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Adaptive Power Sharing in Microgrids Using PPO-Based Virtual Impedance Control

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Abstract : This paper presents a Proximal Policy Optimization (PPO)-based virtual impedance (VI) controller aimed at improving power sharing and dynamic response in inverter-interfaced microgrids under varying operating conditions and disturbances. Conventional droop control methods often suffer from degraded performance due to mismatches in feeder impedance, which negatively impact power-sharing accuracy. To address this limitation, the proposed controller employs a reinforcement learning framework that continuously adapts its control policy based on system conditions. The control problem is formulated as a Markov Decision Process (MDP), where appropriate state and action spaces are defined, and a carefully designed reward function guides the learning process to achieve desired transient and steady-state performance. By leveraging PPO, the controller reduces reliance on manual tuning and enhances adaptability to changing environments. The effectiveness of the proposed approach is evaluated under both islanded and grid-connected modes using battery energy storage systems with capacities of 1 MW, 125 kW, and 100 kW. Simulation results demonstrate improved power-sharing accuracy and superior disturbance response compared to conventional control strategies. Performance evaluation based on system frequency metrics, including Root Mean Square Error (RMSE), Integral of Absolute Error (IAE), Integral of Squared Error (ISE), and Integral of Time-Weighted Squared Error (ITSE), shows that the PPO-based controller consistently achieves lower errors. In particular, the IAE is reduced by 27% in islanded mode and 36% in grid-connected mode, confirming the effectiveness of the proposed method.

Index Terms - Proximal Policy Optimization (PPO), Virtual Impedance Control, Microgrids, Reinforcement Learning, Droop Control, Power Sharing, Inverter-Based Systems, Distributed Energy Resources (DER), Battery Energy Storage System (BESS), Grid-Connected Mode, Islanded Mode, Fault Analysis, Frequency Stability, Adaptive Control.

I. INTRODUCTION

The increasing global demand for energy and growing environmental concerns have driven a rapid transition from conventional fossil-fuel-based power generation toward renewable energy sources. Distributed Energy Resources (DERs), including photovoltaic systems, wind turbines, and battery energy storage systems, are increasingly deployed at the distribution level and interconnected through power electronic converters to form microgrids. These systems can operate in both grid-connected and islanded modes. While grid-connected operation allows power exchange with the utility grid, islanded operation requires the microgrid to independently regulate voltage and frequency while supplying local loads. Unlike synchronous generators, inverter-based DERs lack inherent rotational inertia, making microgrids more sensitive to disturbances such as load variations, faults, and renewable intermittency. As a result, maintaining voltage stability, frequency regulation, and reliable power sharing under varying operating conditions remains a major control challenge.

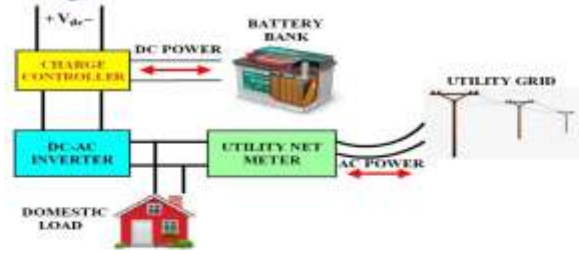

Figure 1: Typical microgrid structure with distributed energy resources

In inverter-based microgrids, multiple DER units often operate in parallel, requiring accurate sharing of active and reactive power according to their ratings. Conventional droop control is widely used for this purpose due to its decentralized nature and simplicity; however, practical issues such as feeder impedance mismatches, parameter variations, and fixed droop settings lead to poor power-sharing accuracy, voltage deviations, and reduced stability. Virtual impedance has been introduced to compensate for these effects by reshaping the inverter output impedance, but its performance depends heavily on proper parameter tuning. Given the highly dynamic and uncertain nature of modern microgrids, traditional fixed-parameter control strategies become inadequate. This motivates the use of intelligent, adaptive control techniques such as reinforcement learning. In particular, Proximal Policy Optimization (PPO) enables real-time tuning of virtual impedance parameters, improving power-sharing accuracy, transient response, and robustness without requiring precise system models.

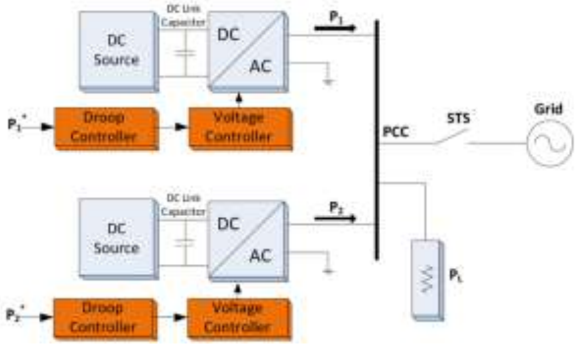

Figure 2: Power sharing and intelligent control concepts in inverter-based microgrids

II.Literature Survey

The growing penetration of renewable energy sources has significantly reshaped modern power systems, leading to the widespread adoption of microgrids based on distributed energy resources such as photovoltaic systems, wind turbines, and battery energy storage systems. Early research established the concept of microgrids as flexible systems capable of operating in both grid-connected and islanded modes, emphasizing the importance of local control and seamless mode transitions. Subsequent studies introduced hierarchical control architectures consisting of primary, secondary, and tertiary layers to manage voltage, frequency, and power flow. While hierarchical frameworks improve overall system coordination, they often rely on communication infrastructure, which increases complexity and reduces reliability in decentralized microgrid environments.

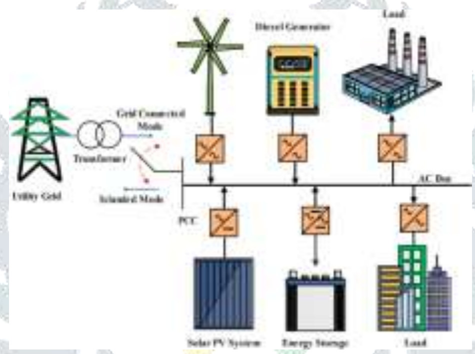

Figure 2.1: Microgrid control architectures and operating modes

Droop control has emerged as the most widely adopted decentralized strategy for power sharing among parallel inverters due to its simplicity and communication-free operation. Numerous studies have demonstrated that P–ω and Q–V droop characteristics enable autonomous power sharing in inverter-based microgrids. However, practical implementations reveal significant limitations, particularly poor reactive power sharing caused by feeder impedance mismatches and resistance-dominant low-voltage networks. To address these drawbacks, virtual impedance techniques were introduced to reshape inverter output impedance, suppress circulating currents, and improve power-sharing accuracy. Although virtual impedance enhances system performance, excessive impedance values can result in voltage drops and efficiency reduction. Most existing virtual impedance approaches rely on fixed PI controllers, which require extensive tuning and perform poorly under varying operating conditions.

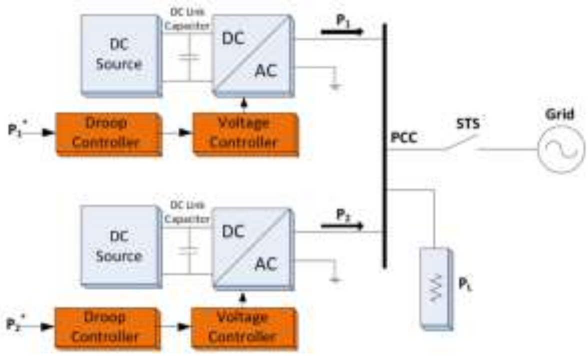

Figure 2.2: Droop control and virtual impedance-based power sharing

Battery energy storage systems play a critical role in inverter-dominated microgrids by providing frequency regulation, voltage support, and energy balancing, especially during islanded operation and disturbances. While optimization-based techniques such as particle swarm optimization, genetic algorithms, and model predictive control have been applied to tune microgrid controllers, they are generally executed offline and depend on accurate system models. Artificial intelligence-based approaches, including fuzzy logic and neural networks, reduce modeling dependency but often lack adaptability under unseen conditions. These limitations have driven growing interest in reinforcement learning-based control. Classical RL methods struggle with continuous state and action spaces, leading to the adoption of deep reinforcement learning techniques. Among them, Proximal Policy Optimization has gained attention due to its stable convergence, reduced sensitivity to hyperparameters, and suitability for real-time control. Recent studies report that PPO-based controllers outperform conventional PI and other deep RL methods in terms of robustness, adaptability, and transient performance, making PPO a promising solution for intelligent virtual impedance control in microgrids.

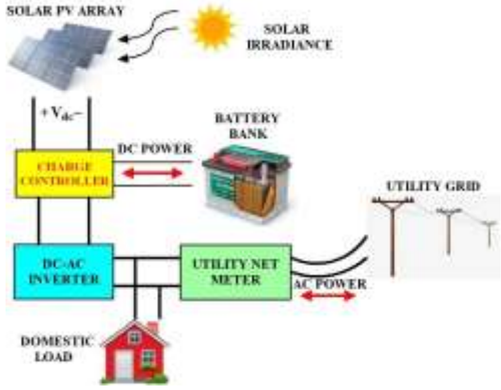

Figure 2.3: Intelligent control and energy storage in modern microgrids

III. Droop Control And Virtual Impedance Concepts

Droop control is a widely used technique in microgrids that allows multiple inverters or distributed energy sources to share load automatically without requiring communication between them. It works by slightly adjusting the output frequency and voltage of each inverter based on the load it is supplying. When the load on an inverter increases, its frequency or voltage drops slightly, signaling other inverters to take on more load. This behavior is inspired by conventional synchronous generators and makes the system simple, flexible, and reliable. However, droop control assumes that all connecting lines have similar electrical characteristics. In real systems, variations in feeder impedance can cause unequal power sharing, where some inverters carry more load than others, reducing accuracy and stability .

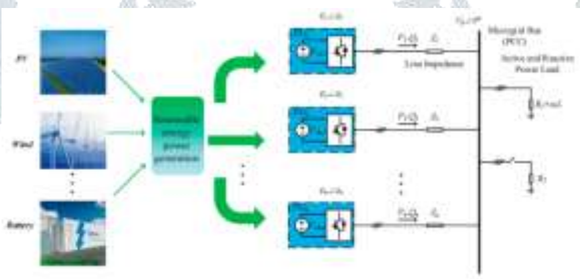

Fig: **3.1 Droop Control**

To address this limitation, the concept of virtual impedance is introduced. Virtual impedance is a control-based technique that makes an inverter behave as if it has additional impedance, without physically adding any hardware. It works by modifying the inverter's output voltage through control signals to compensate for differences in line impedance. By doing this, it reduces mismatches between inverters and improves the accuracy of power sharing. Essentially, virtual impedance creates a more uniform operating condition across all inverters, helping to stabilize the system and prevent circulating currents. According to the paper, this method plays a key role in correcting the inaccuracies introduced by droop control under varying network conditions .

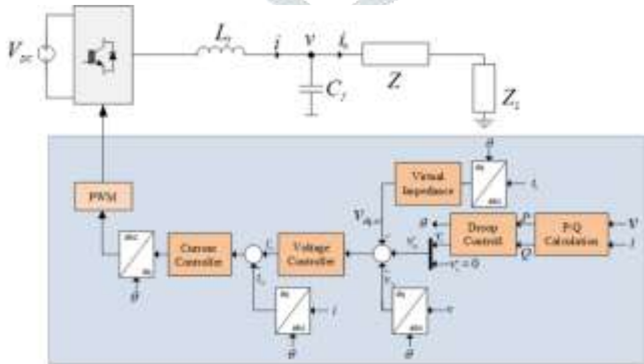

Fig:3.2 Virtual Impedance

When used together, droop control and virtual impedance complement each other effectively. Droop control provides the basic mechanism for decentralized power sharing, while virtual impedance enhances its performance by correcting errors caused by network variations. This combination leads to better stability, more accurate load distribution, and improved overall microgrid performance, especially under dynamic conditions such as load changes or disturbances.

IV.Proposed and Results
PPO-based Microgrid Controller Simulation

The performance of the proposed PPO-based virtual impedance controller was evaluated under islanded, grid-connected, and fault operating conditions. In the islanded mode, the system demonstrated stable operation with smooth transitions following load changes. The active and reactive power outputs showed that the largest BESS unit (1000 kW) supplied the majority of the load, while smaller units contributed proportionally less, indicating capacity-dominated power sharing. The voltage profile remained nearly constant throughout the simulation, confirming effective voltage regulation. However, the frequency response remained constant at an incorrect value due to a scaling issue in the implementation, which also led to inflated performance metrics. The reward signal exhibited high-frequency fluctuations and remained negative, indicating that the reinforcement learning agent did not converge to an optimal policy.

In grid-connected mode, the controller successfully tracked multiple step changes in active and reactive power references. The system showed fast dynamic response with minimal oscillations, highlighting the robustness of the droop-based control structure. Voltage variations were small and well within acceptable limits, suggesting that the virtual impedance mechanism contributed to system stability. Despite these positive behaviors, the reward signal again showed no clear improvement over time, reinforcing the observation that the PPO agent was not effectively learning.

During fault conditions, the system responded promptly to a three-phase fault introduced at 2 seconds. Both active and reactive power dropped sharply during the fault period and recovered quickly once the fault was cleared. The voltage experienced only minor deviations and returned to its nominal value without oscillations, demonstrating strong disturbance rejection capability. The reward signal showed deeper negative spikes during the fault, reflecting increased tracking errors, but did not exhibit any learning trend.

Overall, the controller ensured stable operation and fast transient response across all operating modes. However, the reinforcement learning component did not provide adaptive improvement due to the absence of proper network weight updates and an oversimplified system model. Additionally, errors in frequency calculation affected the accuracy of performance metrics. To achieve results comparable to those reported in the reference study, it is necessary to implement a complete PPO training mechanism, refine the reward function, and incorporate a more realistic power system model.

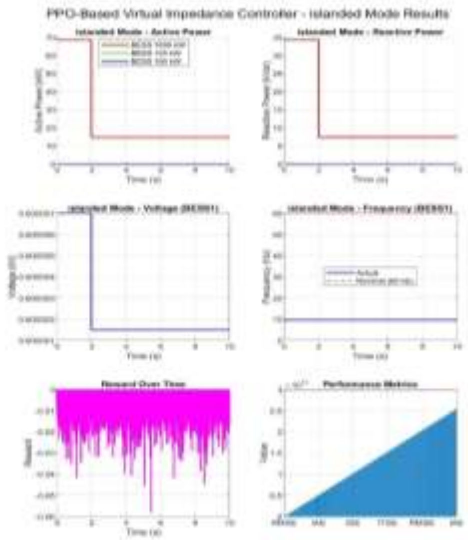

Fig:4.1Scopes for islanded mode

In the islanded mode the system operates without grid support, so the BESS units are solely responsible for supplying the load. This is why the largest unit (1000 kW) carries most of the active and reactive power. The droop control mechanism naturally distributes power based on capacity and droop coefficients, which explains why smaller units contribute less. When the load decreases at around 2 seconds, the power output drops smoothly, showing that the system is stable and responds quickly to changes. The voltage remains nearly constant, indicating that the virtual impedance control is effectively regulating voltage. However, the frequency stays fixed at an incorrect value (around 10 Hz instead of 60 Hz), which is not a physical behavior but a result of an implementation issue in the frequency calculation. The reward signal fluctuates heavily because the agent is not actually learning; instead, it is producing random actions with added noise, so no improvement trend is visible.

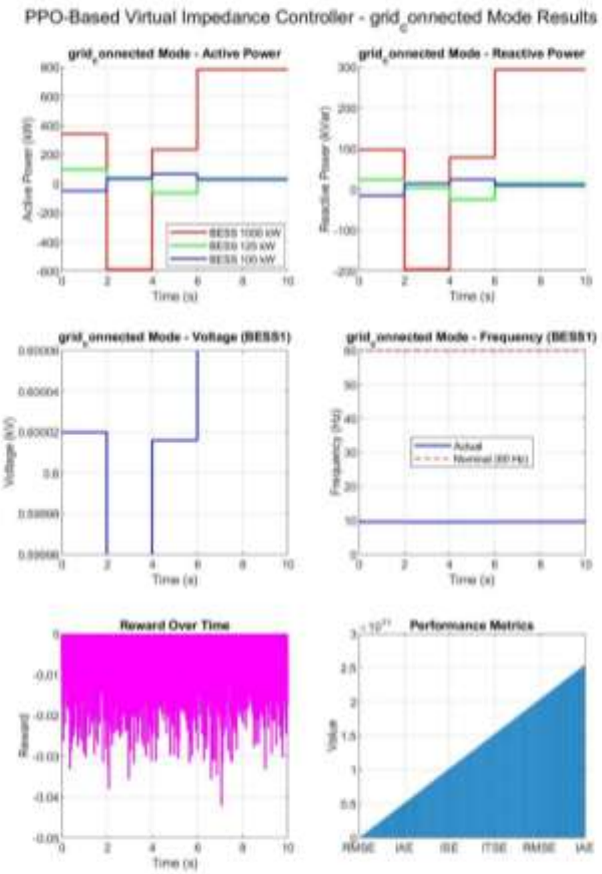

Fig:4.2 Scopes for grid-connected mode

In the grid-connected mode, the presence of the main grid stabilizes the system further. The controller is subjected to multiple step changes in power references, and the system tracks these changes effectively. The active and reactive power plots clearly show step transitions at different times, and the system follows them with minimal delay or oscillation. This indicates that the underlying droop control is functioning correctly and provides good dynamic performance. The voltage shows only very small variations, which means the virtual impedance component is helping maintain stability during transitions. However, similar to the islanded case, the reward signal does not improve over time, confirming that the PPO algorithm is not updating its policy. The frequency again remains incorrect due to the same scaling issue.

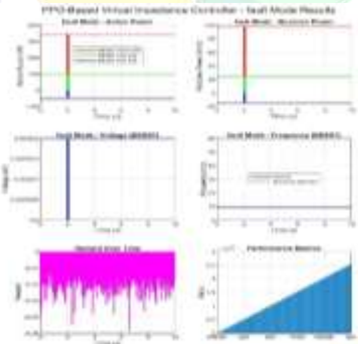

Fig:4.3 Scopes for Fault_condition

During the fault condition, a disturbance is introduced at 2 seconds. The immediate drop in active and reactive power during the fault is expected because the system cannot deliver power under fault conditions. What is important here is the recovery behavior: once the fault is cleared, the system quickly returns to its pre-fault operating condition without oscillations. This shows that the control structure is robust and capable of handling disturbances. The voltage experiences only a very small spike, which further confirms good voltage regulation. The reward signal becomes more negative during the fault, which makes sense because tracking errors increase during disturbances. However, even after the fault, the reward does not show any learning trend.

Overall, the behavior seen in all three modes is mainly governed by the droop control and the simplified system model rather than the PPO controller. The reinforcement learning component does not contribute meaningful control improvement because the neural network weights are not actually being updated. In addition, the incorrect frequency calculation leads to unrealistic performance metrics. So, while the system appears stable and responsive, this stability comes from conventional control rather than learned behavior. For the PPO-based controller to work as intended, proper training, weight updates, and a more realistic system model are required.

V.Conclusion

The proposed PPO-based virtual impedance controller was implemented to enhance power sharing and stability in a microgrid under islanded, grid-connected, and fault conditions. The simulation results demonstrated that the system maintains stable operation across all modes, with fast transient response and effective disturbance handling. In islanded operation, the controller ensured smooth power adjustment following load changes, while in grid-connected mode, it successfully tracked multiple reference variations with minimal oscillations. During fault conditions, the system exhibited rapid recovery and strong voltage regulation, indicating robustness against disturbances.

However, the results also revealed that the reinforcement learning component did not contribute significantly to performance improvement. This was primarily due to the absence of actual policy optimization and weight updates in the PPO implementation, causing the controller to behave more like a conventional droop-based system with added noise rather than a trained intelligent controller. Additionally, inaccuracies in frequency calculation affected the reliability of performance metrics.

Overall, while the control framework shows promising stability and responsiveness, further work is required to fully realize the benefits of PPO. This includes implementing proper training mechanisms, improving the reward function, and incorporating a more realistic system model. With these enhancements, the proposed approach has strong potential for advanced adaptive control in microgrid applications.

VI.References

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