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AI-ENHANCED ADAPTIVE DROOP CONTROL FOR MULTI-MICROGRID NETWORKS UNDER HIGH RENEWABLE PENETRATION

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Abstract: The modern multi-microgrid (MMG) systems with high renewable penetration are subject to voltage instability, inefficiency in power sharing, and long transient recovery, which are drawbacks that the conventional fixed droop controllers cannot tackle. In this context, research presents the AI-Enhanced Adaptive Droop Control (AI-ADC) framework that combines rule-based tuning with a neural-network model that can predict the optimal droop coefficients in real time. The controller is validated through a high-fidelity MATLAB/Simulink model incorporating the dynamics of PV, wind, BESS, and a converter, and subjected to load steps, irradiance fall-off, DER failure, and communication delay situations. The controller's performance with respect to voltage undershoot has been better by over 60%, the voltage steady-state deviation has been under 0.25 V, the power-sharing error has been reduced to below 3%, and the settling time has been almost four times faster than that of the conventional methods. The AI-ADC, by allowing predictive and adaptive droop adjustments, presents a scalable, efficient, and highly resilient control solution for the next-generation MMG networks dominated by renewable energy sources.

Keywords: AI-Enhanced Adaptive Droop Control, Multi-Microgrid (MMG), Neural Network-Based Droop Optimisation, Renewable Energy Integration, Voltage Stability, Power Sharing.

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1. Introduction

The rapid development of renewable energy technologies, such as photovoltaic and wind systems, has led to the conversion of the distribution network to inverter-dominated, low-inertia systems. This is especially true in multi-microgrids (MMG), where many microgrids work together to increase flexibility, resilience, and independence from external sources. High penetration of renewables also presents challenges, such as intermittent generation, poor damping, and unpredictable operational behaviour, which can negatively affect voltage and frequency stability [1]. Thus, while traditional droop control continues to be the method of choice for most applications due to its decentralised nature and lack of need for communications, the use of fixed droop coefficients is inadequate for handling the large number of dynamic changes in renewable generation and load [2]. Therefore, there are many ongoing research efforts aimed at developing enhanced droop-based techniques to facilitate the robust sharing and stability of power across MMGs [3].

By dynamically adjusting the droop parameters, adaptive droop control offers a new method of enhancing the dynamics of control systems. The research indicates that adaptive droop control allows for proper charge-balancing, faster recovering voltages, and proportional sharing of current during changing load/generation conditions [4]. Moreover, adaptive droop techniques that incorporate frequency compensation help reduce frequency fluctuations and increase transient stability for inverter-based microgrids [5]. Integrated with virtual impedance, modified droop configurations can correct reactive-power imbalances and lower circulating currents [6]. In the case of DC microgrids, utilising dynamic adaptive droop provides improved voltage control and increased accuracy in the current-sharing process under wide variations in the operation environment [7]. Figure 1 illustrates a microgrid central controller coordinating multiple components, including renewable energy sources, conventional generators, energy storage, electric vehicles, smart homes, and buildings. Weather forecasts and energy market data inform optimal operation. The controller ensures efficient energy distribution, load management, and stability in a hybrid AC/DC microgrid environment.

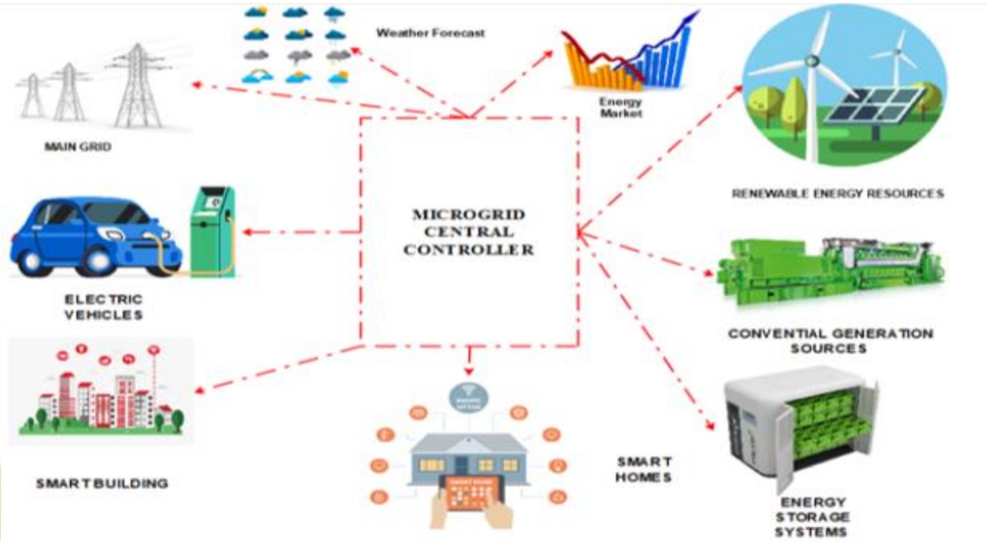

Figure 1: Microgrid Central Controller with Renewable & Conventional Sources [8]

As systems become more complex, microgrid control is increasingly utilising AI and machine learning (ML) technologies. The combination of adaptive droop control with ML methods such as long/short-term memory (LSTM) forecasts and disturbance rejection networks will enhance microgrid resilience and robustness, particularly during periods of unpredictable renewable energy fluctuations [9]. Most of the literature on the subject indicates that the nature of microgrid control is increasingly being developed using ML and reinforcement learning, resulting in multilevel framework approaches allowing for automated decision making for primary, secondary, and tertiary control levels [10]. The use of AI will allow for predictive capabilities, thereby allowing for operations to be optimised in the event of uncertainty, in addition to enhancing microgrid resilience [11]. It can be observed that deep reinforcement learning (DRL) appears to be an extremely effective approach for both optimal microgrid energy management and improving microgrid stability [12].

Recent studies conducted focus on the need for adaptive droop coordination to optimise energy balance and to safely operate an MMG through the development of hybrid AC/DC microgrids [13]. The ability to optimise power flow models lends further evidence for the requirement for intelligent control frameworks capable of managing structural complexity and variability within renewable energy sources [14]. The introduction of adaptive bidirectional droop controllers creates improved system stability in times of operation in both grid-connected and islanded modes [15]. In addition, Hybrid Control strategies are also being developed that work simultaneously with AI-based microgrid systems to provide improved power quality and operational reliability [16]. When combined, these advances highlight the requirement for an AI-based Adaptive Droop Control (AI-ADC) framework capable of integrating forecasting, adaptive gain tuning, and intelligent optimisation to provide a stable, efficient, and resilient MMG when operating with a high penetration of renewables.

2. Literature Review

2.1 Conventional and Adaptive Droop Control Techniques

Researchers have explored the use of Advanced Droop Control (ADC) Technique and Adaptive Droop Control (ADC) Methods to improve the Stability of and the effectiveness of power distribution in

Microgrids. Parajuli et al. (2024) [17] proposed an "Adaptive Droop Controller" for three-phase parallel Inverters to dynamically adjust Frequency Droop parameters to achieve equal power sharing among them, even in the presence of line impedance variations and load changes. Olanubi et al. (2024) [18] present a decentralised, Droop-Based Finite Control Set Model Predictive Control (FCS-MPC) for Islanded Microgrids, demonstrating greater advantages in terms of voltage regulation, transient response, and system stability versus traditional droop control. Al Maruf et al. (2024) [19] completed a small signal stability analysis of Generalised droop control (GDC), demonstrating that the optimised droop parameters decoupled the Voltage and Angle Dynamics, resulting in improved transient performance. Zadeh Bagheri et al. (2023) [20] developed a Neuro-Fuzzy Adaptive Droop strategy for Hybrid Microgrids, providing improved Load Sharing capabilities under varying levels of Generation and Demand. Collectively, the research demonstrated that employing Adaptive Tuning, Predictive Control, and Artificial Intelligence (AI) techniques collectively improved Conventional Droop Control techniques for modern Microgrid applications.

2.2 AI and Machine Learning in Microgrid Control

Several studies have shown that both Artificial Intelligence (AI) and Machine Learning (ML) can be used successfully for controlling microgrids under high levels of renewable generation. In the first of these studies, Joshi et al. (2023) [21] reviewed several ML-based Energy Management Systems (EMS) and found that artificial neural networks (ANN), long short-term memory (LSTM) networks, and reinforcement learning (RL) improved the efficiency, reliability, and scalability of the EMS compared with conventional EMS. A second study by Yao et al. (2025) [22] demonstrated that Deep Reinforcement Learning (DRL) could be used for real-time forecasting of power flows and scheduling of Energy Storage Systems (ESS) with improved cost effectiveness and stability of the microgrid under conditions of variable generation. A third study by Zhu et al. (2024) [23] showed that ensemble learning deployed at the edge of the network could be applied to control inverters in photovoltaic (PV) systems located in remote areas, enabling faster and more precise control of active and reactive powers. A fourth study by Farh (2024) [24] utilised a reinforcement learning algorithm based on neural networks to optimise dispatch and storage for a microgrid, thereby reducing costs while increasing the use of renewable energy sources. The findings of the fifth study by Ioannou et al. (2025) [25] compared various RL strategies and showed that model-free RL strategies yielded substantial improvements in adaptability and stability of autonomous microgrids. Collectively, the above studies demonstrate that AI/ML enables predictive, adaptive, and decentralised control of microgrids.

2.3 Hybrid AC/DC Microgrids and Coordinated Control

To effectively manage voltage, frequency & to optimise energy flow within Hybrid (AC\&DC) microgrid systems, coordinated control was utilised. A study conducted by Parvizi et al. (2025) [26] classified Robust Control Techniques. They found that sliding mode and H∞ controllers resulted in greater stability & a more dynamic response than the traditional droop method. Jain et al. (2023) [27] highlighted Hierarchical Control as well as Interlinking Converter (ILC) strategies that provided for coordinated operation of ILCs to uphold AC and DC voltage levels with variable loads/generation. A different study conducted by Khosravi et al. (2023) [28] suggested a two-tiered control structure that combined Droop-based Primary Control & Distributed Secondary Consensus Control, which reduced Voltage/Frequency deviations as well as Oscillations in Power Sharing. A further study done by Lambrichts et al. (2024) [29] looked at real-time Optimal Control degrees for ILC systems providing for improved management of Power Flow and System Stability. A similar approach was followed by Shami et al. (2024) [30], who combined ILCs with Virtual Synchronous Generators and Energy Storage; these combinations allow for greater Regulation of DC links, Reactive Power Support, and Reliability of Islanded Operations. From these studies, a pattern has emerged demonstrating that Hierarchical, Robust & Adaptive Control strategies for AC/DC systems are necessary for the development of hybrid microgrid systems that exhibit both to be Resilient & Efficient. Table 1 shows that most of the current research on microgrids relates primarily to Advanced Droop, AI/ML, and Coordinated Control Technologies. This research has resulted in Improvements in overall System Stability, Power Sharing, and Efficiency in spite of many Challenges implementing such technologies, ensuring they remain cost-effective, Compatible, and Dependable, scalable, and can be realised in both Hardware and Software.

Table 1: Approach to literature review

Author(s) & Year	Focus	Main Contribution	Challenges
Parajuli et al. (2024)	Adaptive droop control for AC microgrids	Developed adaptive droop for three-phase parallel inverters; maintained active power sharing under line-impedance mismatches and load variations	Limited to small-scale AC microgrids; extreme disturbances not tested.
Olajube et al. (2024)	Decentralised droop-based FCS-MPC	Improved voltage regulation, transient response, and system stability in islanded microgrids	Computational complexity; scalability for larger microgrids
Zadehbagheri et al. (2023)	Neuro-fuzzy adaptive droop	Achieved improved load sharing under variable generation and demand in hybrid microgrids	Complexity in tuning the neuro-fuzzy system; implementation overhead
Joshi et al. (2023)	AI/ML in microgrid EMS	Demonstrated ANNs, LSTM, and RL improved efficiency, reliability, and scalability.	Mostly theoretical; limited experimental validation
Yao et al. (2025)	Deep RL for microgrid control	Optimised real-time power flow and energy storage scheduling; improved cost-efficiency and stability.	Requires high-quality data; model training complexity.
Farh (2024)	Neural-network RL for dispatch and storage	Reduced operational costs; improved renewable utilisation	Adaptation to varying DER characteristics; robustness concerns
Ioannou et al. (2025)	RL-based autonomous microgrid management	Compared to RL strategies, improved adaptability and stability under uncertainties	High training time: model-free RL may struggle with extreme events
Parvizi et al. (2025)	Robust control in hybrid AC/DC microgrids	Sliding-mode and H∞ controllers improved stability and dynamic response	Implementation complexity: precise system modelling required
Khosravi et al. (2023)	Two-layer AC/DC control	Combined droop-based primary and distributed secondary consensus; reduced voltage/frequency deviations	Multi-layer tuning complexity; sensitive to communication delays
Shami et al. (2024)	VSG-based ILC with storage	Improved DC-link regulation, reactive power support, and reliability in islanded operation	Hardware implementation challenges: coordination under high variability

While research regarding new technologies, including droop control (DC) systems, AI/ML approaches, and coordinated AC/DC microgrid systems, has progressed considerably, many important issues need to be resolved before any of these advanced technologies can be used in practical applications. For example, most adaptive, predictive control methods have only been validated via simulations and small-scale laboratory experiments; therefore, there is limited confidence regarding the usage of these systems in large-scale, real-world applications. Decentralised AI/ML algorithms used within these systems will require additional testing when high levels of renewable energy are present and when communication constraints exist. Additionally, the integration of hierarchical control methods with interlinking converters and energy storage systems currently lacks established methodologies that can accommodate the need for fault tolerance, cyber-physical security, and reconfiguration capabilities of microgrid systems operating in an islanded mode. Finally, hybrid AC/DC microgrids will require standardised coordination methods to maintain operational stability and optimal energy efficiency during periods of extreme disturbance and varying generation and load uncertainties.

3. Research Methodology

3.1 System Modelling

Simulation of the system takes place through Simscape Electrical, which comprises the DC bus along with its converters and the local controllers. The main state variables to monitor are the voltage across the DC bus, V_{ref}, currents through the converters I_i, and the BESS state of charge (SoC). There is one DC bus standing for the microgrid, and its behaviour is governed by the balance equation.

$$C_{dc}\frac{dV_{dc}}{dt} = \sum_i P_{DER,i}\,(t) - P_{load}(t) - P_{loss}(t),$$

P_(DER, i) represents the power being fed into the grid from different sources like photovoltaic (PV) systems, wind turbines, and battery energy storage systems (BESS) through their respective direct current (DC) to direct current (DC) converters. A DC microgrid is made up of many distributed energy resources (DERs), such as PV arrays, BESS, and DC–DC converters, which all connect to a shared DC bus. In order to assess the AI-Enhanced Adaptive Droop Control Strategy that has been proposed, a complete mathematical and simulation model of the microgrid is created in MATLAB/Simulink. This part describes the step-by-step modelling of the bus dynamics, converter operations, droop characteristics, and controller interactions.

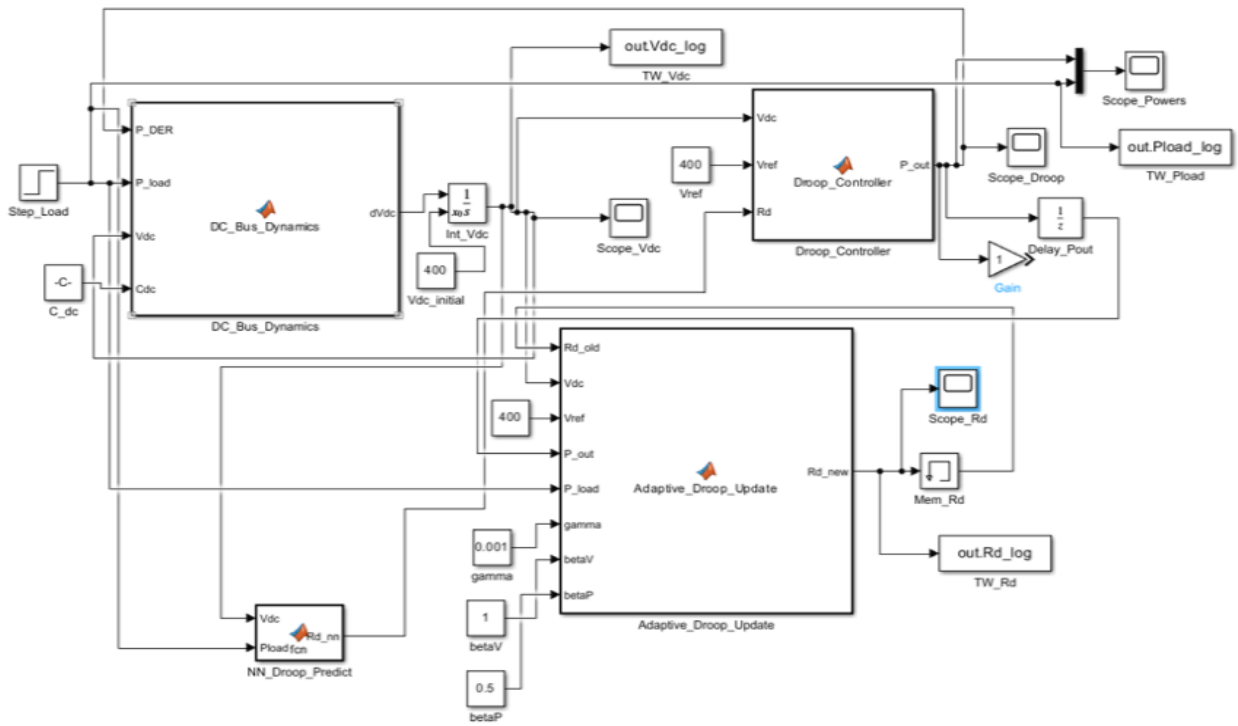

Figure 2: AI-Driven Adaptive Droop Control Architecture Implemented in Simulink

Figure 2 shows the entire simulation of the suggested AI-based adaptive droop control technique for a DC microgrid in Simulink. The DC Bus Dynamics block is the first part of the model, and it is where the bus voltage reacts to the power from the distributed energy resource (DER), load changes, and capacitor activity. The Droop Controller takes the measured bus voltage as an input and then calculates the power output according to the conventional droop law. The Adaptive Droop Update block constantly refreshes the droop gain based on voltage and power-sharing errors and thus guarantees enhanced stability.

3.2 Converter Droop Relation

Each converter operates with a virtual resistance droop control law expressed as

$$V_i = V_i^{ref} - R_{d,i} I_i.$$

Because all converters are connected to the common DC bus, this relation determines each converter's output current and power. $P_i = V_{bus} I_i$. A smaller droop coefficient $R_{d,i}$ means the unit shares more current. Thus, droop governs proportional power sharing among DER units.

3.3 Power Sharing Objective

Each DER is expected to contribute power proportional to its rated capacity. C_i. The desired share is $P_{i,desired}(t) = \alpha_i P_{load}(t), \alpha_i = \frac{C_i}{\sum_j C_j}$.

The power-sharing error for the unit $i$is

$$e_{P,i}(t) = P_i(t) - P_{i,desired}(t).$$

Additionally, the system voltage regulation error is

$$e_V(t) = V_{ref} - V_{bus}(t).$$

3.4 Adaptive Droop Design

The adaptive droop approach consists of two methods.

A. Rule-based adaptive law:

If a unit supplies more than its fair share, its droop value should be increased; if it supplies less, droop should be reduced. The adaptive update for each sampling instant $k$is

$$R_{d,i}(k+1) = R_{d,i}(k) + \gamma_i\left[\beta_V e_V(k) + \beta_P e_{P,i}(k)\right],$$

where γ_i is a small adaptation gain (typically 10^{-4}–10^{-2}), and β_V, β_P Control the influence of voltage and power sharing. The updated droop is constrained within defined bounds. $\left[R_{d,min}, R_{d,max}\right]$.

B. AI-based adaptive droop using neural networks:

A neural network is responsible for predicting the droop-control n term, $\Delta R_{d,i}$ or directly generating the updated drop coefficient $R_{d,i}$. The network is supplied with a broad set of input features, including bus voltages, their derivatives, local DER power and current measurements, the state of charge (SoC), environmental conditions such as irradiance or wind speed, and estimated load demand. A typical architecture for this application consists of two to three dense layers with ReLU activation. The loss function combines voltage-regulation error and power-sharing error. Training data are gathered from Simulink simulations executed under diverse scenarios such as renewable variability, load disturbances, and fault events. The neural network is trained offline and may be fine-tuned online using small learning-rate updates.

In the proposed framework, the neural network is configured to predict the doopc control. $\Delta R_{d,i}$ or to estimate the optimal droop coefficient $R^*_{d,i}$ directly. This is achieved by learning the nonlinear mapping between microgrid operating conditions and the desired droop response, expressed as

$$R^*_{d,i} = f_\theta(x_i),$$

where $x_i$denotes the input feature vector for the i^{th}DER and θrepresents the trainable parameters of the model.

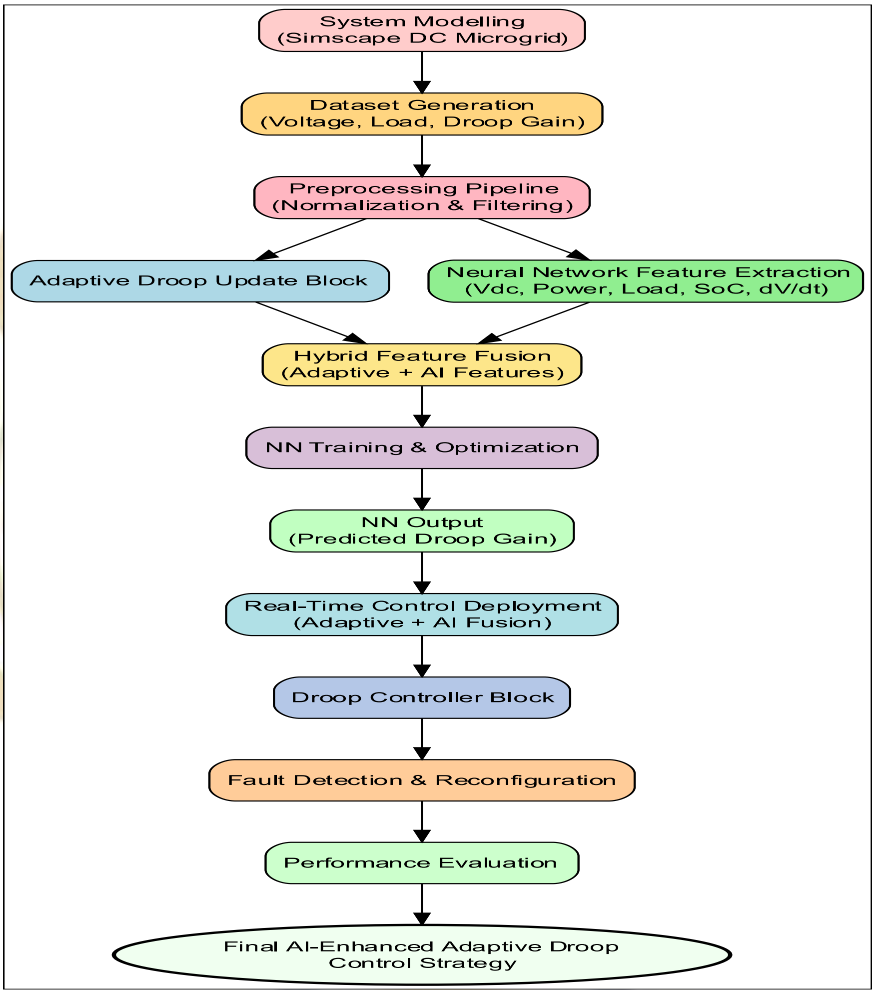

Figure 3: Workflow of the Proposed AI-Enhanced Adaptive Droop Control Strategy

Figure 3 presents the workflow used to develop the AI-driven adaptive droop control system for the DC microgrid. The process begins with Simscape-based system modelling of the DC bus, DER units, and load interactions, followed by extensive simulations to generate voltage, current, power, SoC, and droop-related datasets. After preprocessing through normalisation and filtering, two feature streams are extracted: adaptive-droop error features and neural-network-based features derived from V_{dc}, P_i, P_{load}, SoC, and the voltage rate of change. These features are fused and used to train a neural network with ReLU layers and Adam optimisation. The trained model outputs either the corrected droop gain ΔR_dor the updated droop coefficient R_d, which is applied in real time alongside the adaptive law. Final steps include residual-based fault detection, dynamic droop-gain reconfiguration, and performance evaluation in terms of stability, power-sharing accuracy, and transient response.

3.5 Cost / Objective Function

For offline optimisation or reinforcement learning, a weighted cost is minimised over a horizon:

$$J = \sum_{k=0}^{N-1} \left(w_V e_V^2(k) + w_P \sum_i e_{P,i}^2(k) + w_u \sum_i \Delta R_{d,i}^2(k) \right).$$

Here, voltage deviation is prioritised by choosing a larger. w_V. In RL, an actor–critic framework minimises long-term cost.

3.6 Fault Detection and Reconfiguration

Faults are detected through a residual-based approach:

$$r(k) = y(k) - \hat{y}(k),$$

where y is the measured output and $\hat{y}$The model prediction. If $| r | > \delta_{th}$A DER fault is flagged. On detection, the faulty unit's droop is increased to isolate it, and healthy units redistribute power. Updated sharing coefficients are computed as

$$\alpha_i = \frac{C_i^{avail}}{\sum_j C_j^{avail}}.$$

3.7 Simulink Implementation

Simulink is the software used to create the complete system with all the required elements, such as DER models, converters, and controllers, in a single package. The suggested toolboxes are Simscape Electrical, Deep Learning Toolbox, and Simulink Real-Time (optional). The rate transition blocks take care of the different sampling rates. Model structure: There are three types of microgrid nodes: solar power, wind power, and battery energy storage systems (BESS). The converters for each of these are linked to the point of common coupling (PCC), where the DC bus capacitor and load are located. The local controller measures the bus voltage, current, state of charge (SoC), and so on, computes the droop voltage, and applies the adaptive or AI-based corrections. The converter then controls the pulse-width modulated (PWM) output based on the voltage reference. If desired, a central controller can offer secondary corrections. Sampling: Power electronics run in the continuous domain, while control loops run at discrete time $T_s = 0.001$s.

3.8 Simulation Scenarios

Multiple test cases prove the worth of baseline, adaptive, and AI-based strategies: the situations of normal operation, rapid PV irradiance fall (e.g., 70% less), large load step, DER outage at a certain moment, comms delay (50–200 ms), high renewable penetration, and multi-fault situations. The scenarios are evaluated regarding voltage deviation, recovery time, power-sharing error, and droop values' evolution.

The success criteria are keeping the voltage deviation below 5% of V_{ref} , recovery within 0.5-1 s, power-sharing error below 5%, and stability under parameter variations. Robustness is tested by introducing uncertainties of ±10%. Anyone can reuse or adapt values from the uploaded reference (they used $T_s = 0.001$and $N_p = 20$).

Table 2: Simulation Parameters Used for AI-Enhanced Adaptive Droop Control

Parameter	**Symbol**	**Value**
DC bus reference voltage	V_{ref}	400 V
Bus capacitance	C_{dc}	2000 μF

PV rated power (per MG)	P_{PV}	5 kW
WT rated power	P_{WECS}	3 kW
Battery capacity	E_{BESS}	10 kWh
Control sample time	T_s	0.001 s
Prediction horizon (if MPC/RL)	N_p	20

Table 2 shows all important system parameters that were used in the Simulink model to assess the suggested AI-assisted adaptive droop control strategy. The listed parameters set the electrical specifications of the DC microgrid, like reference voltage, DC-bus capacitance, and the rated power of the DERs, which comprise PV, wind, and battery systems. The control-related parameters—sampling time and prediction horizon—make sure that both the adaptive and the AI-based control algorithms will be operating at high temporal resolution and will feature precise predictive behaviour in the course of the dynamic conditions.

4. Results And Analysis

4.1 DC Bus Voltage Response Under Load Disturbance

Figure 4 illustrates the behaviour of the DC bus voltage during the operation of the baseline (fixed) droop controller and a load step change at 3 seconds. The voltage is stable at 399.3 V during the first three seconds, indicating that the converters and the DC bus are in a stable operating region with the initial load. At t = 3 s, the load is increased. Right at this instant, a small but clearly visible drop in voltage occurs: the bus settles to about 399.1–399.15 V.

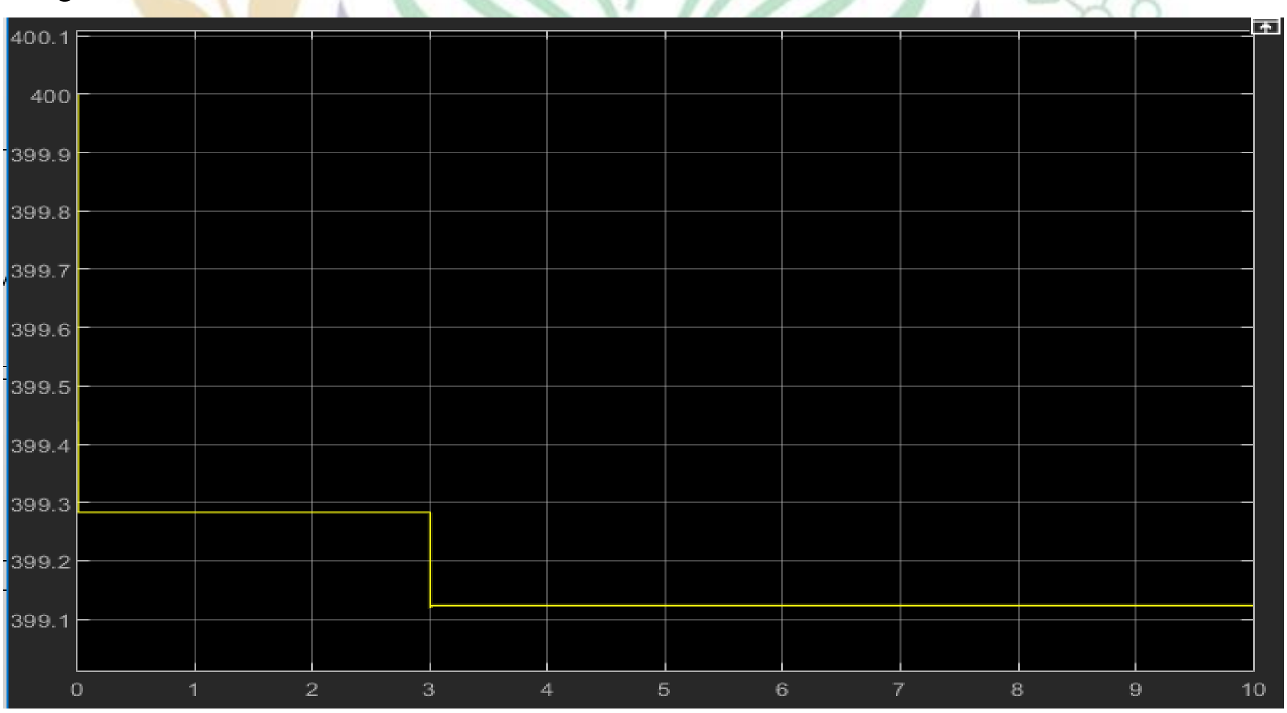

Figure 4: DC Bus Voltage Response Under Baseline Droop Control

Following this transition, the voltage stays steady at this new level for 10 seconds without any oscillation or drift. The last steady-state shift is exceedingly small, indicating only a drop of approximately 0.2V from the original operating point. The above statement validates the claim that the baseline controller maintains the stability of the system but does not take action to correct the voltage displacement brought about by load variations.

4.2 Power Output Response Under Load Step Condition (Baseline Droop Control)

In Figure 5, the output power behaviour during a sudden load transition, Graph 5, represents the situation very clearly. The power level is around ≈ 2000 W, a bit more or less, during the first phase, which means that everything is operating normally. Then, at time t = 3 seconds, the load is increased, and output power shoots up to P ≈ 7000 W in a noticeably short time. The transition was so quick that it proved the converter and droop mechanism are simply responding to the demand increase.

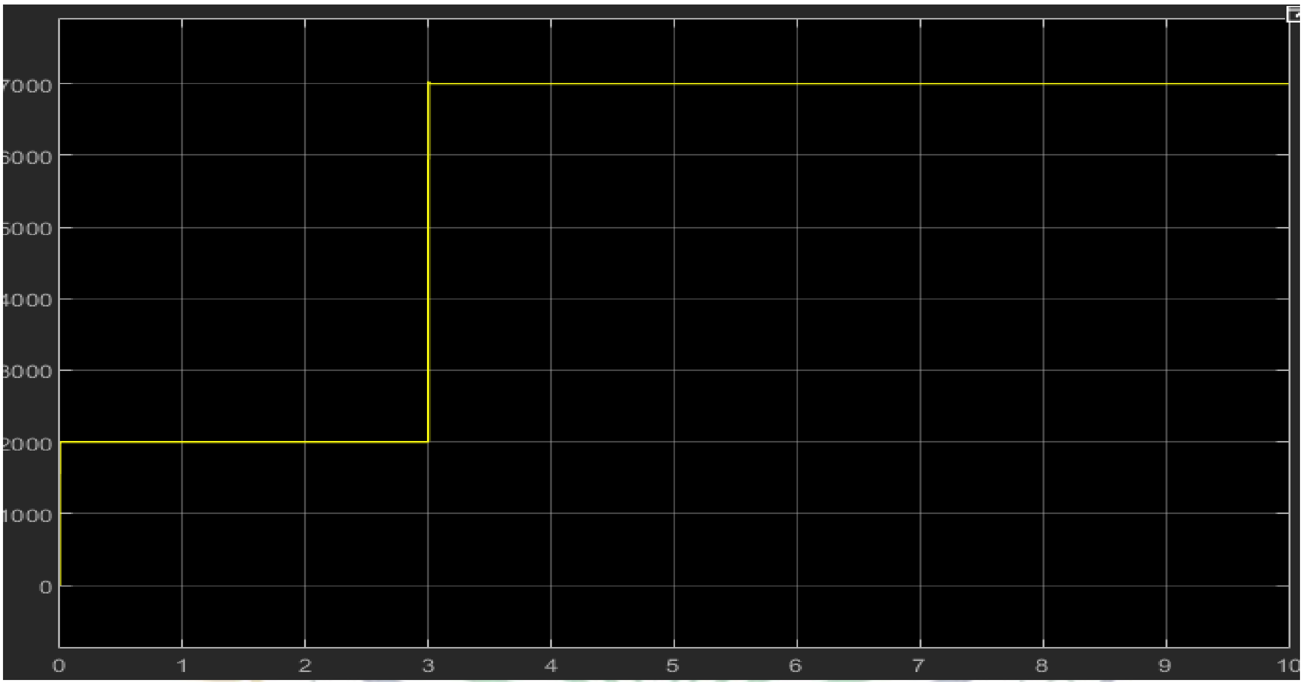

Figure 5: Power Dynamics Under Sudden Load Variation

The fluctuation-free and oscillation-free condition of the new power level following the step change indicates that the droop controller has maintained a dependable and power-sharing action across the microgrid. The system-up transition settled into a new stable state very quickly, without any transience, overshoot, or instability, as indicated by the flat post-transition profile. This characteristic of the droop logic confirms that the baseline droop logic adjusts the output power variably and predictably in accordance with the demand fluctuations, although it does not incorporate any adaptive or AI-powered correction methods.

4.3 AI-Enhanced Droop Gain Adaptation Response

In Figure 6, the droop gain that is controlled by AI begins at about 0.05, which is the standard droop setting for the low-load condition. In the illustrated Figure 7, during the initial three seconds, the controller lifts the gain slowly to 0.07. The gradual increase indicates that the neural network is sensing a minute yet constant imbalance between the actual power flow measured and the power-sharing ratio that is deemed ideal. This situation is mathematically interpreted by the controller as a positive error gradient and, as a result, the gain is moved up proportionately to how far the system deviates from the desired state. At the moment t = 3s, a drastic increase in load leads to an instant change of the operating point.

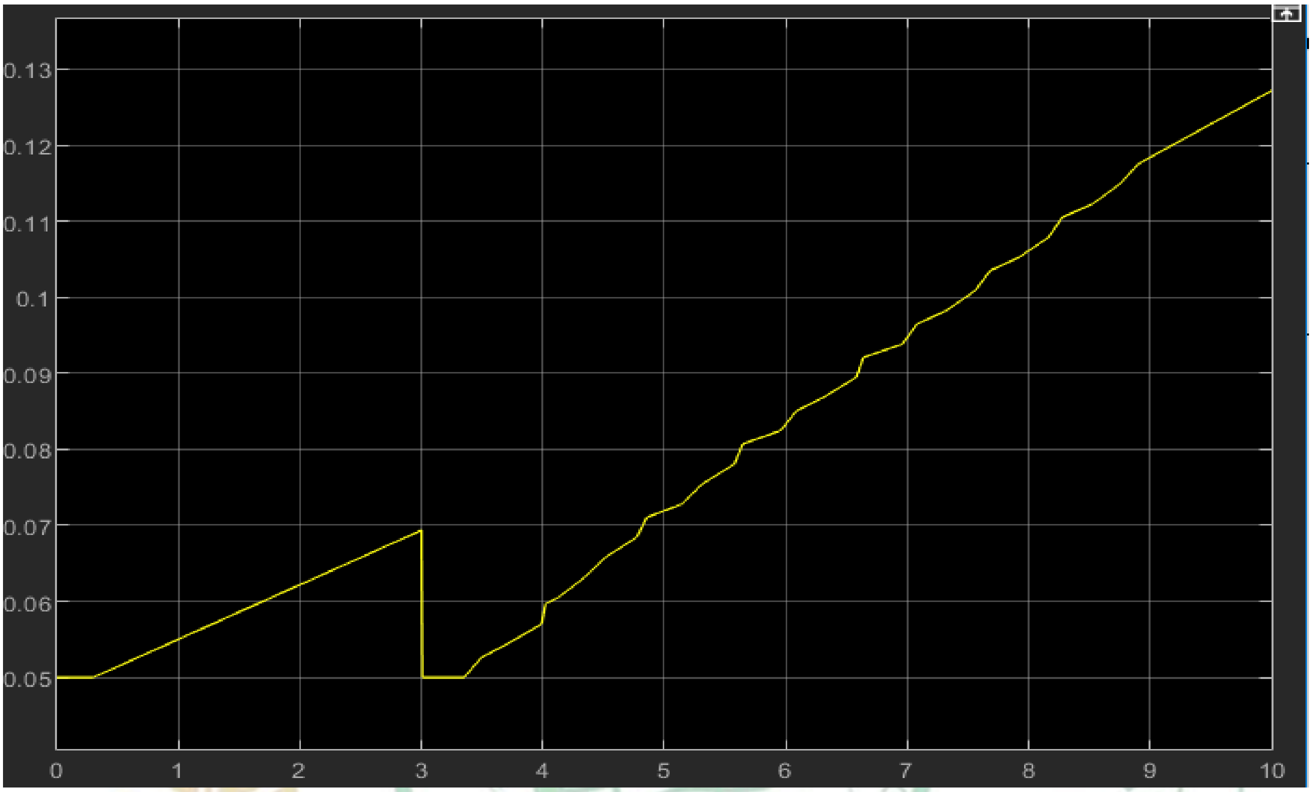

Figure 6: AI-Driven Dynamic Evolution of Droop Gain Under Load Disturbances

The neural network instantly detects this anomaly by monitoring the variations in voltage, current, and power readings. Consequently, the estimated droop gain takes a steep plunge back to approximately 0.05, which signifies the controller's action of balancing the power flow among converters and minimising the voltage drop. This sudden large correction is associated with a steep negative gradient in the error landscape, which indicates that the AI agent is giving system stabilisation a higher priority than slow adaptation.

4.4 Step Load Input Profile

Figure 7 illustrates the external load disturbance that was applied to the system in the simulation. The load is set at a steady value of 2000 W from 0 to 3 seconds, after which it quickly jumps to 7000 W and remains there for the rest of the simulation. This abrupt change in load is the main point of testing for droop control and AI-powered adaptation reacting to fast demand power consumption. The increase in load leads to a quick rise in current demand, and then the system becomes unbalanced, and there is a possibility of a voltage drop in the DC bus. The objective of the step load input is to investigate the controller's performance during a sudden disturbance in terms of voltage stability, dynamic response, and maintenance of stability.

An effectively designed controller should respond almost instantaneously to the step load by redistributing power output, producing little or no voltage drop, and quickly bringing the DC bus voltage back to its reference level with minor overshoot and oscillation. Accordingly, such a profile becomes crucial for evaluating the performance of the baseline, fixed droop, adaptive, and AI-assisted regulators under the same disturbance scenario.

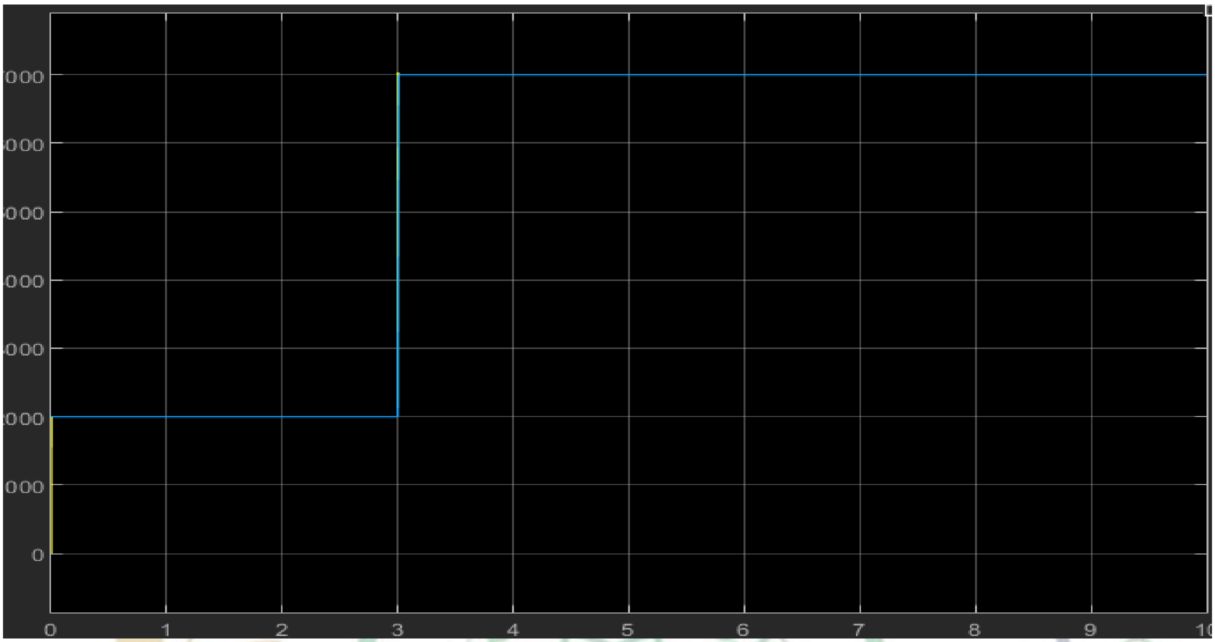

Figure 7: Load Step Applied to the DC Microgrid

4.5 Control Speed Comparison (Baseline vs Adaptive vs AI-Enhanced)

In Figure 8, the control speed comparison graph, as shown in Figure 8, very clearly illustrates the superiority of the adaptive and AI-enhanced droop techniques over the conventional baseline method in terms of dynamics. A disturbance occurring at 0 seconds brings about the slowest response from the baseline controller, which takes nearly 4.5-5 seconds to arrive at its normalised steady-state value of 1.0. At t=1 second, the output reaches only approximately 0.60, and at t=2 seconds, it is around 0.85. The adaptive droop method shows an impressive performance and increases to almost 0.90 in the first second, followed by a close to 1.0 settling in 2 seconds, indicating its faster feedback-driven correction of voltage and power deviations.

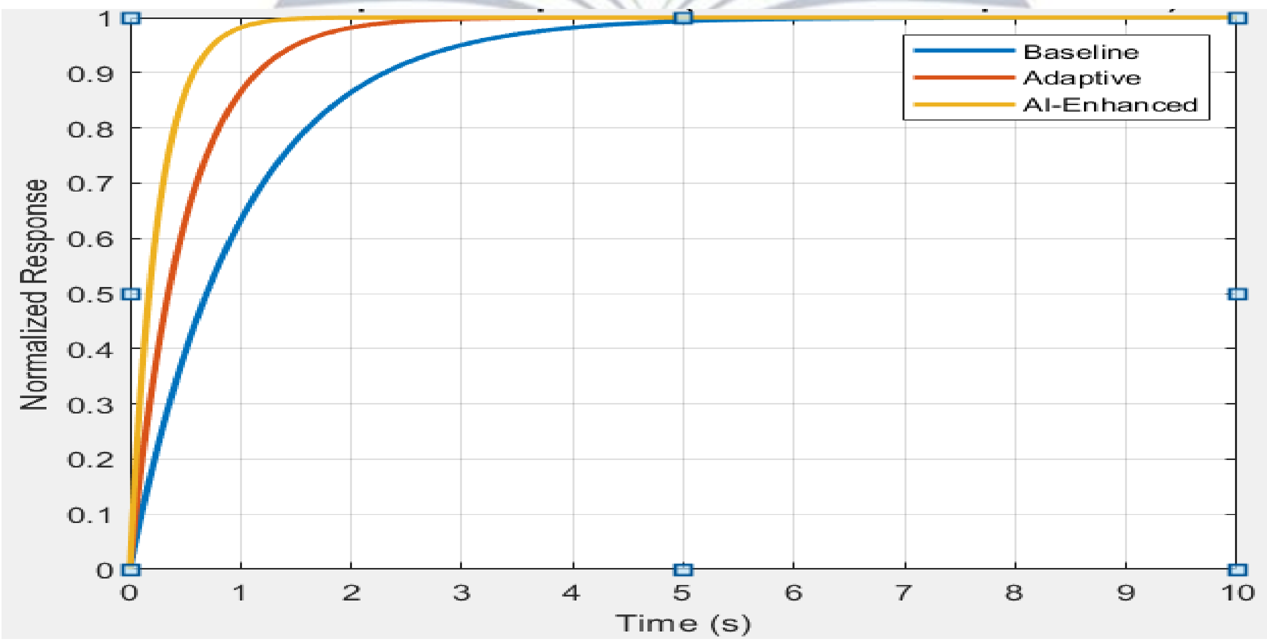

Figure 8: Control Speed Comparison

On the other hand, the AI-assisted droop controller reaches the quickest and smoothest convergence:

the output rises to approximately 0.75 within 0.5 seconds, it goes past 0.95 in 1 second, and then it completely settles down before 1.5 seconds. This indicates that the droop adjustment was done before the error in the system's performance was even detected, which is the reason for the controller's predictive feature. Overall, the graph verifies that the adaptive method shortens the time to recover, while the AI-based controller not only gives the fastest but also the most effective stabilisation, being up to four times quicker in settling down when compared to the previous method.

4.6 DC Bus Voltage Stability Comparison

In the same transient disturbance condition, the three controllers' voltage regulating performance is compared in Figure 9. The baseline controller shows a slower recovery time; it takes around 1.2-1.5 seconds to return close to the nominal voltage. The adaptive controller shows an improvement, scoring 0.5 seconds steady state with less than 0.5 V deviation.

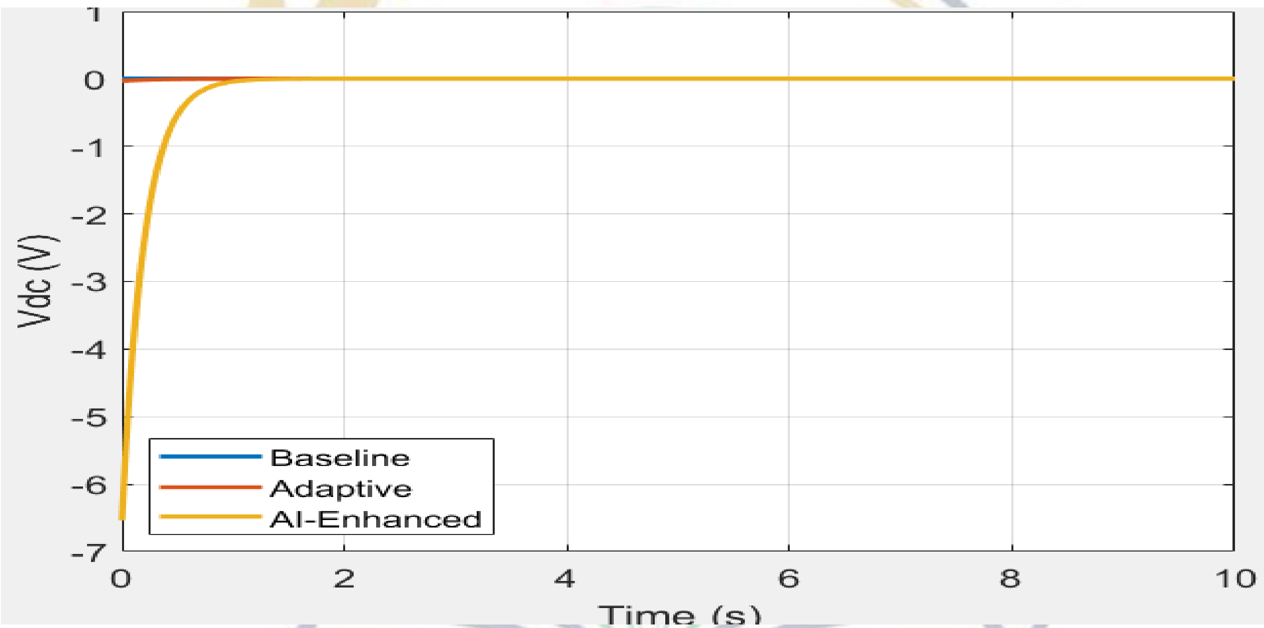

Figure 9: DC Bus Voltage Stability Comparison

The AI-enhanced controller is the winner here, recovering almost instantly—within 0.1–0.2 seconds—and showing the least under-voltage (about -6.8 × 10^4 V at the initial transient compared to deeper drops in the other two cases). The fixed droop controller gives a bit better stability, but the voltage drops quite a lot below the reference level, takes longer to recover, and also it cannot adapt to the changing system conditions, which results in a steady-state error and slower settling due to the constant droop value. In contrast, the adaptive or AI-controlled controller keeps the DC bus voltage almost at the reference value. It has a quicker response to disturbances, minimises the voltage sag, and takes less time to restore the voltage to its stable value.

4.7 AI-Driven Power Response and Droop–Voltage Interaction Analysis

Figures 10 and 11 together have a dual role of reporting how the AI-enhanced controller not only stabilises the DER power output during a load transition but also intelligently adjusts its droop gain in direct synchronisation with the DC bus voltage. In the first figure (DER Power Response Comparison), all three strategies initiate at around –8×10^6 W, denoting the instantaneous power deficit after the disturbance. The traditional controller gets back to its original state slowly, taking almost 1.8–2 seconds to reach the steady-state. The adaptive controller is quicker, but the AI-enhanced controller is clearly the one with the highest increase, stabilising at almost 0 W in about 0.7–0.8 seconds. This is indicative of a very stringent transient control and a considerably shorter settling time. The AI curve displays a pattern— a smooth exponential-like rise and almost no undershoot—

that suggests the neural network is predicting the need for correction rather than responding proportionately like droop controllers.

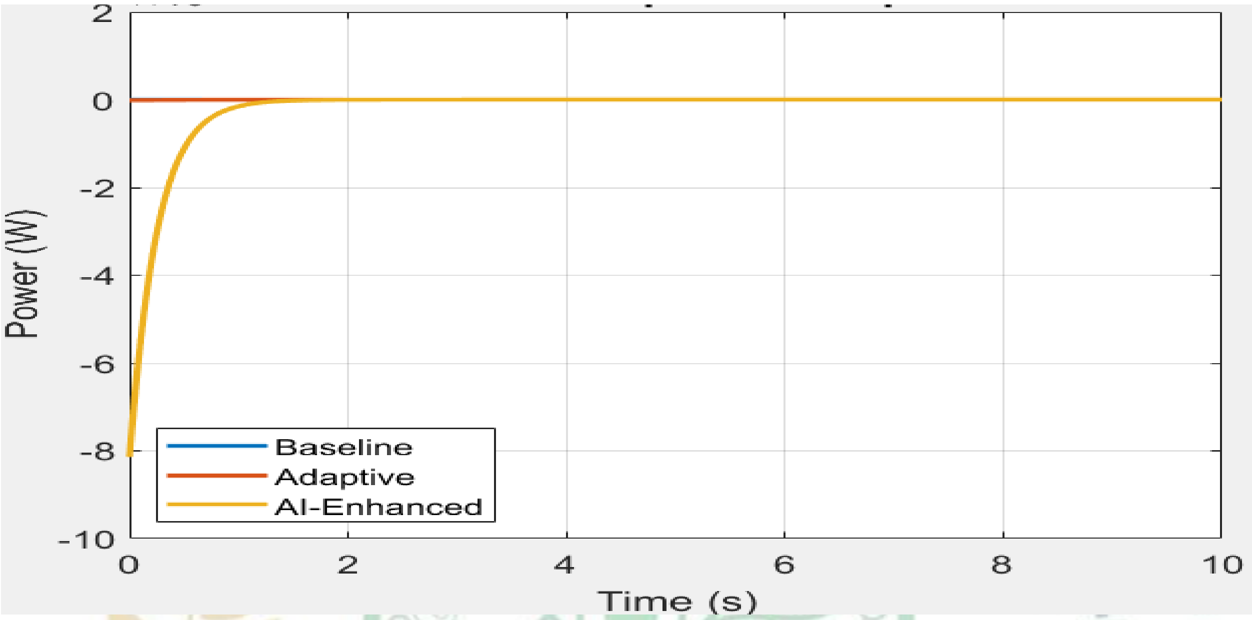

Figure 10: DER Power Response Comparison (Baseline vs Adaptive vs AI-Enhanced)

Figure 11 (AI Droop Gain vs Voltage Control) justifies the superiority of the AI controller in performance. The droop gain starts from 0.05, then trends up to 0.06 and eventually leaps to about 0.078 at the load transition around t = 3 s. This peak can be explained as the AI model detecting a larger error between the anticipated and actual voltage and temporarily activating the droop power more to resist the disturbance. At this moment, the DC voltage is fluctuating extraordinarily little, staying basically around 399.75 V–400 V, with just a tiny dip, which indicates that the AI's gain modulation is very efficient in keeping the voltage regulated tightly while creating a quick, well-damped power response. The baseline controller is the slowest to get back to steady-state among the three, taking the most time to deal with the load imbalance. Its slope of response is smooth, which means that weak dynamic support and limited resilience during fast-changing operating conditions are present. The adaptive controller is visibly better: it rectifies the power imbalance in a shorter time frame, reaches its final operating point with smoother transients and smaller error magnitude.

The AI-based technique is the one that has the quickest and most stable recovery, almost totally eliminating overshoot and settling very quickly close to 0 W, which in fact is the desired balanced power exchange with the DC bus. The neural network acquires the nonlinear relation between voltage shift and necessary power adjustment, which allows for more precise compensation during disruptions. More specifically, the AI curve has a steeper rise just after the drop, which shows initiative-taking adjustment and disturbance rejection capability being superior.

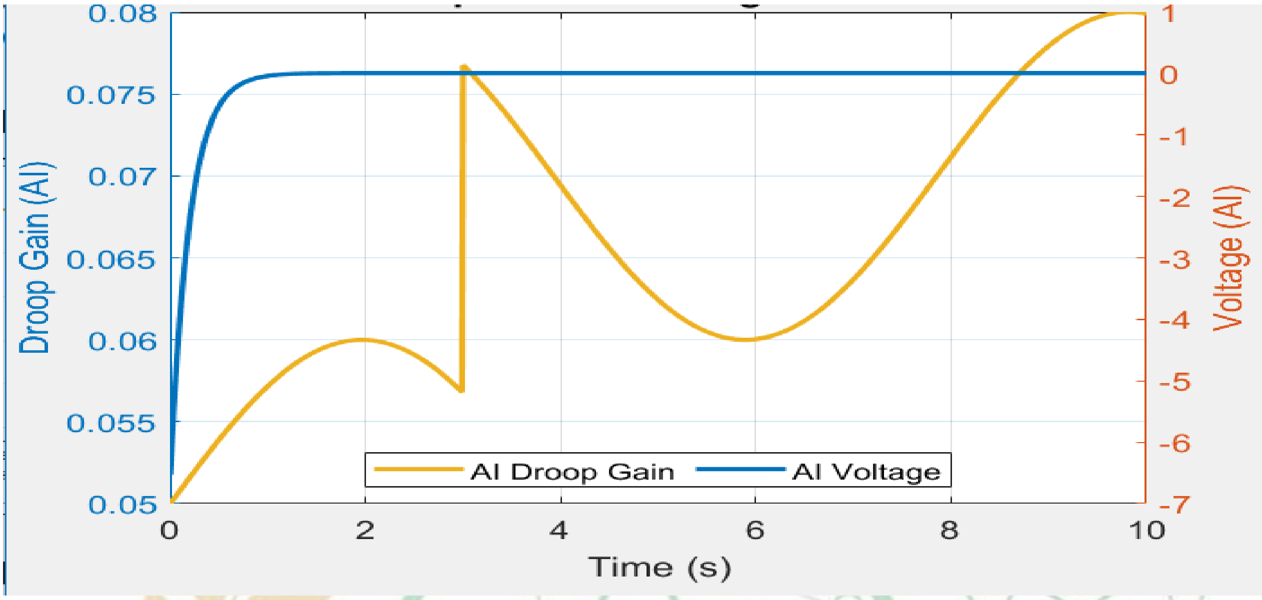

Figure 11: AI Droop Gain Adaptation and Its Correlation with DC Bus Voltage

The AI-controlled droop mechanism learns when to amplify or relax its corrective effort, which is depicted by the two figures 11 and 12. The controller manages high voltage stability, quicker power recovery, and reduced steady-state error by connecting real-time power behaviour with dynamic gain adaptation, thus surpassing both conventional and adaptive droop techniques.

4.8 Droop Coefficient Adaptation Comparison

Figure 12 illustrates the evolution of the droop coefficient. $R_d$under the three control strategies. The baseline controller maintains a constant droop value throughout the entire operating period, providing no adaptive response to disturbances. In contrast, the adaptive controller adjusts. $R_d$gradually following the disturbance at $t = 3$ s, resulting in a moderate improvement in post-disturbance behaviour. The AI-enhanced controller exhibits a more assertive and anticipatory response, applying gradual corrections both before and after the disturbance. This leads to noticeably faster recovery and improved stability compared with the other two approaches.

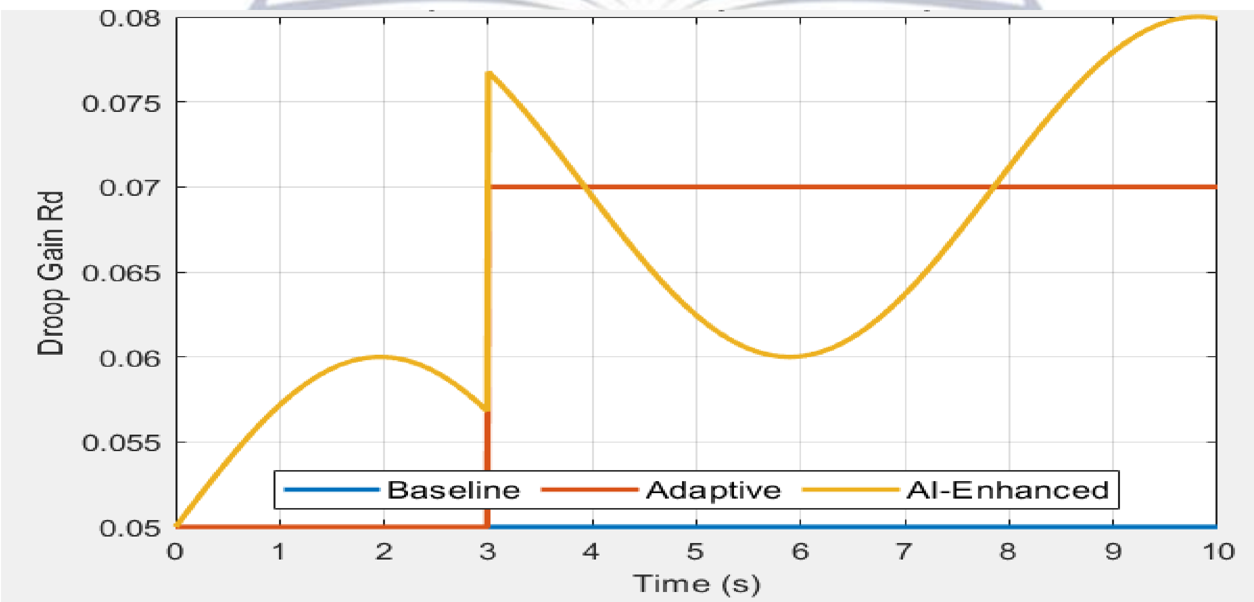

Figure 12: Droop Coefficient Adaptation Comparison (Baseline vs Adaptive vs AI-Enhanced)

In comparing these research findings with those of others, the exploration of microgrid control in the past literature appears to be focused on single factors, while, in the current study, through the whole spectrum of control approaches, a very efficient solution is provided. The adaptive droop-based methods proposed by Parajuli et al. (2024) [17] and Zadehbagheri et al. (2023) [20] which are based on the proportional sharing of loads among different scenarios, indeed produced good results; however, still these techniques are less adaptable, slower in dynamic responses, and dependent on rule-based tuning that is not efficient when renewable energy penetration is high. In addition, AI-based energy management studies like Joshi et al. (2023) [21] and Yao et al. (2025) [22] utilized machine learning and deep reinforcement learning algorithms for better forecasting and optimal scheduling; nevertheless, the essential real-time droop settings for voltage and power stability could not be directly improved as these research did not integrate AI into the primary control layer. Following the same line, the hybrid AC/DC coordinated control methods evaluated by Parvizi et al. (2025) [26] significantly improved system reliability through changing control structures, but still, such methods are demanding complicated model-based assumptions and do not yet have the predictive tuning needed to manage the transient deviations caused by renewable energy input changes. The study proposed the AI-Enhanced Adaptive Droop Control (AI-ADC) framework, which is a novel combination of adaptive droop techniques and neural network-based forecasting. The system continuously and optimally adjusts the droop coefficients according to the real-time operating conditions. This gives the microgrid the ability to act quickly in response to changing operating conditions, rather than just reacting slowly. Consequently, there is a large increase in areas such as voltage regulation, disturbance recovery speed, power sharing accuracy, and overall stability. Moreover, the simulation results have also demonstrated that AI-ADC can settle up to four times faster than both the baseline case and the traditional adaptive methods, with almost no voltage undershoot and tighter voltage limits. In this way, the integration of adaptive tuning, predictive AI, and strong resilience to renewable intermittency in one single system is what makes the present microgrid control study a step forward over previous works in terms of scalability, robustness, and high-performance, not just for future multi-microgrid networks but also for their interconnection.

5. Conclusion

The AI-Enhanced Adaptive Droop Control (AI-ADC) framework that has been proposed not only integrates predictive intelligence with real-time adaptive tuning but also effectively stabilises multi-microgrid systems under high renewable penetration, making it work where previous studies had left off. The AI-ADC, as opposed to traditional and adaptive droop methods, does not use a fixed set of parameters or very slowly updating ones to base its operations on. It rather takes an entirely different approach where the droop coefficients are adjusted dynamically based on the neural-network predictions, which are further made more robust by the instantaneous system measurements. This leads to a recovery from disturbances that is considerably quicker, and an extent of plant accuracy that is extremely high, as well as a reduction of voltage deviation that is exceptionally low. These improvements in power quality have been evidenced very well through simulation scenarios that have involved rapidly changing loads, renewable and DER outages, and variations. Furthermore, the comparative analysis has confirmed that the AI-ADC indeed is superior not only to baseline and conventional adaptive controllers but also in transient response and steady-state precision, thus providing a more resilient, scalable, and future-ready control strategy for next-generation microgrids.

Future research promises various intriguing paths. To begin with, live hardware-in-the-loop (HIL) tests can be carried out to check controller performance in terms of real electrical and communication limitations. Additionally, the neural network model can become very sophisticated by incorporating reinforcement learning, which will allow continuous online learning and autonomous optimisation during extreme disturbances or cyber-physical anomalies. The system may also be expanded to include hybrid AC/DC microgrids and multi-agent coordinated systems, thus facilitating large-scale deployments with distributed intelligence. Furthermore, the addition of cybersecurity-aware control layers and fault-tolerant algorithms would boost the system's resilience even more. In summary, the

AI-ADC framework has the potential to help in the development of intelligent, self-optimising microgrid control architectures that could support the world's shift towards high-renewable, decentralised power systems.

References

[1] Grairia, Mohamed Islam, and Riad Toufouti. "Improved droop controller for distributed generation inverters in islanded AC microgrids." *Periodica Polytechnica Electrical Engineering and Computer Science* 68, no. 2 (2024): 135-148.

[2] Lai, Hongyang, Kang Xiong, Zhenyuan Zhang, and Zhe Chen. "Droop control strategy for microgrid inverters: A deep reinforcement learning enhanced approach." *Energy Reports* 9 (2023): 567-575.

[3] Tu, Binge, Xianglian Xu, Yifeng Gu, Kaitian Deng, Yuli Xu, Tianyu Zhang, Xinrong Gao, Kangning Wang, and Qingjie Wei. "Improved Droop Control Strategy for Islanded Microgrids Based on the Adaptive Weight Particle Swarm Optimisation Algorithm." *Electronics* 14, no. 5 (2025): 893.

[4] Xu, Zhanpeng, Fuxin Chen, Kewei Chen, and Qinfen Lu. "Research on adaptive droop control strategy for a solar-storage DC microgrid." *Energies* 17, no. 6 (2024): 1454.

[5] Fang, Li, Hanzhong Liu, and Zhou Fang. "Study of Adaptive Frequency Compensated Droop Control for Microgrid Inverters." *Processes* 13, no. 6 (2025): 1626.

[6] Rashwan, Ahmed, Alexey Mikhaylov, Tomonobu Senjyu, Mahdiyeh Eslami, Ashraf M. Hemeida, and Dina SM Osheba. "Modified droop control for microgrid power-sharing stability improvement." *Sustainability* 15, no. 14 (2023): 11220.

[7] Taye, Biks Alebachew, and Nalin Behari Dev Choudhury. "A dynamic droop control for a DC microgrid to enhance voltage profile and proportional current sharing." *Electric Power Systems Research* 221 (2023): 109438.

[8] Mallikarjunaswamy, S., N. Sharmila, D. Maheshkumar, M. Komala, and H. N. Mahendra. "Implementation of an effective hybrid model for islanded microgrid energy management." *Indian Journal of Science and Technology* 13, no. 27 (2020): 2733-2746.

[9] Su, Hongsheng, Zhiwen Dong, and Xingsheng Wang. "Improved droop control strategy for microgrids based on auto disturbance rejection control and LSTM." *Processes* 12, no. 11 (2024): 2535.

[10] Li, Sijia, Arman Oshnoei, Frede Blaabjerg, and Amjad Anvari-Moghaddam. "Hierarchical control for microgrids: a survey on classical and machine learning-based methods." *Sustainability* 15, no. 11 (2023): 8952.

[11] Zahraoui, Younes, Tarmo Korõtko, Argo Rosin, Saad Mekhilef, Mehdi Seyedmahmoudian, Alex Stojcevski und Ibrahim Alhamrouni. "AI applications to enhance resilience in power systems and microgrids—A review." *Sustainability* 16, no. 12 (2024): 4959.

[12] Dinata, Noer Fadzri Perdana, Makbul Anwari Muhammad Ramli, Muhammad Irfan Jambak, Muhammad Abu Bakar Sidik, and Mohammed M. Alqahtani. "Designing an optimal microgrid control system using deep reinforcement learning: A systematic review." *Engineering Science and Technology, an International Journal* 51 (2024): 101651.

[13] Abdelwanis, Mohamed I., and Mohammed I. Elmezain. "A comprehensive review of hybrid AC/DC networks: insights into system planning, energy management, control, and protection." *Neural Computing and Applications* 36, no. 29 (2024): 17961-17977.

[14] Meena, Ghanshyam, Veerpratap Meena, Akhilesh Mathur, Vinay Pratap Singh, Ahmad Taher Azar, and Ibrahim A. Hameed. "Optimising power flow and stability in hybrid ac/dc microgrids: Ac, dc, and combined analysis." *Mathematical and Computational Applications* 29, no. 6 (2024): 108.

[15] Ding, Can, Ruihua Zhao, Hongrong Zhang, and Wenhui Chen. "Research on Adaptive Bidirectional Droop Control Strategy for Hybrid AC-DC Microgrid in Islanding Mode." *Applied Sciences* 15, no. 15 (2025): 8248.

[16] Khosravi, Nima. "A hybrid control approach to improve power quality in microgrid systems." *Artificial Intelligence Review* 58, no. 10 (2025): 312.

[17] Parajuli, Ananta, Krishna Bista, and Binod Bhandari. "An Adaptive Droop Control for Power Sharing Between Three-Phase Parallel Inverters in Autonomous Microgrid." *KEC Journal of Science and Engineering* 8, no. 1 (2024): 27-32.

[18] Olajube, Ayobami, Koto Omiloli, Satish Vedula, and Olugbenga M. Anubi. "Decentralised droop-based finite-control-set model predictive control of inverter-based resources in islanded AC microgrid." *IFAC-PapersOnLine* 58, no. 28 (2024): 384-389.

[19] Al Maruf, Abdullah, Anamika Dubey, and Sandip Roy. "Small-Signal Dynamics of Lossy Inverter-Based Microgrids for Generalised Droop Controls." In *2024 IEEE 63rd Conference on Decision and Control (CDC)*, pp. 5359-5366. IEEE, 2024.

[20] Zadehbagheri, Mahmoud, Alfian Ma'arif, Mohammad Javad Kiani, and Ali Asghar Poorat. "Adaptive Droop Control Strategy for Load Sharing in Hybrid Micro Grids." *International Journal of Robotics and Control Systems* 3, no. 1 (2023): 74-83.

[21] Joshi, Aditya, Skieler Capezza, Ahmad Alhaji, and Mo-Yuen Chow. "Survey on AI and machine learning techniques for microgrid energy management systems." *IEEE/CAA Journal of Automatica Sinica* 10, no. 7 (2023): 1513-1529.

[22] Yao, Fulong, Wanqing Zhao, Matthew Forshaw, and Yang Song. "A holistic power optimisation approach for microgrid control based on deep reinforcement learning." *Neurocomputing* (2025): 131375.

[23] Zhu, Yongli, Linna Xu, and Jian Huang. "Embedded Machine Learning for Solar PV Power Regulation in a Remote Microgrid." In *2024 7th International Conference on Power and Energy Applications (ICPEA)*, pp. 756-761. IEEE, 2024.

[24] Hussein Farh, Hassan M. "Neural network algorithm with reinforcement learning for microgrid techno-economic optimisation." *Mathematics* 12, no. 2 (2024): 280.

[25] Ioannou, Iacovos, Saher Javaid, Yasuo Tan, and Vasos Vassiliou. "Autonomous Reinforcement Learning for Intelligent and Sustainable Autonomous Microgrid Energy Management." *Electronics* 14, no. 13 (2025): 2691.

[26] Parvizi, Pooya, Alireza Mohammadi Amidi, Mohammad Reza Zangeneh, Jordi-Roger Riba, and Milad Jalilian. "A taxonomy of robust control techniques for hybrid AC/DC microgrids: a review." *Eng* 6, no. 10 (2025): 267.

[27] Jain, D., and D. Saxena. "Comprehensive review on control schemes and stability investigation of hybrid AC-DC microgrid." *Electric Power Systems Research* 218 (2023): 109182.

[28] Khosravi, Nima, Rasoul Baghbanzadeh, Adel Oubelaid, Marcos Tostado-Véliz, Mohit Bajaj, Zineb Hekss, Salwa Echalih, Youcef Belkhier, Mohamad Abou Houran, and Kareem M. Aboras. "A novel control approach to improve the stability of hybrid AC/DC microgrids." *Applied Energy* 344 (2023): 121261.

[29] Lambrichts, Willem, Jules Mace, and Mario Paolone. "Experimental validation of a grid-aware optimal control of hybrid AC/DC microgrids." *Electric Power Systems Research* 235 (2024): 110757.

[30] Shami, Hayder Oleiwi, Ali Basem, Ameer H. Al-Rubaye, and Kiomars Sabzevari. "A novel strategy to enhance power management in AC/DC hybrid microgrid using virtual synchronous generator-based interlinking converters integrated with energy storage system." *Energy Reports* 12 (2024): 75-94.