A NOVEL REINFORCEMENT LEARNING - BASED CONTROL APPROACH FOR GRID-INTEGRATED PV-FESS SYSTEMS USING INDUCTION MOTORS

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ABSTRACT

This study introduces a novel reinforcement learning-based control strategy for a grid-connected photovoltaic system integrated with a flywheel energy storage system. The proposed method replaces the conventional dual-loop current control of the Field-Oriented Control scheme for the induction motor within the FESS with a single-agent controller based on the Deep Deterministic Policy Gradient algorithm. This intelligent controller leverages the strengths of Reinforcement Learning to handle the nonlinearities and parameter uncertainties inherent in the Flywheel Energy Storage System. Simulations in MATLAB/Simulink evaluate the performance of the proposed control system under various operating conditions. Results demonstrate that the Deep Deterministic Policy Gradient -based controller outperforms traditional Proportional-Integral controllers in ensuring stable power output to the grid, even under significant fluctuations in photovoltaic generation. The proposed control method enhances system stability, optimizes energy storage dynamics, and maintains power quality, contributing to the broader adoption of intelligent energy storage solutions in renewable energy integration.

THIẾT KẾ ĐIỀU KHIỂN HỌC TĂNG CƯỜNG CHO HỆ THỐNG PV-FESS TRONG VI LƯỚI

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TỪ KHÓA

Gradient chính sách xác định sâu
Hệ thống lưu trữ năng lượng bánh đà
Máy điện cảm ứng
Vi lưới
Học tăng cường

TÓM TẮT

Nghiên cứu này giới thiệu một chiến lược điều khiển dựa trên học tăng cường mới cho hệ thống quang điện kết nối lưới tích hợp với hệ thống lưu trữ năng lượng bánh đà. Phương pháp được đề xuất thay thế điều khiển dòng điện vòng kép thông thường của sơ đồ Điều khiển định hướng trường cho động cơ cảm ứng trong FESS bằng một tác nhân học tăng cường dựa trên thuật toán Gradient chính sách xác định sâu. Bộ điều khiển thông minh này tận dụng điểm mạnh của học tăng cường để xử lý các tính phi tuyến tính và sự không chắc chắn của tham số vốn có trong hệ thống bánh đà lưu trữ năng lượng. Các mô phỏng trong MATLAB/Simulink đánh giá hiệu suất của hệ thống điều khiển được đề xuất trong các điều kiện hoạt động khác nhau. Kết quả chứng minh rằng bộ điều khiển dựa trên Gradient chính sách xác định sâu vượt trội hơn các bộ điều khiển Tích phân tỷ lệ truyền thống trong việc đảm bảo sản lượng điện ổn định cho lưới điện, ngay cả khi có những biến động đáng kể trong việc phát quang điện. Phương pháp điều khiển được đề xuất giúp tăng cường độ ổn định của hệ thống, tối ưu hóa động lực lưu trữ năng lượng và duy trì chất lượng điện, góp phần áp dụng rộng rãi hơn các giải pháp lưu trữ năng lượng thông minh trong tích hợp năng lượng tái tạo.

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1. Introduction

The growing global demand for clean and sustainable energy has fueled the development and integration of renewable energy systems, particularly photovoltaic (PV) and wind power technologies, into modern power grids. These energy sources, characterized by their intermittent and stochastic nature, often present challenges in maintaining grid stability and power quality. Distributed generation (DG) systems, which encompass these renewable sources, are inherently small-scale and variable, necessitating advanced energy management strategies to address issues such as power imbalance, voltage fluctuations, and frequency instability in microgrids (MGs) [1] – [2].

Energy storage systems (ESS) have emerged as indispensable components of modern power systems, providing a buffer to balance supply and demand dynamically. Among the various ESS technologies, the flywheel energy storage system (FESS) stands out for its unique advantages, including high energy density, rapid response, long lifecycle, minimal maintenance requirements, and eco-friendly operation [3], [4]. Despite the higher initial investment cost, FESS offers low operational and maintenance expenses, making it a practical solution for stabilizing renewable energy-based systems. While previous research has largely focused on integrating FESS with wind power systems, its application in grid-connected solar power systems remains underexplored [4] – [6].

Traditional control strategies for FESS, such as those employing permanent magnet synchronous machines (PMSMs) or induction machines (IMs), often rely on linear controllers, including proportional-integral-derivative (PID) controllers. While these methods are straightforward and easy to implement, they struggle to accommodate the nonlinear characteristics and parameter uncertainties inherent in FESS and its associated power electronic converters. Recent advancements in nonlinear control approaches, such as backstepping, sliding mode control, and fuzzy logic control, have addressed some of these limitations [7], [8]. However, these strategies typically require precise knowledge of system parameters, limiting their adaptability in dynamic environments.

In parallel, artificial intelligence (AI)-based control techniques, including artificial neural networks (ANNs) and reinforcement learning (RL), have gained traction in addressing complex control problems. ANN-based controllers demonstrate the potential for adaptive control without detailed system modeling but face challenges in data collection and training, especially under variable operating conditions [9], [10]. RL control (RLC), on the other hand, offers a promising alternative by integrating optimal control principles with online learning capabilities. Over the past decade, advancements in computational power, algorithmic development, and data processing have significantly enhanced RLC's applicability to nonlinear and uncertain systems [11], [12]. Notable studies, such as those by Kushwaha and Gopal [11], and Memon et al. [12], have demonstrated the efficacy of RL algorithms, including Q-Learning and Twin Delayed DDPG (TD3), for motor control applications. However, these methods often require extensive data and computational resources, which may limit their real-time applicability.

Building upon this foundation, this study proposes a novel RL-based control strategy for a grid-connected photovoltaic system integrated with a flywheel energy storage system (PV-FESS). Specifically, the two current control loops of the conventional Field-Oriented Control (FOC) scheme for the induction motor in FESS are replaced by a single RL agent utilizing the DDPG algorithm. This approach simplifies the control structure while ensuring fast and accurate responses to dynamic changes in system parameters. The key novelty of this research lies in the application of the DDPG algorithm to replace traditional linear controllers, providing a robust and adaptive solution for managing the nonlinear dynamics of the PV-FESS system.

The proposed PV-FESS system, illustrated in Figure 1, integrates the FESS with the PV system at the DC bus through bidirectional power converters. The system's objective is to maintain a stable power output to the grid (Pgrid) by compensating for fluctuations in the PV power output (Ppv) using the flywheel power (Pfly), ensuring that Pgrid = Ppv + Pfly ≈ const. The operating principle of FESS involves energy storage and release through adjustments in the flywheel's angular velocity, governed by the equations of kinetic energy and power transfer dynamics. By leveraging the DDPG algorithm, the control strategy enables real-time adaptation to varying operating conditions, enhancing the system's overall stability and performance.

The next part of this article: Part 2 provides details the design of the proposed control strategy for the PV-FESS system. Section 3 presents simulation results under various operating scenarios, comparing the proposed RL-based control with conventional PI controllers. Finally, Section 4 concludes with insights into the findings and potential future research directions.

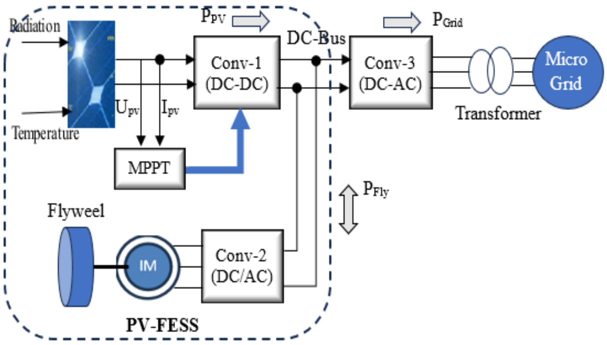

Figure 1. *Block diagram of the PV-FESS system connected to the grid*

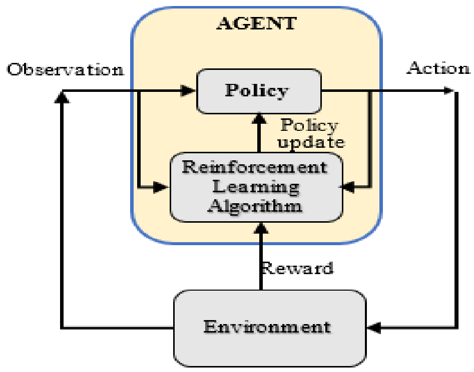

Figure 2. *Control system diagram with reinforcement learning technique*

2. Reinforcement learning control design for FESS

2.1. Reinforcement learning with DDPG Agent

To address the complex, dynamic control demands of FESS in real-time microgrid environments, RL offers an innovative solution. RL algorithms enable intelligent agents to autonomously learn optimal control policies by interacting with their environment. Unlike supervised learning, where predefined datasets are used for training, RL relies on the agent's experience gained through actions and feedback. An RL-based system's key components include the Agent and the Environment, illustrated in Figure 2.

The Agent itself consists of a policy (decision-making strategy) and an RL algorithm. A DNN is often employed to model the policy, enabling the Agent to identify and execute optimal actions for each observed state. Rewards, a critical element in RL, quantify the "goodness" of an action within a specific state. Unlike the cost function in traditional control methods like Linear Quadratic Regulator (LQR), RL rewards can take various forms, offering greater flexibility for complex, non-linear environments.

In an RL-based control system:

- The Agent executes actions that influence the Environment, receiving rewards and observing subsequent states.
- The Environment represents the dynamic system model influenced by the Agent's decisions.
- The Agent's behavior is governed by a Policy, typically modeled by a deep neural network, which maps observed states to actions.
- The Reward evaluates the Agent's performance, analogous to the cost function in optimal control theory, but tailored to maximize a desired outcome.

The iterative process of training an RL-based system involves defining the problem, modeling the environment, designing a reward function, constructing and training the Agent, and deploying the optimized control policy.

The DDPG algorithm is particularly well-suited for continuous action spaces, making it ideal for controlling systems like FESS, where actions (e.g., speed adjustments) are not discrete. DDPG combines the strengths of reinforcement learning with deep learning, leveraging neural networks to optimize policies and evaluate actions.

The DDPG algorithm employs an Actor-Critic architecture (illustrated in Figure 3) comprising two neural networks:

Actor Network: Responsible for policy modeling, the Actor predicts optimal actions for given states. It is updated to maximize the expected reward.

Critic Network: This evaluates the chosen actions by estimating their associated value functions, guiding the Actor's policy updates.

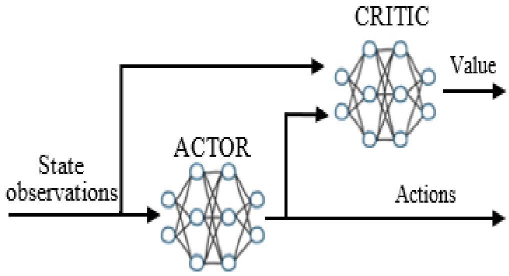

Figure 3. *Actor-Critic learning algorithms*

In DDPG, the Actor network generates continuous-valued actions based on observed states, while the Critic network provides feedback by approximating the action-value function.

The training process for the DDPG algorithm is iterative and involves: the environment provides the current state to the Agent; the Actor network determines the optimal action; the selected action influences the environment, producing a new state and reward; the Critic network evaluates the action, providing a learning signal to refine the Actor's policy; both Actor and Critic networks are updated using gradients computed from the reward and predicted value functions.

By combining these components, DDPG offers a robust framework for learning high-dimensional, continuous control policies. This integration of advanced RL techniques with FESS highlights a novel approach to energy management in microgrids, addressing the challenges of dynamic environments and promoting sustainable energy solutions.

2.2. Conventional FOC for FESS

Conventional FOC for the FESS is based on maintaining system stability during fluctuations in renewable energy generation, ensuring minimal variations in power fed to the grid. For this purpose, the control strategy aims to satisfy the following condition:

$$p_{grid} = p_{pv} + p_{fly} \approx const \tag{1}$$

where p_{grid} , p_{pv} *and* p_{fly} represent the power supplied to the grid, the power generated by photovoltaic sources, and the power from the FESS, respectively.

The mathematical model of IM in the rotating (d,q) coordinate system is described by [8]:

$$\frac{d}{dt}\begin{bmatrix}\varphi_{dr}\\ \kappa_{qr}\\ i_{sd}\\ i_{sq}\end{bmatrix} = \begin{bmatrix} \frac{-R_r}{L_r} & (\omega_s - p\omega_{Ffly}) & \frac{MR_r}{L_r} & 0\\ (\omega_s - p\omega_{Fly}) & \frac{-R_r}{L_r} & 0 & \frac{MR_r}{L_r}\\ \frac{MR_r}{\sigma L_s L_r^2} & \frac{Mp\omega_{Fly}}{\sigma L_s L_r} & \frac{-R_{sr}}{\sigma L_s} & \omega_s\\ -\frac{Mp\omega_{Fly}}{\sigma L_s L_r} & \frac{MR_r}{\sigma L_s L_r^2} & -\omega_s & \frac{-R_{sr}}{\sigma L_s}\end{bmatrix}\begin{bmatrix}\varphi_{rd}\\ \varphi_{rq}\\ i_{sds}\\ i_{sq}\end{bmatrix} + \begin{bmatrix}0 & 0\\ 0 & 0\\ \frac{1}{\sigma L_s} & 0\\ 0 & \frac{1}{\sigma L_s}\end{bmatrix}\begin{bmatrix}u_{sd}\\ u_{sq}\end{bmatrix} \tag{2}$$

where, $R_{sr} = R_s + \frac{M^2}{L_r^2}R_r$, $\sigma = 1 - \frac{M^2}{L_s L_r}$, R_s, R_r are the stator phase resistance and the rotor phase resistance; L_s, L_r are is the stator phase inductance and the rotor phase inductance; M is the mutual inductance; u_{ds}, u_{qs} are the orthogonal components of stator voltage; i_{ds}, i_{qs} are the orthogonal components of stator current; ϕ_{dr}, ϕ_{qr} are the orthogonal components of rotor flux; p is the number of pole pairs; ωs is the rotational speed of the stator magnetic field:

$$\varphi_{rd} = \varphi; \;\; \varphi_{rq} = 0 \tag{3}$$

The state equations (2) become:

$$\frac{d}{dt}\begin{bmatrix}\varphi\\ i_{sd}\\ i_{sq}\end{bmatrix}=\begin{bmatrix}\frac{-R_r}{L_r} & \frac{MR_r}{L_r} & 0\\ \frac{MR_r}{\sigma L_s L_r^2} & \frac{-R_{sr}}{\sigma L_s} & \omega_s\\ -\frac{Mp\omega_{fly}}{\sigma L_s L_r} & -\omega_s & \frac{-R_{sr}}{\sigma L_s}\end{bmatrix}\begin{bmatrix}\varphi\\ i_{sd}\\ i_{sq}\end{bmatrix}+\begin{bmatrix}0 & 0\\ \frac{1}{\sigma L_s} & 0\\ 0 & \frac{1}{\sigma L_s}\end{bmatrix}\begin{bmatrix}u_{sd}\\ u_{sq}\end{bmatrix} \tag{4}$$

The reference flux linkage is defined by the expression:

$$\varphi_{ref}=\begin{cases}\varphi_{rn} & \text{khi } |\omega_f|\le\omega_{fn}\\ \varphi_{rn}\frac{\omega_{fn}}{|\omega_f|} & \text{khi } |\omega_f|>\omega_{fn}\end{cases} \tag{5}$$

$$\varphi_{rn}=\frac{L_r}{M}\varphi_{sn} \tag{6}$$

φ_{rn} is the reference flux linkage of the rotor, φ_{sn} is the reference flux linkage of the stator

$$\varphi_{sn}=\sqrt{3}\frac{u_s}{\omega_s} \tag{7}$$

With u_s being the effective value of the stator phase voltage, ω_s being the angular velocity of the grid voltage with a value of 314.16 rad/s, we have: $\varphi_{rn}=\sqrt{3}\frac{L_r}{M}\frac{u_s}{\omega_s}$ (8)

The reference stator current is determined by: $i_{ds-ref}=\mathrm{PI}(\varphi_{ref}-\varphi_{est})$ (9)

PI stands for Proportional-Integral control law. The estimated value of the rotor flux linkage is:

$$\varphi_{est}=\frac{M}{1+\frac{L_r}{R_r}s}i_{sd} \tag{10}$$

where: s is the Laplace operator

The reference power of the IM is determined by formula (1). From there, the reference speed of the flywheel is calculated: $\omega_{fly-ref}=\sqrt{\frac{2E_{fly-ref}}{J_{fly}}}$ (11)

Where $E_{fly\_ref}=E_{0\_fly}+\int p_{fly}dt$, E_{0_fly} is the initial kinetic energy of the flywheel. Using these equations, the reference flux linkage and stator current values are derived to optimize the control strategy. The proportional-integral (PI) controllers used in the outer loops regulate the speed and flux, while the inner loops control d- and q-axis currents. The block diagram for conventional FOC control of FESS is depicted in Figure 4, where the system relies on cascaded PI controllers for maintaining operational efficiency.

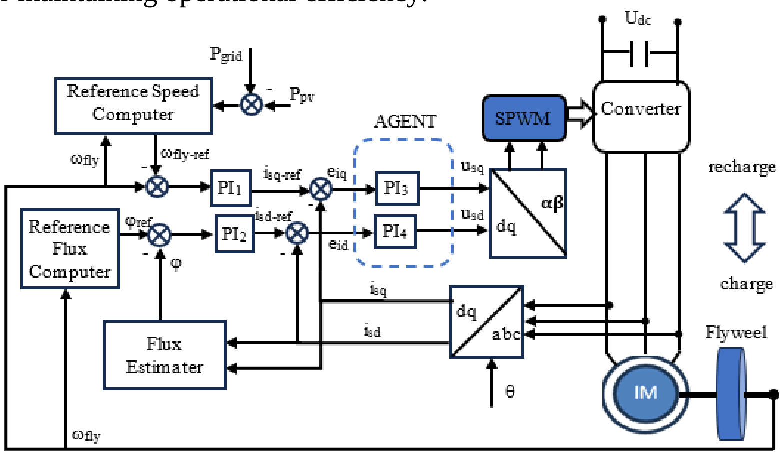

Figure 4. *Conventional FOC control block diagram for FESS*

While conventional FOC control methods are widely adopted, they exhibit limitations in handling nonlinearities and dynamic system changes, necessitating constant tuning of the PI controllers under varying conditions. This highlights the need for advanced control strategies, such as RL, to enhance performance and adaptability.

2.3. Reinforcement Learning Control for FESS

Building on the foundation of conventional FOC, this study introduces a RL-based control design that replaces the inner-loop PI controllers with an intelligent agent. The RL agent, implemented using the DDPG algorithm, is especially compatible with nonlinear and dynamic systems like FESS, offering the ability to adapt without the need for manual controller tuning.

Design Overview: The RL environment for the FESS control system includes all system components except the inner current control loops, which are replaced by the RL agent. The agent observes the system state variables, including i_{sd}, i_{sq}, and their errors $e_{id} = i_{sd\_ref} - i_{sd}$ and $e_{iq} = i_{sq\_ref} - i_{sq}$. The agent outputs control signals u_{sd} and u_{sq}, which are fed to the Space Vector Pulse Width Modulation (SVPWM) block.

Reward Function Design: The reward function, critical for guiding the agent's learning, is defined to encourage accurate tracking of reference currents and minimize control effort. It is expressed as: $r_t = -\left(\lambda_1 * e_{id}^2 + \lambda_2 * e_{iq}^2 + \lambda_3 u_{t-1}^2\right) = -\left(1 * e_{id}^2 + 1 * e_{iq}^2 + 0{,}01 u_{t-1}^2\right)$ (12)

where: e_{id} is the error of the d-axis current; e_{iq} is the error of the q-axis current; u_{t-1} is the previous control signal, and $\lambda_1, \lambda_2, \lambda_3$ are weighting factors. For this study, $\lambda_1 = \lambda_2 = 1$, and $\lambda_3 = 0.01$.

The RL agent employs the DDPG algorithm, which uses Actor-Critic neural networks to approximate the optimal policy. The Actor network determines the optimal action for a given state, while the Critic network evaluates the action by estimating its Q-value. The continuous action space of DDPG makes it ideal for controlling the analog signals usd and usq . Training is performed in MATLAB-Simulink using the RL Toolbox. The training process involves 1900 cycles, with termination when the agent achieves an average reward exceeding a predefined threshold. This process ensures the agent learns to effectively handle the nonlinearities and dynamics of the FESS system.

The proposed RL-based control strategy demonstrates significant innovation by leveraging the adaptability and decision-making capabilities of RL. Unlike traditional PI controllers, which require frequent recalibration, the RL agent dynamically optimizes its control actions based on real-time interactions with the environment. Not only is this approach refine control interpretation but also reduces the need for manual intervention, making it highly scalable and robust for modern energy systems. By integrating the DDPG algorithm into the FESS control framework, this research highlights the potential of RL to revolutionize energy storage management, offering a novel solution for enhancing grid stability in renewable energy systems.

3. Simulation and Discussion

To evaluate the effectiveness of the proposed RL control strategy and its capacity to manage energy fluctuations in the PV-FESS system, simulations were conducted using Matlab-Simulink under a realistic scenario. The objective of these simulations was to demonstrate the ability of the FESS to compensate for irregularities in solar power generation, ensuring stable energy delivery to the grid. The simulation parameters and results highlight the novelty and robustness of the RL approach compared to conventional control techniques.

3.1. Simulation Setup

Under typical operating conditions, the PV-FESS system ensures that the total power injected into the grid remains stable, with $P_{pv\text{-}fess} = P_{Grid}$. In this study, we simulated a scenario where solar power generation experiences abnormal fluctuations of ±50 kW. The FESS compensates for these variations by absorbing or releasing power to maintain grid stability. The power balance is described by: $P_{Fly} = P_{Grid} - P_{pv} = \mp 50\text{kW}$ (13)

Here, P_{Fly} serves as the reference signal for controlling the FESS operation. The simulation parameters as follows: P = 7.5kW; Poles = 2; R_s = 0.6837Ω; R_r =0.451Ω; L_s = 0.04152H; L_r =

0.04152H; L_m = 0.1486H; J = 12.5kg.m^2; Simulation time: 1sec; PI_1 (K_p = 50, K_I = 65); PI_2 (K_p = 55. K_I = 102)

In the simulation, the desired power output from the PV-FESS system was maintained at P_{Grid} = 500kW, while the solar power generation Ppv(t) varied randomly over time. The power required from the FESS at the DC bus was calculated as:

$$P_{fly}(t) = P_{grid} - P_{pv}(t) = P_{Fly\text{-}ref.} \tag{14}$$

To compare the performance of RL and conventional FOC, simultaneous simulations were performed for both control schemes under two conditions: (1) Nominal machine; (2) Modified machine parameters, where stator and rotor resistances were doubled (Rs = 1.3674Ω and Rr = 0.902Ω) when it comes to the temperature rise of the electrical machine during operation.

3.2. Simulation results

Figure 5 and Figure 6 illustrate the power and flux responses of the FESS under nominal conditions. Both the RL-based control and conventional FOC schemes demonstrated effective tracking of the reference power, ensuring stable grid operation. The minor differences between the two methods under nominal conditions suggest that conventional FOC can meet basic control requirements.

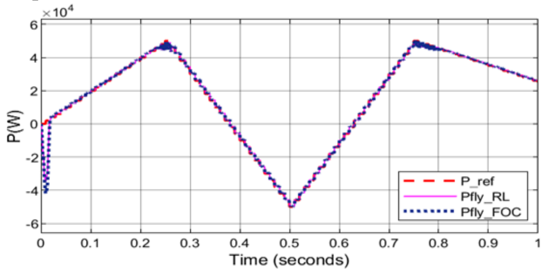

Figure 5. *The power response of FESS when use RL and FOC*

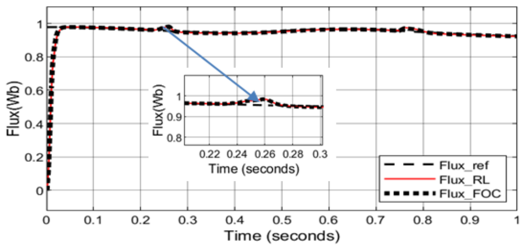

Figure 6. *The fux response of FESS when use RL and FOC*

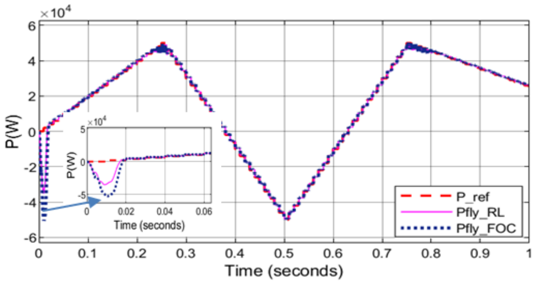

Figure 7. *The power response of the FESS when using RL and FOC as the parameters of the electric machine varies*

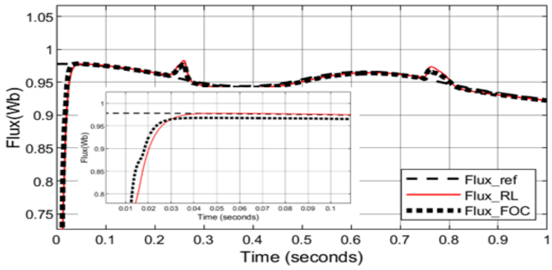

Figure 8. *The flux response of the FESS when using RL and FOC as the parameters of the electric machine varies*

However, when the machine parameters were modified, as shown in Figure 7 and Figure 8, the RL-based control scheme exhibited superior adaptability. The power response and phase response of the RL system closely followed the reference values, while the conventional FOC scheme showed significant deviations. This result highlights the ability of RL to handle parameter variations and dynamic operating conditions without requiring manual retuning, unlike the fixed-gain PI controllers in conventional FOC.

Finally, Figure 9 demonstrates the power response of the PV-FESS system when subjected to random fluctuations in solar power generation. The RL-based FESS maintained a nearly constant total power delivery to the grid, effectively compensating for irregularities in solar power. This confirms the capability of the RL approach to achieve robust and adaptive control, ensuring grid stability under varying conditions.

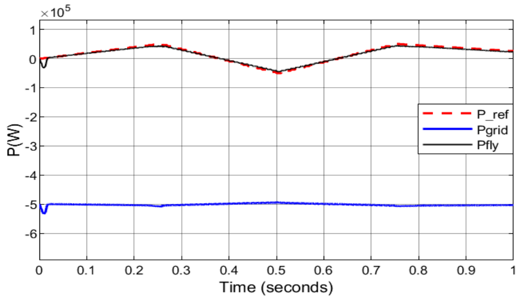

Figure 9. *Power response of the PV-FESS with RL technique*

3.3. Discussion

The simulation results underscore the novelty and creativity of integrating RL into FESS control. Unlike conventional FOC, which relies on fixed-gain PI controllers, the RL agent dynamically adjusts its control strategy based on real-time feedback from the system. This adaptability is particularly advantageous in nonlinear and time-varying systems, such as the PV-FESS system, where parameter uncertainties and external disturbances are common. Moreover, the RL-based control reduces the need for manual tuning and improves system performance across a wide range of operating conditions. These features make RL a promising alternative to traditional control methods for advanced energy storage and grid stabilization applications. The findings of this study contribute to the growing body of research on intelligent control systems, paving the way for more efficient and resilient renewable energy systems.

4. Conclusion

This study proposes a RL-based control algorithm using the DDPG agent to regulate a PV and FESS integrated with the grid, ensuring stable power delivery despite solar generation fluctuations and parameter variations. Simulation results confirm the RL-based controller’s ability to maintain consistent grid power under dynamic conditions, outperforming the conventional proportional-integral (PI) control, particularly when system parameters deviate. The research highlights the novel application of RL for adaptive management of renewable energy systems, contributing to the development of robust, efficient, and intelligent grid-integrated solutions. While promising, the study represents an initial step validated through simulations. Future work should focus on comparative evaluations with other RL algorithms, real-world experimentation, sensorless control strategies, and optimization of the DC-AC interface for enhanced practicality and performance. These directions offer significant potential to advance RL-based control for renewable energy integration, fostering resilient and sustainable energy systems.

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