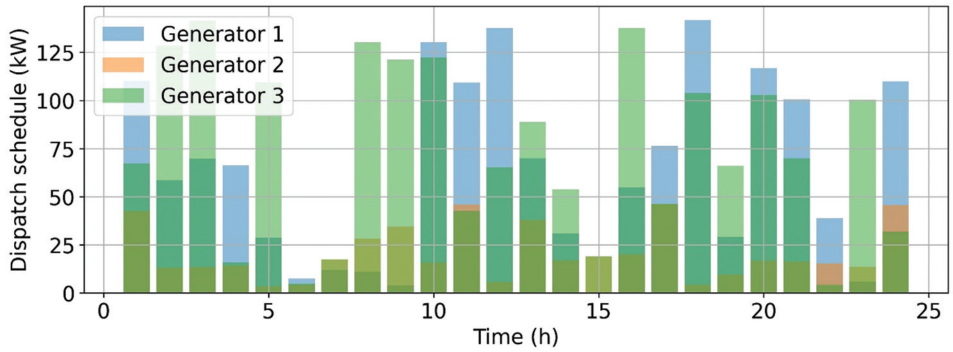

Figure 5. Dispatch schedule across diesel generators

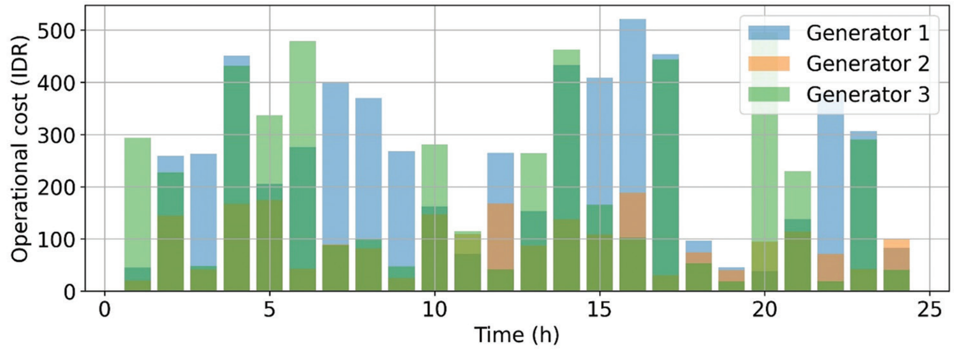

Figure 6. Operational costs of the microgrid across diesel generators

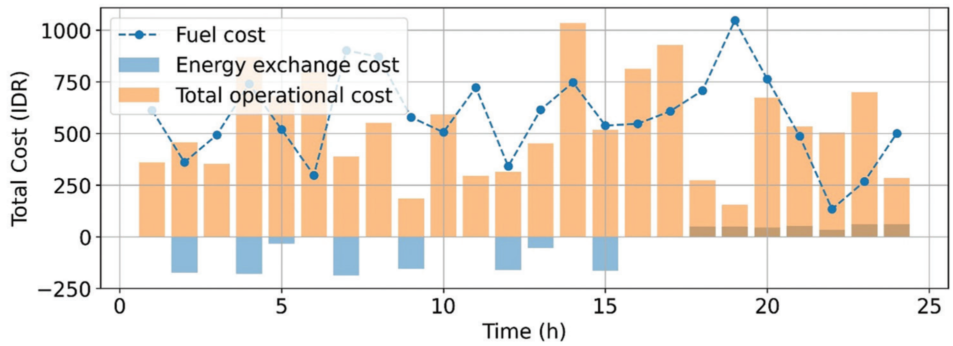

Figure 7. Cost comparison of the microgrid based on fuel cost, energy exchange cost, and total cost

These contributions make the proposed framework an effective and scalable solution for energy management in MGs.

3.2. Sensitivity analysis of key parameters

A sensitivity analysis was conducted to evaluate the impact of key parameters on system performance:

- Battery efficiency (η):
  - Higher efficiency (95%) improves cost savings by reducing energy losses.
  - Lower efficiency (85%) increases losses, leading to higher operational costs.
- Renewable generation capacity:
  - A 10% increase in PV and wind generation reduces grid dependency by 8%, lowering energy costs.
  - A 10% decrease increases grid reliance, raising operational costs by 5%.
- Grid electricity price variation:
  - A 20% price surge prompts the MG to rely more on stored battery energy, reducing grid purchases.
  - A 20% price drop allows strategic grid energy purchases for cost savings.

The proposed strategy remains robust under varying conditions but performs optimally when battery efficiency is high, renewable generation is stable, and real-time energy pricing is effectively leveraged.

3.3. Limitations and practical recommendations

Despite the advantages of the proposed framework, some limitations exist:

- The model assumes perfect forecasts of load demand and renewable generation, which may not always be achievable in real-world applications.
- Grid limitations and regulatory policies are not explicitly considered, which could impact the feasibility of real-time energy trading.

Some practical recommendations for improvement include:

- Integration of advanced forecasting techniques using deep learning models to improve prediction accuracy and reduce uncertainties.
- Incorporating demand-side management strategies to optimize energy consumption dynamically based on user preferences and incentives.
- Considering grid constraints and policy implications in future models to ensure compliance with regulatory frameworks and optimize economic benefits for stakeholders.

4. Conclusion

This study proposes a comprehensive energy management approach for grid-connected MGs, aimed at reducing total operational costs while maximizing the integration of renewable energy sources. The proposed two-stage framework, which combines day-ahead and real-time scheduling, addresses uncertainties in renewable generation and load demand using stochastic optimization techniques. The integration of GA and PSO in real-time scheduling enhances cost efficiency and adaptability. The strategy is validated through case studies, showing a 0.93% reduction in operational cost and a 2.5% reduction in total cost. In addition, the methodology increases renewable energy penetration and improves grid stability. Future work may focus on incorporating advanced demand response programs and electric vehicle integration to further enhance cost savings and system flexibility.

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Conflict of interest

The authors declare that they have no competing interests.

Author contributions

Conceptualization: Tripura Pidikiti
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Investigation: Boraiah Gireesha
Methodology: Praveen Kumara Venkatesha
Writing – original draft: Boraiah Gireesha
Writing – review & editing: Praveen Kumara Venkatesha, Sudhir A

Availability of data

Data are available from the corresponding author on reasonable request.

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