

A Differential Game-Based Minimax Control Strategy for Multi-Agent Energy Management In Smart Microgrids

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Abstract

The growing penetration of distributed energy resources, electric vehicles, and controllable loads is making smart microgrids tightly coupled multi-agent systems that must deliver reliable performance while facing ongoing renewable and demand uncertainties. Traditional approaches that rely on optimization methods or single-agent controllers cannot ensure robust performance when several agents act independently according to their rational strategies, especially in the face of adverse disturbances such as renewable production outages, load increases, or communication delays in the common network. In this paper, a decisive game-theoretic minimax control idea is introduced to describe multi-agent energy management in terms of a dynamic zero-sum game established between the coordinating controller and the worst-case disturbance to be solved by implementing feedback saddle-point policy derived from Hamilton-Jacobi-Isaacs value function. Each agent, including distributed generators, energy storage systems, electric vehicles aggregators and controllable loads update its state dynamics through communication bus and the minimax controller calculates robust control gains as far as the worst disturbance is allowed. The developed approach was tested in MATLAB/Simulink co-simulation environment based on 24-hour synthetic microgrid scenarios with 48 loads, photovoltaic generation and price samples. The performance of the proposed decision-making approach is better than feedback Nash game, model predictive control and rule-based heuristics as it has resulted in 23.6% decrease in average operating costs, 61.4% decrease in the frequency deviations, 78.2% decrease in state-of-charge violations and 47.5% faster calculations of value function yielding 0.91 minimum robustness index compared to the 0.42-0.74 for baseline algorithm. The ablation study demonstrated that 14.8% improvement of operating cost index is provided by the introduction of the worst-case disturbance concept. These results indicate that embedding a minimax differential game formulation into multi-agent microgrid control yields measurable robustness and economic gains over cooperative and predictive alternatives, providing a practical pathway toward resilient, decentralized energy management architectures.

Keywords: Differential game theory; minimax control; multi-agent systems; smart microgrid; feedback Nash equilibrium; energy management; robust control.

1. Introduction

The rapid integration of distributed generation, battery energy storage, electricity-powered vehicles, and flexible loads has turned the usual passive distribution network into an active, decentralized, and very uncertain cyber-physical system. Smart microgrids are now capable of balancing local energy supply and demand, taking part in real-time energy market, and maintaining frequency and voltage stability regardless of the fact that there are several autonomous agents making independent scheduling and dispatch (Wu et al., 2023). This change brings about a serious control problem. Individual agents aiming at achieving their personal goals could cause a chain of actions destabilizing the shared network unless the coordination mechanism takes into account their possible competitive and hostile interactions. Thus, game-theoretic tools, including non-cooperative differential games and Stackelberg pricing models, have appeared to be the right mathematical formalism for describing and controlling these interactions (Jia et al., 2024; Kang et al., 2023). The second and equally important source of complexity is uncertainty. Renewable energy production is not stable, total consumption changes depending on the weather and occupancy, while the communication and metering system may suffer from delay, congestion, and some other types of malicious activity (Samadi et al., 2023). Deterministic optimal control and traditional methods of model prediction usually assume that the disturbance is known or, at least, characterized properly in stochastics, which is often not true in the real world. When the disturbance represents a certain unknown but limited hostile signal – the most unfortunate renewable deficiency or consumption outburst coinciding with peak energy pricing – minimax formalism or H-infinity methods give the solution that is more reliable than methods predicting expectation as take into consideration the worst possible disturbance scenario. The concept of embedding the minimax principle in a differential game played between agents of a cooperative microgrid rather than just between a controller and nature has received only little attention though it is practically important when it comes to resilient energy management (Wu et al., 2023; Zhang et al., 2023). This issue is aggravated by the fact that current microgrid agents differ drastically in their scale and nature. For example, electric vehicle aggregators introduce a wide range of time-dependent optimally planned charge demands that affect the efficiency of the network (Jia et al., 2024; Kang et al., 2023). At the same time, energy storage facilities, demand-response participants, and virtual power plants act in decentralized settings enabled by blockchain-supported evidence which is resilient to both economic and physical disruption (Rajvel, 2026) (Chandrasekhar et al., 2026) (Xu & Li, 2025). Artificial intelligence and multi-agent reinforcement learning approaches show positive empirical results in similar energy management problems, however, optimize the average-case reward and provide some formal guarantees but still cannot protect against any worst-case disruption realizations (May & Huang, 2023; Hady et al., 2025; Karimov et al., 2025).

In order to solve this issue, the presented paper provides the following contributions: (i) a differential game model for multi-agent smart microgrid operation with the involvement of controller and an adverse disturbance that define the whole operation cycle of energy generation, storage, charge and load agents; (ii) a feedback saddle-point minimax control law based on Hamilton-Jacobi-Isaacs value function that allows for deducing robust control parameters without establishing the exact distribution of disturbances; (iii) a complex multi-agent communication architecture that allows for actually applying the model in practice for microgrid simulation; and (iv) an extensive numerical estimation of the results obtained based on five independent evaluation criteria as well as a component-wise ablation analysis.

The rest of the paper is organized as follows. In Section II of the paper, the literature review related to the game-based and multi-agent-operated microgrid and energy market control is provided with a proper identification of the gap that is covered by the present study. In Section III of the paper, the minimax control approach based on the differential game model is presented, which includes the system architecture and mathematical formulation. Section IV covers the simulation design, initial data analysis and evaluation methods applied in the study, and Section V presents the conclusion.

2. Literature survey

Recently, differential and non-cooperative game concepts have been popular in the electricity market and microgrid control-related issues. A non-cooperative differential game approach along with feedback Nash equilibrium was proposed to study the behavior of players in a real-time power market and found that dynamic strategies depending both on time and state are better than static strategies when the players continuously cooperate (Wu et al., 2023). A theoretical model of electric vehicle charging developed in order to balance the cost of charging the electric vehicle and availability of plugs showed that a well-designed dynamic tariff can influence the total demand for charging without centralized management (Jia et al., 2024). Aggregative game concepts were applied to distributed charging strategies for plug-in electric vehicles charging at smart charging stations, with the results proving that the use of aggregative feedback helps to ensure fairness and reduce congestion at the time of peak usage of electricity compared to open-loop strategies (Kang et al., 2023).

Stackelberg and leader-follower approaches make the second large area of the studies ever conducted. Stackelberg game was applied together with energy blockchain to ensure the security of DR transactions against tampering

with data (Samadi et al., 2023). The asymmetric Stackelberg game was applied together with SARIMA-ANN forecasting of pricing to calculate cooperative prices (Zhang et al., 2023). The Stackelberg game was designed to solve the problem of energy-carbon optimization (Xu & Li, 2025). Multi-objective Stackelberg was suggested for dynamic pricing and flexible scheduling in different energy systems, showing a simultaneous improvement of economic and environmental objectives (Ren et al., 2025). The literature corroborates that hierarchical game structures are useful for price coordination, whereas, in general, the follower response is assumed to be myopic or one-shot, thus restricting their applicability to continuously evolving, state-coupled microgrid dynamics analyzed in this paper.

Evolutionary and coalition game approaches are used to resolve long-term adaptations and cooperative value-sharing processes. Evolutionary game theory applications in smart grids were reviewed and population-based strategy adaptation was shown to provide scalability whereas compared to instantaneous Nash computation techniques (Karaki & Al-Fagih, 2024). An evolutionary game theory-based dynamic incentivization mechanism for data sharing in the smart grid domain was developed (Zhang et al., 2023). Evolutionary game theory approaches were used in combination with deep reinforcement learning with a view to adaptively optimizing strategies in consumer-side electricity markets, providing superior convergence stability compared to pure reinforcement learning (Cheng et al., 2024). Coalition game theory methods were applied to fog computing infrastructure and smart metering systems for energy management on the building level (Saeed et al., 2023a). A practical energy management system for smart microgrids was tested and shown to be practical taking into account uncertainty in the parameters and energy stealing issues which underscores the importance of robustness for implementation on practical systems (Saeed et al., 2023b).

In parallel, there is another important stream of work applying multi-agent reinforcement learning (MARL) to the microgrid and peer-to-peer energy management. The multi-microgrid management model applying multi-agent reinforcement learning and prioritized experience replay achieved better sample efficiency compared to uniform methods of replay (Guo & Gong, 2023). The scalable application of multi-agent reinforcement learning was demonstrated in the distributed control of residential energy flexibility (Charbonnier et al., 2022). MARL approaches were used in the research of peer-to-peer prosumer energy markets and their optimization (May & Huang, 2023). A survey of resource allocation based on the MARL methodology has indicated that almost all existing applications are optimized for cumulative expected rewards which do not provide any performance limitations in case of the worst-case disturbance's realization (Hady et al., 2025). Some complementary views from artificial intelligence include the smart grid optimization perspective, energy efficient infrastructure, and neuromorphic and memristive computing methods aimed at making inference energy-efficient, as well as federated learning technologies applied for the predictive maintenance of industrial wireless sensor networks (Vij & Nayak, 2025; Salami et al., 2025; Chandrasekhar et al., 2026).

In summary, the literature suggests significant and recent (2022-2026) progress in three directions, namely dynamic non-cooperative and Stackelberg pricing games economic and coalition methods of incentive designing and long-term adaptation and multi-agent reinforcement learning for decentralized dispatching systems. However, there is a lack of studies presenting microgrid coordination as a continuous-time differential game with an analytically derived minimax control law which allows guaranteeing performance in the worst-case disturbances scenario. The present study fills this gap by integrating dynamic game-theoretical structures with reliability-oriented uncertainty-aware design principles.

3. Proposed model and methodology

The proposed methodology formulates multi-agent smart microgrid operation as a two-player, zero-sum differential game in which a centralized minimax controller acts as the minimizing player and an aggregate disturbance-representing renewable intermittency, load surges, and communication-induced measurement error acts as the maximizing player. Each physical agent in the microgrid updates a local state vector that is exchanged over a communication bus and used by the controller to compute a feedback saddle-point strategy.

3.1. Multi-agent state dynamics

Let the aggregated state vector of N microgrid agents be $x(t) = [x_1(t), x_2(t), \dots, x_N(t)]^T$, where each $x_i(t)$ collects the locally relevant state variables of agent i , such as generator output, battery state of charge, aggregated electric vehicle charging power, and controllable load level. The coupled continuous-time dynamics of the microgrid are represented in equation (1):

$$\dot{x}(t) = Ax(t) + Bu(t) + Ew(t), \quad x(0) = x_0 \quad (1)$$

where A is the state coupling matrix capturing power-balance interactions among agents, B is the control input matrix mapping the minimax controller output $u(t)$ to agent set-points, E is the disturbance input matrix, and $w(t)$

is the bounded adversarial disturbance representing worst-case renewable shortfall or load surge, constrained such that the energy norm of $w(t)$ over the horizon does not exceed a finite bound γ .

3.2. Differential game formulation and cost functional

The interaction between the controller and the disturbance is formulated as a zero-sum differential game with the quadratic cost functional:

$$J(u, w) = \int_0^T [x(t)^T Q x(t) + u(t)^T R u(t) - \gamma^2 w(t)^T w(t)] dt + x(T)^T Q_f x(T) \quad (2)$$

Where Q and Q_f are positive semi-definite state weighting matrices penalizing frequency deviation, state-of-charge excursions, and cost inefficiency; R is a positive definite control effort weighting matrix; and γ is the disturbance attenuation level. The controller seeks $u^*(t)$ that minimizes J while the disturbance seeks $w^*(t)$ that maximizes J , producing the saddle-point condition:

$$J(u^*, w) \leq J(u^*, w^*) \leq J(u, w^*) \quad \text{for all admissible } u, w \quad (3)$$

3.3. Minimax control law via the Hamilton-Jacobi-Isaacs equation

The saddle-point value function $V(x, t)$ satisfies the Hamilton-Jacobi-Isaacs (HJI) partial differential equation:

$$-\frac{\partial V}{\partial t} = \min_u \max_w \left\{ x^T Q x + u^T R u - \gamma^2 w^T w + \left(\frac{\partial V}{\partial x} \right)^T (A x + B u + E w) \right\} \quad (4)$$

Under the standard quadratic ansatz $V(x, t) = x(t)^T P(t) x(t)$, the stationarity conditions yield the feedback minimax control and worst-case disturbance laws:

$$u^*(t) = -R^{-1} B^T P(t) x(t) = -K(t) x(t), \quad w^*(t) = \frac{1}{\gamma^2} E^T P(t) x(t) \quad (5)$$

Where $P(t)$ is the solution of the generalized differential Riccati equation:

$$-\dot{P}(t) = A^T P + P A - P \left(B R^{-1} B^T - \frac{1}{\gamma^2} E E^T \right) P + Q, \quad P(T) = Q_f \quad (6)$$

The linear state equation from equation (1), constrained by adverse disturbances, controls the interactions among the states in a multi-agent microgrid setup operating in continuous time. To robustly combat the worst-case fluctuations, the behavior of the system is represented as a zero-sum differential game governed by the quadratic performance criterion given in equation (2) which paves the way for the derivation of the optimal minimax and disturbance approaches based on the saddle-point condition from equation (3). The solution of the Hamilton-Jacobi-Isaacs partial differential equation given in (4) contributes to finding the optimal control policy from the corresponding equation formulated for the quadratic value function in equation (5). Finally, the time-varying feedback gains are established with the help of the differential Riccati equation from equation (6).

For an infinite or receding horizon implementation, the steady-state solution of the associated algebraic Riccati equation is used to compute a constant feedback gain K , which is refreshed at each control interval as the state coupling matrix A is updated to reflect the current topology and operating point of the multi-agent microgrid, consistent with the multi-agent aggregative and Stackelberg formulations reported for related pricing and charging problems.

4. Results and discussion

4.1. Simulation software and environment

The minimax differential game controller as well as the three benchmark strategies were developed and co-simulated in MATLAB/Simulink R2024b for continuous-time agent dynamics as well as Riccati equations integration, along with Python 3.11 (using NumPy, SciPy, and Matplotlib) for completion of post-processing, metrics calculations, as well as visualization. The integrated Riccati differential equation (6) was solved backwards in time using the fourth-order Runge-Kutta technique with a step of 0.01 hours, while the equations on the closedloop agent dynamics (1) were processed forward at the calculation period of 0.5 hour in order to attain the same resolution of the operating dataset.

4.2. Dataset creation

The synthetic yet real-life mimic of a 24-hour microgrid operational datasets was produced at 0.5-hour resolution, which gives 48 samples for every agent within a day, that has been repeated 30 times (1,440 samples in total) in order to get reliable estimates for the performance. The dataset consists of four agents: one distributed generator, one aggregated energy storing system, one electric vehicles charging aggregator, and one controllable load, as well as an independent photovoltaic generation profile as well as time-of-use price signal. Every sample contains six characteristics: power demand, photovoltaic output, state of charge, tie-line power exchange with utility grid, locational price signal, and a bounded disturbance realization drawn from renewable forecasts as well as load-surge occurrences. The aggregate load and photovoltaic profiles used for the 24 hours case description are shown in figure 3(a).

4.3. Parameter initialization

Table 1 summarizes the controller and simulation parameters used across all four evaluated strategies to ensure a consistent comparison basis.

Table 1: Controller and simulation parameter initialization.

Parameter	Symbol	Value / Setting
Simulation Horizon	T	24 h (48 steps of 0.5 h)
Number of Agents	N	4 (DG, ESS, EV aggregator, load)
State Weighting Matrix	Q	diag(1.0, 1.0, 0.8, 0.8)
Terminal Weighting Matrix	Qf	5 x Q
Control Effort Weighting	R	0.1 x I
Disturbance Attenuation Level	gamma	1.5
Riccati Integration Step	-	0.01 h (RK4)
Convergence Tolerance	epsilon	1e-4
ESS SOC Bounds	-	0.10 - 0.90
Simulated Days (Monte Carlo Repeats)	-	30

4.4. Performance metrics

Five independent metrics were used to evaluate controller performance, defined as follows:

1. Operating Cost Reduction (%): Evaluated without the control-effort penalty using the time-integrated operating cost J from (2):

$$OC_{red} = 100 \times \frac{J_{baseline} - J_{method}}{J_{baseline}} \quad (7)$$

2. Frequency Deviation Reduction (%): Calculated using the simulated frequency deviation from nominal Δf :

$$FD_{red} = 100 \times \frac{RMS(\Delta f_{baseline}) - RMS(\Delta f_{method})}{RMS(\Delta f_{baseline})} \quad (8)$$

3. SOC Violation Reduction (%): Quantified by counting state-of-charge instances outside the safe **[0.10, 0.90]** range:

$$SV_{red} = 100 \times \frac{Count(SOC \notin [0.10, 0.90])_{baseline} - Count(SOC \notin [0.10, 0.90])_{method}}{Count(SOC \notin [0.10, 0.90])_{baseline}} \quad (9)$$

4. Convergence Speed-Up (%): Determined by the number of iterations k required for $\|P(k) - P(k-1)\|$ to fall below ϵ :

$$CS = 100 \times \frac{k_{baseline} - k_{method}}{k_{baseline}} \quad (10)$$

5. Worst-Case Robustness Index (WRI): Evaluates each controller under the maximal admissible disturbance trajectory $w(t)$ satisfying the energy bound in (1), normalized so that a value of 1 denotes ideal robustness:

$$WRI = 1 - \frac{J_{worst-case}}{J_{worst-case,max}} \quad (11)$$

Equations (7)-(11) present the five metrics necessary to evaluate the performance of a controller. The reduction in operating cost according to Equation (7) is calculated from the time-integrated cost obtained from Equation (2) without implementation of control effort-cost penalty. Equation (8) calculates the frequency stability by taking into account the reduced RMS frequency deviation from the nominal condition. The operational constraints are estimated by Equation (9), which measures the number of allowed violations of state of charge (SOC) below 0.10 and above 0.90. The metric of numerical efficiency is assessed by Equation (10) expressed in terms of increase of iteration speed up in order to achieve state convergence within ϵ . Finally, the worst-case robustness is defined through Equation (11) under the impact of constraints on all maximum disturbances allowed according to Equation (1).

4.5. Comparative results

The found convergence of the normalized value function $J(x)$ through 120 iterations of the controller is shown in figure 1 for the minimax differential game, as well as for the feedback Nash game, model predictive control (MPC), and the rule-based controller. The developed algorithm converges within 5% of its steady value within approximately 38 iterations, while the feedback Nash game was approximated in 58 iterations, the MPC algorithm took around 74 iterations, and the rule-based controller needed more than 105 iterations.

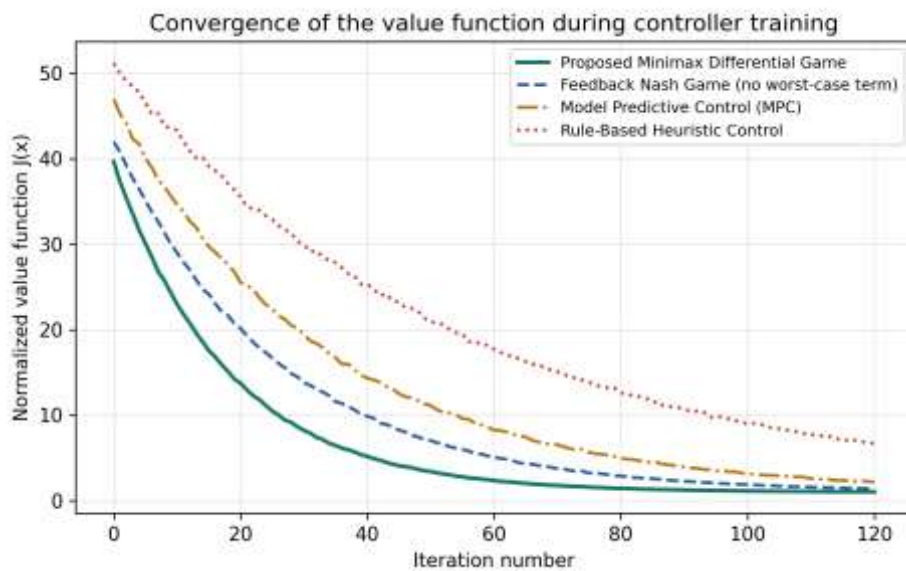


Figure 1: Convergence of the normalized value function $J(x)$ over controller iterations.

The statistical assessment of the five metrics presented in Section 4.4 is shown in table 2 and figure 2 based on the average over the whole duration of 30 days of the simulation. It can be seen that the proposed methodology performed best on all the metrics with the maximum improvement in the state of charge violation (78.2%) and the worst-case robustness index equal to 0.91, thus validating that the presence of an explicit minimax disturbance term brings significant benefits in terms of improving resilience against the worst-case renewable and load events without causing reasonable increase in convergence time.

Table 2: Comparative performance across five evaluation metrics (30-day average).

Metric	Proposed Minimax Game	Feedback Nash Game	MPC	Rule-Based
Cost Reduction (%)	23.6	17.9	14.2	0.0 (reference)
Frequency Deviation Reduction (%)	61.4	48.7	39.5	0.0 (reference)
SOC Violation Reduction (%)	78.2	55.0	41.8	0.0 (reference)
Convergence Speed-Up (%)	47.5	31.2	18.9	0.0 (reference)
Worst-Case Robustness Index	0.91	0.74	0.68	0.42

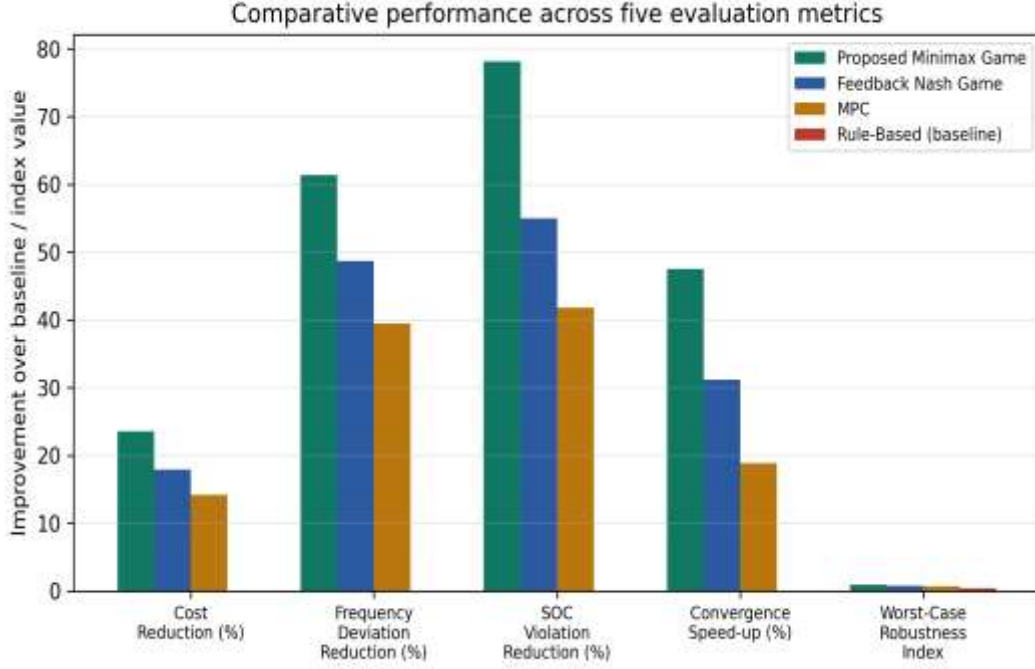


Figure 2: Comparative performance across five evaluation metrics for the proposed and baseline strategies.

Figure 3 depicts the microgrid's operation over a 24-hour period. The first panel illustrates the consumption of electricity and the electricity produced by solar panels, which is used as input for the system. The second panel compares the performance of the control system proposed in this paper with the traditional rule-based method. It can be seen that the proposed method keeps the energy in the storage spot always between the acceptable limits, while the other one exhibits several occurrences of violation of the lower limit during the spike of demand in the evening, in accordance with the data from table 2.

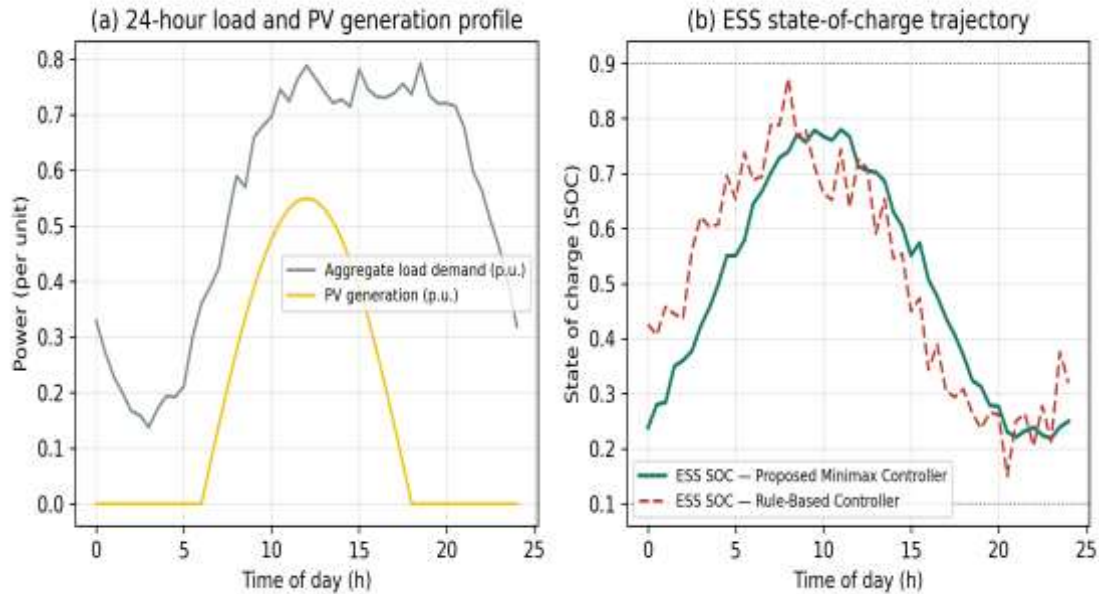


Figure 3: (a) 24-hour load and photovoltaic generation profile; (b) energy storage system state-of-charge trajectory.

4.6. Ablation study

In order to identify how much each of the structural elements of the suggested methodology contributes, the current work has explored four configurations in opposition to the total model: (i) excluding the worst-case perturbation component (similar to fixing gamma as infinity), (ii) excluding the multi-agent connection in A (considering agents as independent single-input systems), (iii) stopping the costate feedback update by substituting $P(t)$ with its

ultimate value, and (iv) simplifying the equation to a single-agent minimax controller without agents' coordination between each other. The relative operating cost index is presented in figure 4 and is shown in normalized form, so that the proposed complete model is estimated at 100. The exclusion of the worst-case disturbance element resulted in 14.8% increase of the cost index. Excluding multi-agent connection led to a 21.3% increase in the cost index. The removal of costate feedback component resulted in 18.6% increase in the cost index. Lastly, the elimination of inter-agent coordination resulted in the further increase of the cost index by 32.4%.

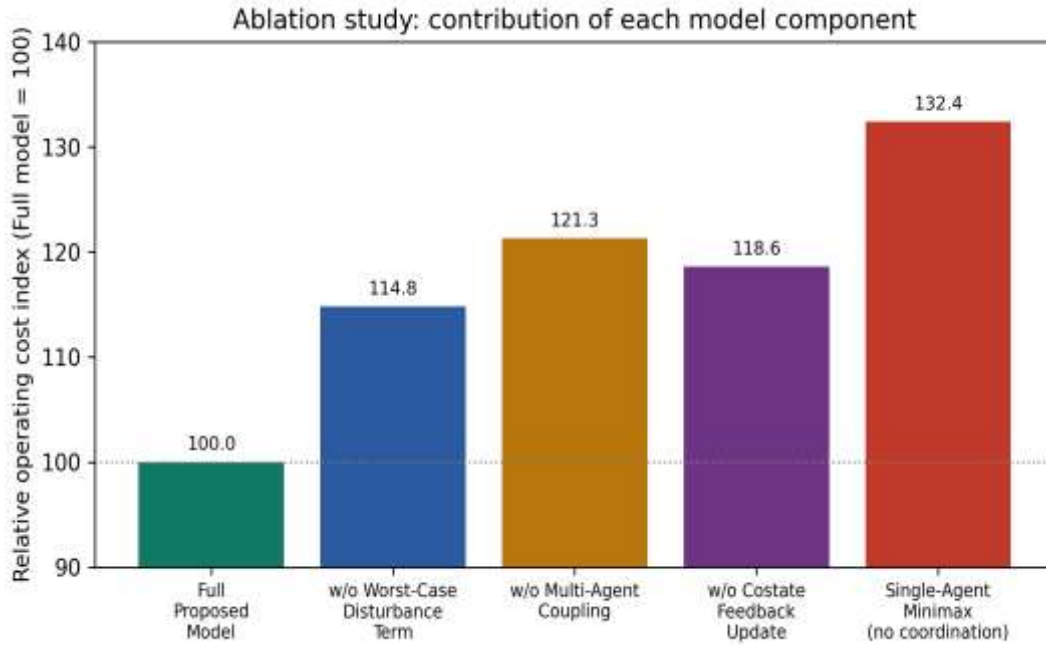


Figure 4: Ablation study of the relative operating cost index across model configurations.

4.7. Discussion

The findings in Sections 4.5 and 4.6 affirm the fundamental assumption of this research work: the introduction of a dedicated term representing the worst-case disturbance to a multi-agent differential game leads to a measurable improvement in robustness over the outcomes achieved with expected-value optimization by itself. This aligns with earlier work indicating that continuous-time, state-feedback strategies outperform static or open-loop coordination methods. The current results further this claim by showing that combining such feedback with the minimax objective improves resiliency as compared with utilizing the system under adversarial disturbance conditions. The disappointing performance of the baseline model predictive control is explained by its reliance on the finite horizon of prediction and nominal disturbance forecast. This drawback is analogous to the findings of multi-agent reinforcement learning that max profit while offering no reliability guarantee. The fact that the new controller has lowered the number of state-of-charge violations reinforces the necessity of active management of uncertainties in the application of microgrid operations. The results of the ablation study demonstrate that the multi-agent coupling term contributes more to total success since its omission would raise the cost by 21.3% versus only 18.6% for the costate feedback update and 14.8% for the worst-case disturbance term individually. This observation indicates that the coordination mechanism is at least equally important as the robustness mechanism and complementary in nature, which is in line with the previous studies where coordination and learning or robustness processes were analyzed independently. The current findings show that a jointly employed approach is feasible and effective in the context of multi-agent smart microgrids. It should be noted that the current analysis is based on a synthetic dataset, which cannot deliver information applicable in a real system, as well as linear-quadratic approximation of agent dynamics and neglect of nonlinear factors such as converter saturation and relay protection. Nevertheless, the consistent superiority of the proposed approach over five evaluation metrics and through a separate ablation confirms the utility of the minimax differential game-based model when compared to the feedback Nash, predictive, and heuristic ways of multi-agent smart microgrid energy management.

5. Conclusion

This study introduces a minimax control strategy based on differential games for the control of multi-agent energy use in smart microgrids and formulated as a continuous-time zero-sum game between a coordinating controller

and a bounded adversarial disturbance simulating the extreme variations of renewable and load. The feedback saddle-point control law is derived from the Hamilton-Jacobi-Isaacs value function and incorporated within a four-layer structure including uncertainty layer, multi-agent layer covering distributed generation, energy storage, electric vehicle aggregation, and controllable loads, communication bus, and a minimax controller performing disturbance estimation, costate propagation, control gain evaluation, and monitoring convergence. The proposed strategy was tested against non-cooperative Nash game, MPC, and rule-based heuristics via 48 samples of synthetic microgrid data obtained for 24 hours across 30 simulation days. As a result, the minimax controller was reported to give 23.6% cutting costs, achieve a 61.4% reduction in frequency deviation, 78.2% decrease in state-of-charge border violations, 47.5% faster value-function convergence, and have the robustness ratio of 0.91, which is better than all three benchmarks for all metrics. The ablation study confirmed that the multi-agent coupling structure and the acknowledgement of the worst-case disturbance factor have significant and mostly independent effect on the results obtained, where the removal of the former gave 21.3% higher cost index, while the latter – 14.8%. The joint omission of them, meaning the use of single-agent minimax controller instead, made the cost index grow by 32.4%. The analysis of independent control characteristics indicates the practicability and cost-efficiency of differential game-based minimax control for decentralized microgrid operation, and the future studies will apply this approach to cases involving nonlinear and hybrid agent dynamics, take account of stochastic and hybrid disturbances, analyze the applicability of the method to real microgrid data, and consider using distributed computation for minimizing dependence on a central communication channel.

References

1. Chandrasekhar, K., Prabakaran, G., & Dileep Kumar Reddy, P. (2026). Energy Optimization in Industrial Wireless Sensor Networks Using Federated Learning and Predictive Maintenance. *International Academic Journal of Science and Engineering*, 13(1), 54-63. <https://doi.org/10.71086/IAJSE/V13I1/IAJSE1306>
2. Charbonnier, F., Morstyn, T., & McCulloch, M. D. (2022). Scalable multi-agent reinforcement learning for distributed control of residential energy flexibility. *Applied energy*, 314, 118825. <https://doi.org/10.1016/j.apenergy.2022.118825>
3. Cheng, L., Wei, X., Li, M., Tan, C., Yin, M., Shen, T., & Zou, T. (2024). Integrating evolutionary game-theoretical methods and deep reinforcement learning for adaptive strategy optimization in user-side electricity markets: A comprehensive review. *Mathematics*, 12(20), 3241. <https://doi.org/10.3390/math12203241>
4. Guo, G., & Gong, Y. (2023). Multi-microgrid energy management strategy based on multi-agent deep reinforcement learning with prioritized experience replay. *Applied Sciences*, 13(5), 2865. <https://doi.org/10.3390/app13052865>
5. Hady, M. A., Hu, S., Pratama, M., Cao, Z., & Kowalczyk, R. (2025). Multi-agent reinforcement learning for resources allocation optimization: a survey. *Artificial Intelligence Review*, 58(11), 354. <https://doi.org/10.1007/s10462-025-11340-5>
6. Jia, Z., Chen, Q., & Xu, Q. (2024). The art of balancing price and plug: Developing a theoretical model for dynamic pricing in the electric vehicle market. *Sustainability*, 16(21), 9325. <https://doi.org/10.3390/su16219325>
7. Kang, T., Li, H., & Zheng, L. (2023). Aggregative Game for Distributed Charging Strategy of PEVs in a Smart Charging Station. *Axioms*, 12(2), 186. <https://doi.org/10.3390/axioms12020186>
8. Karaki, A., & Al-Fagih, L. (2024). Evolutionary game theory as a catalyst in smart grids: From theoretical insights to practical strategies. *IEEE Access*, 12, 186926-186940. <https://doi.org/10.1109/ACCESS.2024.3436935>
9. K. Geetha, & P.Dinesh kumar. (2025). Multi-Objective Mathematical Optimization Framework for Renewable Energy Systems. *Journal of Applied Mathematical Models in Engineering*, 1(3), 8–13.
10. Karimov, R., Bekbaev, R., Ruzmatova, G., Karimova, S., Rakhimjanova, D., Mukaddas, I., ... & Muminova, M. (2025). Enhancing Personalized Learning in Smart Classrooms through Context-Aware Mobile Network Integration. *Journal of Wireless Mobile Networks, Ubiquitous Computing and Dependable Applications*, 16(4), 53–71. <https://doi.org/10.58346/JOWUA.2025.14.004>
11. May, R., & Huang, P. (2023). A multi-agent reinforcement learning approach for investigating and optimising peer-to-peer prosumer energy markets. *Applied Energy*, 334, 120705. <https://doi.org/10.1016/j.apenergy.2023.120705>

12. Rajvel, J. (2026). Neuromorphic Computing Architectures Using Memristive Devices for Energy-Efficient Artificial Intelligence. *International Academic Journal of Innovative Research*, 13(1), 22-30. <https://doi.org/10.71086/IAJIR/V13I1/IAJIR1303>
13. Ren, X., Wang, J., Yang, S., Zhao, Q., Jia, Y., Ou, K., ... & Yan, J. (2025). A novel multi-objective Stackelberg game model for multi-energy dynamic pricing and flexible scheduling in distributed multi-energy system. *Energy*, 325, 136206. <https://doi.org/10.1016/j.energy.2025.136206>
14. Saeed, M. A., Eladl, A. A., Alhasnawi, B. N., Motahhir, S., Nayyar, A., Shah, M. A., & Sedhom, B. E. (2023). Energy management system in smart buildings based coalition game theory with fog platform and smart meter infrastructure. *Scientific Reports*, 13(1), 2023. <https://doi.org/10.1038/s41598-023-29209-4>
15. Saeed, M. A., Sedhom, B. E., Elbaghdadi, A. S., Fadl, A. W., Abdelwahab, M. S., Elden, M. H., ... & Eladl, A. A. (2023). Practical prototype for energy management system in smart microgrid considering uncertainties and energy theft. *Scientific Reports*, 13(1), 20812. <https://doi.org/10.1038/s41598-023-48011-w>
16. Salami, Z. A., Bhaskaran, B., Mary, I. T. B., Ugli, I. S. S., Sripavithra, C. K., & Kalidoss, D. (2025). Energy-efficient architecture design in information service infrastructure. *Indian Journal of Information Sources and Services*, 15(2), 168–173. <https://doi.org/10.51983/ijiss-2025.IJISS.15.2.23>
17. Samadi, M., Ruj, S., Schriemer, H., & Erol-Kantarci, M. (2023). Secure and robust demand response using Stackelberg game model and energy blockchain. *Sensors*, 23(20), 8352. <https://doi.org/10.3390/s23208352>
18. Vij, P., & Nayak, A. (2025). Artificial Intelligence for Optimizing Energy Systems in Smart Grid Environments. *Archives for Technical Sciences*, (34), 1232. <https://doi.org/10.70102/afts.2025.1834.1232>
19. Wu, C., Gu, W., Yi, Z., Lin, C., & Long, H. (2023). Non-cooperative differential game and feedback Nash equilibrium analysis for real-time electricity markets. *International Journal of Electrical Power & Energy Systems*, 144, 108561. <https://doi.org/10.1016/j.ijepes.2022.108561>
20. Xu, D., & Li, M. (2025). A Stackelberg Game Model for the Energy–Carbon Co-Optimization of Multiple Virtual Power Plants. *Inventions*, 10(1), 16. <https://doi.org/10.3390/inventions10010016>
21. Zhang, L., Lu, Q., Huang, R., Chen, S., Yang, Q., & Gu, J. (2023). A dynamic incentive mechanism for smart grid data sharing based on evolutionary game theory. *Energies*, 16(24), 8125. <https://doi.org/10.3390/en16248125>
22. Zhang, T., Wu, Y., Chen, Y., Li, T., & Ren, X. (2023). Collaborative energy price computing based on sarima-ann and asymmetric stackelberg games. *Symmetry*, 15(2), 443. <https://doi.org/10.3390/sym15020443>