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AI-Driven Energy Management for Interconnected Microgrids: A Comparative Performance Analysis

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Abstract. This paper proposes a lightweight AI-based energy management framework for the coordinated operation of interconnected microgrids and evaluates its performance relative to conventional non-cooperative operation. The study examines two microgrids with photovoltaic generation and battery storage operating in parallel with the main grid. The proposed coordination strategy is based on key system variables, including battery state-of-charge and local power imbalance, enabling real-time decision-making without reliance on complex optimization or large-scale data-intensive training, while requiring only a lightweight offline training phase. A time-series simulation framework is used to assess system performance through key indicators, including grid-imported energy, excess energy, battery utilization, and power exchange. The results show that cooperative operation improves performance and resource utilization, reducing total grid-imported energy from 279.71 kWh to 269.61 kWh and curtailed energy from 69.66 kWh to 61.00 kWh. More balanced battery state-of-charge profiles also confirm improved battery management through coordinated energy sharing. Although the improvements are moderate due to the short simulation horizon, the findings demonstrate that even simple coordination strategies can enhance flexibility and resilience in networked microgrids. The proposed framework provides a promising and scalable basis for real-time energy management, with future work focused on long-term techno-economic assessment and optimal system design.

Key words. AI-based decision making, cooperative microgrids, energy management systems, interconnected operation, renewable energy integration.

1. Introduction

The increasing penetration of distributed renewable energy resources is progressively reshaping conventional power systems into decentralized, flexible, and highly dynamic energy networks [1]. In this transition, microgrids (MGs) have emerged as key building blocks capable of integrating local generation, storage systems, and controllable loads within well-defined electrical boundaries [2]. Their ability to operate in both grid-connected and islanded modes makes them particularly attractive for enhancing reliability and facilitating the integration of renewable energy [3].

Despite extensive research on optimal control and energy management of individual MGs, most practical implementations still treat MGs as isolated operational entities [4]. However, in future distribution systems, neighboring MGs are expected to be electrically and functionally interconnected, enabling structured energy exchange [5]. Such coordination can potentially improve local resource utilization, reduce dependency on the main grid, mitigate renewable intermittency, and enhance resilience during grid disturbances [6]. Nevertheless, designing coordination strategies that remain simple, computationally efficient, and suitable for real-time deployment remains an open, practically relevant challenge [7].

Although several studies have demonstrated the technical potential of coordinated MG operation, many existing energy management approaches rely on optimization-intensive formulations or data-demanding intelligent techniques [8]. While such methods may yield high-quality operational decisions, they often require substantial computational effort, forecasting, or complex training, which may limit their practical applicability [9]. This creates a clear need for lightweight, interpretable coordination frameworks that deliver the benefits of cooperation without excessive algorithmic burden.

Motivated by this need, the present work investigates the operational impact of cooperative energy management between two interconnected MGs and compares it with non-cooperative operation. The primary objective of this study is to quantitatively evaluate the benefits of cooperation under grid-connected conditions. In particular, the work aims to assess how structured energy sharing affects battery utilization, power exchange dynamics, reliance on the main grid, and overall system performance. In this context, the main contribution of the paper is the development and evaluation of a practical coordination framework for energy sharing between neighboring MGs, based on a lightweight, interpretable AI-driven strategy with a compact offline training process.

The remainder of the paper is organized as follows. Section 2 describes the studied system configuration, component modeling, and the proposed energy management strategy. Section 3 presents the simulation results and provides a comparative performance analysis based on key technical indicators. Section 4 discusses the main findings and possible directions for future research. Finally, Section 5 concludes the paper.

2. System Modeling

The studied system consists of two interconnected MGs used to evaluate the operational impact of a cooperative energy management strategy. As shown in Fig. 1, each MG includes a photovoltaic (PV) unit, a battery energy storage system (BESS), and a local electrical load.

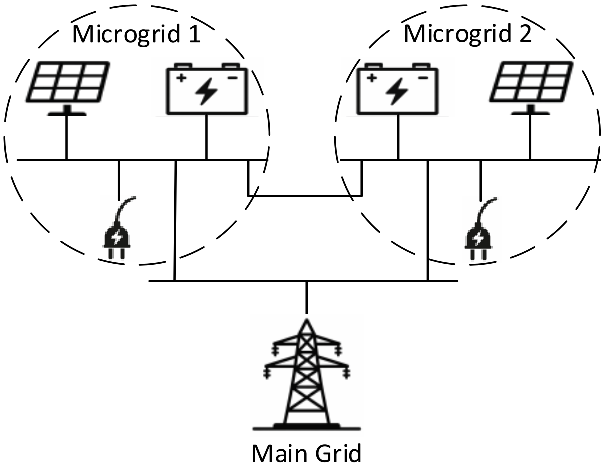

Fig. 1. Studied interconnected MG configuration.

In this study, both scenarios are grid-connected, with the main grid acting as a backup source when needed. Therefore, the comparison focuses on the non-cooperative and cooperative operation of interconnected MGs, aiming to evaluate whether cooperation can reduce grid dependence and improve local resource utilization. The load and PV generation profiles of the two MGs are shown in Fig. 2.

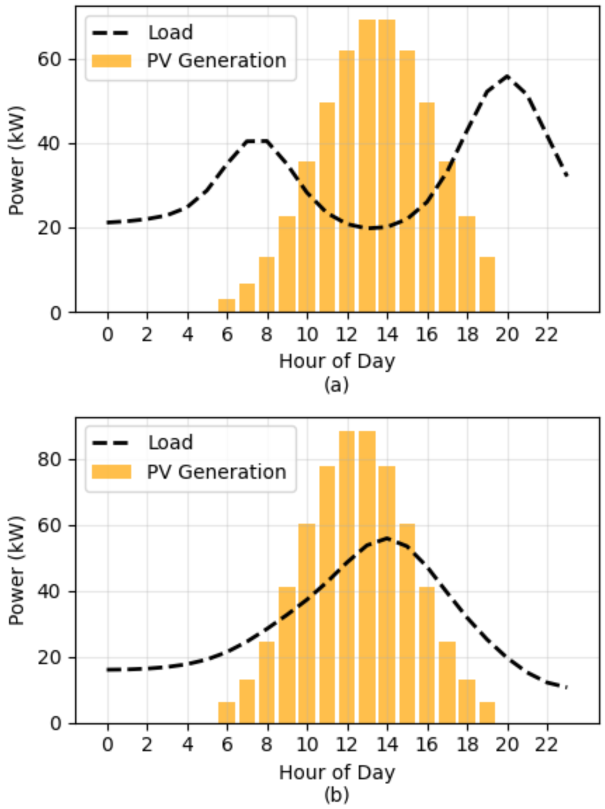

Fig. 2. Load and PV generation profiles: (a) MG1, (b) MG2.

Simplified models are used to represent the main components of each MG. As shown in Fig. 2, electrical demand is represented by predefined daily load profiles: MG1 follows a residential profile with morning and evening peaks, whereas MG2 follows a commercial profile with daytime demand. PV generation is modeled using normalized bell-shaped curves centered around midday, with zero output at night.
Each MG is equipped with a BESS characterized by its energy capacity, charging/discharging power limits, and state of charge (SOC), which is updated at each step within predefined bounds. Key parameters are shown in Table I.

Table I. BESS parameters of the two MGs.

Parameter	**MG1**	**MG2**	**Unit**
Capacity	300	120	kWh
Max power	80	50	kW
Initial SOC	60	50	%
SOC range	20-100	20-100	%
Charge/Discharge efficiency	95/95	95/95	%

The PV and battery capacities of the two MGs are selected to reflect their distinct operating characteristics. The commercial MG is assigned a larger PV capacity due to its higher daytime demand and stronger alignment between solar generation and consumption, allowing the use of a smaller battery. In contrast, the residential MG exhibits morning and evening demand peaks that are less aligned with solar production, requiring a larger battery to store midday surplus energy.
To enable cooperative operation, the two MGs are interconnected through a bidirectional tie line with a maximum transfer capacity of 60 kW.
At each simulation step, the operation of each MG is governed by the balance among local generation, storage, power exchange, and load demand, as expressed in (1).

$$P_{PV_i}(t) + P_{\mathrm{BESS}_i}(t) + P_{Tie_i}(t) + P_{Grid_i}(t) = P_{\mathrm{Load}_i}(t) \quad (1)$$

where $P_{PV_i}(t)$ is the PV generation, $P_{\mathrm{BESS}_i}(t)$ represents the battery power (positive during discharge and negative during charging), $P_{Tie_i}(t)$ is the power exchanged with the neighboring MG, $P_{Grid_i}(t)$ denotes the power supplied by the upstream grid when required, and $P_{\mathrm{Load}_i}(t)$ is the local demand. The battery compensates for short-term mismatches between generation and demand within its operational limits, while the main grid supplies any remaining deficit.
Based on this formulation, the system's operation can be analyzed under two energy management modes: non-cooperative and cooperative.

1. Non-cooperative Operation

In this mode, each MG manages its local resources without exchanging power with neighboring MGs. At each step, the local power balance is defined as the difference between PV generation and load demand, as given in (2).

$$P_{Net}(t) = P_{PV}(t) - P_{Load}(t) \quad (2)$$

If $P_{Net}(t) > 0$, the surplus is used to charge the BESS within its power and capacity limits, and any remaining energy is treated as excess energy (EE). If $P_{Net}(t) < 0$, the battery is discharged within its SOC and power constraints. If the deficit cannot be fully covered, the remaining deficit is supplied by the main grid and recorded as grid-imported energy (GIE).

This mode serves as the baseline strategy, in which each MG relies on its local PV generation, battery storage, and the main grid, without support from the neighboring MG.

2. Cooperative Operation

In interconnected MGs, determining the optimal operational decision at each time step can be challenging due to the large number of possible system states. Even in a relatively small system with two MGs, the decision depends on several variables, including the SOC of both batteries and the instantaneous power surplus or deficit in each MG.

Although traditional rule-based or lookup-table approaches can provide feasible operational decisions, they cannot guarantee that the selected action maximizes overall system performance. For example, when surplus power is available in one MG, several options may be possible, such as charging the local battery, exporting energy to a neighboring MG, or combining both. The most beneficial action depends not only on the current system state but also on its effect on future energy availability.

To address this challenge, a lightweight reinforcement learning (RL) approach is adopted to enable adaptive decision-making. In this work, a Q-learning framework is employed to determine cooperative energy-exchange and battery-operation decisions between the two MGs. Through repeated interactions with the system, the algorithm updates a Q-table that estimates the expected cumulative reward for each state–action pair, gradually converging toward a policy that reduces grid-imported energy, minimizes unnecessary energy curtailment, and promotes efficient use of available storage resources.

The decision-making process is based on a discretized representation of the system state. Specifically, the state is defined by the battery SOC of both MGs and the instantaneous power condition of each MG. The SOC of each battery is discretized into five levels between its minimum and maximum limits. At the same time, the net power condition is represented by the sign of net power, indicating whether the MG is in surplus or deficit. Accordingly, the system state is defined as in (3).

$$S = \left(SOC_1.SOC_2.sign\left(P_{Net_1}\right).sign\left(P_{Net_2}\right)\right) \quad (3)$$

where SOC_1 and SOC_2 denote the discretized state of charge of the batteries in MG_1 and MG_2, respectively, and $sign\left(P_{Net_i}\right)$ indicates whether MG_i experiences a power surplus or a power deficit. This representation results in a total of $5 \times 5 \times 2 \times 2 = 100$ possible states, enabling the use of a compact Q-table while keeping the learning process computationally efficient.

Based on the observed state, the RL agent selects one of four discrete actions, $A = \{a_0, a_1, a_2, a_3\}$, each representing a different coordination policy between the two MGs. These actions determine the priority for surplus-energy allocation through predefined rules, specifying whether surplus power is directed first to local battery charging, to support the neighboring MG's demand, or to charge the neighboring MG's battery. In practice, each action corresponds to a predefined priority rule that specifies whether local battery charging/discharging or inter-MG power exchange is given precedence under the current surplus/deficit conditions. Under the selected policy, battery charging and discharging continue to follow local surplus or deficit conditions, while power transfer through the tie line is either enabled or restricted accordingly.

Table II. Action definitions for cooperative MG operation.

Action	Description	Energy management policy
a_0	Non-cooperative operation	MGs operate independently with no interconnection or power exchange.
a_1	Conservative cooperation	Local storage charging is prioritized; remaining surplus may be shared.
a_2	Balanced cooperation	Surplus energy is first used to support the neighboring MG deficit; any remaining surplus is then used to charge the local battery.
a_3	Aggressive cooperation	Surplus energy is first used to support the neighboring MG deficit, then to charge the neighboring MG battery, and finally to charge the local battery.

The RL agent evaluates the quality of each selected action through a reward function that reflects the operational performance of the interconnected MGs. The primary objective is to reduce reliance on the main grid while minimizing unnecessary energy curtailment. The reward at each time step is defined as in (4).

$$R = -\left(GIE_1 + GIE_2 + \lambda \times (EE_1 + EE_2)\right) \quad (4)$$

where GIE_i represents the grid-imported energy in corresponding MG, EE_i denotes the curtailed surplus energy that cannot be utilized locally or exchanged between MGs, and λ is a weighting factor that penalizes energy curtailment.

This formulation prioritizes reducing grid-imported energy while also encouraging efficient utilization of available renewable energy. In the present study, a small penalty coefficient is assigned to curtailed energy so that reducing reliance on the main grid remains the primary objective of the learning process. The Q-learning update rule is given by (5).

$$Q(s,a) \leftarrow (1-\alpha)Q(s,a) + \alpha\left[r + \gamma \max_{a'} Q(s',a')\right] \quad (5)$$

where s and a denote the current state and selected action, respectively, whereas s' denotes the next state and a' represents a possible action in that next state. Here, r denotes the immediate reward obtained after applying action a in state s, while α and γ are the learning rate and discount factor, respectively.

During the training phase, an ε-greedy policy is adopted to balance exploration and exploitation. With probability ε, a random action is selected to explore new state–action combinations, while with probability $1-\varepsilon$, the action with the highest Q-value is chosen. After training, the learned Q-table is used to determine the cooperative control policy during system operation.

In the implemented model, training was conducted over 200 episodes using a learning rate of $\alpha = 0.1$, a discount factor of $\gamma = 0.95$, and a fixed exploration rate of $\varepsilon = 0.2$. These parameters were selected to ensure stable learning while balancing convergence toward effective policies and sufficient exploration of the discrete state–action space.

3. Results

The results presented in this section aim to evaluate and compare the performance of non-cooperative and cooperative energy management strategies. The analysis is based on time-series simulations using synthetic yet realistic load and generation profiles. Key performance indicators, including battery utilization, inter-MG power exchange, reliance on the main grid, and curtailed generation, provide a clear, quantitative assessment of system behavior.
To establish a reference point for subsequent comparisons, Fig. 3 illustrates the hourly power balance of a representative MG operating under the non-cooperative strategy.

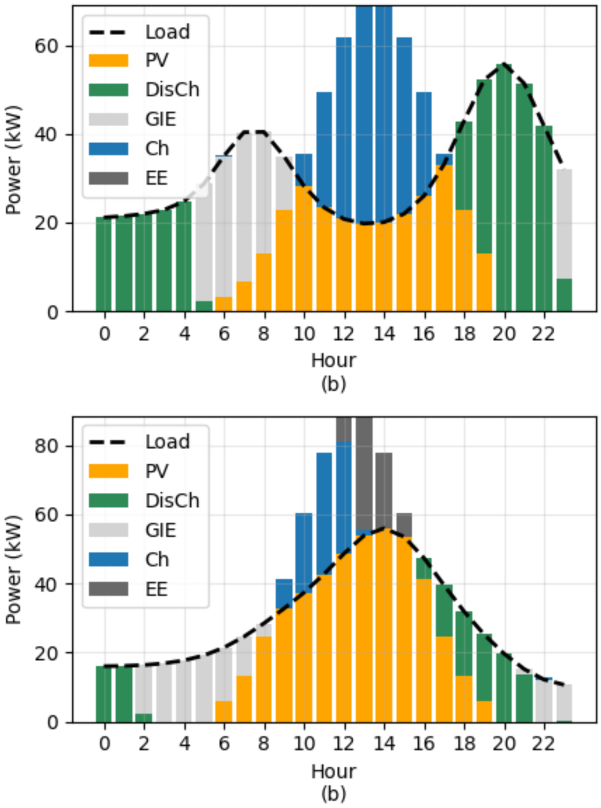

Fig. 3. Hourly power balance of the two MGs under non-cooperative operation: (a) MG1, (b) MG2.

The results clearly show that non-cooperative operation leads to inefficient energy utilization. Despite surplus energy during midday, the system still relies on grid imports during low-generation periods. As shown in Fig. 3, the absence of energy exchange prevents surplus power in one MG from offsetting deficits in the other, resulting in simultaneous curtailment and grid dependence across the interconnected system over the same operating horizon, even under local constraints.
Building upon the limitations observed in non-cooperative operation, the cooperative strategy is now analyzed. Fig. 4 presents the resulting power balance when energy sharing between MGs is enabled, allowing surplus energy in one MG to compensate for deficits in another. This coordinated interaction provides a direct basis for assessing how cooperation improves overall energy balancing between the interconnected MGs.

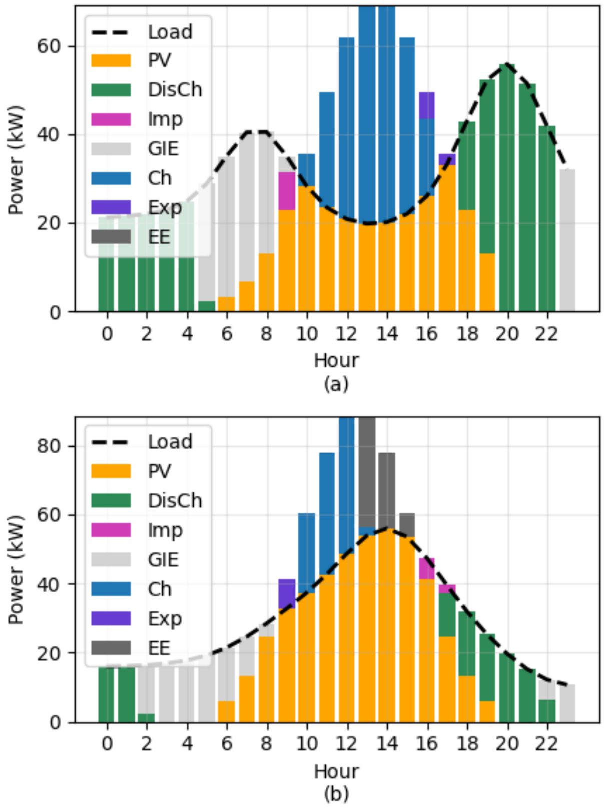

Fig. 4. Hourly power balance of the two MGs under cooperative operation: (a) MG1, (b) MG2.

As illustrated in Fig. 4, cooperative operation improves the overall energy balance. Surplus energy generated in one MG is effectively transferred to support the neighboring MG during deficit periods, reducing the magnitude of GIE. Compared to the non-cooperative case, both the magnitude and duration of GIE are reduced, indicating lower dependence on the main grid. This behavior confirms that inter-MG energy sharing enhances the use of locally available resources and allows deficits to be addressed more effectively within the interconnected system.
At the same time, EE is better utilized through inter-MG exchange rather than being curtailed. This leads to a more efficient use of locally available renewable resources and reduces wasted energy. The presence of both imported and exported power further underscores the dynamic interaction among MGs, enabling a more flexible and adaptive response to variations in generation and demand.
To complement the visual interpretation of the results, a quantitative comparison of key performance indicators under non-cooperative and cooperative operation is presented in Table III.

Table III. Quantitative comparison of GIE and EE under non-cooperative and cooperative operation.

Metric	**Non-cooperative**			**Cooperative**		
	MG1	**MG2**	**Total**	**MG1**	**MG2**	**Total**
GIE (kWh)	156.33	123.38	279.71	155.11	114.50	269.61
GIE (%)	20.56	17.57	19.13	20.40	16.31	18.44
EE (kWh)	0.00	69.66	69.66	0.00	61.00	61.00
EE (%)	0.00	11.16	6.13	0.00	9.77	5.37

As shown in Table III, cooperative operation improves the overall system performance indicators. The total GIE decreases from 279.71 kWh in non-cooperative operation to 269.61 kWh under cooperation, confirming the reduced grid dependence observed in the graphical results. This trend is also reflected in the percentage values, where GIE declines from 19.13% to 18.44%.
At the MG level, both MG1 and MG2 benefit from cooperation, although the improvement is more pronounced in MG2, where GIE decreases from 123.38 kWh to 114.50 kWh. This suggests that the cooperative framework effectively redistributes available energy to support the MG with higher support requirements.
In terms of EE, total curtailed energy decreases from 69.66 kWh to 61.00 kWh, confirming that surplus energy is more effectively utilized through inter-MG exchange. MG2 also shows a reduction in EE percentage from 11.16% to 9.77%, further indicating improved resource utilization.
Overall, the results show that cooperative operation improves efficiency and system performance by reducing curtailed energy and dependence on the main grid, leading to a more balanced use of distributed energy resources.
To further investigate the impact of cooperative operation on system performance, SOC profiles of the battery systems in both MGs are analyzed, as shown in Fig. 5.

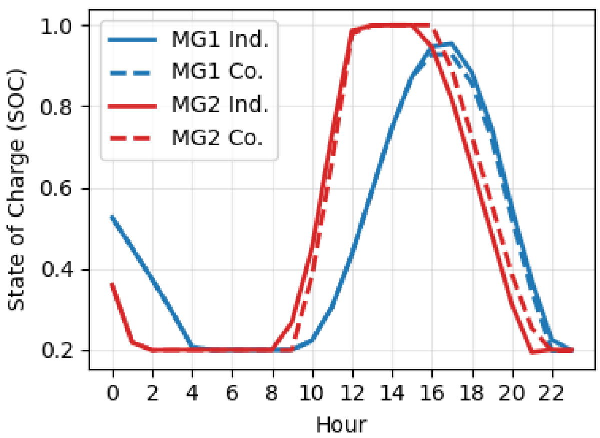

Fig. 5. SOC profiles of both MGs under non-cooperative and cooperative operation.

As illustrated in Fig. 5, cooperative operation leads to a more coordinated and balanced utilization of battery storage across both MGs. Under non-cooperative operation, each MG charges and discharges its battery solely based on local conditions, leading to steeper SOC variations and less-synchronized behavior.
In contrast, under cooperative operation, SOC profiles become smoother and more aligned, reflecting energy exchange between MGs. The batteries also tend to avoid prolonged extreme conditions, indicating more controlled charging and discharging. This coordinated behavior helps reduce unnecessary deep discharges and overcharging, improving operational stability and potentially extending battery lifetime.
Furthermore, the SOC trajectories suggest that energy is redistributed between MGs, allowing one system to support the other when needed. This indicates that cooperative energy management enhances both power balance and storage utilization.

4. Discussion

The results demonstrate that cooperative energy management reduces grid dependence and improves resource utilization by lowering both GIE and EE, while enabling more coordinated battery operation. Although the improvements observed in the presented case study are moderate, they consistently confirm the effectiveness of the proposed lightweight AI-based coordination strategy.
The proposed framework combines two complementary decision-making strategies. In the non-cooperative operating mode, each MG follows a rule-based local energy management scheme based on its PV generation, battery state, and load demand. In contrast, the cooperative mode is governed by a lightweight tabular reinforcement learning approach, namely Q-learning, enabling adaptive selection among predefined surplus-allocation policies for interconnected MGs. This combination allows the study to compare a conventional non-cooperative baseline with an AI-driven cooperative strategy within a consistent operational framework. It should be noted, however, that the comparison reflects both the effect of cooperation and the different decision-making structures adopted in the two modes.
A key advantage of the implemented AI model lies in its simplicity, interpretability, and low computational burden. Although the cooperative strategy requires a training phase, the adopted tabular RL formulation remains computationally efficient due to the reduced state-action space and the explicit Q-table representation. Unlike deep reinforcement learning or forecasting-driven optimization approaches, the proposed method does not require large training datasets or complex optimization routines, making it potentially suitable for practical real-time applications. At the same time, its transparent structure allows the relationship between system states and control actions to be directly examined, which is a useful advantage for control-oriented implementation.
The performance of the proposed framework is assessed using system-level indicators, including GIE, EE, battery utilization, and power exchange. These metrics provide a practical measure of the effectiveness of the energy management strategy in reducing grid dependence and improving local resource coordination. In addition, the smoother SOC trajectories observed under cooperative operation further support the view that the proposed method enables more balanced battery utilization.
From a control perspective, the proposed cooperative mechanism operates at the tertiary control level, where decisions regarding inter-MG energy exchange and interaction with the main grid are made. The results indicate that even a simple coordination strategy at this level can enhance system flexibility and improve the utilization of distributed energy resources. This highlights the practical relevance of the approach for real-world networked MG implementations.
From an economic perspective, the proposed framework can be readily extended to incorporate cost indicators, such as electricity purchase costs, battery degradation costs, and potential revenues from energy exchange. Integrating such economic signals into the reward structure would allow the model to move beyond purely technical objectives toward techno-economic

optimization. This represents an important direction for future development.

It should also be noted that the observed improvements are limited in magnitude due to the short simulation horizon, which is restricted to a single day. Under such conditions, the system does not fully experience longer-term variability in renewable generation and demand, and therefore, the cumulative benefits of cooperation may not be fully visible. A more comprehensive evaluation over seasonal or annual horizons would provide deeper insight into the practical value of the proposed strategy. In particular, integrating the framework into long-term planning and optimal sizing studies could better reveal its economic and operational benefits.

5. Conclusion

This paper presented a lightweight AI-based energy management strategy for the coordinated operation of interconnected MGs and compared its performance against conventional non-cooperative operation under grid-connected conditions. The proposed framework combines a rule-based non-cooperative baseline with a lightweight, interpretable Q-learning strategy trained offline for cooperative operation.

The results demonstrate that cooperative operation reduces grid dependence and improves resource utilization. Quantitatively, the total GIE is reduced from 279.71 kWh to 269.61 kWh, corresponding to a decrease from 19.13% to 18.44%. Similarly, EE is reduced from 69.66 kWh to 61.00 kWh, confirming a more efficient use of locally generated renewable energy. The smoother battery SOC profiles and the effective redistribution of energy between MGs further support these improvements.

Overall, the findings highlight that even a simple coordination mechanism can introduce meaningful operational benefits by enabling energy sharing and improving flexibility. The proposed framework offers a balanced trade-off between performance improvement and implementation simplicity, making it a promising option for real-time applications in future distributed energy systems.

However, the analysis is limited to a short-term simulation horizon, and the observed improvements remain moderate. Future work should focus on long-term evaluations, including seasonal variability and integration with techno-economic optimization and MG sizing, to fully capture the potential benefits of cooperative energy management.

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