# DEVELOPMENT OF INTELLIGENT CONTROLLED MICROGRID

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***Abstract*—This paper presents smart voltage controller for designing and implementation of an online-trained smart voltage controller for transient response and stability of islanded microgrid under droop control. The droop control in conventional control schemes is widely used; however, it has the disadvantage of slow load shedding and weak load perturbation resistance, resulting in power quality degradations and the risk of the system being. stalled in a stand-alone condition is a heavy load. To achieve this goal, in , a new Petri Probabilistic Wavelet Fuzzy Neural Network (PPWFNN) controller is used to substitute the conventional PI controller in a droop controller, which would enhance power sharing and the reliability and stability of the microgrid across different operating situations.**

***Index Terms*—Droop Control, Microgrid, Petri Probabilistic Wavelet Fuzzy Neural Network (PPWFNN), Power Sharing, Voltage Control.**

## I. INTRODUCTION

The growing use of renewable sources and the urgent need for environmental sustainability have necessitated the development of traditional power systems to be more efficient, intelligent, and decentralized structures. Microgrids, which consist of local loads, distributed generators(DGs), and energy storage systems, are being presented as a viable solution to mitigate energy emergencies and environmental issues. Electronic power converts are utilized in these systems to integrate heterogeneous sources of energy to deliver power reliably.

One of the most commonly used techniques in microgrid control is droop control, which allows decentralized power sharing among DGs without requiring real-time communication. It operates by simulating the operation of synchronous generators, enabling stable load sharing using local measurements. Two main types of droop control are:

### *A. p-f Droop(Active Power-Frequency)*

controls system frequency based on active power mismatch.

### *B. Q–V Droop (Reactive Power–Voltage Control)*

modifies voltage magnitude in response to reactive power mismatch.

These strategies allow distributed generators to share both active and reactive power effectively without centralized coordination.

Yet, conventional droop-based systems have intrinsic limitations. They experience slow transient response, inferior disturbance rejection, incorrect power sharing, and tardy load shedding. These flaws undermine the microgrids capacity to ensure stability and performance when experiencing sudden changes in loads or unforeseen disturbances, Despite utilizing proportional-integral (PI) controllers to improve droop control, problems like sluggish dynamic response and poor adaptability still exist.

To counteract these issues, intelligent control schemes are being incorporated into microgrids. Particularly, substituting the traditional PI controller of the Battery Energy Storage System (BESS) with a Particle Physics Wavelet-based Fuzzy Neural Network (PPWFNN) controller facilitates more rapid and responsive voltage control. This hybrid scheme maintains the decentralized control aspect of droop control but enhances system response and stability during dynamic conditions significantly.

This work introduces the development of an intelligent smart microgrid by integrating conventional droop control with advanced AI controllers. The introduced framework seeks to obtain precise power sharing, high-stability, and rapid response to load changes—requirements essential in today's, robust, and autonomous power systems.

## II. LITERATURE REVIEW

The research paper points to limitations in traditional load-shedding methods such as Under-Frequency Load Shedding (UFLS) and Rate-of-Change-of-Frequency [4] (ROCOF) relays, which tend to result in excessive disconnections of loads owing to fixed thresholds. Although AI-based approaches based on neural networks and metaheuristics are promising, their complexity holds back practical applications. The presents a Dynamic Load-Shedding (DLS) scheme through IEC 61850-based SCADA and IED coordination, taking advantage of GOOSE messaging for real-time, prioritized load shedding. Their simulations on a Penghu microgrid showed accurate power balance with negligible shedding, performing better than traditional methods while fulfilling Taiwan Power Company's 1.2-second response requirement. This method offers a standardized, pragmatic solution without complicated algorithms, which makes it applicable to actual microgrid practices.

The research offers [2] an AI-based smart microgrid system that integrates solar- and wind-powered microgrids with the main grid to improve power sharing and quality. The system utilizes an intelligent $\cos\varphi$ control algorithm, enhanced with a fuzzy logic controller (FLC), to counteract nonlinear loads, minimize harmonics, and facilitate dynamic power flow. The controller takes into account state of charge (SoC), source current, and tariff values to calculate an adaptive gain factor for active and reactive power sharing. Simulation and hardware results prove substantial total harmonic distortion (THD) reduction—from 30.66% to 3.64%—under different tariff and load conditions. Moreover, a cost–benefit analysis proves economic viability with a payback period of 8.7 years, making the system both technically effective and financially sustainable.

The paper present [3] a decentralized droop-based finite-control-set model predictive control (FCS-MPC) method for managing inverter-based resources (IBRs) in islanded AC microgrids. Traditional droop control faces challenges with power sharing and voltage regulation due to line impedance and system nonlinearity. The proposed approach integrates droop control in the outer loop with FCS-MPC in the inner loop, enabling direct switching signal generation without modulators, reducing computational burden, and improving transient performance. A formal condition for bounded stability is derived for the FCS-MPC. The control method ensures accurate voltage tracking, effective frequency regulation, and proportional active/reactive power sharing without requiring communication links. Simulations on a system of three IBRs demonstrate fast dynamic response, voltage stability despite load variations, and minimized frequency and power oscillations.

The paper proposes the Petri Probabilistic Wavelet Fuzzy Neural Network (PPWFNN) [**?**] as a sophisticated control method for islanded microgrids, responding to the drawbacks of traditional Proportional-Integral (PI) controllers in the event of load disturbances. The PPWFNN combines fuzzy logic, neural networks, probabilistic models, wavelet analysis, and Petri nets to provide enhanced frequency stability and response time. It substitutes the conventional PI controller in the Battery Energy Storage System (BESS) droop control loop and is online trained with a supervised gradient descent algorithm. Experimental results prove that the PPWFNN performs better than PI and Fuzzy Neural Network (FNN) controllers in voltage and frequency regulation, transient response, and under-frequency load shedding (UFLS) efficiency, while ensuring real-time applicability. This study brings to the forefront the capability of intelligent control to improve microgrid performance for smart energy networks.

Chakraborty et al. [5] suggest a hierarchical control structure to provide long-term sustainability in networked microgrids (NMGs) by mitigating challenges due to renewable energy intermittency and dynamic load fluctuations. The approach involves a modified local droop-based primary control for voltage and frequency stability and a new two-stage secondary control. The secondary layer incorporates (i) intelligent load management (ILM) based on deep learning for maximum thermostatically controlled load (TCL) aggregation, and (ii) a priority dispatching index (PDI)-based interlinking converter (ILC) control to manage power sharing among microgrids. The system provides critical load support in high-priority MGs (HPMGs) by tapping excess energy from low-priority MGs (LPMGs), even during peak demand or low generation scenarios. Hardware-in-the-loop (HIL) real-time validation ensures the efficacy of the method in frequency restoration, SoC management, and simultaneous load supply and BESS charging. Comparative evaluation with current schemes illustrates better resilience, autonomous adaptability, and energy optimization.

In [6], Tan et al. present an intelligent control method for microgrids by suggesting a dynamic droop coefficient algorithm improved with a new Chebyshev Petri fuzzy neural network (CPFNN). Traditional droop control using fixed coefficients tends to result in slow transient response, poor disturbance rejection, and poor power sharing during abrupt load changes. In order to combat these problems, the suggested technique dynamically adapts the active power/frequency droop coefficient based on CPFNN, which is a composite of fuzzy logic, Petri nets, and Chebyshev polynomial-based neural networks. This structure provides fast adaptation, better interpretability, and stable control performance. Experimental results indicate the suggested CPFNN-based method considerably enhances power quality, minimizes active power settling time to 75 ms (compared with 257 ms in traditional systems), and stabilizes frequency and voltage during dynamic operations, outperforming traditional PI and standard FNN-based control.

## III. METHODOLOGY

This section describes the modeling, control strategy, and simulation process for an islanded microgrid incorporating both conventional and intelligent controllers. The proposed system aims to enhance voltage regulation, power sharing, and load shedding performance under dynamic operating conditions. The study is conducted using MATLAB/Simulink.

### *A. Microgrid Configuration*

The proposed islanded microgrid consists of the following key components:

- A Photovoltaic (PV) system
- A Battery Energy Storage System (BESS)
- Static Switch Relay (SSR) for load shedding
- Multiple loads (critical and non-critical)

The PV and BESS systems are interfaced through Voltage Source Converters (VSCs) and operate under droop control. Two control system architectures are developed:

- PC-Based Control System : Uses PI controller for power regulation in the PV inverter.
- DSP-Based Control System: Uses either PI or PPWFNN controller for voltage regulation in the BESS inverter.

### B. Droop Control Strategy

Droop control enables decentralized operation of distributed generators (DGs) without communication links. Two types of droop are used:

- P–$\omega$ Droop for active power sharing
- Q–V Droop for reactive power sharing

The droop equations are defined as:

$$\omega_{sm} = \omega_{sref} + K_{sp}(P_{sref} - P_{sout}) \tag{1}$$

$$E_{sm} = E_{sref} + K_{sq}(Q_{sref} - Q_{sout}) \tag{2}$$

Where:

- $\omega_{sm}$: Output angular frequency
- $E_{sm}$: Voltage amplitude
- $K_{sp}$, $K_{sq}$: Droop coefficients
- $P_{sout}$, $Q_{sout}$: Output active and reactive power

These outputs are used to generate current references for dq-axis control.

### C. Voltage Control Loop

The voltage control loop is designed to regulate the q-axis current $I_{sq}^*$ based on the voltage error $e = E_{sm} - V_{an,peak}$ and its derivative $\dot{e}$. This control mechanism is critical for maintaining stable voltage levels throughout the microgrid under varying load conditions and generation uncertainties.

- In the **PI Controller** implementation, a fixed gain approach is used to generate $I_{sq}^*$. The controller utilizes proportional and integral terms to minimize steady-state error:
$$I_{sq}^* = K_p e + K_i \int e dt \tag{3}$$
where $K_p$ and $K_i$ represent the proportional and integral gains, respectively. These parameters are tuned to achieve an optimal balance between response speed and system stability.
- In the proposed **PPWFNN Controller** (Parallel Processed Wavelet Fuzzy Neural Network), an intelligent, adaptive learning method dynamically computes $I_{sq}^*$ for better performance during transients and load variations. This controller combines the advantages of wavelet transforms, fuzzy logic, and neural networks to adapt to changing system conditions:
$$I_{sq}^* = f_{\text{PPWFNN}}(e, \dot{e}, \omega_{sm}, P_{sout}, Q_{sout}) \tag{4}$$
where $f_{\text{PPWFNN}}$ represents the mapping function implemented by the neural network. The controller continuously updates its parameters through a learning algorithm to optimize voltage regulation performance.

The voltage control loop operates in conjunction with the droop control mechanism to ensure proper power sharing while maintaining voltage stability. The controller outputs serve as references for the inner current control loops, which ultimately determine the switching signals for the voltage source converter.

### D. PPWFNN Controller Architecture

The PPWFNN controller comprises a seven-layer structure, each responsible for processing and transforming information to generate accurate and adaptive control signals. The architecture is described in detail as follows:

*1) Input Layer:* This layer receives real-time system input signals. These primarily include the voltage error $e = E_{\text{sm}} - V_{\text{an,peak}}$, and its time derivative $\dot{e}$. This enables the controller to capture both the magnitude and rate of change of deviations.

*2) Membership Layer:* Crisp input variables are fuzzified using Gaussian membership functions:

$$y_j^2 = \exp\left(-\frac{(y_i^1 - m_{ij}^2)^2}{(\sigma_{ij}^2)^2}\right) \tag{5}$$

where $m_{ij}^2$ and $\sigma_{ij}^2$ represent the mean and standard deviation, respectively. This captures the imprecise and nonlinear nature of microgrid behavior.

*3) Petri Layer:* This layer models event-driven transitions using a dynamic token mechanism:

$$t_p^3 = \begin{cases} 1, & \text{if } y_j^2 \geq d_{\text{th}} \\ 0, & \text{otherwise} \end{cases} \tag{6}$$

The threshold $d_{\text{th}}$ adapts through a sigmoid function based on performance feedback, enabling the modeling of discrete events and transitions.

*4) Probabilistic Layer:* Pattern recognition is performed using Gaussian receptive fields:

$$y_{pq}^4 = \exp\left(-\frac{(y_p^3 - m_{pq})^2}{(\sigma_{pq})^2}\right) \tag{7}$$

This provides robustness in uncertain conditions such as fluctuating renewable energy and dynamic loads.

*5) Wavelet Layer:* Multi-resolution analysis is performed using Mexican-hat wavelets:

$$\phi_{ik}^5 = \frac{1}{|\sigma_{ik}^5|}\left[1 - \frac{(x_i^1 - m_{ik}^5)^2}{(\sigma_{ik}^5)^2}\right] e^{-\frac{(x_i^1 - m_{ik}^5)^2}{2(\sigma_{ik}^5)^2}} \tag{8}$$

This allows for localized feature extraction from both fast and slow system dynamics.

*6) Rule Layer:* This layer constitutes the fuzzy rule base:

$$y_l^6 = \prod y_{qi}^5 \psi_k^5 \tag{9}$$

Each node represents a fuzzy rule based on domain knowledge and control experience.

*7) Output Layer:* The output signal is computed as:

$$y_o^7 = \sum_{l=1}^{9} w_l^7 y_l^6 \tag{10}$$

Here, $w_l^7$ are learnable weights tuned during training. The output corresponds to the reference $I_{sq}^*$, which directs the BESS inverter for power regulation.

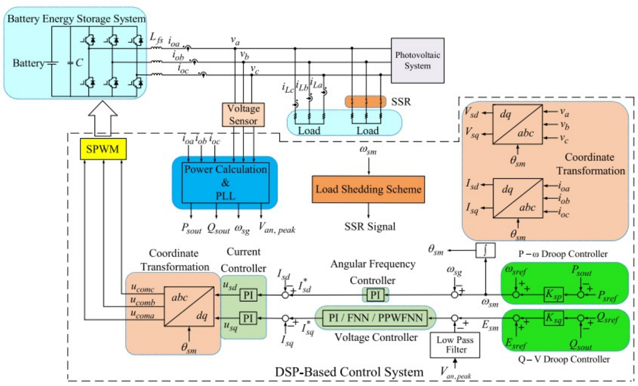


**Fig. 1:** Control block of BESS (DSP).

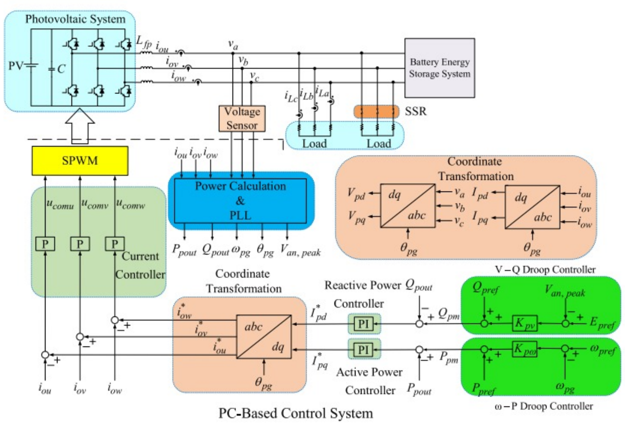


**Fig. 2:** Control block of BESS (PC).

### *E. Online Learning Algorithm*

The PPWFNN (Parametric Piecewise Wavelet-based Fuzzy Neural Network) is trained online using a supervised gradient descent algorithm. The learning rates are derived from a discrete Lyapunov function to ensure convergence and stability. The learning rules update the weights $w_7^l$, wavelet parameters $w_{5ik}$, and membership function parameters $m_{2ij}, \sigma_{2ij}$ in real-time.

### *F. Load Shedding Scheme*

An Under-Frequency Load Shedding (UFLS) scheme is embedded into the DSP control logic. The controller continuously monitors the microgrid frequency $f_{sm}$. If it drops below 59.3 Hz for more than 0.2 seconds, the SSR (Smart Switch Relay) disconnects non-critical loads to prevent system instability or blackout.

### *G. Simulation Cases*

To evaluate and compare the performance of the conventional Proportional-Integral (PI) controller and the proposed Piecewise Partial Weight Function-based Neural Network (PPWFNN) controller, two simulation test cases are considered. These test cases are designed to assess controller performance under varying load conditions, focusing on stability, dynamic response, and system resilience.

- Case 1: Power Sharing Test
  The load changes from 1 kW to 3 kW and then to 2 kW. This case is used to measure power allocation, voltage/frequency response, and transient performance.
- Case 2: Load Shedding Test
  The load increases from 1 kW to 3.5 kW. This case tests the frequency response, UFLS trigger time, and system recovery.

## IV. RESULT

The performance of the proposed Petri Probabilistic Wavelet Fuzzy Neural Network (PPWFNN) controller was evaluated and compared against conventional Proportional-Integral (PI) and Fuzzy Neural Network (FNN) controllers. The comparison was conducted under two critical operational scenarios in an islanded microgrid: power sharing during load variation and under-frequency load shedding (UFLS).

- Case 1: Load Variation – Power Sharing Performance
  The PPWFNN controller demonstrated superior dynamic performance in response to load variation. It achieved the fastest and most stable voltage and frequency response among all tested controllers. The controller significantly reduced overshoot and transient duration compared to PI and FNN controllers. Furthermore, it minimized both active and reactive power errors, indicating improved power sharing coordination between Battery Energy Storage Systems (BESS) and Photovoltaic (PV) systems.
- Case 2: Sudden Load Increase – Load Shedding Performance
  In the scenario of a sudden load increase, the PPWFNN controller exhibited the fastest load shedding response, triggering action within 0.24 seconds after system frequency dropped below 59.3 Hz. This quick response effectively prevented deep frequency drops and allowed the system to stabilize more rapidly than with PI or FNN controllers. Additionally, the PPWFNN controller achieved lower voltage recovery time and minimized disturbances in reactive power.

## V. CONCLUSION

Due to the inherent limitations of conventional droop control, which negatively impacts system stability and results in delayed load shedding in islanded microgrids, this study introduces an online-trained PPWFNN-based voltage controller as an alternative to the traditional PI controller used in the BESS. This enhancement addresses the instability challenges posed by droop control under load variation and also contributes to improved UFLS performance.

The effectiveness and practicality of integrating the proposed PPWFNN controller within a droop-controlled BESS have been validated through experimental investigations. Compared to the performance outcomes of BESS systems employing conventional PI and FNN voltage controllers, the proposed PPWFNN controller significantly enhances transient response characteristics, such as voltage regulation, power output stability, and frequency control, especially during dynamic load conditions. Additionally, it enables faster execution of UFLS owing to its robust control capabilities.

The key contributions of this study are summarized as follows:

- Development and deployment of an islanded microgrid architecture employing droop control methodology.
- Design and implementation of a novel, online-trained PPWFNN voltage controller.

Integration of the proposed controller into the BESS framework, demonstrating superior performance in terms of power sharing accuracy and improved responsiveness during load shedding scenarios.

## VI. REFERENCE

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