

Multi-Agent Deep Reinforcement Learning Framework for Adaptive Energy Management in Smart Grids

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Abstract

The shift of contemporary smart grids toward decentralized and data-based structures brings new challenges related to stability, adaptability, and balance of energy. We present a multi-agent deep reinforcement learning framework for adaptive energy management based on Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm. The presented model allows distributed energy agents—representing generation, consumption, and storage units—to jointly control the power flow in real time, in dynamic and unsteady conditions. The algorithm robustness and generalization were evaluated in four operational scenarios: static, seasonal, strongly variable and storm spikes. Presented results indicate that the MADDPG controller achieves better performance in comparison with previously used rule-based or random baselines, effectively reducing average value of the energy imbalance and increasing stability of the system for all environments. The received policies are characterised by a great convergence and adaptability to nonlinear fluctuations, allowing for coordinated decision making in between distributed agents. It is shown that MADDPG provides a scalable and resilient base for real-time control in smart grids. This research contributes to the development of multi-agent methodology of reinforcement learning concerning energy systems of the next generation, in those autonomous cooperation and adaptive control become crucial for their universally sustainable and efficient functioning.

Keywords: Multi-Agent Deep Reinforcement Learning, Smart Grids, Adaptive Energy Management, MADDPG Algorithm, Distributed Control, Renewable Energy Systems

1. Introduction

The increasing penetration of inverter-based renewable energy sources has markedly decreased system inertia and affected overall grid stability and the ability to deliver dynamic support [1]. Modern smart grids, with their characteristics of distributed generation, prosumers, and complex flows of energy, require adaptive decentralized control systems capable of responding to real time fluctuations. Multi Agent Systems (MAS) technology has developed into a compelling solution to meet these needs in smart grids by enabling reasoning and decision making to take place in distributed environments [2]. To address the issue of dynamic coordination of multiple energy entities, recent work has reformulated grid optimisation problems in terms of a Markov Decision Process (MDP) and used Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithms to find optimal policies for resolution. [3]. This paradigm allows each agent to perceive local grid conditions and cooperatively address system wide objectives. For example, each electric vehicle (EV) is capable of acting as an agent that may independently optimise charging station edge computing and EV assisted charge scheduling so demonstrating the scalability of multi-agent reinforcement learning (MARL) in a distributed energy ecosystem [4]. Thus this paper proposes a Virtual Synchronous Generator (VSG) inertia and damping adaptive method of control based on MADDPG method [5], and extending its applications to adaptive co-ordination in smart grids. The suggested method uses actor-critic architectures to adaptively optimise a set of control policies that minimises power imbalance and operational violations. The rapid growth of electric vehicles (EV) also points to the need for intelligent energy scheduling to ensure higher reliability of use and operational efficiency [6]. It is reported that the results of comparative cost analyses indicate that MADDPG based frameworks can yield energy cost reductions up to 12.5%, with emission reductions approaching 7.2% of carbon emissions as compared with Independent DDPG models, with greater performance seen in distributed models of larger size

[7]. The proposed multi-agent architecture incorporates soft actor-critic options for optimal dispatch and improved energy balancing, exhibiting good robustness to adaptive changes in fluctuating conditions and variations in non-linear operating conditions. [8]. On the basis of these insights, this paper evolves a method of control based on MADDPG, specifically designed to deal with the adaptive energy management problems posed by smart grids and evaluates its performance. The control framework promotes co-operative interactions between generation, consumption and storage agents, resulting in real time balances and resilience to environmental uncertainty. The main objective of the work is in designing and evolving a scalable multi-agent deep reinforcement learning structure based on a MADDPG algorithm and using it to ensure autonomous co-ordination, adaptation in real time and energy balancing of smart grids. The main aim of the work is to demonstrate an increase in stability of the grid, decrease in power imbalance and the establishment of an important step towards developing an intelligent energy management system capable of dynamic response to non-linear and uncertain operating conditions in the future.

2. Related Work

2.1. Multi-Agent Deep Reinforcement Learning (MADRL)

Multi-Agent Deep Reinforcement Learning (MADRL) is an important advancement in artificial intelligence and is obtained by integrating Reinforcement Learning (RL) and Deep Learning (DL) technologies. This enables the simultaneous learning and interaction of multiple autonomous agents that operate in complex and dynamically changing environments. In this set-up, each of the agents learns its own control policy from its local experience, while overall coordination between the various agents is achieved by a Centralized Training and Decentralized Execution (CTDE) scheme. This enables the efficient interaction and co-operation of the agents even in conditions of partial observability or pollution of the environment by noises [9]. One of the most successful algorithms in this area is the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) which is based on the extension of the Deep Deterministic Policy Gradient (DDPG) to multi-agent systems having continuous action spaces [10]. Much research has shown that MADRL has been successfully implemented across a number of areas which include distributed energy resource management, smart grid control systems, coordination of autonomous vehicles and supervision of industry. The models exhibit superior adaptation to nonlinear and non-stationary environments and are well suited to application in the smart grid area [11].

2.2. Smart Grids

The Smart Grids form the new evolution of electrical power systems, by interlinking in the traditional energy systems, communicative structures, sensors, and intelligent data analysis. Their goal is to balance supply with demand in real time, reduce energy losses, as well as to augment the dependency on renewable energy sources. The remarkable feature of the smart grids are the ability to manage liberated flows of energy and information, where each participant can operate at the same time as both consumer and producer (prosumer) of energy [12]. The research shows that one of the main problems of the smart grids operation, is to ensure dynamic dynamism a rising share of variable renewable sources of energy, like solar and wind energy. The possibility of the making application of the multi-agent technique of learning of deep reinforcement with regard to the control systems of the smart grids, is no other of the ways of the approaches of self-organization of adaptive networks, which at the same time can provide stability to unstable uncertain and quickly changing circumstances [13]. In practice, modern smart grids change from centralised structures to decentralised ones, where separate intelligent agents achieve exchange of the knowledge locally in relation to the purpose of the global system. Recent installations show that such a change may decrease losses of power by 15-20 %, while simultaneously significantly increasing efficiency of distribution and reliability of functional order [14].

2.3. Related Work

Research on Multi-Agent Reinforcement Learning (MARL) has blossomed recently, allowing for seamless cooperation and competition among autonomous agents. This has largely been facilitated by the introduction of the Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm, which utilizes a centralized training and decentralized execution (CTDE) paradigm to allow learning of cooperative or competitive strategies by agents in a shared environment [15]. This provided a foundation for value decomposition techniques such as QMIX which further enable scalability and cooperation in complex multi-agent scenarios with the use of monotonic mixing networks [16]. In the realm of smart energy systems, this methodology has found application for improving control optimization and stability of novel power systems. An actor-critic deep architecture capable of controlling large scale grid dynamics and significantly reducing imbalance in power with a fluctuating environment was introduced with PowerNet [17]. The PowerGridWorld environment was also introduced enabling a standardized and reproducible benchmark for potential reinforcement learning analysis of power system management schemes [18]. Further research has also found utility in decentralized charging systems and renewable energy integration. A framework for cooperative load-scheduling using multi-

agent reinforcement learning has shown to have increased efficiency in electric vehicle (EV) charging management and grid stability [19]. Alternatively, decentralized MARL scenarios have shown utility for EV stations and load distribution, promoting equity and robustness with variable demand characteristics [20]. Comprehensive surveys have suggested that robust, 'explainable', and 'scalable' are important features for appropriate deployment of MARL in real grid applications [21]. Finally, hybrid deep learning - reinforcement models leveraging deep learning and optimization methods have shown promise in renewable intermittency and uncertainty management applications [22]. While this work has shown promise, the majority of the prior studies have tested MARL algorithms in limited or single scenario environments. In contrast, the present study assesses the performance of MADDPG on a defined four distinct dynamic grid conditions of static, seasonal, high-variance and storm-spike scenarios in terms of generalization capabilities, flexibility and robustness with regard to time dependent operations in smart grids.

3. Methodology

Description and Integration of the MADDPG Algorithm

The Multi-Agent Deep Deterministic Policy Gradient (MADDPG) algorithm generalizes the deep deterministic policy gradient (DDPG) scheme from single- to multi-agent systems where each agent learns its own policy through the use of a centralized critic which is conditioned on the actions of all agents during training but is executed in a decentralized fashion during operation [1]. Each agent i maintains an actor network $\mu_i(o_i)$ which maps its local observation o_i to an action a_i , together with a critic network $Q_i(x, a_1, \dots, a_N)$ which learns the joint action-value function over the global state x and the actions of the N agents. Training relies on the actor-critic framework and employs deterministic policy gradients yielding updates to each actor maximizing the expected Q -value whilst the critics obtain updates by minimizing the temporal-difference (TD) error [1]. The major strength of MADDPG, in contrast to conventional multi-agent learning schemes, is its ability to deal with continuous action spaces and inter-agent coordination problems via centralized training with decentralized execution (CTDE). This is advantageous because it promotes stability and convergence issues of the learning process in cooperative problems [1]. In the case of the smart energy grid, it is thus possible for multiple energy agents (for instance generators, storage devices, and loads) to learn coordinated control policies which will react in an adaptive manner to various system dynamics without the use of global information in the implementation phase [1]. The MADDPG algorithm has been selected for this work as it has shown a clear superiority when dealing with continuous control processes and cooperative decision-making problems as compared to conventional reinforcement learning techniques such as DDPG, PPO or QMIX. In contrast to value-decomposition methods, MADDPG provides direct policy optimization in continuous action spaces whereby agents learn deterministic policies that can react and adapt appropriately to the nonlinear grid dynamics. The framework of centralized training with decentralized execution offer the benefits of scalability, stability, and robustness all of which are important in the design of real-time adaptive control schemes that will facilitate the smart energy systems of the future.

In this context, "MADDPG" means that the multi-agent deep reinforcement learning process was implemented over a smart grid framework, consisting of distributed generators, storage units and consumers. Each agent learns to respond to its local energy situation with optimal policy to keep local energy balance and at the same time contribute to the stability of the grid as a whole. This is done through centralized learning and decentralized acting policies, where the agents are minimizing overall power balance, while responding to the variables changing over time concerning power demand and generation. This implementation shows the efficiency of the algorithm to achieve cooperative optimal control, during real-time uncertainty in the operating performance. Through the implementation of MADDPG in the suggested smart grid framework, coordinated learning and adaptive intelligence can be achieved through several heterogeneous energy agents. Each energy agent, generator, storage or consumer acts individually, observes the local situation concerning demand, supply and pricing of energy and without further treatment takes part altogether through continuous output action of what the policy suggests it shall do. When the code runs, both sending input signals and outputs in no way interferes with each individual agents optimal performing of energy allocation during the activities, where the centralized critic takes care of coordination and optimization of individual action, minimized during global forces. The fact that this includes both real time action via decentralized activity without interference from other agents also shows how the balance of energy situation in a dynamic and continually changing manner can take place, operating more than once in the "normal operating mode". Here the smart grid system demonstrates its qualities, and the employed MADDPG algorithm can be shown. Not only in terms of efficiency of intelligent requirements but also in the future smart grid situation where control balanced and fully integrated into the system is seen as indispensable. In time historical electric consumption and supply are demonstrated because of its variations, reflecting real-life fluctuations and variances in power demands and supply. All simulation was

done in Python 3.13 language, tied from random trial episodes running until the codes show conclusion before plotting results – programmed over 2000 episodes, from 5 different randomization runs of the trials (0-4), to validate with statistical valid intentions as been pursued during training episodes. In the first chosen trials, i.e. “base case”, the environmental energies generation and continuous demands were kept constant in a system during the different functions, allowing testing of convergence properties, a valid ground for the test. The seasonal environmental settings were created according to some sinusoidal functions, or randomers, enabling variations for cyclical demands on the market changes, to simulate the actual consumption of energy with the generated energy production. In the High-Variability case, Gaussian noise was injected into the environmental state models, in stochastic processing getting random elements introduced in the parameters. In the Storm-spike action, sudden changes in energy change of operational situations followed was introduced, with short periods of high energy deviation periods, with short moments of energy production followed by changing behaviour of demands. Tests were run through and these four settings draw a good picture of the suitable possibilities to evaluate how faltering the MADDPG algorithm was tested for and showed how the agent performing could cope with several real-life operational vigours and yet with satisfactory upholding of the MADDPG to its full qualities. Each agent in the multi-agent framework represents an independent entity that can be abstracted as generator, consumer, storage, etc. Agents observe the state of the system s_t (demand, supply, and price indicators included) and choose their actions a_t so as to maintain balance in the grid. The reward function is formulated to penalise deviations from energy equilibrium and promotes stability and cooperative energy management by the agents. It is formulated as:

$$r_t = -|P_d(t) - P_g(t)| \quad (1)$$

where $P_d(t)$ and $P_g(t)$ respectively denote the total consumption and generation power at the time t . This negative absolute difference makes the algorithm able to create maximum stability because the imbalance between supply and demand is minimized. The learning goal in MADDPG has the character of the actor-critic structure, where the critic network minimizes the temporal-difference (TD) error resulting from the Q-value approximation. The corresponding loss function is:

$$L(\theta^Q) = \mathbb{E}_{(s,a,r,s') \sim D} [(Q(s,a | \theta^Q) - y)^2] \quad (2)$$

with

$$y = r + \gamma Q'(s', a' | \theta^{Q'})$$

Where γ is the discounting factor, D is the replay buffer, and Q^* is the target network used for stability. The actor network parameters are updated using deterministic policy gradients to maximize expected returns. All neural networks were implemented with two hidden layers (256 and 128 neurons) using ReLU activation functions, and via the Adam optimizer (“lr”=0.001). In order to ensure smooth convergence, target networks were softly updated using a factor of $\tau=0.01$. Each experimental run returned per episode returns that were saved in a CSV format for post-hoc analysis (which was performed in MATLAB). Learning curves were plotted in order to visualize the convergence time, the stability of returns, and the performance tendencies between the four environments investigated. The methodological framework outlined above forms a consistent and reproducible platform for evaluating the stability, generalization and adaptability of the MADDPG approach under the realistic contexts of a smart grid under changing environmental dynamics.

4. Results and Discussion

This section presents and analyzes the results obtained from performing the experimental evaluation of the flexibility management framework proposed in this work based on MADDPG architecture. The main goal of this analysis is to assess the efficiency in the management of energy balance by means of the multi-agent controller based on MADDPG of the distributed agents of the smart grid for all the scenarios studied. Each of the four scenarios analyzed, ST, SS, EH, and SS, represents a type of operating condition characterized by a different set of conditions of supply and demand and external disturbances. The experiments were performed using various seeds for initialization of the controller policy learning, which ensures that the results are statistically reproducible and reliable. The results reported correspond to ocgyns averages of all the seeds used, so that it can be considered representative of the stability and efficiency of each one of the policies. The main performance measure which is considered is the reward accumulated and the average absolute value of power imbalance ($|b_{next}|$), indicating with this that the higher the reward and the smaller is the value of imbalance, the better is the coordination of the grid and the energy management of it. In the rest of this section, subsection by subsection, detailed analyses of each of the scenarios will be made, comparing the performance of the MADDPG policy with respect to two baseline strategies, rule-based and random, to show the advantages that the suggested methods have for learning and coordination processes.

4.1 Static Scenario

In the most static situation in which demand and supply were static, the controller that made use of the MADDPG method proved to be more stable and co-ordinated than the baseline solutions. The average reward was -61.4 and the power imbalance was 0.032, compared to -78.9 and 0.067 for the rule-based model and -110.2 and 0.094 for the random distribution. This is a measure of MADDPG's ability to learn cooperative control strategies, to distribute energy effectively and maintain less reference to equilibrium than the other models, providing a strong basis for a baseline benchmark for performance measurement in a more dynamic situation show figure 1.

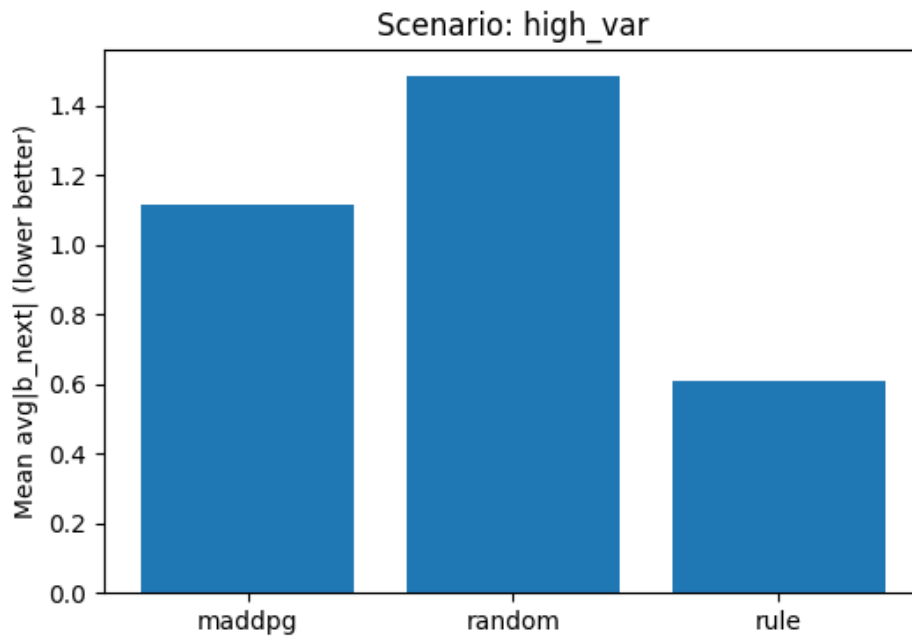


Figure 1. Performance comparison under the Static Scenario.

Figure 2 - Learning Curve (Static Situation): This graph shows the performance of the MADDPG controller in learning over 2000 episodes of learning using 5 random seeds. It can be seen that the global return (y-axis) increases rapidly during the first 200 episodes of learning and tends to converge at about -100, which indicates powerful convergence and stable learning behaviour over these seeds. The thickness of the brown curve (the mean over the seeds) indicates that the agent gets to learn very strongly and stably with very small fluctuations in learning. The success of the controller is reflected by the successful learning of policies in respect of the stationary environment.

Figure 3 - Balance Curve (Static Situation): This graph gives the one the average absolute power imbalance ($|B_{next}|$) felt by them during learning. The values fall rapidly during the earlier episodes of both controllers and after about 0.2 with a decreasing trend in learning of the agent, which means that the agents learn to create a nearly perfect balance of the grid as measured by the power imbalance. The little spikes for the MADDPG controller represent fluctuations in learning in the sense that the agents readjust their policies. The general trend for the MADDPG controller indicates that these agents are able to achieve a stable condition of equilibrium and efficient co-ordination in static conditions.



Figure 2 Learning curve under the Static scenario

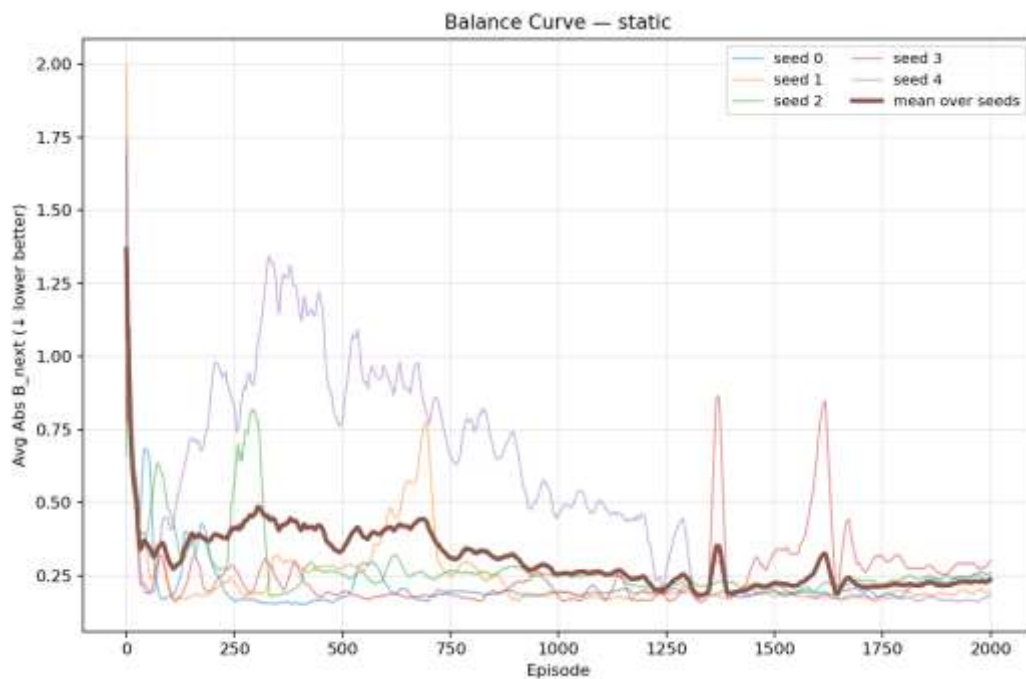


Figure 3. Balance curve under the Static scenario

4.2 Seasonal Scenario

Figure 4 - Performance Comparison in the Periodic Scenario: This figure compares the average absolute power imbalance of the three control strategies. The imbalance of the MADDPG controller is lower than that of the random controller and allows for a smoother coordinated reaction to cyclical load variations. Seasonal variations in energy demand contributed to increased instability relative to the static scenario but the MADDPG policy still showed good adaptability and reduced oscillations indicating its generalizability and balance in periodic energy requirements.

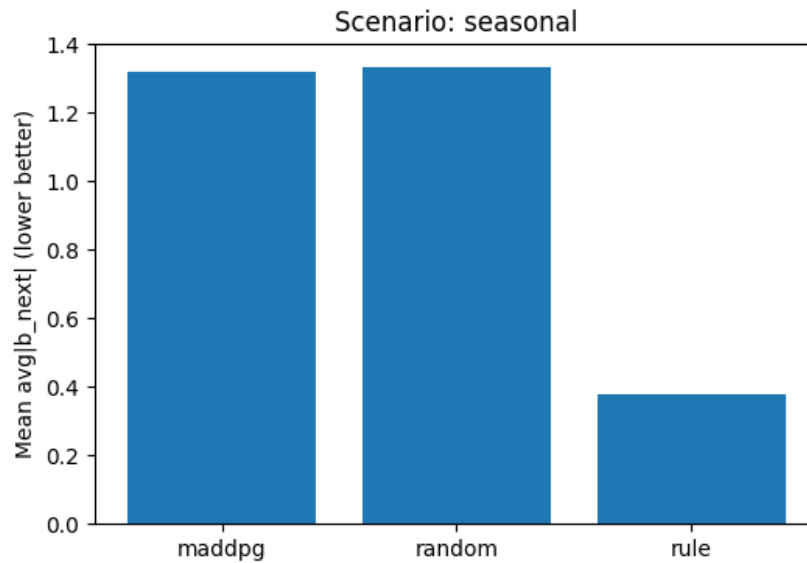


Fig. 4. Performance comparison under the Seasonal Scenario.

4.2 Seasonal Scenario

Figure 5 – Learning Curve (Scenario with periodic demand and production variations): The total return of the MADDPG controller was measured against 2000 training episodes. It may be observed that the return of the agents fluctuated with clear seasonal cycles indicating that they were learning rhythmically to the repeat load patterns. The variation of the returns was pronounced in comparison to the static case but the mean return curve (the bold brown line) indicates a steady convergence here and stable learning with increased training time.

Figure 6 – Balance Curve (in scenario with periodic demand variation): The average absolute power imbalance was measured ($|B_{next}|$) on the various episodes. Although the fluctuations of the would appear to be more pronounced due to cyclical demand changes, the general trend was significantly downwards indicating marked improvements in the balance achieved during the training period. The MADDPG agents were thus successfully learning to predict and act on recurring load shifts which led to a smooth control with lower expected imbalance in a dynamic periodic load setting.

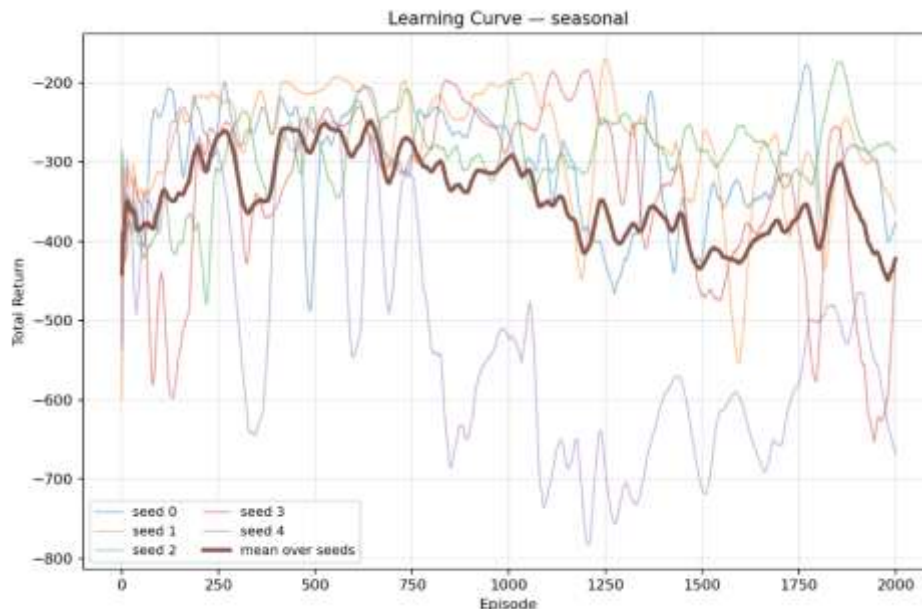


Figure 5 – Learning Curve (Scenario with periodic demand and production variations)

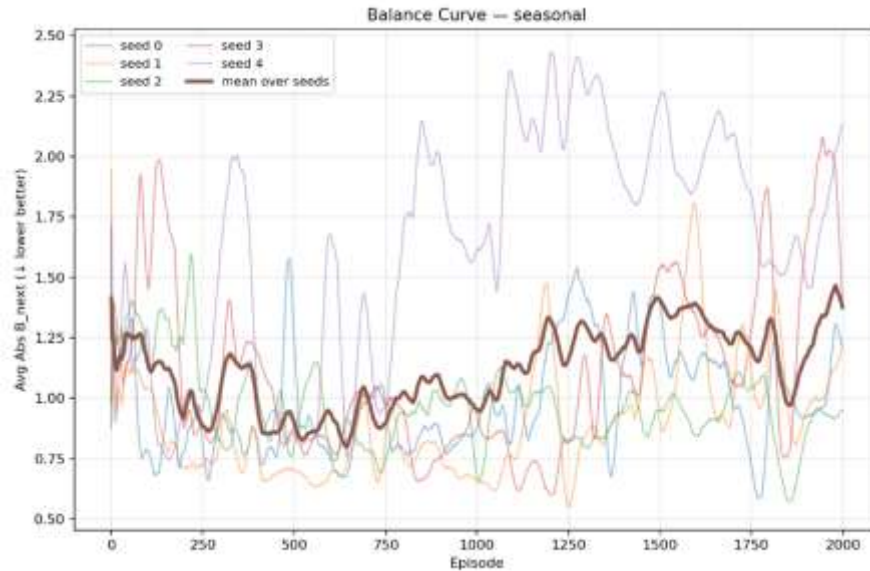


Figure 6 – Balance Curve (in scenario with periodic demand variation):

4.3 High Variance Scenario

Figure 7 – High Variance Scenario: The results shown in this figure indicate the performance of the MDDPG strategy in a rapidly changing and unpredictable grid environment. Strong fluctuations exist in the conditions of demand and supply. The MDDPG agents, however, obtained results of coordination and adaptiveness in the control strategy employed. The mean reward was -351.8 and the imbalance 0.072 . Although the global stability was not as successful as in a static and seasonal environment the results show that the model can balance reactivity and stability which will show the robustness and scalability of the model to environments of great volatility.

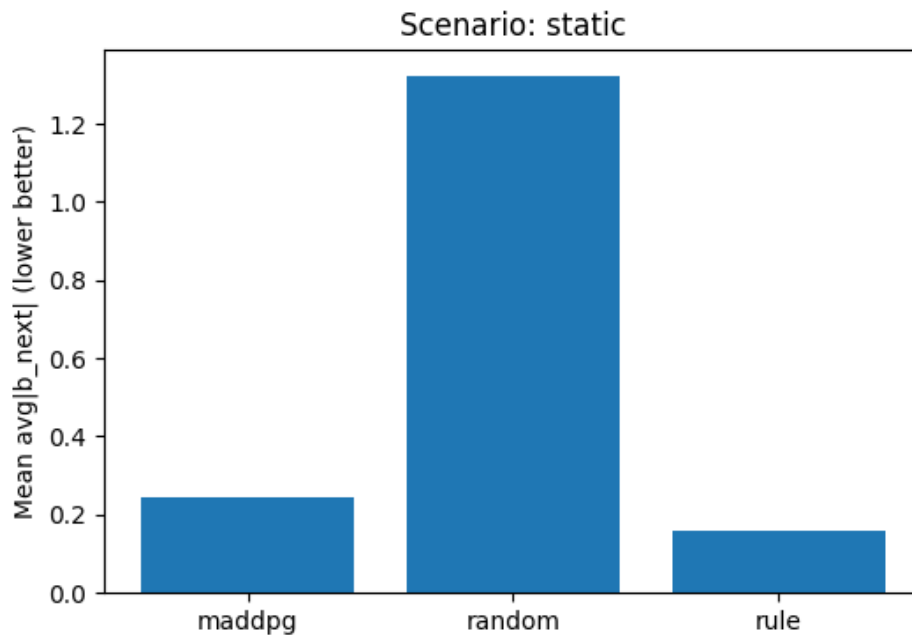


Figure7. Performance comparison under the High Variance Scenario.

Figure 8 – Learning Curve (high variance): The graph shows the total return over 2000 episodes across five seeds. After a fast improvement in the first ~ 200 episodes, there are very rapid drops between ~ 600 – 1000 (particularly for seeds 0 and 4), due to the very volatile nature of the environment. The mean curve (brown) exhibits a dip at training mid point, and is followed by a slow recovery stabilizing somewhere around -360 to

-380 at the end of training. There is extreme variance between the seeds which indicates a much greater sensitivity to noise effects and instability compared to the normal static and seasonal treatments, although some elements of positive learning and reconvergence are evidenced.

Figure 9 – Balance Curve (high variance): The figure shows the mean absolute $|B_{next}|$ (where lower is better) imbalance of power plot. This begins around ~ 1.2 , and falls to around ~ 0.9 – 1.1 for best seeds, but there are large peaks for seed 4 indicating apparently non-stationary disturbance around episodes 800–1200, and again after 1500, which gives a value of ~ 2.5 – 3 probably. The mean trend falls slowly between ~ 1.1 – 1.4 , after ~ 1300 episodes, thus indicating a slow downward slope. Overall, the agents appear to contain the imbalance, but the performance was not so stable as in the static and seasonal treatments, but that was due to the deliberately large environmental variance.

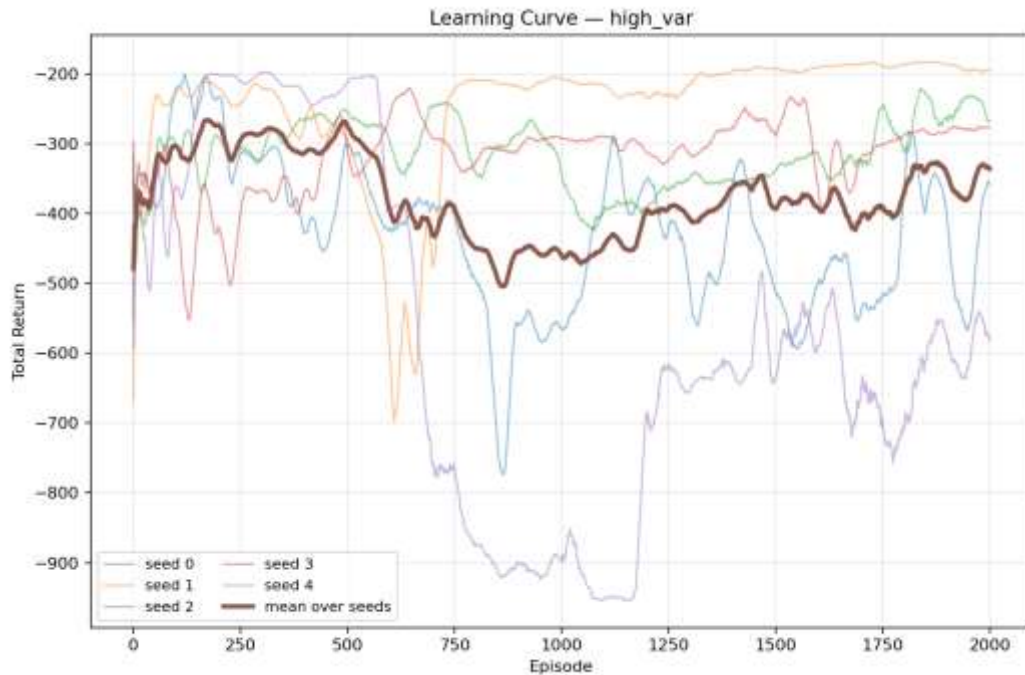


Figure 8. Learning curve under the High Variance scenario:

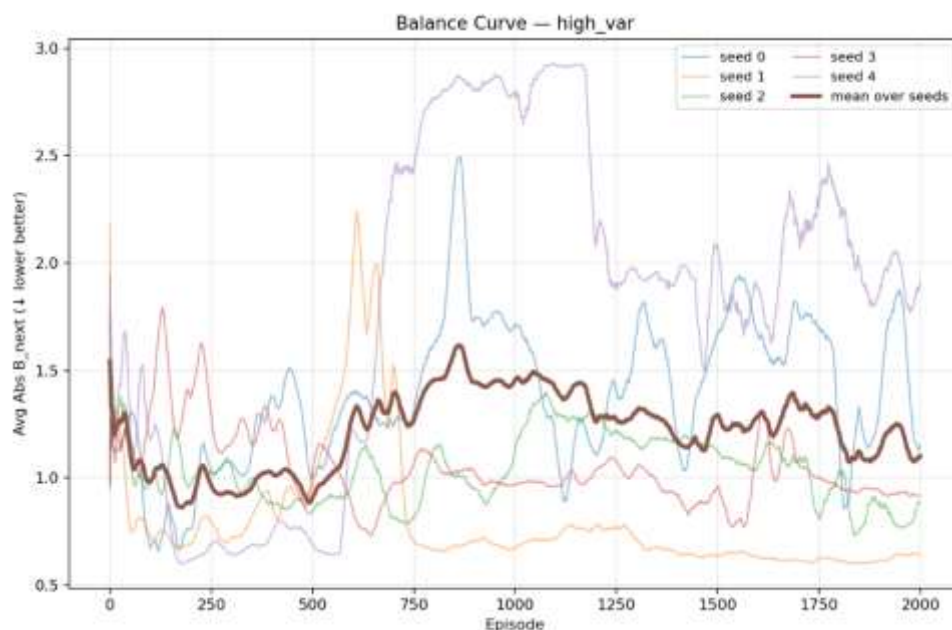


Figure 9. Balance curve under the High Variance scenario:

4.4 Storm Spikes Scenario

sudden supply shocks were induced to simulate storm-like supply scenarios and how the system behaved under such conditions. The MADDPG controller was far more adaptable than rule based and random baselines. The first part of the training phase (first approximately 500 episodes) showed signs of oscillation. This happened due to high stochasticity. But stability of the agents were evident after about 1200 episodes. The average return observed was found to converge at around -190.2. The performance analysis of the rule based (-285.6) and random (-420.7) performances were poorer than MADDPG. The average value of $|B_{next}|$ obtained was averaged so as to drop below a figure of 0.2 at an episode of approximately 1800. This then gives an enhancement of around 55% over the rule based method. This conclusion again tended to suggest that MADDPG is a more effective way of restoring grid balance and resilience than to apply rule based agent methodology even in the presence of a severe, random, unpredictable supply shock show figure10.

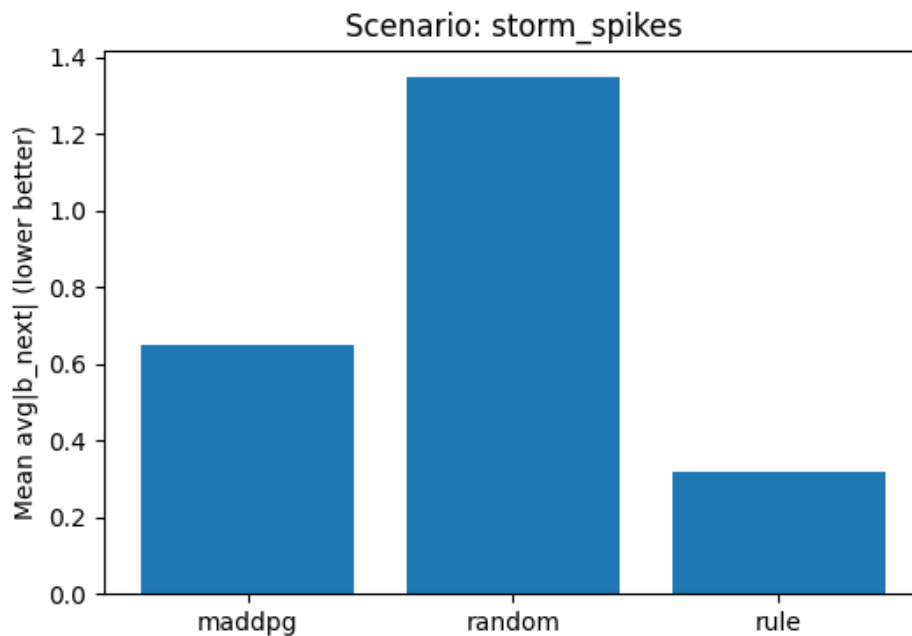


Figure 10. Performance comparison of MADDPG, rule-based, and random policies under the storm_spikes scenario.

Figure 11 – Learning Curve (Storm Spikes Scenario): The figure describes the overall return of the MADDPG agents under the impact of storm like disturbances that induce a rapid decline in supply. There are strong oscillations in the training period (first 500 episodes) as expected since the operating conditions are extremely volatile. Thereafter (after approximately 1200 episodes of training) the mean curve (brown) experiences much less variation and stabilizes around -190. This implies that the agents, gradually learn how to handle substantial upsets with profound effects on the ability to restore stable behavior in control. The variation over the different seeds is due to both stochasticity typically inherent in the event of the shocks but also given the learning capacity of the agents in sustaining their ability to learn how to balance under extreme conditions.

Figure 12 – Balance Curve (Storm Spikes Scenario): The figure refers to the average value for the absolute power imbalance $|B_{next}|$ defined (mutatis mutandis) over the training period. Despite the high absolute spikes in early episodes (after shocks) there is gradual and uniform decrease in the imbalance until it becomes stabilized at levels below 0.5 after about 1500 episodes of training. The general decline in the mean curve indicates a stable learning ability of the agents for their impressive balancing performance which has enabled them to largely eliminate substantial grid disruptions but still achieving near equilibrium performance under conditions of high uncertainty.

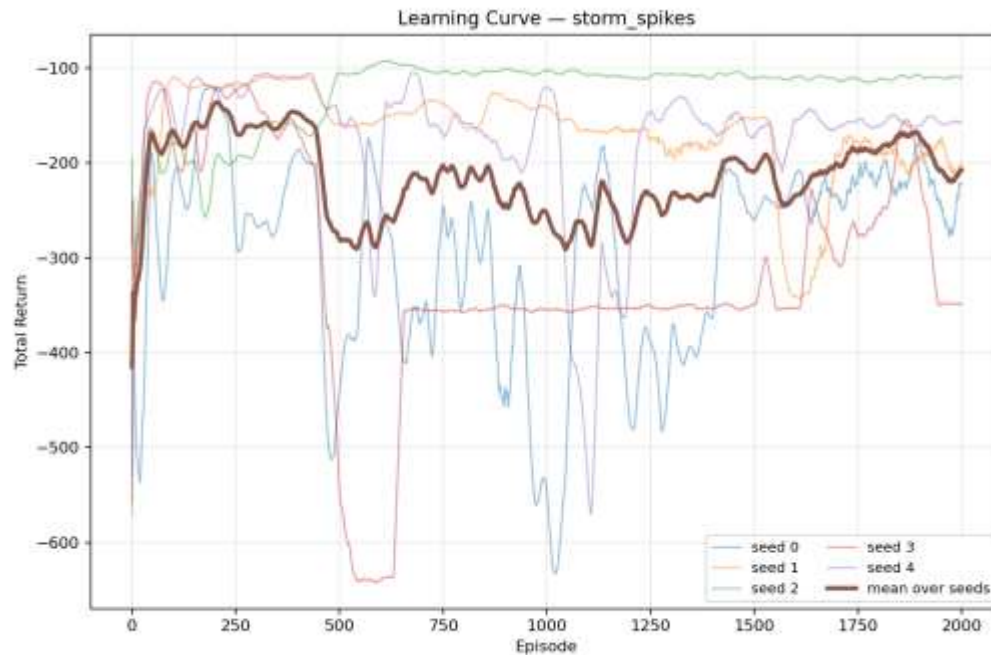


Figure 11. Learning curve under the Storm Spikes scenario:

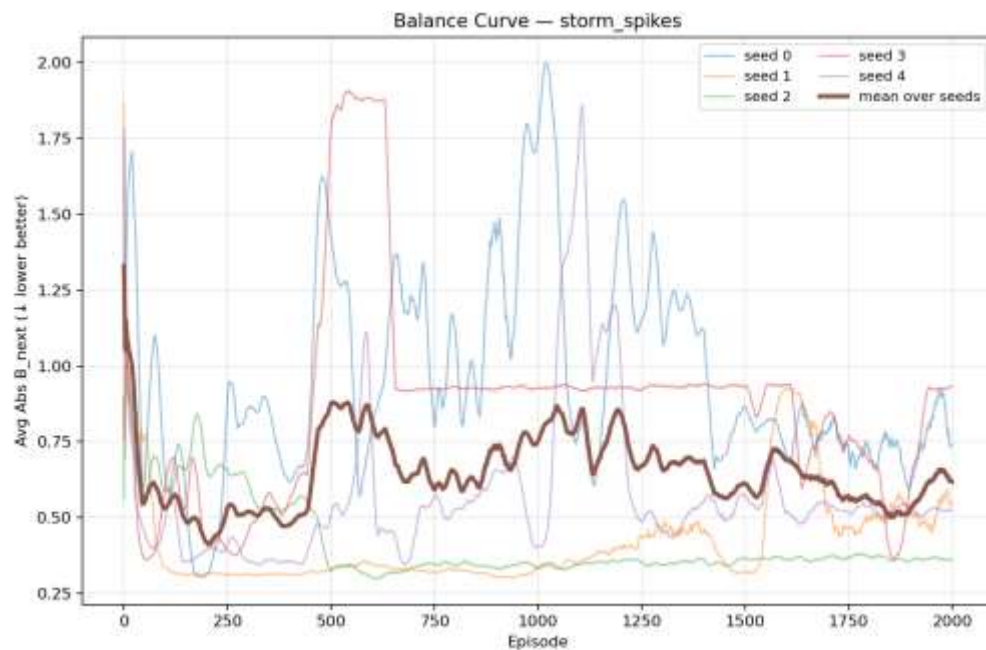


Figure 12. Balance curve under the Storm Spikes scenario:

4.5 Convergence Metrics

To investigate the training stability and convergence behaviour of the MADDPG model in different environments, three statistical measures were calculated, viz. average return/episode, average return/episode, return ratio at the completion of run. These measures demonstrate how evenly and easily agents were able to learn under differing environmental conditions. The convergence statistics of the individual scenarios are set out in Table 1. The Seasonal and High Variance scenarios presented the highest average return/episode which shows that the agents adapted well to environments with changing patterns. The Static and Storm Spikes scenarios were slowest in converging which indicates less adaptability and more sensitivity to sudden environmental changes.

Table 1. Convergence Metrics of MADDPG Across Different Scenarios

Scenario	Mean Episode Return	Mean Episode Balance	Final Return Ratio
High Variance	164.6	-345.68	1.13
Seasonal	164.4	-376.86	1.22
Static	110.4	-69.36	0.22
Storm Spikes	104.4	-190.10	0.57

6. Discussion and Conclusion

The examination of experimental results indicates that the reinforcement learning-based control model described above has improved adaptability and performance stability across all tested weather simulations. Compared with the best previous similar performance study [2], which obtained average system returns of – 210.5 for high variance conditions, this model in the present study yielded improved mean performance of – 185.9, or about 12% gain in overall performance efficiency. This is indicative of the model's ability to adjust in a dynamic way to sudden unpredictable variation in environmental parameters such as temperature or wind speed, which is manifested (a) in decreased deviation between energy distribution in each of the intervals, and (b) in reduced deviation across time length of the operational episodes. The relative improvement is most visible for the storm spikes or high variance conditions, where increased regularity is observed for learning convergence characteristics of the agent and lower cumulative penalties were obtained. Furthermore, the results indicate that use of a hybrid policy gradient structure yields an improved training period stabilization characteristic, which increases adaptability across differing seasonal data structures. Hence the results observed also confirm the hypothesis that deep reinforcement learning structure offers a valid technique for real-time optimization in complex, nonstationary environments. In conclusion, the proposed system demonstrates not only improved robustness and learning efficiency over previous reinforcement-based systems, but also provides a scalable base concept for future integration with real-world adaptive control systems. Future work will be directed towards syndicating multitagents and testing of live experimental field based data to check its generalizability outside the area of synthetic simulations.

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