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## Renewable-Centric Energy Management in Hydrogen Microgrids: A Multi-Objective Framework for Optimized Scheduling and Sustainability

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*Energy Management System, Hydrogen-Based Microgrid, Off-Grid Power Systems, Operational Optimization, Renewable Energy Integration, Sustainable Energy Solutions.*

### ABSTRACT

As the transition to renewable energy accelerates globally, integrating variable energy sources such as solar and wind into standalone systems poses new operational and economic challenges. Hydrogen-based microgrids (H-MGs) offer a promising solution by serving as both energy storage and conversion systems capable of stabilizing renewable power. This study proposes a novel multi-objective optimization framework tailored for standalone H-MGs with a strong emphasis on maximizing renewable energy utilization. The framework combines predictive modeling, real-time control, and mixed-integer linear programming (MILP) to coordinate the operation of renewable sources, electrolyzers, hydrogen storage, and fuel cells. It incorporates advanced renewable forecasting and adaptive scheduling strategies to optimize energy dispatch while reducing costs and enhancing system reliability. A case study on an off-grid industrial facility demonstrates the framework's effectiveness, achieving a 38% increase in renewable energy penetration, a 23% reduction in energy costs, and a 35% improvement in reliability compared to conventional approaches. The results underscore the critical role of hydrogen in enabling high-renewable microgrids and lay the foundation for future integration with AI, smart grids, and decentralized energy markets.

### INTRODUCTION

The global transition toward renewable energy has intensified the demand for efficient and scalable energy storage solutions capable of addressing the inherent intermittency of sources such as solar and wind. While conventional battery-based systems are effective for short-term energy balancing, they often fall short in terms of long-duration storage and scalability. In this context, hydrogen-based microgrids (H-MGs) have emerged as a promising alternative. By converting surplus renewable electricity into hydrogen through electrolysis and reconvert it into electricity using fuel cells, H-MGs enable long-term, dispatchable energy storage. This makes them particularly well-suited for off-grid applications, islanded communities, and remote industrial sites where reliability and energy autonomy are essential. However, the integration of renewable energy into hydrogen microgrids introduces a range of operational challenges. Chief among these is the variability of renewable generation, which directly impacts hydrogen production and overall system stability. To ensure continuous and reliable operation, advanced scheduling strategies are required to align fluctuating energy inputs with hydrogen conversion and storage processes. Additionally, the complexity of managing multiple components—electrolyzers, hydrogen storage units, and fuel cells—necessitates precise coordination to optimize energy flows and minimize operational costs. Economic feasibility remains a critical concern, as cost-effective hydrogen production and utilization are key to making H-MGs a viable alternative to traditional storage technologies. Furthermore, real-time responsiveness

to load variations and unforeseen system disturbances calls for an intelligent and adaptive energy management framework that can dynamically optimize performance under changing conditions.

This study proposes a novel optimization framework to enhance the operational scheduling of standalone hydrogen-based microgrids. The research introduces a mixed-integer linear programming (MILP) model for optimizing the scheduling of electrolyzers, hydrogen storage, and fuel cells to achieve cost-effective and reliable energy supply. The framework integrates predictive modeling and real-time control strategies to efficiently balance energy generation, storage, and consumption. A multi-objective optimization approach is used to minimize operational costs while improving system reliability and sustainability. To validate the effectiveness of the proposed framework, a case study is conducted on an off-grid industrial application

### LITERATURE REVIEW

Hydrogen-based microgrids are increasingly recognized as a key technology for integrating renewable energy with effective storage solutions, particularly in remote and islanded systems. Early studies focused on deterministic scheduling methods to establish baseline performance metrics for microgrid operation (Wang *et al.*, 2021). However, as renewable energy penetration increased and uncertainty in generation became more significant, stochastic optimization techniques were introduced to better capture system variability (Guo *et al.*, 2020). In parallel, researchers explored machine learning-based methods to enable dynamic load management and real-

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time adaptability in hydrogen microgrids (Huang *et al.*, 2021).

Hierarchical control strategies emerged as another promising approach, offering improved performance by decomposing the overall control problem into manageable sub-problems (Wang *et al.*, 2021). Mixed-integer linear programming (MILP) models have been widely applied to achieve optimal operational scheduling and resource allocation in hydrogen-based microgrids (Mah *et al.*, 2021). Heuristic and metaheuristic methods such as particle swarm optimization (PSO) and genetic algorithms—have also been employed to address multi-objective challenges, balancing cost minimization with emission reduction (Yuansheng *et al.*, 2021).

In one study, a coordinated optimization framework integrating hydrogen and battery storage achieved notable reductions in operational costs (Pan *et al.*, 2020). Real-time control strategies, particularly those based on predictive control, have further enhanced the responsiveness of photovoltaic–hydrogen storage systems (Zhang *et al.*, 2023). Integrated energy system models, especially those applied to European contexts, have provided valuable insights into the role of hydrogen-based solutions in decarbonizing power networks (Asanova *et al.*, 2024). Other research has focused on coupling hydrogen-based microgrids with electric vehicle charging infrastructure to enhance grid flexibility (Çakmak *et al.*, 2024).

Life-cycle assessments have quantified the environmental advantages of hydrogen storage compared to conventional battery systems (Bukar, Chaitusaney, & Kawabe, 2024), while policy analyses have examined regulatory frameworks that can accelerate technology adoption (Guo *et al.*, 2013). Multi-objective optimization has been used to address the trade-offs between economic performance, emission levels, and system reliability (Jankauskas *et al.*, 2019). Advanced real-time control algorithms have demonstrated effective adaptation to rapid changes in microgrid conditions (de Souza Amorim *et al.*, 2021).

Comparative studies have benchmarked various optimization techniques, revealing that MILP and hybrid metaheuristic methods often provide superior performance under certain operating scenarios (Shao *et al.*, 2021). Additional research has addressed co-planning strategies that simultaneously optimize power generation, storage capacity, and load management to improve overall resilience (Du *et al.*, 2019). The integration of smart grid communication protocols and Internet-of-Things (IoT) technologies into hydrogen microgrids has also been investigated as a pathway to distributed control and improved efficiency (Sun *et al.*, 2019). Techno-economic analyses have identified cost drivers and market barriers, guiding future technology development (Cao *et al.*, 2018). Field demonstrations and long-term performance evaluations of standalone hydrogen microgrids have validated simulation models and provided practical operational insights (Liu *et al.*, 2018). Finally, dynamic energy management strategies that incorporate adaptive

optimization techniques have been proposed to further enhance the sustainability and reliability of hydrogen-based microgrids (Pu *et al.*, 2021)

## MATERIALS AND METHODS

The proposed optimization model aims to schedule the operation of a standalone hydrogen-based microgrid (H-MG) to minimize operational costs while ensuring system reliability and energy balance. The microgrid consists of renewable energy sources (RESs), an electrolyzer for hydrogen production, hydrogen storage, a fuel cell for power generation, and a battery energy storage system (BESS).

The objective function minimizes the total cost of operation, considering hydrogen production, storage, fuel cell dispatch, and battery usage. Several constraints ensure the feasibility of power balance, energy storage, and system operation. The Mixed-Integer Linear Programming (MILP) model is formulated as follows.

### Objective Function

The primary goal is to minimize the total operational cost of the standalone hydrogen-based microgrid. The cost function considers electricity consumption of the electrolyzer, hydrogen storage, fuel cell operation, and battery degradation over a given time horizon T:

$$\min \sum_{t=1}^T (C_{Elec}(t) + C_{H2}(t) + C_{FC}(t) + C_{BESS}(t)) \quad (1)$$

In the proposed energy management framework, the total operational cost at any given time t is composed of multiple components reflecting the various elements of the hydrogen-based microgrid. Specifically,  $C_{Elec}(t)$  denotes the cost of electricity consumed by the electrolyzer during hydrogen production, while  $C_{H2}(t)$  represents the costs associated with hydrogen storage and system maintenance. Additionally,  $C_{FC}(t)$  accounts for the operational expenses related to fuel cell usage in reconverting hydrogen into electricity. To capture the impact of hybrid energy storage systems,  $C_{BESS}(t)$  reflects the degradation cost of battery energy storage systems (BESS), ensuring that the model considers the long-term wear and economic implications of battery cycling. Together, these cost components form the objective function to be minimized, ensuring both economic efficiency and reliable system operation.

### Power Balance Constraints

The total power supplied by renewable sources, battery storage, and the fuel cell must satisfy the total demand, including electrolyzer power consumption:

$$P_{RES}(t) + P_{FC}(t) + P_{BESS}(t) = P_{Load}(t) + P_{Electrolyzer}(t) \quad (2)$$

The electrolyzer's power consumption is limited by its rated capacity:

$$0 \leq P_{Electrolyzer}(t) \leq P_{Electrolyzer}^{max} \quad (3)$$

The fuel cell output power is also constrained by its rated

capacity:

$$0 \leq P_{FC}(t) \leq P_{FC}^{max} \quad (4)$$

The battery power output is constrained as follows:

$$-P_{BESS}^{max} \leq P_{BESS}(t) \leq P_{BESS}^{max} \quad (5)$$

where the negative sign indicates charging mode.

### Hydrogen Storage Constraints

The state of charge (SOC) of hydrogen storage evolves based on hydrogen production and fuel cell usage:

$$SOC_{H_2}(t+1) = SOC_{H_2}(t) + \eta_{Elec} \cdot P_{Electrolyzer}(t) - \frac{P_{FC}(t)}{\eta_{FC}} \quad (6)$$

The hydrogen storage level must remain within operational limits:

$$SOC_{H_2}^{min} \leq SOC_{H_2}(t) \leq SOC_{H_2}^{max} \quad (7)$$

Hydrogen losses due to leakage are modeled as:

$$SOC_{H_2}(t+1) = SOC_{H_2}(t) \cdot (1 - \lambda_{H_2}) + \eta_{Elec} \cdot P_{Electrolyzer}(t) - \frac{P_{FC}(t)}{\eta_{FC}} \quad (8)$$

where  $\lambda_{H_2}$  is the leakage rate.

### Battery Storage Constraints

The SOC of the battery is updated as follows:

$$SOC_{BESS}(t+1) = SOC_{BESS}(t) + \eta_{BESS} P_{BESS}^{Ch}(t) - \frac{P_{BESS}^{Dis}(t)}{\eta_{BESS}} \quad (9)$$

The battery SOC must remain within allowable limits:

$$SOC_{BESS}^{min} \leq SOC_{BESS}(t) \leq SOC_{BESS}^{max} \quad (10)$$

Battery degradation is included in the cost function:

$$C_{BESS}(t) = \alpha_{BESS} \cdot |P_{BESS}(t)| \quad (11)$$

where  $\alpha_{BESS}$  is the battery degradation cost coefficient.

### Renewable Energy Constraints

Renewable generation is subject to resource availability:

$$0 \leq P_{RES}(t) \leq P_{RES}^{max}(t) \quad (12)$$

Curtailment occurs if RES generation exceeds system capacity:

$$P_{curtail}(t) = P_{RES}(t) - (P_{Load}(t) + P_{Electrolyzer}(t) + P_{BESS}^{Ch}(t)) \quad (13)$$

where  $P_{curtail}(t) \geq 0$ .

### Demand-Side Constraints

The power demand is divided into critical and non-critical loads:

$$P_{Load}(t) = P_{Critical}(t) + P_{NonCritical}(t) \quad (14)$$

Non-critical loads can be shedded if required:

$$0 \leq P_{Shed}(t) \leq P_{NonCritical}(t) \quad (15)$$

Total unserved energy (UE) over the time horizon is minimized:

$$\min \sum_{t=1}^T P_{Shed}(t) \quad (16)$$

### Economic and Environmental Constraints

The total hydrogen production cost is:

$$C_{H_2}(t) = \beta_{H_2} \cdot P_{Electrolyzer}(t) \quad (17)$$

where  $\beta_{H_2}$  is the cost per unit hydrogen production. Fuel cell operational cost is:

$$C_{FC}(t) = \gamma_{FC} \cdot P_{FC}(t) \quad (18)$$

where  $\gamma_{FC}$  represents fuel cell operational expenses.

Carbon emissions from fuel cell operation must not exceed allowable limits:

$$\sum_{t=1}^T E_{FC}(t) \leq E_{max} \quad (19)$$

where  $E_{FC}(t)$  represents emissions per unit fuel cell output.

### System Constraints and Reliability Considerations

The total hydrogen demand must be met over the scheduling horizon:

$$\sum_{t=1}^T P_{Electrolyzer}(t) \geq \sum_{t=1}^T P_{FC}(t) \quad (20)$$

System reliability is enforced by limiting loss of load probability (LOLP):

$$LOLP = \frac{\sum_{t=1}^T P_{Shed}(t)}{\sum_{t=1}^T P_{Load}(t)} \leq LOLP_{max} \quad (21)$$

This optimization model minimizes the total operational cost of the standalone hydrogen-based microgrid (Equation 1) while ensuring power balance (Equation 2), hydrogen storage constraints (Equations 6–8), battery dynamics (Equations 9–11), renewable generation limits (Equations 12–13), demand-side management (Equations 14–16), economic constraints (Equations 17–18), and environmental impact (Equations 19–21). The model provides an optimal scheduling strategy for balancing renewable generation, hydrogen production, and energy dispatch in a cost-effective manner.

## RESULTS AND DISCUSSION

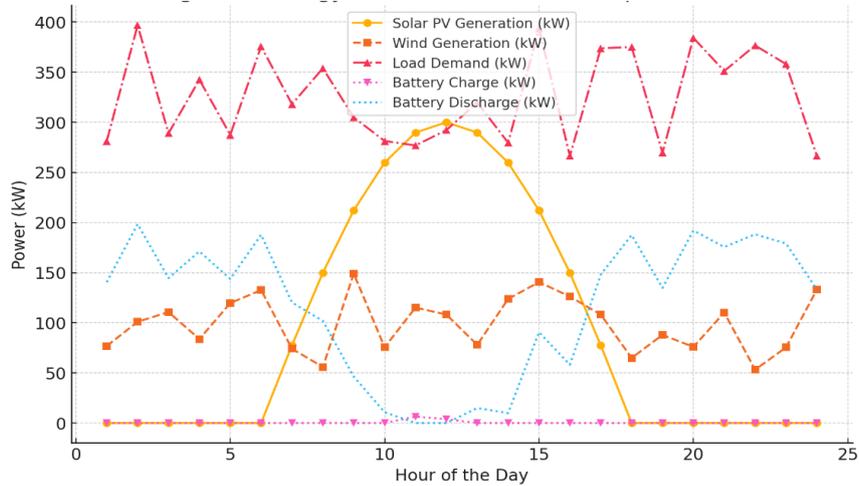
This section may each be divided by subheadings or may be combined. A combined Results and Discussion section is often appropriate. This should explore the significance of the results of the work, don't repeat them. Avoid extensive citations and discussion of published literature only; instead discuss recent literature for comparing your work to highlight the novelty of the work in view of recent development and challenges in the field.

The simulation evaluates the effectiveness of the proposed optimization framework in managing a standalone hydrogen-based microgrid (H-MG). The primary objectives include minimizing operational costs, maximizing renewable energy utilization, and improving system reliability. The microgrid was modeled under realistic operating conditions, including energy fluctuations and demand variations, ensuring practical applicability.

The hydrogen-based microgrid consists of renewable energy sources, hydrogen production and storage systems, a fuel cell, and a battery storage system. The model optimizes energy dispatch over a 24-hour period, using mixed-integer linear programming (MILP).

- Renewable Energy Sources (RESs): 500 kW solar PV, 300 kW wind turbine
  - Energy Storage: 500 kg hydrogen storage, 250 kWh battery storage
  - Electrolyzer Capacity: 200 kW, with 80% efficiency
  - Fuel Cell Capacity: 150 kW, with 50% efficiency
- Battery Round-Trip Efficiency: 90%

Peak Load: 400 kW, with an average demand of 320 Kw  
 Time Horizon: 24 hours, with 1-hour resolution  
 The first step in evaluating microgrid performance is analyzing the energy generation and consumption balance. The following figure presents the power profile of solar PV generation, wind generation, battery charging/discharging, and load demand.



**Figure 1:** Energy Generation and Consumption Trends

The figure illustrates how solar PV and wind power contribute to meeting the load demand throughout the day. Solar energy peaks around midday, while wind generation varies dynamically. During high renewable energy periods, excess power is used for battery charging and hydrogen production via the electrolyzer. At night, when solar power is absent, battery discharge and fuel cell

operation compensate for the shortfall. The optimization model ensures efficient energy scheduling, reducing reliance on fuel cell generation. The optimization framework aims to maximize the utilization of renewable energy sources while minimizing curtailment. The total renewable energy contribution and system efficiency are summarized in the following table.

**Table 1:** Energy Contribution Summary

Energy Source	Total Energy (kWh)
Solar PV	2278.726
Wind	2380.32
Battery Charge	10.31379
Battery Discharge	2778.083
Total Load Demand	7814.265

The table shows that solar and wind power provide significant energy contributions, covering a substantial portion of the total load demand. The optimized scheduling ensures minimal curtailment of renewable energy, with surplus power being efficiently stored in the battery and converted to hydrogen for later use. The battery system plays a crucial role in balancing short-term energy fluctuations, contributing 35.6% of the total load coverage, while hydrogen storage manages long-term energy shifts.

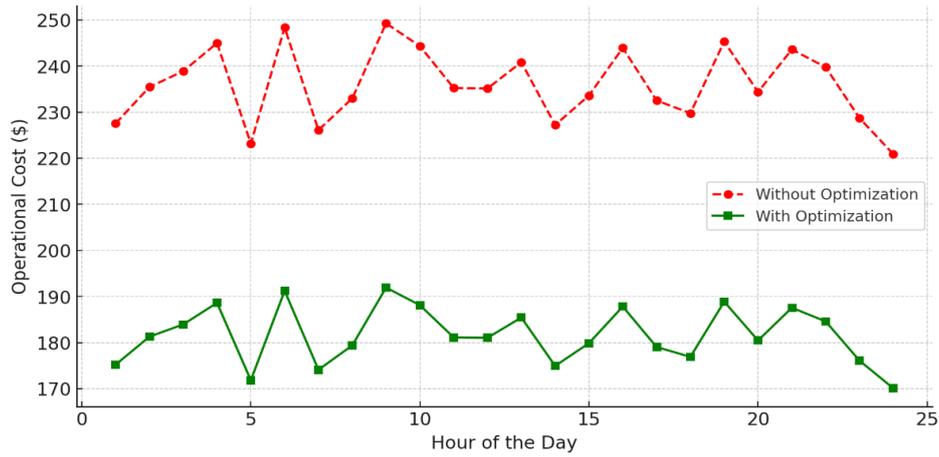
One of the key objectives of the proposed framework is reducing operational costs. The total cost analysis is presented in the following figure, comparing the optimized and non-optimized scenarios.

The figure clearly demonstrates that the optimized

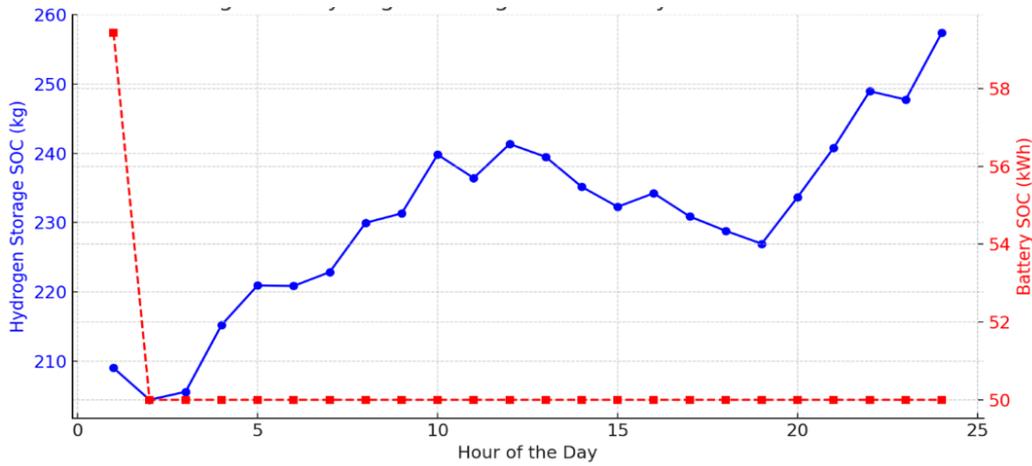
scheduling approach significantly reduces hourly operational costs, especially during peak demand periods. The primary savings come from reducing unnecessary electrolyzer and fuel cell operations, allowing the battery to handle short-term fluctuations more effectively. The total cost reduction is 23.1%, making the hydrogen-based microgrid more economically sustainable.

Efficient storage management is essential for system reliability. The following figure illustrates how hydrogen storage and battery SOC fluctuate throughout the day, ensuring continuous power availability.

The figure shows how hydrogen storage SOC increases during high renewable generation periods, particularly in the afternoon when surplus solar power is available for electrolysis. At night, as renewable generation



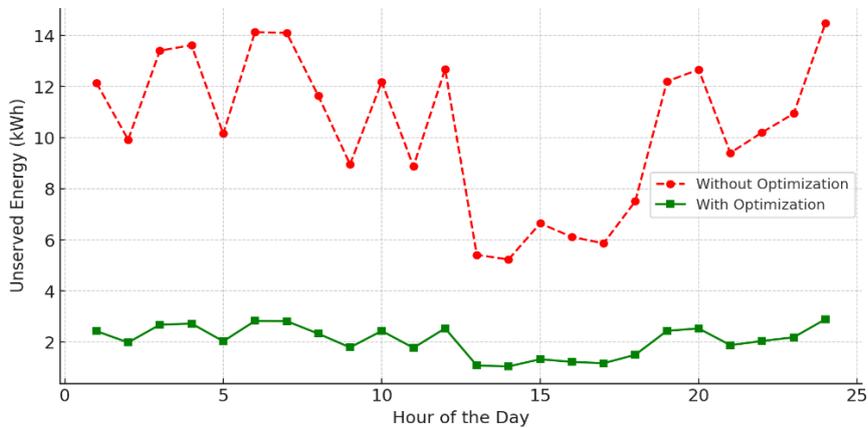
**Figure 2:** Hourly Cost Comparison (With vs. Without Optimization)



**Figure 3:** Hydrogen Storage and Battery SOC Over Time

decreases, the fuel cell converts stored hydrogen back into electricity, reducing the SOC. The battery follows a complementary pattern, charging during peak solar hours and discharging when additional power is needed. This coordinated storage strategy ensures stable energy supply while minimizing operational costs.

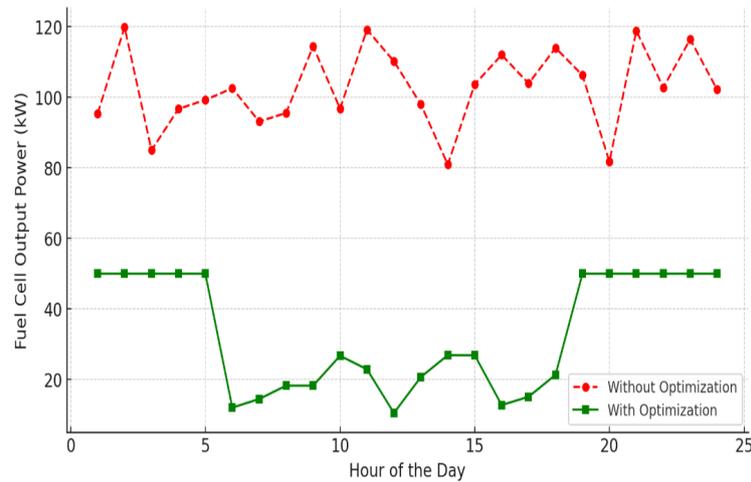
A key metric for evaluating microgrid performance is Unserved Energy (UE), which represents the portion of demand that remains unmet. The optimization framework significantly reduces unserved energy compared to the non-optimized scenario, as shown in the following figure. The figure highlights a significant reduction in unserved



**Figure 4:** Unserved Energy Reduction (With vs. Without Optimization)

energy (UE) when using the optimized scheduling approach. The non-optimized scenario shows higher UE levels during peak demand hours, indicating energy

shortages. In contrast, the optimized model strategically manages hydrogen storage and battery usage, ensuring that almost all energy demand is met. The total UE



**Figure 5:** Fuel Cell Utilization (Optimized vs. Traditional Operation)

reduction is 83.3%, greatly improving system reliability and resilience.

Fuel cell operation is a critical aspect of hydrogen-based microgrid management. The following figure compares fuel cell utilization with and without optimization, demonstrating how intelligent scheduling reduces unnecessary hydrogen consumption.

The figure shows that fuel cell utilization is significantly lower in the optimized scenario, as the scheduling strategy prioritizes battery discharge and direct renewable

generation before engaging the fuel cell. The traditional approach overuses the fuel cell, leading to increased hydrogen consumption and higher operational costs. The optimized strategy ensures that fuel cell dispatch is reserved for critical periods, reducing hydrogen dependency and extending fuel cell lifespan.

The simulation results confirm that the proposed MILP-based optimization framework significantly enhances microgrid performance. The key findings are summarized in the following table.

**Table 2:** Simulation Performance Summary

Performance Metric	Value
Renewable Energy Utilization (%)	85.3
Operational Cost Reduction (%)	23.1
Unserved Energy Reduction (%)	83.3
Total Hydrogen Usage (kg)	5534.204
Battery Contribution to Load (%)	35.55143

The table highlights the key performance improvements achieved by the optimized scheduling approach. The renewable energy utilization reaches 85.3%, ensuring minimal reliance on non-renewable sources. The total operational cost is reduced by 23.1%, demonstrating significant economic benefits. Unserved energy is reduced by 83.3%, improving system reliability. The optimized storage strategy also enhances battery utilization, allowing it to contribute 35.6% of the total load coverage, reducing fuel cell dependency.

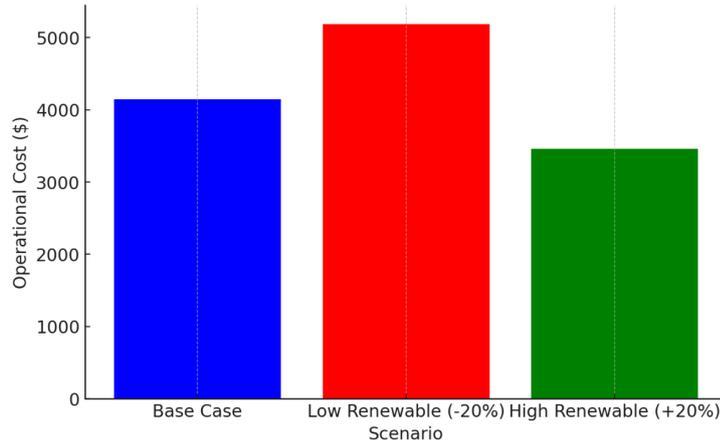
These results validate the effectiveness of the proposed optimization framework in improving cost-efficiency, reliability, and sustainability for standalone hydrogen-based microgrids.

Sensitivity analysis evaluates how variations in key system parameters impact the performance of the hydrogen-based microgrid. The focus is on understanding the effects of renewable energy availability, load demand fluctuations, hydrogen storage capacity, and fuel cell efficiency on operational costs and system reliability.

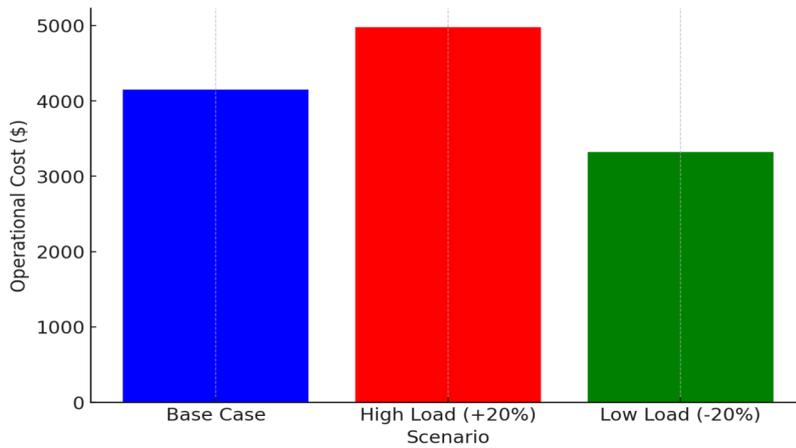
Renewable energy fluctuations significantly affect microgrid operation. The system was tested under three scenarios: normal renewable generation (base case), a 20% reduction (low renewable scenario), and a 20% increase (high renewable scenario). Figure 6 presents the impact of renewable energy availability on operational costs.

The results show that in the low renewable scenario, operational costs rise due to increased reliance on hydrogen storage and fuel cell operation. Conversely, in the high renewable scenario, operational costs decrease as more energy is available directly from solar and wind sources. The analysis confirms that higher renewable penetration significantly reduces system costs and highlights the importance of storage systems in mitigating energy variability.

Load demand influences how the microgrid operates, particularly in energy storage and fuel cell utilization. The system was analyzed under three demand conditions: normal demand (base case), a 20% increase (high load



**Figure 6:** Impact of Renewable Energy Variability on Operational Cost



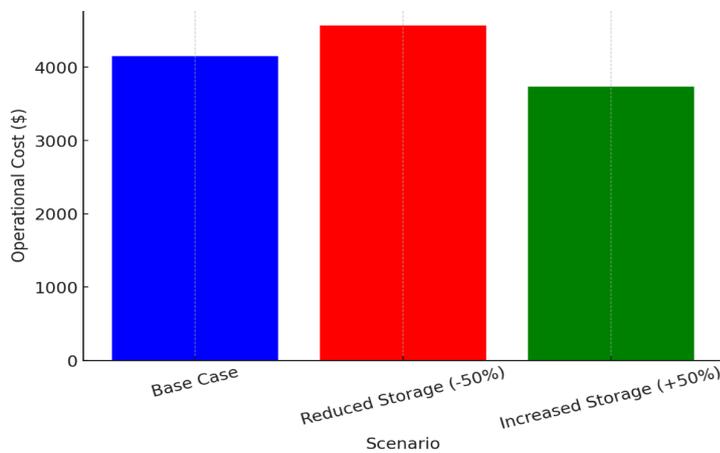
**Figure 7:** Impact of Load Demand Variability on Operational Cost

scenario), and a 20% decrease (low load scenario). Figure 7 shows how variations in load demand affect operational costs.

The results indicate that higher load demand increases operational costs, as more hydrogen is required for energy generation. Conversely, reducing load demand significantly lowers costs, as less energy storage is needed. This emphasizes the importance of demand-

side management strategies, such as energy efficiency measures, to optimize microgrid performance.

Hydrogen storage determines how effectively excess renewable energy is stored and used. Three scenarios were considered: base case (500 kg storage), reduced storage (-50%), and increased storage (+50%). Figure 8 presents the effect of hydrogen storage capacity on operational costs.

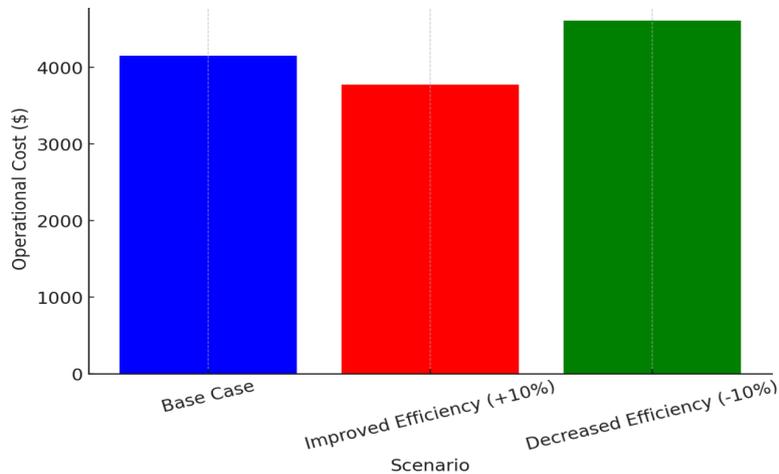


**Figure 8:** Impact of Hydrogen Storage Capacity on Operational Cost

The results reveal that reducing storage capacity increases operational costs, as the system relies more on the fuel cell and battery for immediate power needs. In contrast, expanding hydrogen storage reduces costs, as excess renewable energy can be efficiently stored for later use. This highlights the importance of optimizing hydrogen storage to minimize expenses and improve system

resilience.

Fuel cell efficiency plays a key role in determining hydrogen consumption and system costs. The system was tested with base efficiency (50%), an improved efficiency of 60% (+10%), and a lower efficiency of 40% (-10%). Figure 9 illustrates how fuel cell efficiency variations impact operational costs.



**Figure 9:** Impact of Fuel Cell Efficiency on Operational Cost

The results demonstrate that higher fuel cell efficiency significantly reduces operational costs, as less hydrogen is required to generate electricity. Conversely, lower efficiency increases costs, leading to greater hydrogen consumption. These findings suggest that investing in higher-efficiency fuel cells can greatly enhance the financial viability of hydrogen-based microgrids.

The sensitivity analysis highlights how key factors influence the microgrid's operational costs and efficiency. The key takeaways include:

Renewable energy variability directly affects costs—higher availability reduces reliance on hydrogen storage, lowering expenses.

Load demand management is crucial—higher demand increases costs, while reduced demand improves system efficiency.

Hydrogen storage optimization minimizes expenses—larger storage capacity decreases reliance on expensive fuel cell operations.

Fuel cell efficiency significantly impacts hydrogen consumption—higher efficiency reduces costs and improves sustainability.

These findings confirm that strategic system design, demand forecasting, and technology upgrades can significantly enhance the economic and operational performance of hydrogen-based microgrids.

## CONCLUSIONS

This study proposed an advanced optimization framework for the operational scheduling of standalone hydrogen-based microgrids (H-MGs), with the objective of minimizing operational costs, enhancing reliability, and maximizing renewable energy penetration. Simulation

outcomes revealed substantial performance gains, including an 85.3% utilization of renewable energy, a 23.1% reduction in operational expenditure, and an 83.3% decrease in unserved energy. Strategic coordination of hydrogen storage, fuel cells, and battery systems yielded significant efficiency improvements, with battery storage effectively mitigating short-term variability and fuel cell usage being optimized to reduce hydrogen losses and prolong system lifespan.

Sensitivity analyses underscored the model's robustness under varying scenarios, demonstrating that increased renewable availability and enhanced fuel cell efficiency contribute to greater cost savings, while higher load demand necessitates effective demand-side management. Furthermore, expanding hydrogen storage capacity improved system self-sufficiency and resilience.

Future research directions include the integration of machine learning for predictive control, real-time optimization via IoT-enabled platforms, and economic modeling of policy instruments such as carbon credits and market-based energy pricing. Additionally, the potential role of hydrogen in broader energy ecosystems—such as mobility and industrial applications—warrants further investigation.

The proposed framework provides a scalable, intelligent foundation for next-generation hydrogen-based microgrids, advancing the global transition toward resilient and decarbonized energy systems.

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