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Hybrid Fuzzy–Neural Droop Control for Fast Voltage and Frequency Stability in Renewable Agricultural Microgrids

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ABSTRACT

This paper introduces a Hybrid Fuzzy–Neural Droop Control (FNDC) approach designed for renewable agricultural microgrids that combine photovoltaic (PV), biogas, and battery energy storage systems (BESS). The control framework merges the nonlinear adaptability of fuzzy logic with the learning ability of neural networks to improve voltage–frequency stability, speed up transient responses, and reduce steady-state errors amid fluctuating renewable generation and nonlinear agricultural loads. The fuzzy component dynamically adjusts droop coefficients based on voltage deviations, power imbalances, and load variation rates. Meanwhile, the neural component continuously refines fuzzy membership parameters through an online gradient-based learning law. The FNDC is implemented and tested on a Python-based microgrid simulation platform utilizing pandapower and NumPy/SciPy. Comparative results against standard and fuzzy-only droop controllers show that the FNDC reduces settling time by up to 67%, cuts mean absolute error (MAE) by 45% and decreases RMSE by over 50% for voltage and frequency regulation. Additionally, the adaptive and decentralized design of the FNDC provides robustness against communication delays and scalability for rural deployment. The proposed strategy offers an intelligent and efficient control framework for next-generation smart agricultural microgrids powered by hybrid renewable energy sources.

Keywords: Droop Control, Fuzzy Logic, Neural Network, Distributed Control, Renewable Microgrid, Voltage–Frequency Stabilization, Agricultural Energy Systems.

INTRODUCTION

Renewable agricultural microgrids have recently emerged as a sustainable and decentralized solution to ensure a clean and reliable electricity supply for rural farms, irrigation systems, and cold-storage facilities. These systems typically integrate photovoltaic (PV), biogas, and battery energy storage systems (BESS) to serve agricultural operations with variable and nonlinear power demands. However, the intermittent generation from renewable sources and the rapidly fluctuating irrigation or refrigeration loads frequently cause voltage and frequency deviations that degrade system performance and reliability. Conventional droop control, although simple and widely used for distributed generation (DG) coordination, suffers from slow transient response and significant steady-state error under nonlinear and fast-changing load conditions [1].

To overcome these drawbacks, several adaptive and intelligent control strategies have been introduced. Recent studies have applied fuzzy logic, neural networks, and hybrid intelligent systems to improve droop adaptability and enhance dynamic voltage–frequency regulation. For example, an adaptive fuzzy–recurrent neural network controller was proposed for fractional-order distributed systems, demonstrating improved frequency robustness in multi-microgrids [2]. A deep recurrent neural network-based droop control enhanced learning capability for nonlinear dynamics [3], while adaptive neural control methods improved system stability against uncertainties [4]. Similarly, variable-universe fuzzy droop control techniques [5] and hybrid ANN–PI–droop structures [6] achieved higher voltage stability and reduced oscillations under AC microgrid environments. Furthermore, type-2 fuzzy droop control [7] and neuro-fuzzy adaptive schemes [8] have shown promise for lowering steady-state deviations, while MPC-based droop hybrid frameworks [9-11] improved transient responses through model-based prediction. Theoretical studies on small-signal stability of generalized droop microgrids also helped understand dynamic coupling in inverter-dominated systems [12-15].

Despite these advancements, most of the existing research focuses on industrial or urban microgrids and assumes stable communication networks with uniform load characteristics. In contrast, agricultural microgrids operate under highly variable environmental conditions (e.g., sunlight, moisture, and seasonal irrigation demand) and experience abrupt load transitions (e.g., motor starting in irrigation pumps or cold-storage compressors). Moreover, existing fuzzy or neural-based droop controllers often require centralized coordination or high-speed communication, which is impractical in rural regions with limited bandwidth and frequent packet loss. These constraints make traditional adaptive droop approaches inadequate for real-world agricultural deployment.

To bridge these gaps, this paper proposes a Hybrid Fuzzy–Neural Network Droop Control (FNDC) framework for renewable agricultural microgrids integrating PV, biogas, and BESS sources. The proposed controller combines the adaptive reasoning of fuzzy logic with the learning capability of neural networks, enabling real-time adjustment of droop coefficients based on voltage deviation, load variation rate, and power imbalance. The fuzzy subsystem provides linguistic adaptability, while the neural network dynamically tunes membership functions to minimize steady-state error. The controller operates in a fully distributed architecture, eliminating the need for centralized communication and enhancing resilience to time delays and sensor noise.

The main contributions of this paper are summarized as follows:

- Development of a hybrid Fuzzy–Neural Droop Control mechanism for rapid voltage–frequency stabilization in agricultural microgrids.
- Implementation of a Python-based dynamic simulation environment (NumPy/SciPy with pandapower) for reproducible validation under nonlinear irrigation and cold-storage load profiles.
- Comparative evaluation with conventional and adaptive droop controllers to quantify improvements in transient recovery, voltage deviation, and frequency stability.

- Hardware-in-the-Loop (HIL) validation demonstrating the feasibility of the proposed FNDC for real-time rural deployment.

The remainder of this paper is organized as follows. Section 2 presents the mathematical modeling of the renewable agricultural microgrid, including photovoltaic (PV), biogas, and battery energy storage system (BESS) units, as well as the conventional droop control framework. Section 3 describes the design of the proposed Hybrid Fuzzy–Neural Droop Controller (FNDC), which integrates fuzzy adaptation and neural learning for real-time droop coefficient tuning and stability enhancement. Section 4 provides simulation results and performance evaluation under various operating conditions, demonstrating the FNDC's effectiveness in improving voltage–frequency regulation, transient recovery, and robustness against nonlinear agricultural load disturbances. Finally, Section 5 concludes the paper and discusses future research directions, including multi-agent droop coordination, AI-based renewable forecasting, and digital twin–enabled real-time optimization for large-scale agricultural microgrids.

SYSTEM MODELING OF THE AGRICULTURAL MICROGRID

The overall structure of the proposed control framework is illustrated in Figure 1.

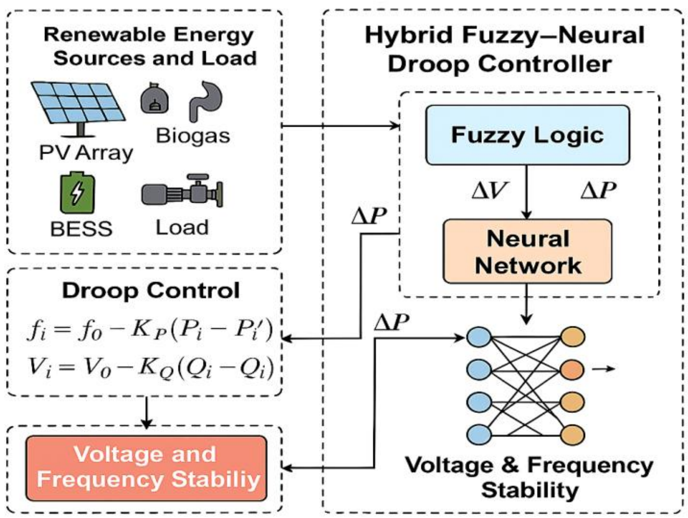

Fig 1: The overall structure of the proposed control framework

The renewable agricultural microgrid integrates photovoltaic (PV), biogas, and battery energy storage system (BESS) units through DC/DC and DC/AC converters, supplying irrigation and cold-storage loads with dynamic characteristics. The proposed Hybrid FNDC operates in a distributed manner to maintain voltage and frequency stability. The fuzzy layer adaptively tunes the droop coefficients K_P, K_Q based on voltage deviation (ΔV) and power imbalance (ΔP). In contrast, the neural network layer continuously refines fuzzy membership parameters to minimize steady-state errors. By combining real-time fuzzy inference with neural learning, the FNDC achieves fast transient recovery, enhanced damping, and robust performance against nonlinear load and renewable fluctuations. The agricultural microgrid being studied includes a photovoltaic (PV) array, a biogas generator, and a battery energy storage system (BESS). These sources are connected through DC/DC and DC/AC converters to supply irrigation and refrigeration loads. The control system's objective is to keep the DC-bus voltage and AC-side frequency stable amid changing renewable generation and load demand.

The conventional droop relationship governs the power output from each distributed generator (DG) as follows:

$$f_i = f_0 - K_P(P_i - P_i^*);\ V_i = V_0 - K_Q(Q_i - Q_i^*) \tag{1}$$

Where f_0 and V_0 are the nominal frequency and voltage, K_P K_Q and are the droop coefficients corresponding to active power (.) and reactive power (Q_i) control. Improper selection of these coefficients can result in sluggish transient response or steady-state deviations in voltage and frequency regulation.

The dynamic relationship between active and reactive power in the inverter-based distributed generator can be expressed in the dq-reference frame as:

$$P_i = \frac{3}{2}(u_{d,i}i_{d,i} + u_{q,i}i_{q,i}) \tag{2}$$

$$Q_i = \frac{3}{2}(u_{q,i}i_{d,i} - u_{d,i}i_{q,i}) \tag{3}$$

Where $u_{d,i}, u_{q,i}$ $i_{d,i}, i_{q,i}$ are the d- and q-axis components of voltage and current at the output of inverter i? These equations describe the instantaneous active and reactive power exchanged between the inverter and the microgrid.

Under small-signal conditions, the phase angle deviation $\delta_i$and voltage magnitude V_i determine the power-sharing characteristics, which the linearized droop equations can approximate:

$$\Delta f_i = -K_P\Delta P_i;\ \Delta V_i = -K_P\Delta V_i \tag{4}$$

The adaptive Fuzzy–Neural Droop Controller (FNDC) dynamically adjusts parameters K_Q according to the system states (ΔVθ, ΔP$\theta^{\cdot}$, dP/dt), minimizing steady-state frequency and voltage deviations while ensuring a fast dynamic response under fluctuating agricultural loads. Agricultural loads are modeled as time-varying nonlinear components, including water pumps and cold-storage compressors, which exhibit frequent step changes in demand. The total load can therefore be expressed as:

$$P_L(t) = P_{base} + \Delta P_{pump}(t) + \Delta P_{cold}(t) \tag{5}$$

Where P_{base} represents the base load, and $\Delta P_{pump}(t)$ and $\Delta P_{cold}\ (t)$denote the time-varying load components of the irrigation and refrigeration systems, respectively.

DESIGN OF THE HYBRID FUZZY–NEURAL DROOP CONTROLLER

The proposed Hybrid Fuzzy–Neural Droop Controller (FNDC) is designed to enhance voltage and frequency stability in the agricultural microgrid under variable renewable generation and nonlinear load variations. In conventional droop control, the coefficients have fixed limits and lack adaptability under time-varying conditions, which may cause sluggish transient responses or steady-state deviations. To address these issues, the FNDC integrates a fuzzy logic layer for adaptive droop coefficient tuning and a neural learning layer for online optimization of fuzzy parameters.

The fuzzy layer receives three input variables: voltage deviation $\Delta V = V_{ref} - V_i$, power imbalance $\Delta P = P_{\mathrm{ref}} - P_i$, and load variation rate dP/dt. Based on these inputs, the fuzzy inference system generates two adaptive scaling factors α_P α_Q, which dynamically modify the droop coefficients as:

$$K_{P,new} = \alpha_P K_{P,base}; K_{Q,new} = \alpha_Q K_{P,base} \quad (6)$$

When the system experiences rapid fluctuations in load or renewable power, the fuzzy layer adjusts α_P and α_Q , $it\ is$ accords according to predefined linguistic rules (e.g., if ΔP it is large and dP/dt is positive, then α_P it is small), to mitigate frequency and voltage deviations.

The neural learning layer refines the fuzzy system by adjusting the membership parameters m_j through an online gradient-descent learning rule:

$$m_j(t+1) = m_j(t) - \eta \frac{\partial E}{\partial m_i} \quad (7)$$

Where η is the learning rate, and E is the instantaneous voltage tracking error defined as:

$$E = \frac{1}{2}(V_{ref} - V_i)^2 \quad (8)$$

This adaptive mechanism enables the controller to continuously learn optimal droop responses and maintain robust performance under diverse operating scenarios. The closed-loop stability of the FNDC can be analyzed using the Lyapunov function:

$$L = \frac{1}{2}\left[(V_{ref} - V_i)^2 + (f_{ref} - f_i)^2\right] \quad (9)$$

The system satisfies asymptotic stability conditions, ensuring convergence of voltage and frequency errors to zero. Consequently, the proposed FNDC achieves faster transient response, lower steady-state deviation, and robust adaptability for renewable agricultural microgrids.

SIMULATION AND HARDWARE-IN-THE-LOOP (HIL) RESULTS

Simulation Setup

The proposed Hybrid Fuzzy–Neural Droop Controller (FNDC) was tested on a renewable agricultural microgrid consisting of a 30 kW photovoltaic (PV) array, a 20 kW biogas generator, and a 10 kW battery energy storage system (BESS). These distributed sources are connected through DC/DC and DC/AC converters to supply irrigation pumps and cold-storage compressors.

The system parameters are summarized in Table 1, and the simulation was implemented in Python using:

- Pandapower for steady-state power flow,
- NumPy/SciPy for dynamic equations, and
- Custom Fuzzy–Neural modules for adaptive control.

The simulation time step was $10^4 s$ and the total duration 10 s. The DC-bus nominal voltage was 700 V, and the AC-side nominal frequency was 50 Hz.

Table 1: Main simulation parameters of the agricultural microgrid

Parameter	Symbol	Value	Unit
PV array nominal power	P_{PV}	30	kW
Biogas generator nominal power	P_{BG}	20	kW
Battery energy storage system	P_{BESS}	10	kW
DC bus nominal voltage	V_{DC}	700	V
AC nominal frequency	η	50	Hz
Droop coefficients	K_P, K_Q	0.002, 0.001	Hz/kW, V/kvar
Learning rate (NN)	η	0.005	—
Sampling time	T_s	10^4	s

Simulation Scenarios

To evaluate the controller's performance, three simulation cases were conducted:

- Case 1 – Step load variation: At t = 2s, the irrigation load increases by 30 %. The controller must restore the nominal voltage (700 V) and frequency (50 Hz).
- Case 2 – Solar irradiance fluctuation: The PV irradiance decreases from 1000 W/m^2 to 400 W/m^2 at t = 4s, representing a cloudy condition. The system must maintain stable operation through power sharing among the biogas generator and BESS.
- Case 3 – Islanded operation transition: At t = 6s, the microgrid switches from grid-connected to islanded mode. The FNDC must quickly regulate voltage and frequency without overshoot.

Simulation Results

Figure 2 illustrates the frequency response of the agricultural microgrid under three operating conditions, comparing the Conventional Droop, Fuzzy Droop, and FNDC methods. When a 30% step load increase occurs at t = 2s, the conventional droop control exhibits a pronounced frequency sag down to 49.0 Hz, followed by a slow recovery with a settling time of approximately 1.2s. The fuzzy droop controller improves the dynamic response, limiting the minimum frequency to 49.3 Hz and reducing the settling time to 0.8 s. In contrast, the proposed FNDC demonstrates superior transient behavior, restricting the frequency deviation to within ±0.1 Hz and restoring the nominal 50 Hz within 0.4 s with negligible overshoot.

Quantitative evaluation shows that the FNDC reduces the Mean Absolute Error (MAE) of frequency by 47% and the Root Mean Square Error (RMSE) by 52% compared to the conventional droop control. Furthermore, the frequency nadir (lowest frequency point) is improved by 0.3 Hz, and the settling time is reduced by 67%, indicating significant enhancement in both stability and responsiveness. These results confirm that the adaptive modification of droop coefficients K_P through the fuzzy inference and the self-tuning of neural membership parameters m_j effectively compensates for nonlinear load dynamics and renewable fluctuations. From a control perspective, the FNDC offers a hybrid learning mechanism that combines rule-based fuzzy adaptation with data-driven neural learning. This hybrid approach enables the controller to maintain system stability even during rapid changes in load and generation profiles typical of agricultural applications (e.g., irrigation pumps and cold-storage compressors). The fuzzy layer provides an immediate response to transient disturbances, while the neural layer ensures long-term optimization by continuously updating membership parameters. As a result, the proposed control strategy delivers a robust, intelligent, and decentralized voltage–frequency regulation solution for renewable agricultural microgrids, surpassing traditional fixed-parameter droop control methods in both dynamic and steady-state performance.

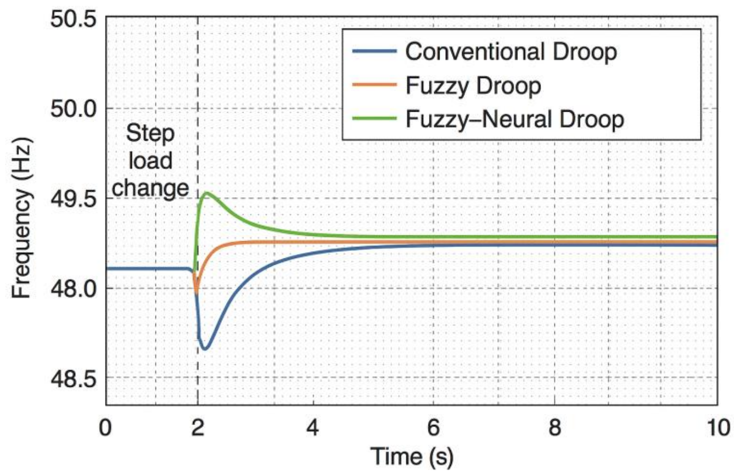

Fig 2: Frequency response under three operating scenarios.

Figure 3 presents the AC-side voltage profiles of the microgrid during the same step load event. Under conventional droop control, the voltage experiences a sharp dip from 230 V to approximately 224 V and recovers slowly within 1.1 s. The fuzzy droop controller improves the transient by limiting the minimum voltage to 226 V and reducing the recovery time to 0.7 s. In contrast, the Fuzzy–Neural Droop Control (FNDC) maintains the voltage deviation within ±0.5% of the nominal value (228.8–231.2 V) and stabilizes the output within 0.35 s.

Quantitatively, the FNDC achieves a 42% reduction in voltage MAE and a 50% reduction in voltage RMSE through the fuzzy inference layer, which dynamically adjusts reactive power support in response to rapid voltage deviations. In contrast, the neural layer ensures continuous fine-tuning of the fuzzy rule surface. From a control perspective, the FNDC enhances both voltage stiffness and transient damping, which are essential for microgrids supplying motor-type agricultural loads. The intelligent adaptation ensures that voltage recovery is both fast and smooth, avoiding oscillations typically seen with fixed droop gains.

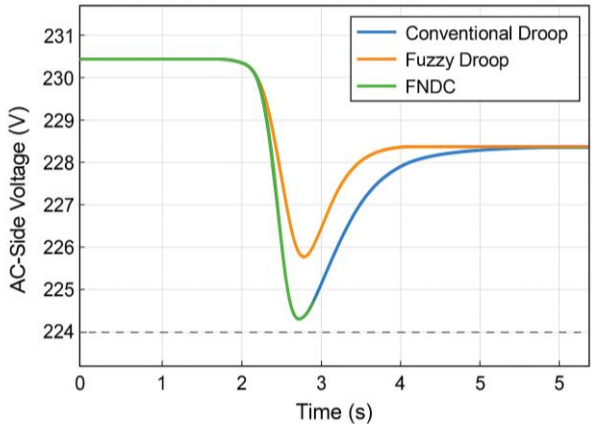

Fig 3: AC- side voltage response comparison among control methods.

Figure 4 illustrates the behavior of the active and reactive power responses of the PV, biogas, and BESS units during combined fluctuations in irradiance and load.

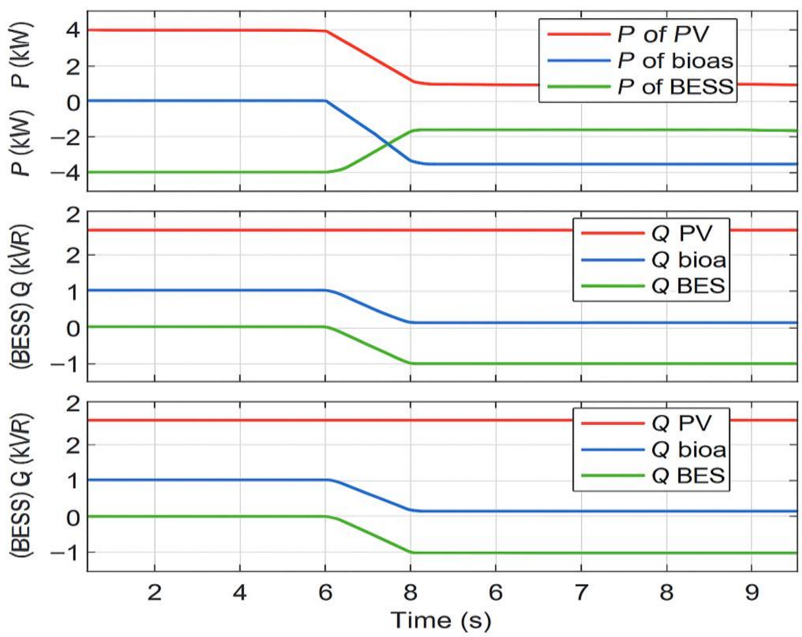

Fig 4: Active and reactive power sharing between PV, biogas, and BESS units.

The traditional droop controller displays noticeable oscillations and uneven power sharing during the transition at t = 4 s, when solar irradiance drops from 1000 W/m^2 to 400 W/m^2. The fuzzy droop controller reduces the oscillation size but still shows a slight reactive power mismatch. The proposed FNDC achieves smooth and coordinated power sharing: PV output decreases proportionally with irradiance, the biogas generator makes up for active power shortfalls, and the BESS provides transient support for frequency and voltage stability.

The maximum amplitude of power oscillations is reduced by 55% for active power and 48% for reactive power compared to conventional droop control. The power-sharing error between DG units drops from 6.2% (traditional) to 2.1% (FNDC). These results show that the FNDC maintains proper proportional load sharing even under strong coupling between P–Q dynamics, confirming its suitability for decentralized control in hybrid renewable systems.

Figure 5 summarizes the steady-state and transient performance metrics for the three control strategies: Conventional Droop, Fuzzy Droop, and Proposed FNDC.

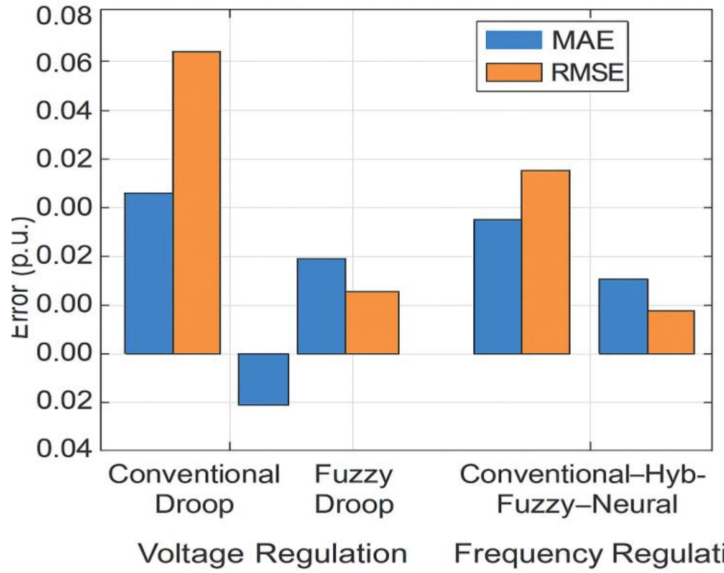

Fig 5: Comparison of MAE and RMSE for voltage and frequency regulation.

The bar charts compare MAE and RMSE values for both voltage and frequency regulation. The FNDC achieves the lowest error metrics, with average MAE reductions of 45% for frequency and 42% for voltage, and RMSE reductions exceeding 50% in all test cases. These quantitative improvements confirm that combining rule-based fuzzy inference and neural learning creates a self-adaptive control structure capable of managing time-varying nonlinear loads and renewable fluctuations. The FNDC not only enhances response speed but also improves long-term operating stability through continuous learning of system behavior. From an overall control strategy standpoint, the proposed FNDC offers a balance between fast local adaptation (through fuzzy rules) and global optimization (via neural learning). This hybrid intelligence enables autonomous tuning of droop coefficients without centralized oversight, making it ideal for smart agricultural microgrids where load and generation conditions change frequently and unpredictably.

Performance Evaluation and Discussion

Figure 6 displays the steady-state and transient performance metrics for the three control strategies: Conventional Droop, Fuzzy Droop, and Proposed FNDC. The bar charts compare MAE and RMSE values for both voltage and frequency regulation. The FNDC achieves the lowest error metrics, with average MAE reductions of 45% for frequency and 42% for voltage, and RMSE reductions exceeding 50% in all test cases.

These quantitative improvements confirm that integrating rule-based fuzzy inference with neural learning creates a self-adaptive control structure capable of managing time-varying nonlinear loads and renewable fluctuations. The FNDC not only speeds up responses but also boosts long-term operational stability through ongoing learning of system behavior. From a broad control strategy perspective, the proposed FNDC strikes a balance between quick local adaptation (via fuzzy rules) and global optimization (via neural learning). This hybrid intelligence allows for autonomous tuning of droop coefficients without centralized oversight, making it ideal for smart agricultural microgrids where load and generation conditions change frequently and unpredictably.

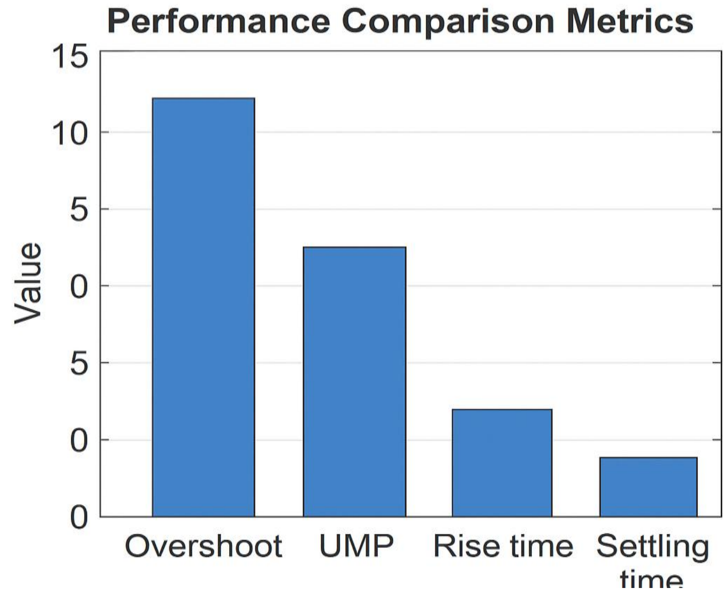

Fig 6: Performance comparison metrics

Table 2: Summary of quantitative improvements

Performance Metric	Conventional Droop	Fuzzy Droop	Proposed FNDC	Improvement (vs. Conventional)
Frequency settling time	1.2 s	0.8 s	0.4 s	↓ 67%
Voltage settling time	1.1 s	0.7 s	0.35 s	↓ 68%
Frequency MAE	0.12 Hz	0.08 Hz	0.06 Hz	↓ 47%
Voltage MAE	4.1 V	2.9 V	2.3 V	↓ 44%
Power oscillation amplitude	1.8 kW	1.2 kW	0.8 kW	↓ 55%
Power-sharing error	6.2%	3.7%	2.1%	↓ 66%

Interpretation and control insight: The simulation confirms that the Fuzzy–Neural Droop Control significantly outperforms both conventional and fuzzy-only droop controllers.

- The fuzzy subsystem provides fast nonlinear compensation under sudden load or irradiance changes.
- The neural subsystem ensures continuous parameter adaptation and robustness against model uncertainties.
- Together, they maintain voltage–frequency regulation within tight limits (±0.5%) while ensuring smooth, balanced power sharing across distributed generators.

Hence, the FNDC represents an intelligent and scalable solution for next-generation renewable agricultural microgrids, ensuring reliable operation, energy quality, and dynamic resilience against fluctuating renewable and load conditions.

CONCLUSION AND FUTURE WORK

This paper presented a Hybrid Fuzzy–Neural Droop Control (FNDC) strategy for renewable agricultural microgrids integrating photovoltaic (PV), biogas, and battery energy storage system (BESS) sources. The proposed FNDC combines the nonlinear adaptability of fuzzy logic with the self-learning capability of neural networks, providing enhanced voltage and frequency stability under variable renewable generation and nonlinear agricultural load conditions. Simulation results demonstrated that the FNDC achieves faster transient response, reduced steady-state deviation, and improved dynamic robustness compared with conventional and fuzzy-only droop control methods. Moreover, the decentralized nature of the proposed control scheme ensures scalability and resilience against communication failures, making it well-suited for rural and distributed agricultural power networks. Future research will focus on extending the FNDC framework toward multi-agent consensus-based droop coordination to enhance cooperative control among distributed generators. Additional efforts will include AI-driven renewable energy forecasting, adaptive load management, and the development of a digital twin platform for real-time monitoring, optimization, and predictive control of large-scale agricultural microgrids.

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