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Original Article

Artificial Intelligence-Based Power Management System for a DC Micro-Grid

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Abstract *- An advanced approach to a power management system for DC microgrids with a combined solar PV and wind energy system and battery storage is presented here. It began by implementing controllers, including fuzzy logic and FO-PID-based control for renewable management with double FO-PID controls for battery operations. Power-output stabilization was obtained effectively by the fuzzy-FO-PID system, but equipment stability suffered from rapid power fluctuations. The controller system installed in source-side converters seeks to extract maximum power output from wind turbines and PV arrays, improving microgrid stability and reliability. A FO-PID controller is an additional control mechanism that specifically operates on the battery storage system to monitor its charging and discharging activities for enhanced battery operation and balanced energy distribution. The research focuses on enhancing the operational connection between the costs of renewable energy systems throughout the system. An ANN-based Radial Basis Neural Network (RBN) controller was designed to regulate solar and wind power outputs, but the battery management system kept its double FO-PID controller. The ANN-RBN controller formed an advanced control system because its adaptive learning capabilities enhanced tracking of dynamic events, along with minimizing voltage swings to enhance power quality. MATLAB/Simulink simulations will be performed to evaluate the ANN-RBN controller's effectiveness in stabilizing DC microgrid performance, with comparisons made against the conventional fuzzy-FO-PID controller in terms of voltage stability and disturbance response under varying operating conditions. The novelty of the work lies in integrating a hybrid control scheme that combines an ANN-RBN controller for adaptive renewable power regulation with a double FO-PID strategy for battery management, enabling stable energy distribution alongside improved power quality.*

Keywords *- DC-Microgrid, Fractional Order Proportional Integral Derivative Control, Fuzzy Logic Control, Radial Basis Neural Network, Renewable Energy Sources, Storage Battery.*

1. Introduction

Global environmental concerns and the surge of interest in sustainable energy have increased the motivation to utilize intelligent control systems with renewable energy platforms. PV and wind energy projects created as hybrid systems present an exclusive solution for dependable source generation. The success of these hybrid systems requires maximum performance at all times, which can be achieved through advanced Maximum Power Point Tracking (MPPT) techniques. Multiple research investigations have used Artificial Neural Networks (ANN) and fuzzy logic as AI branches to boost the global performance as well as the performance-effectiveness ratio of hybrid PV-wind systems. A modern MPPT system based on ANN and fuzzy logic shows great promise for enhancing the power-generation and power-quality of standalone and grid-connected hybrid PV-wind systems. The simulation results under different weather situations prove that the MPPT achieves sustainable power management objectives over specified ranges and validate the overall methodological effectiveness [1, 2]. Load Frequency Controllers (LFCs) show enhanced frequency stability and better transient response to sudden changes in load compared to conventional PID controllers [3]. A new category of MPPT algorithms combines Perturb and Observe (P&O) with Radial Basis Function Neural Networks (RBFNN) to achieve better performance under atmospheric condition fluctuations, thus enabling faster convergence and improved maximum power point tracking [4, 5]. Solar irradiance and power production have been accurately predicted using forecasting models that incorporate RBFNN types II fuzzy double-Gaussian activation functions and display superior forecasting performance than traditional prediction systems [6].

The models operate successfully in hybrid systems to improve system adaptability for weather variations, leading to lower THD levels [7]. Research has investigated MPPT for wind energy systems through models of RBFNN that employed MPSO for online training to optimize torque control and power extraction according to different turbine types [8]. Under dynamic environmental conditions, ANN controllers deliver steady output power to PV-wind hybrid systems that use common DC-DC converters with grid interface inverters [9, 10]. Adaptive HEMS provides a technology foundation that gives residents advanced capabilities to achieve maximum energy cost reduction and operational performance goals.

The successful operation of HEMS relies heavily on optimization through both PSO and BPSO algorithm methods [11]. Modern special economic models using ANN-based wind speed forecasting systems enable users to optimize both wind turbine parameters and network distribution systems in Radial Distribution Networks (RDNs) [12].

Hybrid energy management platforms boost efficiency by employing a predictive control system that uses Gaussian process regression-based vehicle dynamic models [13]. Through AI-based energy management systems that employ machine learning capabilities, the prediction of power delivery can be achieved through sensor inputs along with weather documents, thus lowering expenses [14].

Hybrid energy systems need immediate deployment to establish solutions that enhance rural areas with sustainable and dependable energy distribution [15, 16]. Under continuous varying meteorological conditions, according to researchers, Grey Wolf Optimizer optimized a solar PV microgrid dispatch system to enhance performance while lowering operational expenses [17]. Experimental evidence demonstrates that applying an ANN together with PI control technology in direct current microgrids produces better speed responses while enhancing battery storage defenses [18].

The filing of SVR as a primary energy forecasting method in grid-connected microgrids stands out because of its dual benefit to enhance operational stability and maximize energy resource utilization [19]. The electric transportation sector receives support for its growth through deep learning models, which control renewable-powered electric vehicle fast charging systems to deliver better system performance with accelerated responses [20].

Future generations of commercial Advanced Energy Management and Control Systems (EMCS) for microgrids will enter the market because they use optimization algorithms to manage emissions while increasing efficiency [21]. Smart grids gain better forecasting features because of the implementation of Recurrent Neural Networks (RNN) and Gated Recurrent Units (GRU) [22]. RANNTC controllers enhance the voltage regulation performance and harmonic distortion response by controlling DC-AC converter operations under system condition changes [23]. Artificial intelligence-based power quality management strategies are becoming widely used in renewable energy systems that have substantial investments [15].

The IRES delivers fundamental operational ability to modernized urban societies. When implemented, AI-based optimization brings reliable and efficient energy production ability to renewable energy generation systems [24]. According to research, the stability performance of microgrids powered by electric vehicles and storage equipment increases when MPC and D2C frequency control methods work together [25].

According to recent research, the combination of artificial neural networks and Hybrid Whale Optimization frameworks in hybrid energy management systems proves better than standard techniques for running multiple renewable energy-based microgrids. Bibliometric research highlights scheduling controllers development for microgrids as its central study point while discussing optimization methods and intelligent control systems in detail [26]. Microgrid protection warrants new fault detection techniques for mixed AC/DC systems, per contemporary scholarly findings [27].

The combination of RBFNN with the Squirrel Search Algorithm (SSA) optimizes the costs while improving accurate power fluctuation prediction for hybrid energy systems [28]. The literature shows that the challenge lies in stabilizing DC microgrids integrating solar PV, wind, and battery storage, where conventional fuzzy-FO-PID controllers fail to maintain both power quality and stability under dynamic conditions. This research addresses the problem by developing a hybrid ANN-RBN and double FO-PID control scheme to ensure reliable power regulation, voltage stability, and balanced energy distribution.

2. Configuration of the Proposed System

Figure 1 shows the proposed system, which presents an intelligent control-based DC microgrid integrating solar PV, wind energy, and battery storage through advanced converter interfaces. ANN-RBN controllers are employed for solar and wind MPPT operations, ensuring rapid adaptation to dynamic weather conditions and maximizing renewable energy extraction [1].

A double FO-PID controller effectively manages battery charging and discharging, preserving battery health and maintaining grid stability. The bi-directional converters and coordinated energy management guarantee a stable DC bus voltage and reliable load supply. This architecture offers superior adaptability, improved power quality, and enhanced efficiency compared to traditional control strategies, making it ideal for modern hybrid microgrid applications.

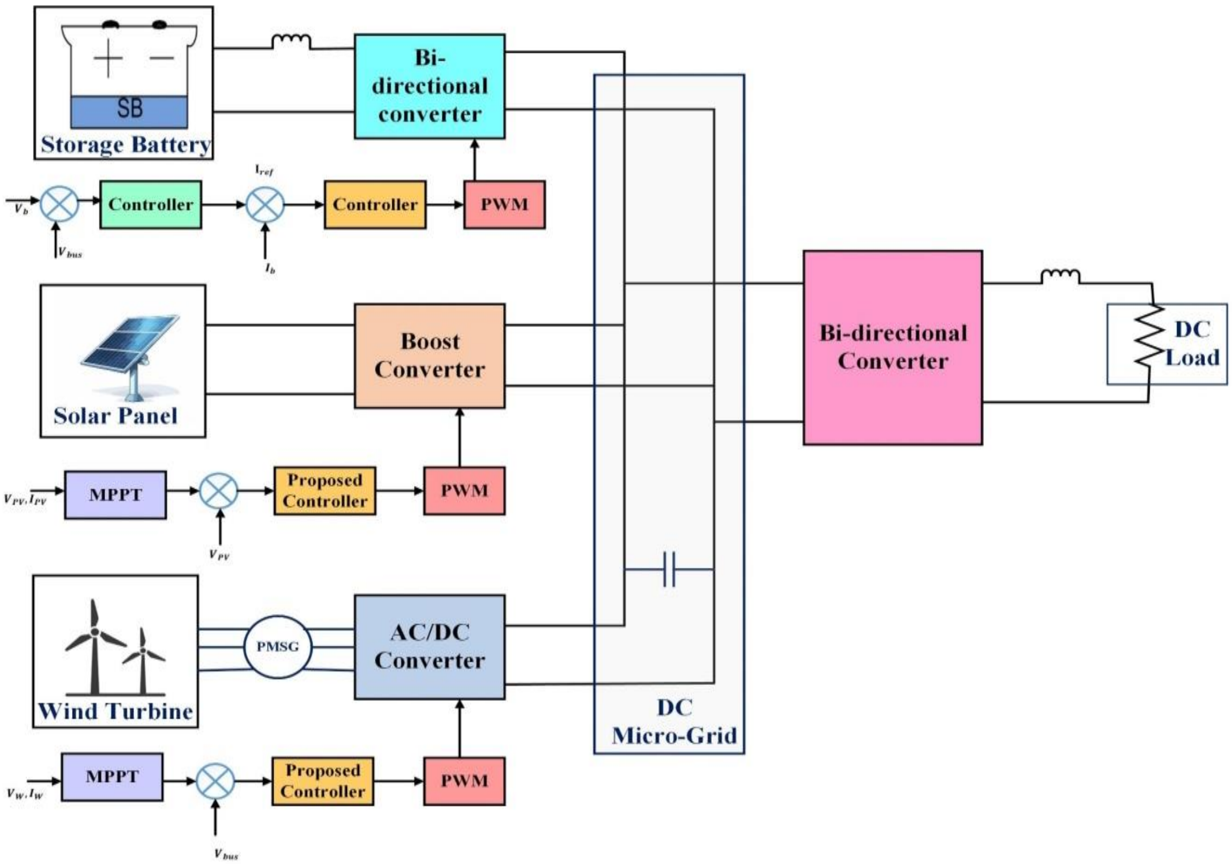

Fig. 1 Proposed block diagram of the system

2.1. Solar PV System

Fundamental mathematical modeling of the solar PV module occurs through application of single-diode equivalent circuit analysis.

The photocurrent output results from irradiation strength and depends on the temperature through this relationship derived from Equation (1).

$$I_{ph} = \left[I_{ph_{ref}} + K_1 \left(T - T_{ref} \right) \right] \times \frac{G}{G_{ref}} \quad (1)$$

The reverse saturation current varies with temperature and is given by Equation (2),

$$I_0 = I_{0ref} \left(\frac{T}{T_{ref}} \right)^3 \exp\left(\frac{qE_g}{nK} \left(\frac{1}{T_{ref}} - \frac{1}{T} \right) \right) \quad (2)$$

Thermal voltage across a single cell is given by Equation (3)

$$V_t = \frac{nKT}{q} \quad (3)$$

Photocurrent I_{ph} depends on irradiance G, temperature T, and reference values G_{ref}, T_{ref}. K_1 is the temperature sensitivity. Reverse saturation current I_{0ref}, charge q =1.6× 10^{-19} C, bandgap E_g, Boltzmann constant K=1.38×10^{-23} J/K, and ideality factor n (1–2) define PV cell behavior in diode modeling. The current through the diode follows Shockley's equation, which is derived from Equation (4),

$$I_d = I_0 \left(e^{\frac{V + I\,R_S}{nV_t}} - 1 \right) \quad (4)$$

parallel resistance (shunt resistance) is given by Equation (5),

$$I_{sh} = \frac{V + I\,R_S}{R_P} \quad (5)$$

The overall output current of the solar panel is given by Equation (6),

$$I = I_{Ph} - I_d - I_{sh} \quad (6)$$

The current movement through solar panel diodes obeys Shockley's diode equation to link voltage and current values. The output voltage of the module corresponds to V, whereas the output current equals I in this situation. The internal series resistance of the panel, denoted by Rs, results in voltage loss during current transmission, shunt current (I_{sh}). The parallel resistance serves to measure leakage current in photovoltaic (PV) cells by representing the term. R_P.

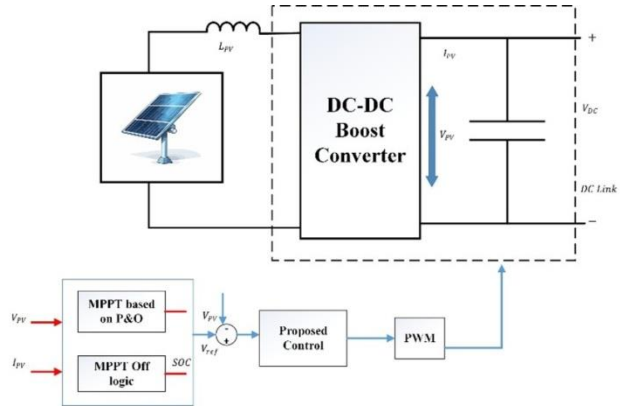

Fig. 2 PV system with MPPT control

The schematic shown in Figure 2 is a solar PV setup connected to a DC-DC boost converter. The converter is used to increase the PV voltage to match the DC link voltage as well. P & O algorithm is implemented as a component of MPPT control for vampires maximizing power extraction. The controller measures PV voltage from a point rectifier and compares it with the reference voltage to produce PWM signals that regulate converter operation. When the battery State Of Charge (SOC) is at full capacity, the MPPT operation occurs. The flowchart shown in Figure 3 serves as a visual guide to the development of how the MPPT control method is implemented.

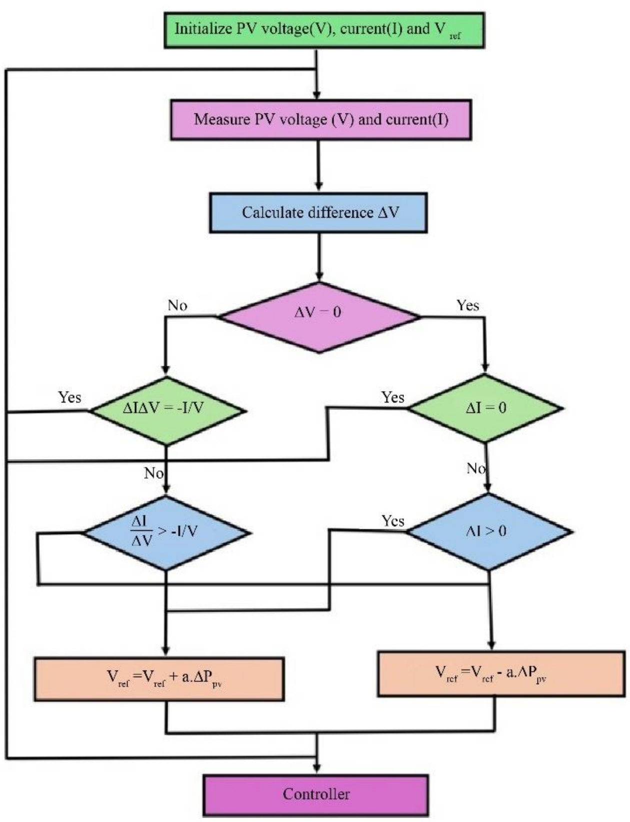

Fig. 3 PV system flow chart

The first step is the measurement of PV voltage and current, then calculating their changes in turn. With the changes measured, the algorithm adjusts the reference voltage to follow the maximum power point. If output power is improved, a corresponding change is made to the voltage.

2.2. Wind Energy System

The wind energy generation process begins when wind turbines convert energy from the wind into mechanical energy. The mechanical energy that is developed will trigger an engine, kicking off the production of AC electricity. Then an AC-DC rectifier converts the generated AC power into DC and injects it into a DC link. A Maximum Power Point Tracking (MPPT) controller, exploiting the Perturb and Observe (P&O) algorithm, improves the power extraction from the wind turbine by adjusting the voltage reference in light of the condition of the wind and the battery SOC.

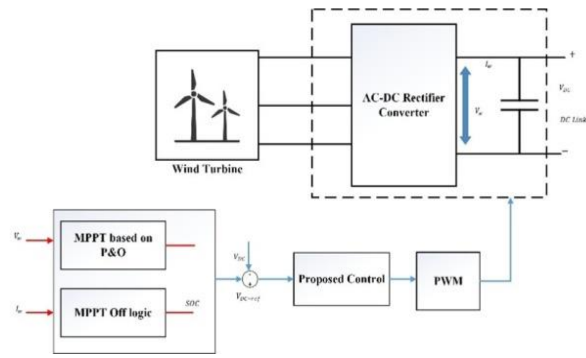

Fig. 4 Wind system with MPPT control

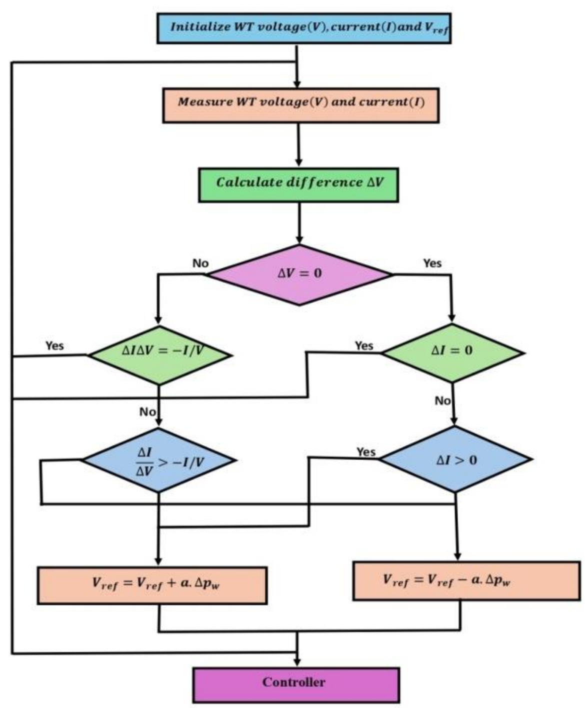

Fig. 5 Wind energy flow chart

The control system computes the difference between the measured DC link voltage and the reference voltage, which is directed to a proposed controller. PWM signals are generated by this controller to control the converter's operation. A complete dynamic model of the wind turbine system is developed for this purpose using a two-mass drive train model. Figure 4 model considers the turbine and shaft dynamics, including inertia and springs' stiffness with mutual damping. When data concerning generator speed and mechanical torque are added, the model provides a viable measure of the dynamics of wind turbines. In addition, a pitch angle controller dictates the blade's orientation at varying wind speeds, protecting the system and increasing performance. The wind flow chart is shown in Figure 5, which is a logic-based maximum power point tracking. Voltage and current are measured, their fluctuations are determined, and the system determines whether the turbine is running at a maximum power point. In response to such comparisons, the reference voltage enhances or inhibits power extraction depending on the necessity.

2.3. Battery Storage System

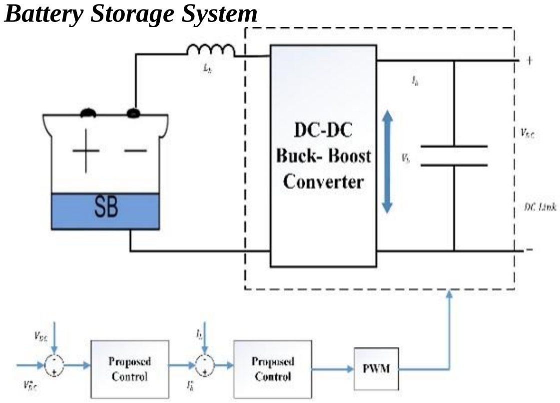

Fig. 6 Battery Storage System with MPPT control

As shown in Figure 6, BESS interfaces with the DC microgrid via a DC-DC buck-boost converter. Through bidirectional power transfer, the converter can maintain the flow of power such that the battery can help contribute or consume a portion of the energy based on the balance of the energy demand in the system. The battery (SB) is coupled to the converter through an inductor. L_b, to stabilize the conduction of currents and lessen the ripple effects. In order to provide the necessary DC link voltage V_{dc}The converter varies the battery voltage V_b and battery current I_b. The integral part of the achieved measured control architecture needs two different control loops nested. With the DC link voltage V_{dc} and a target V_{dc}, monitoring, the outer loop creates a reference battery current I_b. The inner current control loop, when used with the proposed control algorithm, produces a PWM signal by analyzing the gap between the I_b reference battery current and the real I_b Current. PWM signal controls switching in the converter, thereby overseeing the voltage distribution and facilitating a proper flow of power from the battery and onto the DC bus.

3. Controller's Design

3.1. Fuzzy Logic System

From Figure 7, the fuzzy approach adjusts the K_{1j}, K_{2j},and K_{3j}gains operating as a fuzzy supervisor that can deal with indeterminate parameters. The fuzzy inputs were selected as the current error for computing the controller laws or the link error related to a desired current. As indicated, the membership functions were selected according to symmetric and uniformly distributed triangular and trapezoidal types. The process depended on applying the same parameter to multiple membership functions. The benefit of this method is a significant reduction in the number of membership function parameters. The decision-making output was done using a combination of Max and Min fuzzy inference mechanisms, and crisp output was computed using a center of gravity defuzzification method.

Table 1. Fuzzy rule-based system

$e_{j,p}$ \ $\Delta e_{j,p}$	NB	NS	Z	PS	PB
NB	NB	NB	NS	NS	Z
NS	NB	NB	NS	Z	PS
Z	NS	NS	Z	PS	PS
PS	NS	Z	PS	PB	PB
PB	Z	PS	PS	PB	PB

Table 1 shows the linguistic variables appropriate to the fuzzy gain scheduling inputs and outputs. The justification for using a fuzzy controller to derive the gains in the fractional order-PID gains will rely on the feasibility of computing fixed gains when the system changes in parameters. Further, the proofs of stability of the fractional order are well established in the literature; therefore, they will not be included in the present discussion.

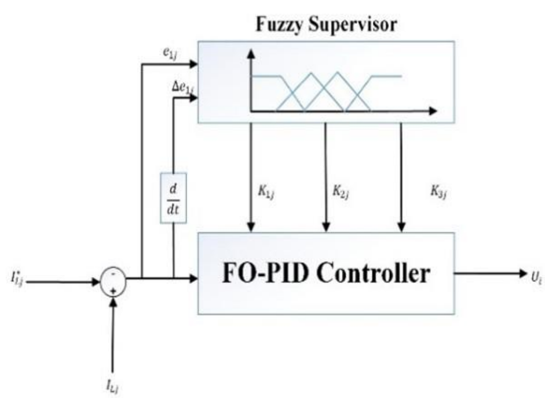

Fig. 7 Fuzzy combined FO-PID logic controller

3.2. Fractional Order Proportional Integral Derivative (FOPID)

A fuzzy-based Fractional-Order Proportional Integral Derivative (FOPID) controller is a specific control method that combines the fractional-order arithmetic, simple to use, with the dynamic properties of fuzzy logic in helping to optimize solar and wind energy systems. With solar Photovoltaic (PV) systems, the fuzzy-based FOPID controller increases and decreases the power converter's duty cycle in real-time to identify the Maximum Power Point (MPP) value due to changing temperature and irradiance conditions. Similarly, the fuzzy-based FOPID controller optimizes a wind energy system's rotor speed or load to yield maximum power extraction from varying wind speeds. The FOPID component (denoted as) is valuable because it employs fractional-order integrals and derivatives to allow for an extra layer of specificity when controlling an energy system's dynamics compared to classical PID controllers.

$$\text{FO-PID} = k_P + k_i \cdot \frac{1}{S^{\alpha}} + k_d S^{\beta} \tag{7}$$

$\frac{1}{s}$ = Integrated

$$Y(s) = k_1(s) - \frac{0.25 \times k_2(s)}{s} + 5 \times A(s) \tag{8}$$

$$A(s) = k_3(s) - \frac{0.25 \times y(s)}{s} \tag{9}$$

By the above Equations(7-9), k_P (k_1) denotes the proportional gain, k_i (k_2) denotes the integral gain, k_d (k_3) denotes the derivative gain, Y(s) denotes the laplace transform of the output signal, A (s) denotes the laplace transform of signal A, α denotes the order of integration ($0 < \alpha < 1$), β denotes the order of differentiation ($0 < \beta < 1$).

3.3. Radial Basis Network

The provided MATLAB script uses an RBF neural network precisely for control. The process begins by describing an input vector consisting of control error or system signals and a constant output vector corresponding to this input. The input and target values are used as MATLAB's tool, which utilizes the input to generate the training data that constructs an RBF network that keeps on adding more neurons until the desired level of accuracy is achieved. Network performance is validated using an in-built MATLAB tool that computes error with reference to how close the actual output is to the desired levels. By data-driven learning, the system can produce dynamic control signals through the use of the neural network, hence improved response and stability compared to traditional controllers.

A Radial Basis Function (RBF) neural network was trained in MATLAB software. Input values that specified system parameters, such as error signals or operational changes, were given in a vector. Fixed values were also provided as target output values with which the network should behave. After training, the network was tested using the same input data, and the output responses were compared with the target values using a performance function. MATLAB's visualization function was used to visualize the training process, and the model has been exported to a Simulink block to be integrated into real-time control systems. This method makes real-time and dynamic control possible, which is suitable for renewable energy systems such as solar and wind power systems.

4. Energy Management Unit

The Energy Management Unit (EMU) plays an important role in the management and operation of a microgrid system. An EMU's role is to generate a voltage as a reference signal to be sent to the source side convertor and load side converter, based on the measured power in from the renewable energy source and the measured power out from consumed loads. In order to meet load demand while maintaining stability in the microgrid system.

The Battery Storage System (BSS) is controlled and operated in charge/discharge mode while maintaining charging of the energy storage system (BSS) at the reference DC-link voltage level and ensuring the power balance as generation and loads vary. If the power generated from the SSCs exceeds the load demand, the excess power will charge the battery system until the battery charge state reaches the maximum state of charge (SOC_{Max}), or if generated power is less than load demand, the BSS will discharge power to supply the load demand until the state of charge reaches the minimum state of charge (SOC_{Min}). The modelling of power balance is represented by Equation(10),

$$P_{Net} = P_L - (P_W + P_{PV} - P_{Loss}) \tag{10}$$

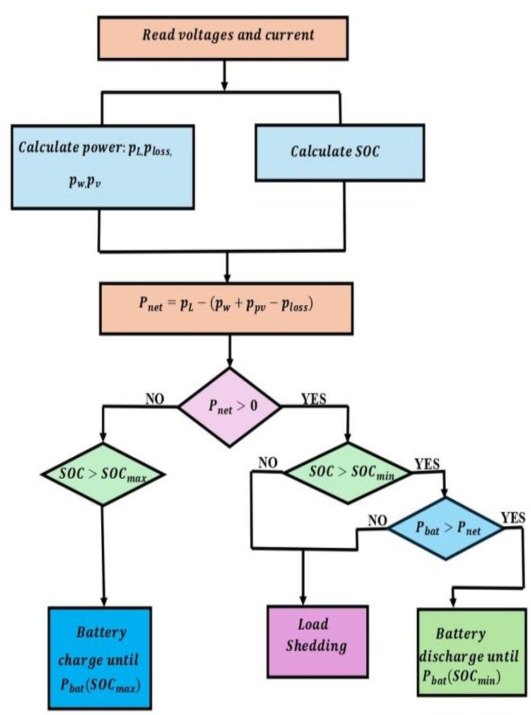

Fig. 8 Flowchart for EMU method

In Figure 8, P_W and P_{PV} Denote wind and solar power, P_{Load} is the load demand, and $P_{Battery}$Indicates the battery power. The EMU consists of two modes, which rely on the battery state and conditions of power generation. In mode one, when renewable generation is greater than load, excess energy can charge the battery. In mode two, when generation is insufficient to meet the load, the EMU can discharge the battery. This dynamic control process achieves the best benefit from renewable energy sources, improves reliability, and controls power balance, making the EMU a necessary part of microgrid systems today. The Simulink diagram of a hybrid renewable energy-based DC microgrid system designed for efficient and stable power distribution, as shown in Figure 9. The system integrates three major energy sources: a lead-acid battery bank, a solar Photovoltaic (PV) system, and a wind generation system.

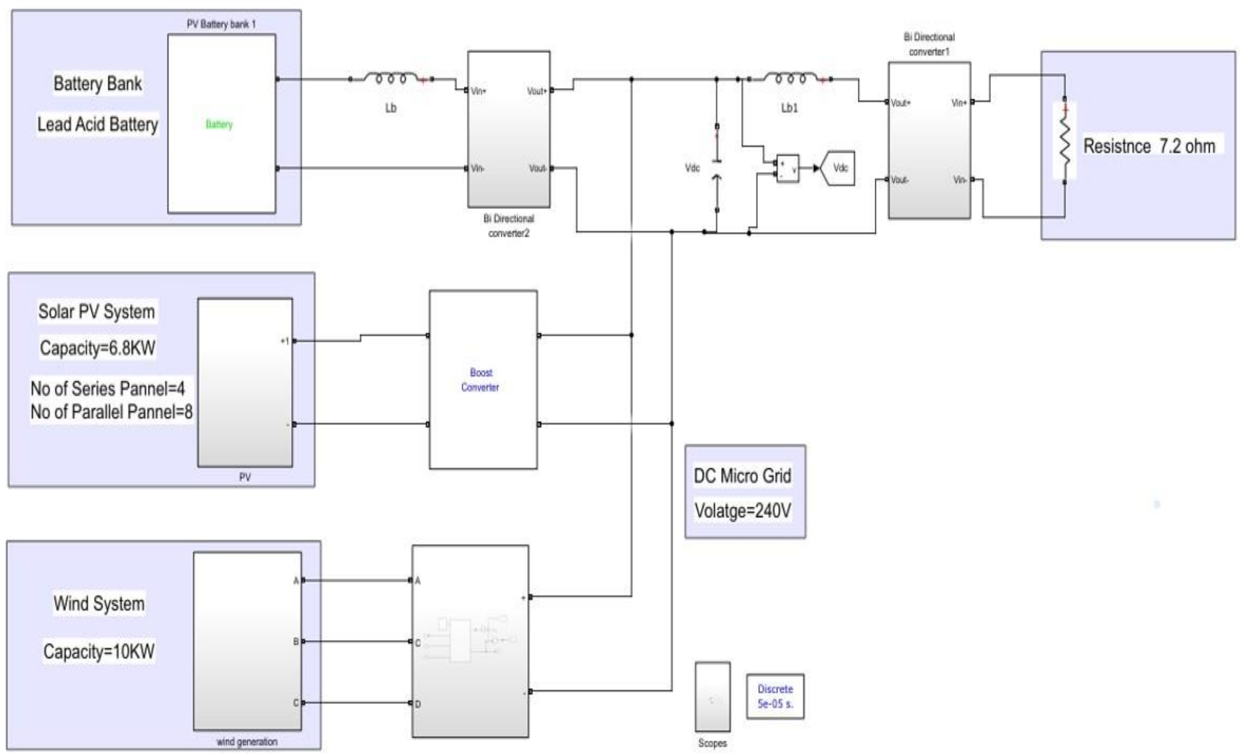

Fig. 9 Simulink block diagram of the system

5. Results and Discussions

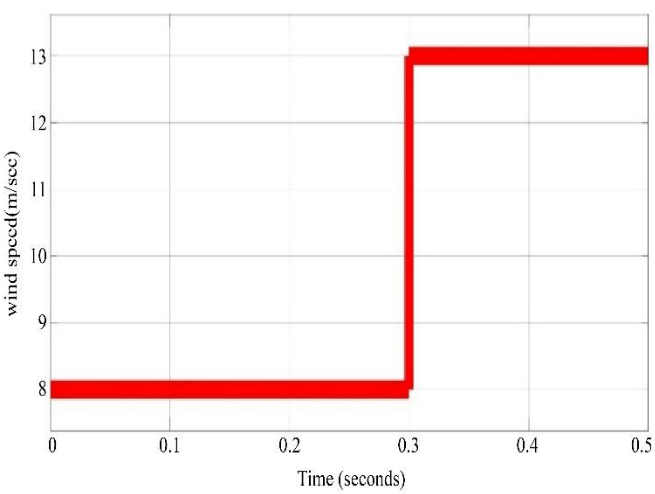

Fig. 10 Wind speed (m/sec)

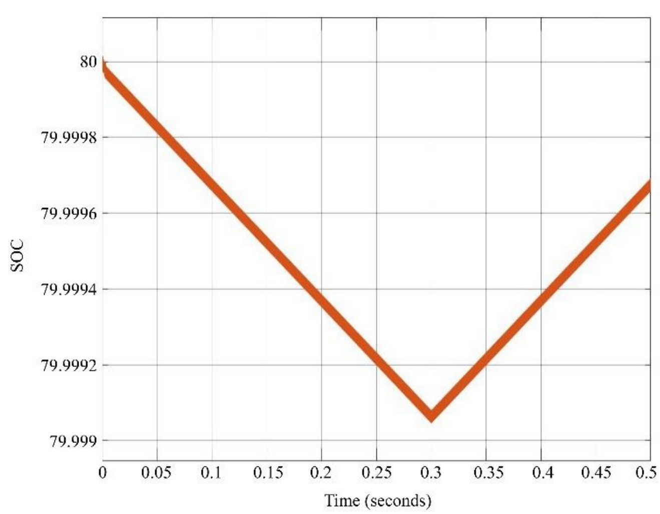

Fig. 11 State Of Charge (SOC)

Figure 10 shows the wind speed (in meters per second) over the same time range. It shows a sudden increase in wind speed at the 0.3-second mark. Before this point, the wind speed stays constant at 8 m/s. At 0.3 seconds, it jumps sharply to 13 m/s and remains there for the rest of the time. The line is bold and red, highlighting the abrupt change clearly. Figure 11 shows the State of Charge (SOC) over time. It starts at 80 and decreases slightly until 0.3 seconds, where it reaches its minimum point. After that, the SOC begins to rise again. The line is thick and orange, and the axes are labelled clearly.

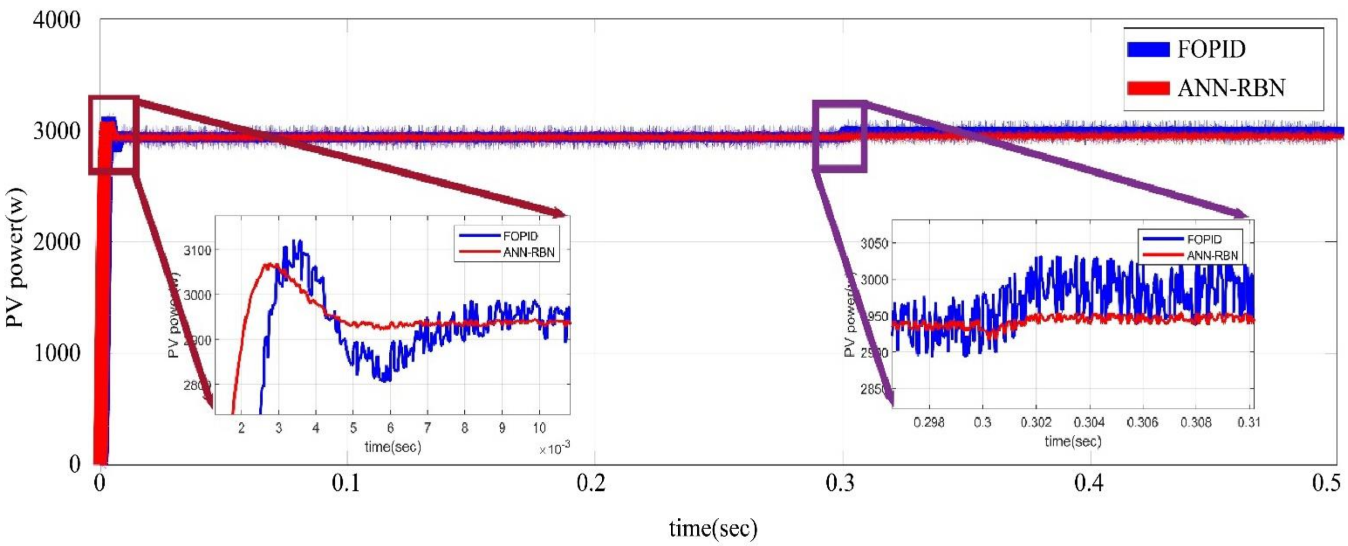

Fig. 12 PV Power (W)

Figure 12 shows the typical solar generation profile, with a bell-shaped curve peaking during midday hours. The graph starts at zero in the early morning, gradually ramps up as the sun rises, and reaches its maximum output around noon before tapering off in the evening. The smoothness of the curve indicates favorable weather conditions with minimal cloud interference. This predictable pattern is ideal for energy planning and scheduling battery charging. However, the absence of PV generation at night underscores the need for complementary power sources or storage systems, such as batteries or wind power, to maintain a continuous energy supply. Figure 13 shows a more variable and less predictable pattern compared to PV power. Wind generation fluctuates significantly, reflecting the intermittent nature of wind resources. The graph includes frequent peaks and dips, with no clear daily cycle, indicating dependence on real-time wind conditions. Despite its irregularity, wind power contributes significantly to the overall energy mix and can complement PV generation, especially during nighttime or cloudy days when solar output is low.

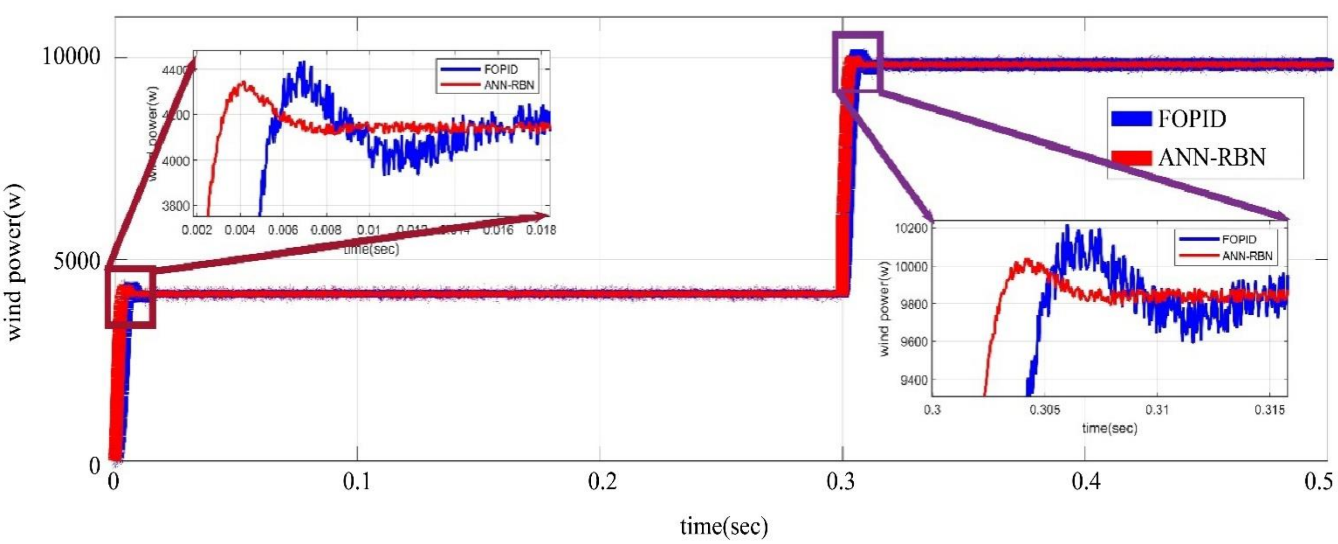

Fig. 13 Wind power (W)

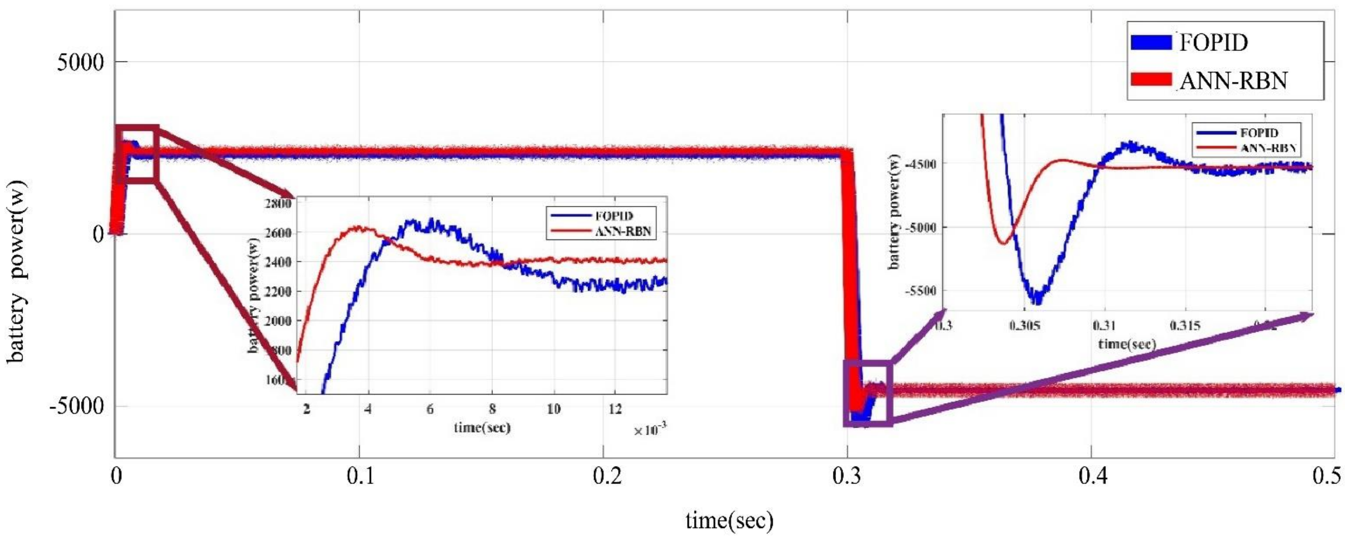

Fig. 14 Battery power (W)

Figure 14 shows the battery output power illustrating the charge and discharge patterns over time. The curve shows frequent fluctuations between positive and negative power values, indicating an active charge-discharge cycle. During periods when battery power is positive, energy is being discharged to support the load, while negative values signify the battery is charging, likely due to excess generation from renewable sources.

These transitions appear consistent, suggesting the battery system is being efficiently utilized to balance the energy supply and demand.

The magnitude of discharge and charge also implies that the battery has a substantial capacity to absorb and supply energy, playing a key role in system reliability and energy stability.

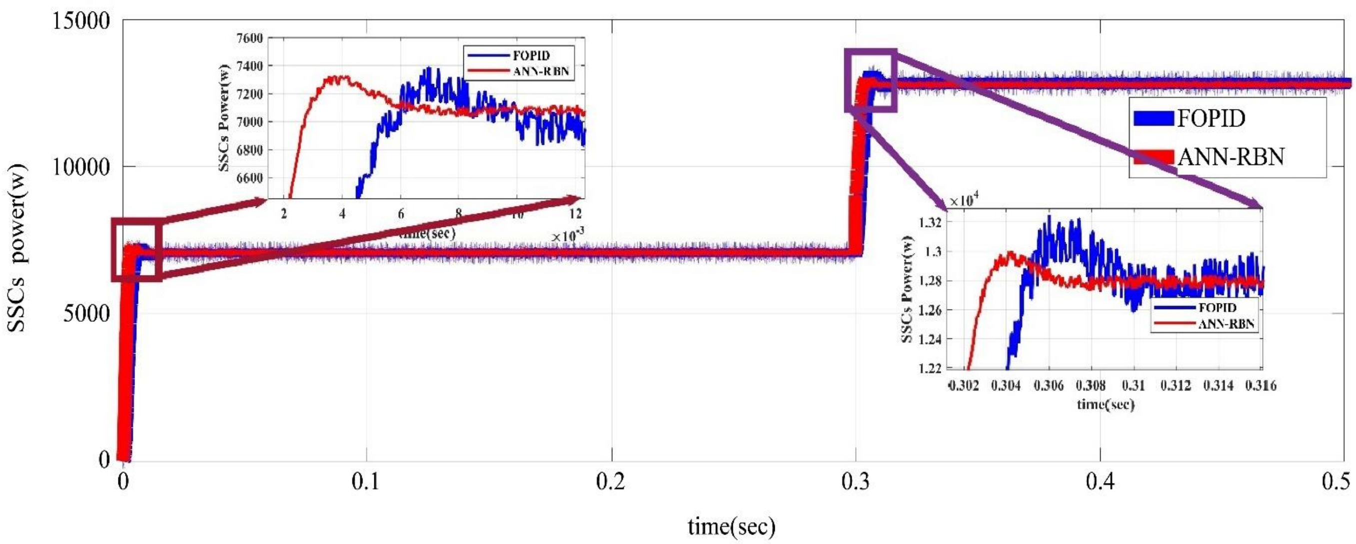

Fig. 15 Source Side Converters (SSCs) power (W)

Figure 15 shows the power of the source side converters, and the dynamic behavior of the power output from the smart storage components is evaluated. At the initial transition (first 0.01 seconds), the FOPID controller again shows a more aggressive response with higher oscillations after the power step change. The ANN-RBN controller delivers a more gradual and stable power transition, minimizing spikes and settling faster. During the second disturbance (around 0.3 seconds), the pattern remains consistent. As seen in the inset, FOPID experiences sharp fluctuations and instability, while ANN-RBN continues to regulate the SSC power output steadily. This consistent pattern reinforces the ANN-RBN controller's superior adaptability and robustness under changing power conditions.

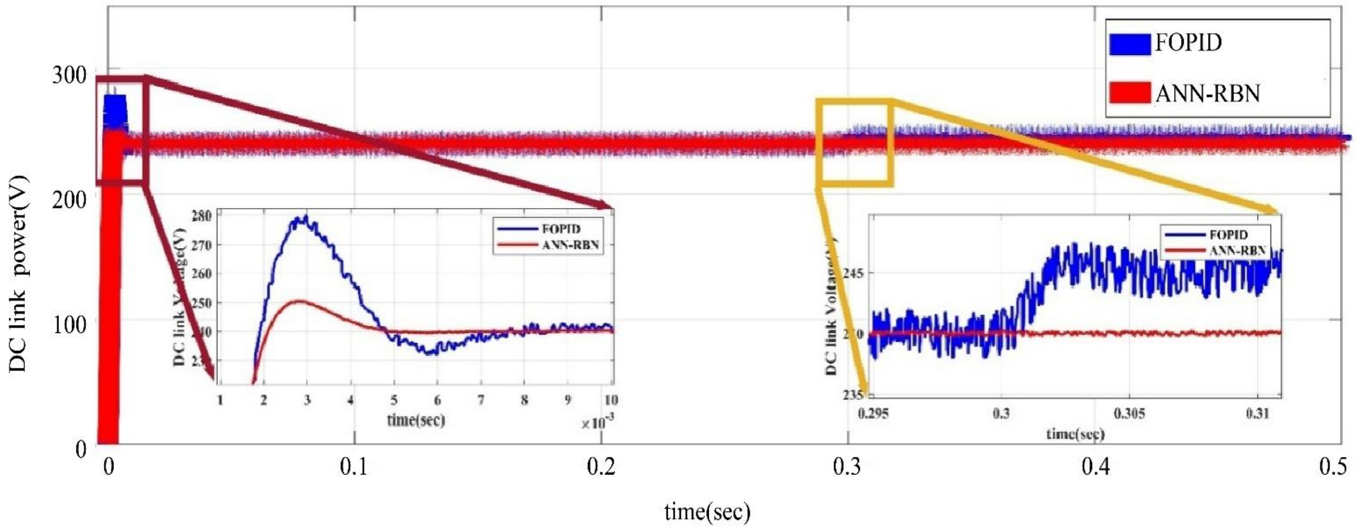

Fig. 16 DC link voltage

Figure 16 shows both control techniques' DC link voltage response under transient and steady-state conditions. Initially, during the transient state, FOPID (blue line) demonstrates a sharp rise in voltage, peaking higher than the ANN-RBN (red line), but it also exhibits a more pronounced overshoot and oscillation. In contrast, the ANN-RBN controller shows a smoother and more controlled rise with significantly reduced overshoot and faster settling time. As time progresses, in the steady-state condition, the ANN-RBN maintains a remarkably stable voltage profile with minimal fluctuation, while the FOPID controller displays small yet noticeable oscillations around the setpoint. This suggests that the ANN-RBN controller offers better damping characteristics and voltage regulation capability.

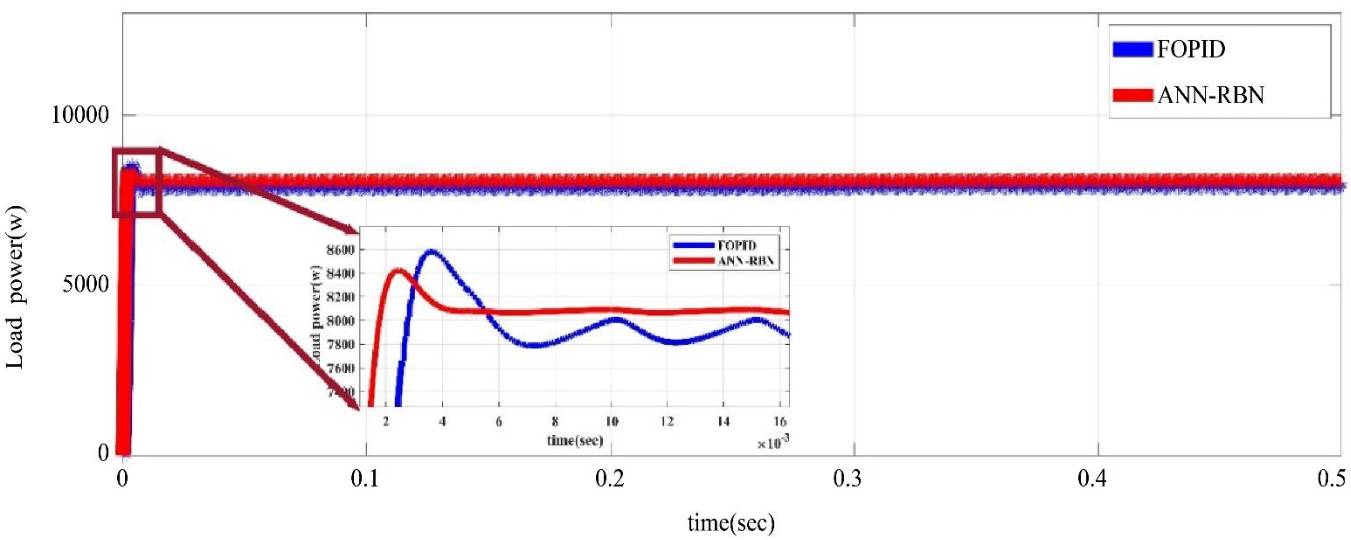

Fig. 17 Load power (W)

Figure 17 showcases the system's response in terms of load power (W) against time (s). The ANN-RBN controller (represented in red) demonstrates a faster rise time and achieves a quicker steady state compared to the FOPID controller (in blue). Both controllers eventually settle at approximately the same power level (~8300 W), but the zoomed-in section highlights key differences in their transient behaviors.

The FOPID controller exhibits a higher overshoot and more pronounced oscillations before settling, indicating a relatively underdamped response. In contrast, the ANN-RBN controller shows lower overshoot and reduced oscillations, indicating a more stable and damped system response. This suggests the ANN-RBN controller is more effective in handling sudden changes and disturbances in load demand, providing a smoother and more reliable output.

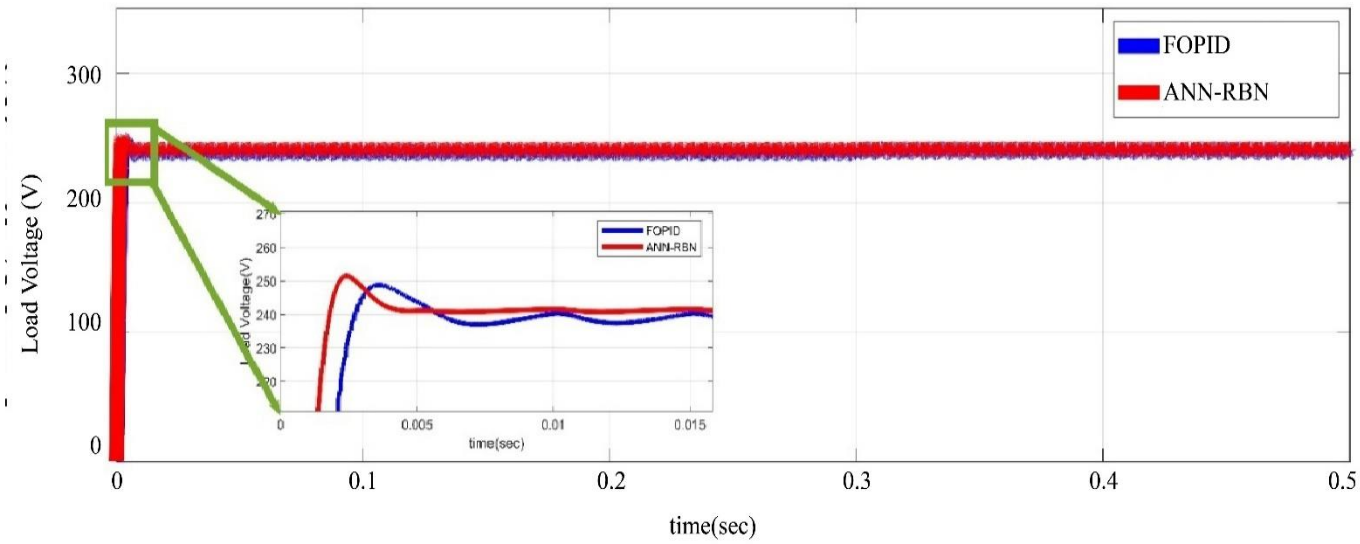

Fig. 18 Load voltage

Figure 18 illustrates the system behavior regarding load voltage (V) over the same time frame. Like the power graph, the ANN-RBN controller again demonstrates a superior transient response. The ANN-RBN curve reaches the steady-state voltage (~240 V) faster with less fluctuation.

In comparison, the FOPID controller shows a higher initial overshoot (around 260 V) and a longer settling time with more evident oscillations. The zoomed-in inset reveals the ANN-RBN's advantage in precision and control, maintaining voltage stability more effectively than the FOPID controller. The smoother curve with minimal deviation from the desired value reflects the neural network's adaptive learning capability, making it better suited for dynamic and nonlinear load conditions.

Table 2. Comparative analysis of peak over shoot with FOPID and ANN controller

Parameters	Peak Over Shoot (FOPID)	Peak Over Shoot (ANN)
DC Link Voltage	280	250
Wind Power	4500	4320
Solar Power	3150	3070
Battery Power	2700	2600
Load Power	8600	8400

Table 2 presents a comparative analysis of peak overshoot values for different parameters when using FOPID and ANN controllers in a DC microgrid system. The ANN controller consistently demonstrates lower peak overshoot values across all parameters, indicating better transient performance and enhanced system stability. Table 3 compares settling time for various parameters using FOPID and ANN controllers in a DC microgrid system. These results demonstrate that the ANN controller consistently outperforms the FOPID controller by achieving faster settling times, thereby enhancing the dynamic response and stability of the system.

Table 3. Comparative analysis of settling time (sec) with FOPID and ANN controller

Parameters	Settling Time (sec) (FOPID)	Settling Time (sec) (ANN)
DC Link Voltage	0.005	0.002
Wind Power	0.007	0.004
Solar Power	0.005	0.002
Battery Power	0.007	0.004
Load Power	0.005	0.003

6. Conclusion

The paper presents an intelligent and adaptive power management system for a DC micro grid that integrates solar Photovoltaic (PV), wind energy, and battery storage to deliver stable, efficient, and uninterrupted power, especially for remote and off-grid applications. Initially, fuzzy logic and Fractional Order PID (FO-PID) controllers were employed to manage renewable energy sources and battery operations. While this method achieved effective power regulation, it was limited in handling fast dynamic fluctuations, leading to reduced system stability during sudden changes in power generation or load demand. To address these limitations, an advanced Artificial Neural Network–Radial Basis Network (ANN-RBN) controller was developed to manage the source-side converters of the solar PV and wind systems.

This intelligent controller dynamically adjusts the power extraction process by learning from real-time input data, enabling better tracking of maximum power points and quick adaptation to environmental changes. The battery system retained the dual FO-PID control structure to ensure safe charging and discharging operations and to extend battery life while maintaining energy balance within the microgrid. The simulation was performed using MATLAB/ Simulink environment, and the results show that the ANN-RBN controller significantly outperformed the earlier fuzzy-FO-PID method.

It offered faster response times, lower overshoot, better voltage regulation, and increased resilience against disturbances. These improvements led to enhanced power quality and more stable DC bus voltage, critical for the reliable functioning of sensitive loads in modern DC microgrid systems.

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