# Abstract

The rapid expansion of urban areas, coupled with the increasing integration of renewable energy sources, electric vehicles, and energy storage systems, has introduced unprecedented challenges to power networks. As industries grow increasingly reliant on stable and reliable electricity, the demand for a resilient, flexible, and adaptive grid has intensified. Traditional grid management strategies, which rely heavily on static models and historical data, struggle to handle the growing complexity and dynamic nature of modern power systems. The rise of distributed energy resources (DERs) has further complicated grid operations, introducing issues such as reverse power flow and load balancing, which require advanced, real-time control strategies to ensure grid stability and operational efficiency.

Deep Reinforcement Learning (DRL) has emerged as a transformative approach to optimizing control in large-scale, dynamic systems like power grids. Its ability to continuously learn from real-time data and adapt to changing environments enables the development of advanced, automated control strategies that surpass the capabilities of conventional optimization methods. DRL is uniquely suited to address the uncertainty, high dimensionality, and nonlinearity characteristic of today's distribution networks.

This report investigates the application of DRL in two key areas of renewable power grid management: (1) parameter calibration of Doubly-Fed Induction Generators (DFIGs) in wind energy systems and (2) real-time power management to address reverse power flow (RPF) in distribution networks. Both applications are critical to improving the stability, efficiency, and resilience of modern power systems.

In the first application, DRL is used to dynamically calibrate the parameters of DFIGs, which are widely used in wind farms. Accurate parameter tuning is essential for maintaining stable operations and maximizing energy output. However, these parameters can drift over time due to environmental changes, equipment aging, and operational stress, leading to inefficiencies and increased risks. To address this, two baseline approaches—Particle Swarm Optimization (PSO) and the Soft Actor-Critic (SAC) algorithm—were explored. A novel hybrid approach, SAC-PSO, was developed, where SAC guided the PSO optimization process. This resulted in an 87.84\% reduction in mean squared error (MSE)

during testing, proving highly effective in scenarios with multiple potential solutions and scalable for power plants with multiple DFIG units.

The second application focuses on addressing reverse power flow (RPF) and load transfer challenges in distribution networks, which are exacerbated by the growing penetration of DERs like solar photovoltaics and electric vehicles. Reverse power flow, caused by excess energy from DERs flowing back into the grid, can destabilize the system and lead to inefficiencies. Traditional load transfer and RPF management methods, often reliant on manual control or predefined algorithms, are insufficient in rapidly changing grid conditions. This study developed a distributed DRL algorithm, Maskable Distributed Proximal Policy Optimization (MaskableDPPO), to automate and optimize the load transfer process in real-time. Using power flow calculations as observation states and grid-switching devices like circuit breakers as action variables, MaskableDPPO achieved 98.6\% accuracy in managing reverse power flow and load transfers, significantly reducing manual intervention, enhancing system reliability, and enabling faster, more efficient real-time load redistribution.

In conclusion, integrating DRL into power grid operations offers a scalable and adaptive framework to address the growing challenges of modern distribution networks. This report provides a comprehensive analysis of how DRL can improve DFIG parameter calibration and optimize load transfer in grids with high DER penetration. The practical benefits of DRL, demonstrated through simulations and case studies, include enhanced load transfer efficiency, improved fault management, and significant energy savings. Future research should explore extending DRL frameworks to handle more complex grid scenarios, incorporating AI-driven forecasting techniques, and developing hybrid models to further optimize grid performance under uncertainty.

This report lays the foundation for future DRL applications in power system management, contributing to the development of more resilient and efficient energy networks capable of meeting future demands.