TWO STAGE ENERGY MANAGEMENT FOR MAXIMIZING RENEWABLE ENERGY PENETRATION

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For environmentally friendly and sustainable power generation, it is essential to maximize the penetration of renewable energy in energy management systems. In order to maximize the integration of renewable energy sources into the grid, this article suggests a two-stage energy management strategy. The methodology combines day-ahead and real-time energy management using stochastic optimization techniques to efficiently utilize renewable energy sources while maintaining grid stability and dependability. The goal of the first stage, or day-ahead, is to minimize operational costs. To this end, a framework for scenario generation, such as Monte Carlo simulation, is used to generate multiple scenarios that consider the uncertainties related to the generation of renewable energy, demand patterns, and external factors. These scenarios facilitate an in-depth assessment of the integration of renewable energy sources by representing a variety of potential future states of the energy system. The efficiency of the proposed methodology is demonstrated through case studies. The total cost in rupees using the proposed technique has recorded 12800, while the Gradient descent optimization as 12950 and 13032 using Golden jackal optimization.

Highlights:

1. In this work, a two-stage energy management strategy designed to enhance the integration of renewable energy sources in both microgrid (MG) and grid-connected systems.
2. Addressed the uncertainties in photovoltaic (PV) and wind power generation.
3. A cost-effective framework was proposed to minimize the total cost of the microgrid under the influence of uncertain sources.

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Acronyms/Nomenclature:

MG	: Microgrid
RES	: Renewable energy sources
PV	: Photovoltaic
GJO	: Golden jackal optimization
BESS	: Battery energy storage system
SOC	: State of charge
DG	: Distribution generation
WT	: Wind turbine
FC_{Gr1}^{t}	: Fuel cost of generator-1
FC_{Gr2}^{t}	: Fuel cost of generator-1
a_0, a_1 and a_2	: Cost coefficients
Pr_{Gr1}^{t}	: Power generated by generator-1
Pr_{PV}^{t}	: Output power output from PV
Pr_{WT}^{t}	: Output power output from wind turbine system
Pr_{Gen}^{t}	: demand for generation power at time 't'
Pr_{load}^{t}	: load demand at time 't'
C_{DS}^{t}	C_{DS}^{t} operational cost of the dispatchable sources

1 Introduction

The world is increasingly concerned about climate change because of increased greenhouse gas emissions [1]. The significance of environmental concerns has led to a greater emphasis on the integration of renewable energy sources (RES's) into microgrids (MG's) [2]. The MG's are local energy systems that can operate independently or in conjunction with the main power grid. They characteristically consist of various energy resources like renewable sources (solar, wind), conventional generators (diesel, gas), and energy storage systems (e.g., batteries) [3]. Their primary aim is to deliver reliable and efficient energy to local loads while integrating renewable energy sources [4]. MG's can function in three main operational modes: grid-connected, isolated (off-grid), and hybrid modes [5]. Effective energy management within these modes is critical to ensure reliable, cost-effective, and sustainable energy delivery [6]. Grid-connected MG's need to manage energy flows to minimize costs, maintain grid stability, and handle contingencies such as voltage/frequency fluctuations or power quality issues [7]. Ensuring reliability is crucial in isolated mode, as there is no external grid to fall back on [8]. Effective management of energy storage, load demand, and dispatchable resources is important [9]. Energy storage systems play a crucial role in balancing supply and demand, especially during periods when renewable sources are unavailable [10]. When renewable generation (such as from solar panels or wind turbines) exceeds the immediate demand within the MG, storage systems can act as energy storage units [11]. This avoids curtailment of renewable energy and helps to store energy that can be used later for grid stabilization [12]. Smooth transitions between grid-connected and isolated modes are essential to avoid disturbances [13]. This necessitates advanced control and synchronization mechanisms to preserve grid stability, voltage, and frequency regulation during mode switching [14]. MG's can participate in wholesale electricity markets by selling surplus energy or providing ancillary services (such as frequency regulation or voltage control) [15]. Optimizing operational costs enables MG's to strategically interact with the market, maximizing revenue from energy sales and minimizing costs from energy purchases [16]. For MG's, especially those that involve significant investments in infrastructure like renewable energy systems, storage, and control systems, optimizing operational costs is essential for ensuring a reasonable ROI. Lesser operational costs lead to quicker payback periods and augmented long-term savings, justifying initial capital investments [17]. MG's, characterized by their ability to function both isolation and in conjunction with the main grid, offer a promising solution to improve the energy efficiency, reliability, and sustainability [18]. RES's offers a cleaner, more sustainable substitute to conventional fossil fuels; nevertheless, its incorporation into the grid introduces complexities due to its inherent unpredictability and uncertainty [19]-[22].

The unpredictable nature of renewable energy generation, coupled with changing demand patterns, requires advanced energy management approaches to safeguard grid stability, cost-effectiveness, and reliability. Efficient management of these uncertainties that are associated with renewable energy generation, fluctuating demand patterns, and external factors is vital for maximizing the penetration of RES's in the grid. Without adequate planning and real-time adjustments, the advantages of renewable energy integration may be undermined by operational inefficiencies, increased costs, and potential grid instability [22]-[24]. In this framework, maximizing the deployment of renewable energy in energy management systems is pivotal for promoting sustainable and environmentally friendly power generation [25]. To achieve this, it is essential to develop optimization techniques that effectively manage the uncertainties associated with renewable energy while maintaining a stable and reliable energy supply [26]. Energy management systems (EMS) in MG's rely on real-time data and optimization algorithms to safeguard reliable and cost-efficient operations. This comprises forecasting demand, predicting renewable generation, and altering the operation of dispatchable sources and storage systems in real time [27]-[28].

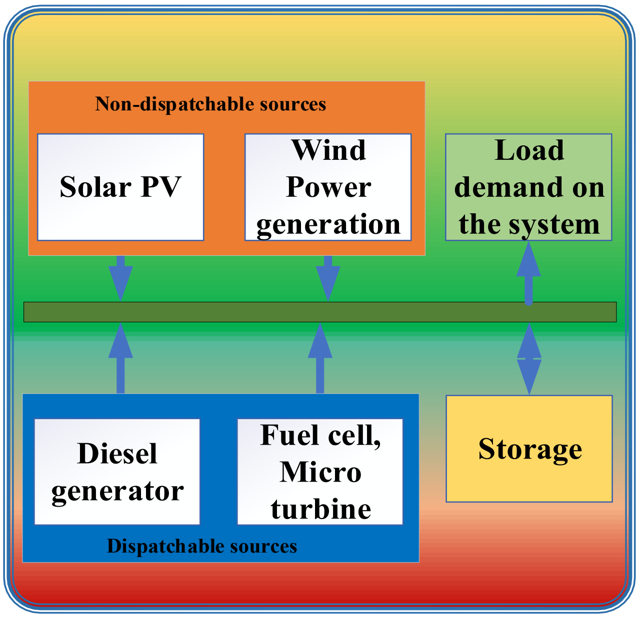

Figure 1. Components of Microgrid.

Linear and non-linear programming solves unit commitment and economic dispatch problems, whereas stochastic programming considers the uncertainties in RES generation and load demand [29]. Meta-Heuristic Algorithms also can solve both linear, non-linear and the problems with uncertainty which includes particle swarm optimization, genetic algorithm, and improved golden jackal optimization for handling complex, non-linear problems [30]. Energy management in a MG is a complex problem demanding the incorporation of advanced technologies and strategies. The shift towards renewable energy, combined with the rise of smart technologies, offers openings to improve sustainability and resilience [31]. Nevertheless, challenges such as uncertainties, cybersecurity, and regulatory issues must be addressed to fully realize the potential of microgrids in modern energy systems [32]. Two-stage energy management in a MG is a robust method that divides operational results into day-ahead scheduling and real-time alterations. The day-ahead stage emphases on optimizing generation schedules, load allocations, and market participation based on forecasts of renewable generation, load demand, and electricity prices. However, the real-time stage adapts these decisions to actual conditions, addressing deviations caused by forecasting errors, unforeseen events, or system disturbances [33]. This method improves cost efficiency and reliability by safeguarding proactive planning while upholding flexibility to handle uncertainties [34]. The amalgamation of optimization techniques and predictive analytics in both stages significantly improves resource utilization and ensures the microgrid operates within technical and economic constraints. This paper proposes a two-stage energy management strategy designed to enhance the integration of renewable energy sources in both MG and grid-connected systems. The first stage, or day-ahead energy management, aims to minimalize operational costs by leveraging stochastic optimization techniques. To account for uncertainties related to renewable energy generation, demand, and external factors, scenario generation methods such as Monte Carlo simulation are employed. This allows for a comprehensive evaluation of potential future states, enabling more informed decision-making. The second stage focuses on real-time energy management, where the system adjusts dynamically to unforeseen deviations in generation and demand, ensuring the stability of the grid. By combining day-ahead planning with real-time adjustments, the proposed strategy enhances the utilization of renewable energy sources while maintaining the balance between supply and demand. The efficiency of the proposed methodology is demonstrated through case studies, which highlight its ability to increase renewable energy penetration, reduce operational costs, and maintain system reliability. This two-stage approach offers a robust framework for integrating renewable energy into modern energy systems, contributing to a more sustainable and resilient energy future.

2 Modelling of Microgrid

In MG systems, energy sources are typically classified into dispatchable or controllable and non-dispatchable or uncontrollable categories based on their capacity to be controlled and adjusted to meet demand. Understanding this distinction is crucial for improving energy management and preserving grid stability.

2.1 Dispatch energy sources

Dispatchable energy sources can be controlled and regulated by grid operators to meet load demand. These sources are flexible, meaning they can increase or decrease their output as needed, allowing for a reliable balance between supply and demand. In the following equations (1)- (4), FC_{Gr1}^{t}, FC_{Gr2}^{t} and, FC_{Gr3}^{t} are the fuel cost of generator-1, 2 and 3, respectively. The a_0, a_1 and a_2 indicates the cost coefficients. Pr_{Gr1}^{t}, Pr_{Gr2}^{t} and Pr_{Gr3}^{t} are the power generated by generator-1, 2 and 3.

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

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

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

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

2.2 Non-dispatch energy sources

Non-dispatchable or uncontrollable energy sources generate power based on environmental conditions, which cannot be controlled by grid operators. Their output is erratic and dependent on issues like weather, making them less dependable for constant energy supply. PV solar panels convert sunlight into electricity and are classified as a non-dispatchable energy source. The output of solar PV systems is determined by solar irradiance, which fluctuates based on time of day, weather conditions, and geographical location. Wind turbines produce electricity by harnessing wind energy, making them another non-dispatchable source. Like solar PV, wind energy production is subject to environmental conditions in specific wind speed and direction. Wind power can be extremely variable, dependent on local wind patterns, seasonal changes, and weather conditions.

3 Problem Formulation

This section discusses the objective function in which the objective is to optimize the total cost of the MG. Eq. (10) indicates the energy balance equation of the MG and Eq. (5-9) represents inequality constraint of the MG. It is necessary to optimize the economic dispatch of dispatchable generators by comparing real-time energy prices and MG operational cost by satisfying the constraints.

3.1 Non-dispatch energy sources

The limits on the power generation i.e., minimum and maximum power outputs and battery charge and discharge limits are limited by inequality constraints. Pr_{PV}^{t}, Pr_{WT}^{t} are the output power output from PV and wind at time 't' respectively.

$$0 \leq Pr_{PV}^{t} \leq Pr_{PV}^{t,max} \tag{5}$$

$$0 \leq Pr_{WT}^{t} \leq Pr_{WT}^{t,max} \tag{6}$$

$$Pr_{Gr1}^{t,min} \leq Pr_{Gr1}^{t} \leq Pr_{Gr1}^{t,max} \tag{7}$$

$$Pr_{Gr2}^{t,min} \leq Pr_{Gr2}^{t} \leq Pr_{Gr2}^{t,max} \tag{8}$$

$$Pr_{Gr3}^{t,min} \leq Pr_{Gr3}^{t} \leq Pr_{Gr3}^{t,max} \tag{9}$$

3.2 Equality constraints

The generation and energy exchange should match the load demand which is governed by equality constraint.

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

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

C_{DS}^{t} indicates the operational cost of the dispatchable sources and Pr_{Gr1}^{t} is the power generation from generator-1, a_0, a_1 and a_2 indicates the cost coefficients of generator 1. Pr_{Gen}^{t}, Pr_{load}^{t} indicates the generation and load demand at time 't' respectively. Eq. (11) indicates the amount of energy exchange with the utility grid. Cost savings can be attained by storing energy, which assists in smoothing out variations in energy generation and utilization. Energy storage is used to store extra energy during off-peak hours and release it during peak usage. A battery energy storage system (BESS) can charge when electricity prices are small or when there is a surplus of renewable energy, such as during the day when solar generation is more. This is particularly important in grid-connected MG's, where energy can be stored at off-peak times to be used during peak periods.

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

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

Eq. (12) and Eq. (13) indicate the limits on state of charge of the battery and state of charge in the current hour respectively.

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

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

By enhancing renewable energy integration, BESS reduce the microgrid's reliance on fossil-fuel-based power generation. This leads to long-term environmental benefits, reduced emissions, and compliance with regulations for clean energy and sustainability targets. The BESS enables microgrids to smoothly transition between grid-connected and islanded modes. In the event of a grid disturbance or outage, BESS can ensure a seamless transition to islanded operation by immediately supplying the required energy to critical loads without disruption. BESS also plays a key role in maintaining voltage levels within the microgrid, especially in systems that integrate a significant amount of distributed generation (DG). By injecting or absorbing reactive power, BESS can help stabilize voltage fluctuations and support voltage control strategies within the microgrid.

4 Proposed Methodology

This section describes about the proposed two-stage scheduling methodology for energy management that combines day-ahead and real-time scheduling to optimize the operation of a MG and ensure efficient integration of renewable energy sources such as PV and wind turbine (WT) power. A flow chart of two-stage scheduling methodology is shown in Figure 2.

4.1 Day-Ahead Scheduling

- The process starts by introducing the day-ahead scheduling phase.
- Read the load demand, day-ahead power generation from PV and WT. The system first reads the forecasted load demand for the next day and the predictable generation from PV and WT sources. These forecasts form the foundation for day-ahead energy planning.
- Generate a preliminary population of candidate solutions. A set of candidates scheduling solutions is generated, typically using the proposed algorithm.
- Each candidate solution is plaid to ensure it follows to the system's operational limits, such as generation capacities, load requirements, and grid constraints.
- Is power generation equal to load demand?

Yes: If power generation from PV, WT, and diesel generator the load demand, there is no need for energy exchange with the grid, and the system proceeds with zero energy exchange.

No: If there is a mismatch between power generation and load demand, energy will flow between the grid and the MG, either through imports (if demand exceeds generation) or exports (if generation exceeds demand).

- The day-ahead operational cost is calculated based on the cost of operating the local energy sources, mainly fuel-based generators, plus or minus the cost of energy exchange with the grid. The energy exchange cost can vary dependent on grid pricing or market conditions.

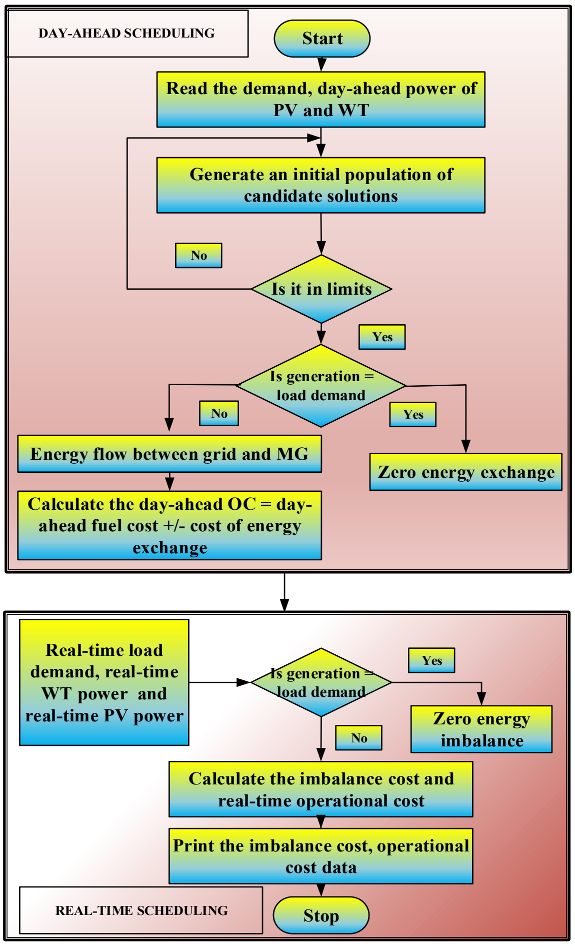

Figure 2. Proposed methodology of two-stage scheduling.

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4.3 Real-time scheduling

- Read real-time load demand, real-time WT and PV power: After the day-ahead schedule is set, the system transfers to the real-time stage. The actual load demand and real-time generation from WT and PV are monitored. These values may fluctuate from the day-ahead forecasts due to variations in weather conditions and unforeseen changes in demand.
- Real-time values are yet again checked to safeguard that they endure within the operational limits.
- Is power generation equal to load demand?

Yes: If real-time power generation matches real-time load, no imbalance occurs, and the system maintains zero energy imbalance.
No: If there is an imbalance power, real-time adjustments must be made, including energy exchange with the grid (either import or export).

- Any deviation from the day-ahead plan results in an imbalance cost. This cost is calculated based on real-time energy prices and the difference between planned and actual energy usage.
- Additionally, the real-time operational cost reflects the cost of operating local generators to meet the updated demand.
- Print imbalance cost and operational cost data: The system outputs the results of the real-time calculations, including both the imbalance cost and the final operational cost.
- End of the Process
- The process concludes once the real-time operational and imbalance costs are calculated, and the energy management system has safeguarded that the balance between generation and load is achieved at minimal cost while observing system constraints.

5 Results and discussion

In this section, the impact of the proposed methodology on total cost minimization was assessed by using two case studies namely, IEEE- 33 bus system and IEEE- 18 bus system. The detailed results of both the test systems are presented in the subsequent sections.

5.1 Case study 1

The test system comprises of IEEE-33 bus system with 3 diesel generators, one PV and one WT. The maximum peak load on the system is 830.3 kW and the minimum load demand on the system is 144.4 kW. The day ahead load demand, generation and energy exchange with grid is shown in Figure 3.

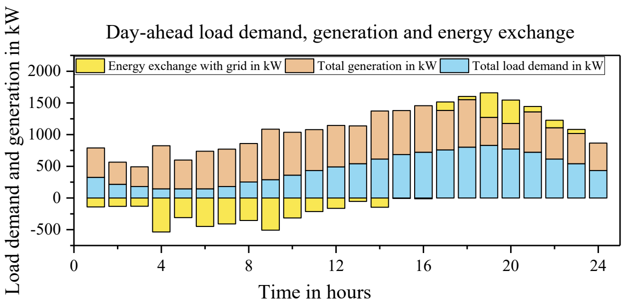

Figure 3. Day ahead load demand, generation and energy exchange with grid.

Figure 4 shows the power generation of two RES's i.e., PV and WT over a 24-hour period. PV power remains constant during night-time (hours 0-5, 18-24), while fluctuating during daylight hours. The WT power shows consistent variability throughout the day, contributing meaningfully to the overall renewable energy output. BESS are crucial for enhancing the performance, reliability, and sustainability of MG's. From load shifting and renewable energy integration to frequency regulation and backup power, the BESS delivers a wide range of functions that improve both grid-connected and islanded MG operations. By enhancing energy dispatch, improving power quality, and enabling participation in energy markets, the BESS contributes significantly to the overall efficiency and cost-effectiveness of MG's, paving the way for a more resilient and cleaner energy future. Figure 5 indicates the dispatch schedule of the diesel generators. From the Figure 5, it is clear that the power generation from generator 3 is less when compared with the other set of generators. Since, the incremental fuel cost of this generator is the highest. Figure 6 represents the total operational cost after application of DR over a 24-hour period.

The operational cost reflects the cost related to running generation units and managing internal power systems within MG. The energy exchange cost shows the cost related to importing or exporting power from/to the grid, which is influenced by market conditions, grid tariffs, and energy demand. Figure 7 indicates the total cost of the MG. Figure 8 indicates the real-time load demand and energy exchange with the grid. Figure 9 indicates the power generation from the PV and wind. During the initial hours (0-5 hours), the total cost is negative, indicating a period of net savings or profit, probably due to power being exported to the grid. This scenario is replicated by negative operational and energy exchange costs. The MG might be generating excess renewable energy, which is sold back to the grid, principal to a reduction in costs. Between hours 5 and 15, the operational cost remains comparatively stable, while the energy exchange cost oscillates as shown in Figure 10. This period might reflect a balance between grid imports and internal power generation, with limited cost disparity. After hour 15, both the operational cost and energy exchange cost rise suggestively, peaking around hour 20 as represented in Figure 11. This growth could be due to higher energy demand, reduced availability of renewable energy, or reliance on more expensive energy imports from the grid. The varying costs suggest that the demand response mechanism has been implemented to minimize operational costs during peak demand periods. The demand response shifts load to lower-cost periods, reflected in the stable cost periods around hours 10-15. However, during certain periods, especially post-hour 15, the demand response strategy might be less effective due to higher grid dependency or reduced renewable generation, leading to higher operational and energy exchange costs. The overall trend demonstrates that integrating demand response mechanisms can effectively reduce costs during specific time periods (0-10 hours) is shown in Figure 12. However, the system faces challenges in maintaining low costs when renewable energy is scarce, and grid dependency increases during peak hours (15-23 hours). The obtained results suggest a well-balanced energy management strategy for a significant portion of the day, though potential improvements could be made to further reduce costs during high-demand periods, possibly by improving storage systems or enhancing the responsiveness to real-time market prices.

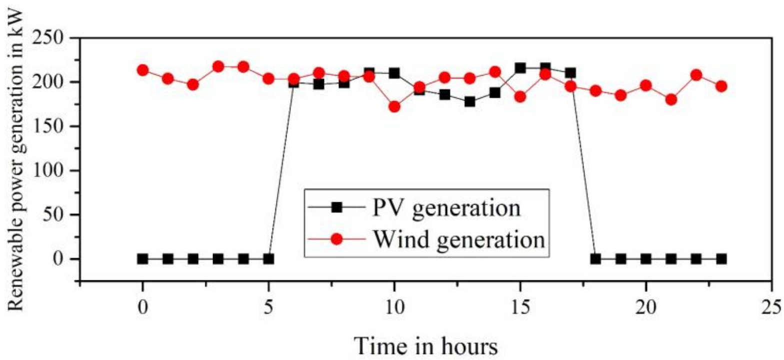

Figure 4. Power generation from PV and wind generator in the day ahead.

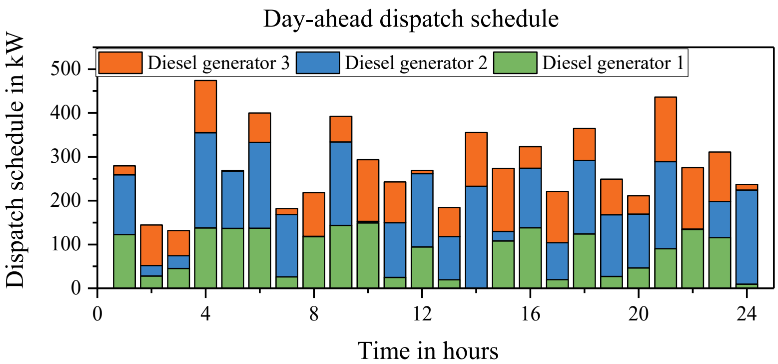

Figure 5. Day ahead dispatch schedule of diesel generators.

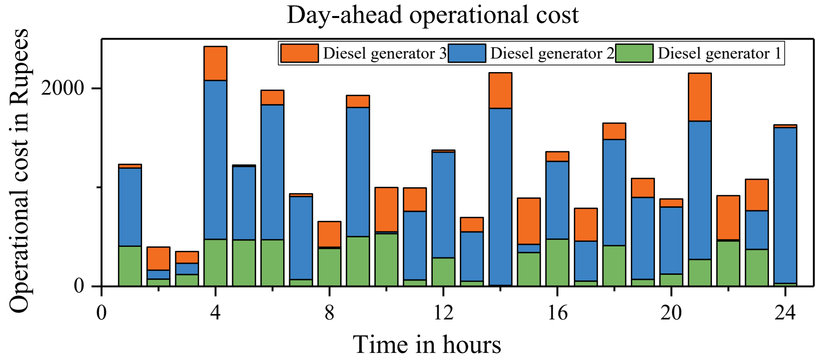

Figure 6. Day ahead fuel cost of diesel generators.

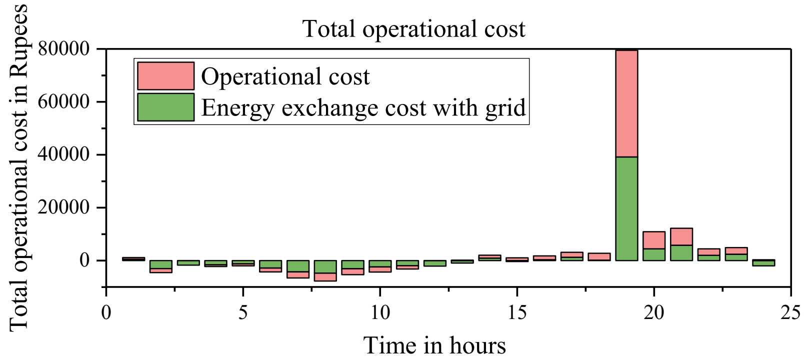

Figure 7. Cost cost of MG.

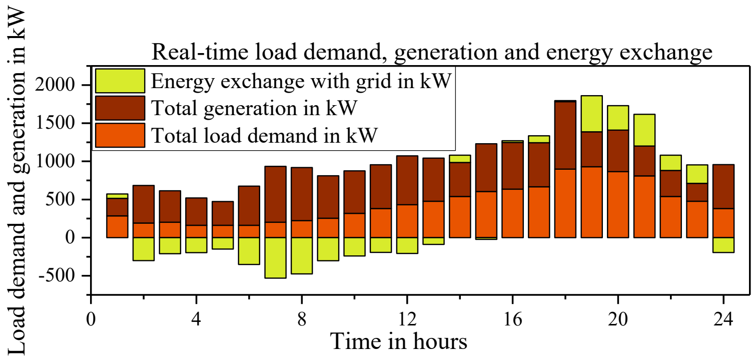

Figure 8. Real-time load demand, generation and energy exchange with grid.

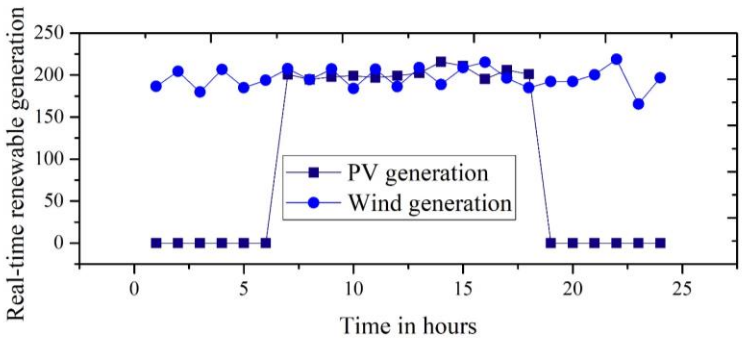

Figure 9. Power generation from PV and wind generator in real-time.

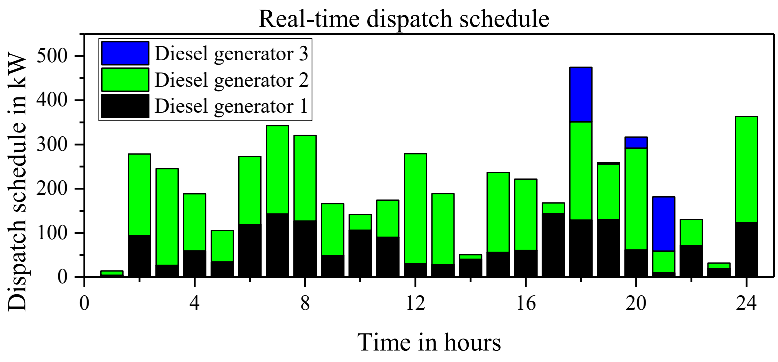

Figure 10. Real-time dispatch schedule of diesel generators.

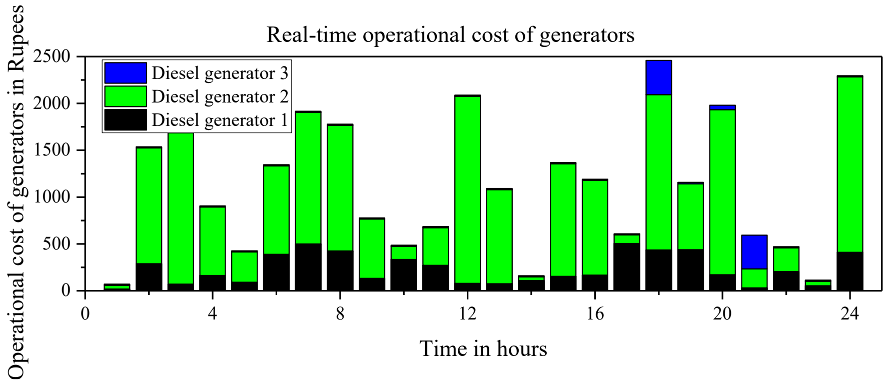

Figure 11. Real-time operational cost of diesel generators.

5.2 Case study 2

Detailed evaluation of various optimization methods has been presented in this section. In this case, an IEEE-18 bus system was considered for studying the impact of proposed methodology on TOC of the MG. The methodology's focus on cost minimization in the day-ahead stage is an important aspect, as it could make renewable integration more economically feasible for grid operators. Figure 12 indicates the load demand profile of the IEEE-18 bus system. It is clear from the Figure 12, the load demand is having its peak at scheduling hours 19 and 20. The performance of the two-stage energy management methodology in large, complex grid setups versus smaller MG systems differs suggestively due to the scale, interdependencies, and uncertainty levels inherent in each scenario. In smaller MG's, the methodology is compatible as it handles limited numbers of distributed generators, storage systems, and loads, with fewer constraints and simpler energy trading scenarios. Real-time adjustments are less computational, and day-ahead forecasting models can be more precise due to localized weather and demand patterns. This frequently leads to optimized cost management and reliable operation. In large, complex grid setups, the method must deal with a higher number of interrelated components, diverse renewable sources, fluctuating load types, and complicated operational constraints such as transmission losses, congestion, and regulatory necessities. The increased dimensionality of the optimization problem can lead to computational challenges, and the precision of forecasts may be condensed due to combined uncertainties over larger geographic areas. stochastic or scenario-based approaches for price uncertainties. This adaptability safeguards the model remains robust and valid under evolving regulatory and market conditions.

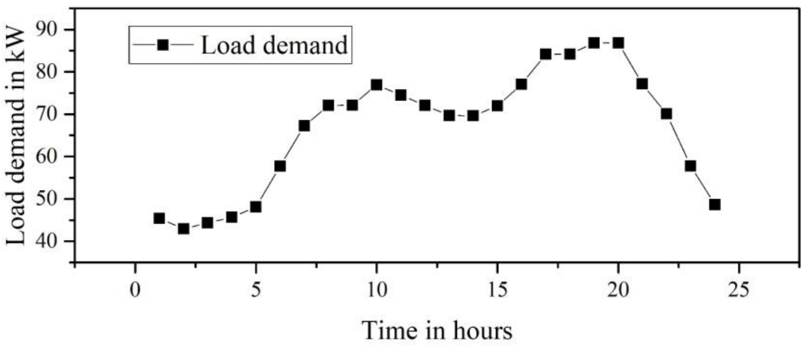

Figure 12. Load profile of the IEEE- 18 bus system.

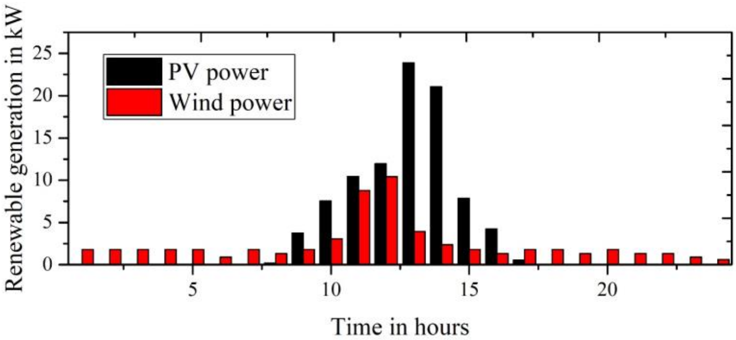

Figure 13. Renewable power generation of the system.

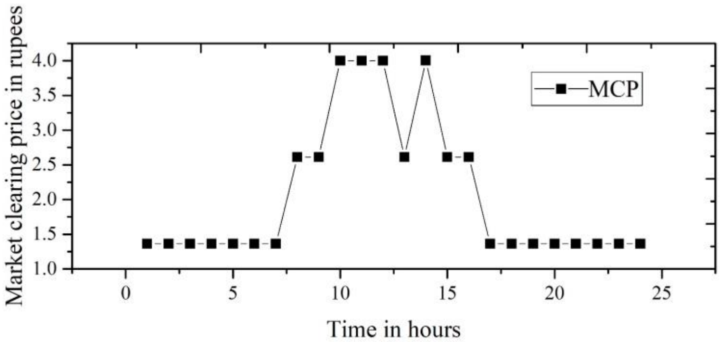

Figure 14. Market clearing price of the system.

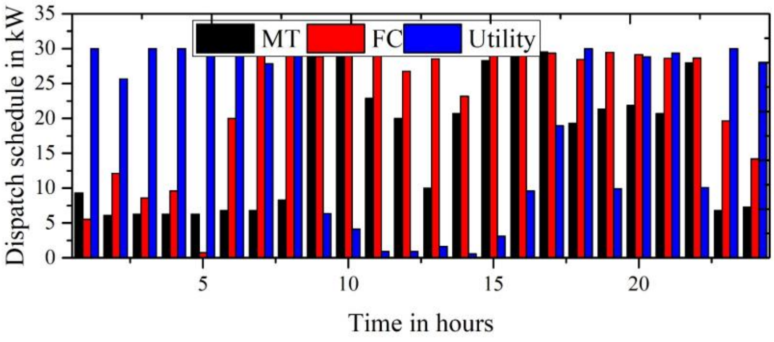

Figure 15. Dispatch schedule of the proposed methodology.

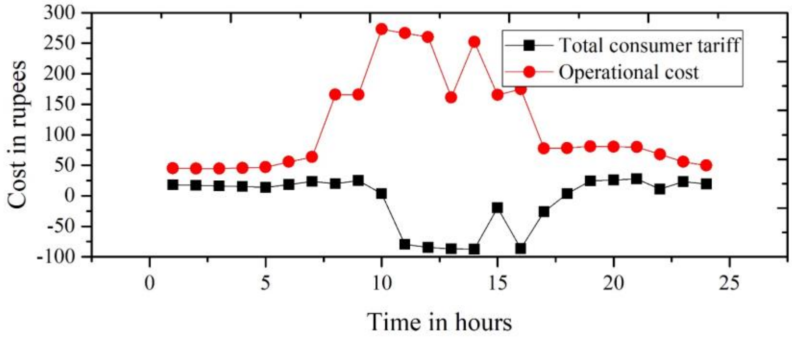

Figure 16. Cost comparison of the MG.

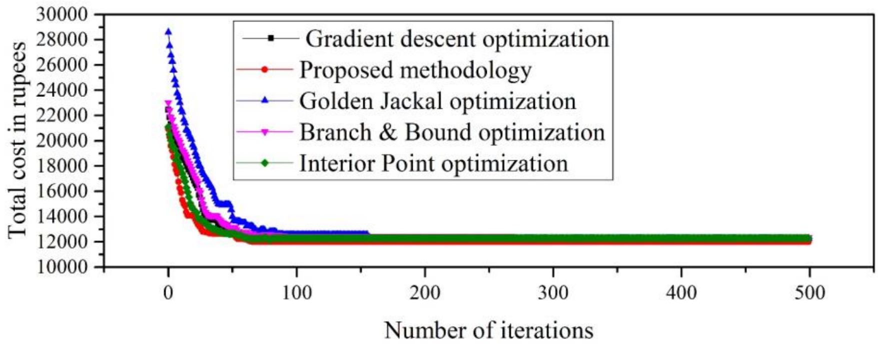

Figure 17. Cost comparison with the other optimization techniques.

Figure 14 indicates the market clearing price of the system for the load demand shown. Figure 15 indicates the dispatch schedule of the controllable sources. Figure 16 indicates the operational cost comparison and energy exchange with the grid during 24-hour scheduling phase. Figure 17 indicates the cost comparison of the proposed methodology with the other optimization techniques. From the Figure 17 it is clear that the proposed two-stage methodology outperforms when compared to gradient descent, branch and bound, interior point optimization and golden jackal optimization. The model's sensitivity to the number of scenarios is a crucial factor in attaining accurate results while handling computational complexity. Increasing the number of scenarios enhances the illustration of uncertainties in renewable energy generation and demand patterns, which improves the robustness of the decision-making process. However, it also intensifies the computational burden. The optimal number of scenarios depends on the trade-off between computational efficiency and the desired accuracy. In general, scenario reduction methods such as K-means or principal component analysis are applied to condense the generated scenarios while preserving their diversity and statistical characteristics. The two-stage approach can be efficiently adapted for various renewable sources with different levels of predictability, such as wind and solar energy. Each source has exclusive characteristics that effect how they are modeled and managed: PV is likely over short time frames but affected by weather conditions like cloud cover. Daytime patterns make day-ahead planning more precise. Whereas, wind Turbines has highly variable and influenced by factors like wind speed, which can fluctuate significantly over short periods and necessitates real-time adjustments. The two-stage methodology can include source-specific forecast error distributions. For instance, solar forecasts may rely on irradiance models, while wind forecasts may depend on statistical or physical wind models. Scenario generation can include probabilistic distributions tailored to each energy source, allowing for a more accurate representation of uncertainties.

6 Conclusion

The integration of RES's is crucial for creating environmentally sustainable and resilient power networks. Besides, the variability and uncertainty accompanying with renewables, such as solar and wind, necessitate sophisticated energy management strategies. In this paper, the authors presented a two-stage energy management approach that effectively addresses these challenges by merging day-ahead and real-time optimization techniques. In the day-ahead stage, stochastic optimization employing scenario generation, such as Monte Carlo simulations, captures the uncertainties in renewable energy generation and demand, enabling cost-effective scheduling. The real-time stage safeguards grid stability by dynamically adjusting to unforeseen deviations between forecasted and actual conditions, maintaining the balance between supply and demand. The proposed strategy boosts renewable energy penetration while minimizing operational costs and guaranteeing system reliability. Through case studies, such as IEEE-33 and IEEE-18 bus systems, the effectiveness of this approach is demonstrated. The total cost using the proposed technique has condensed to 12800 rupees from 12950 by gradient descent and 13032 using GJO.

Future Scope:

The present study can be extended to a scenario where the inclusion of electric vehicles and micro-DC loads through battery packs is an add-on.

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