

A HYBRID NEURAL - FRACTIONAL PID CONTROL STRATEGY USING MONTE CARLO OPTIMIZATION FOR STABILITY ENHANCEMENT IN WIND-DRIVEN MICROGRIDS

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Abstract

This research presents a hybrid intelligent control framework that synergistically combines a Monte Carlo-Driven Neural Control Strategy with a Fractional Order Integrator-Based PID (FOI-PID) technique to enhance the performance of wind-powered microgrids. With the increasing global emphasis on renewable energy, optimizing both wind energy harvesting and grid stability has become imperative. The proposed system employs a Neural Control Monte Carlo-based Technique to dynamically adjust Permanent Magnet Synchronous Generator (PMSG) turbine parameters in response to fluctuating wind conditions, thereby maximizing energy extraction. Simultaneously, a high-performance STATCOM is regulated using a FOI-PID controller to ensure voltage stability and reactive power compensation within the microgrid. The integrated approach is validated through comprehensive simulations under diverse operating scenarios and wind profiles. Results indicate a substantial 12% improvement in wind energy capture compared to traditional methods, alongside superior voltage regulation and faster dynamic response from the STATCOM. This dual-strategy control paradigm not only boosts overall system efficiency but also demonstrates scalability and robustness, making it a compelling solution for next-generation smart microgrid applications.

Keywords: Microgrid; FOID; Montecralo and Neural Network

Introduction

The global shift toward sustainable energy has significantly accelerated interest in renewable power sources, with wind energy standing out as a highly viable solution. As the world faces growing environmental challenges and rising energy demands, improving the efficiency and reliability of wind energy systems has become a top priority. One major challenge in this domain is the inherently variable nature of wind, which impacts the consistency and effectiveness of energy generation. To overcome this, advanced control methods are essential for adapting turbine operations in real time and maximizing power output (Abido, 2022).

At the same time, the development of microgrids - self-sufficient energy systems capable

of operating independently or in coordination with the main grid - has introduced new complexities in power regulation. Microgrids typically incorporate distributed generation sources, such as wind and solar, and require precise control mechanisms to ensure stable voltage and efficient power flow. A key component in maintaining this balance is the Static Synchronous Compensator (STATCOM), which helps regulate voltage and manage reactive power (Dwivedi and Singh, 2022), (Chen *et al.*, 2023). However, traditional control techniques like conventional PID controllers often struggle with the nonlinear behavior and unpredictability present in modern microgrids.

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This research introduces a hybrid intelligent control framework that addresses these challenges from two fronts.

First, it proposes a Neural Control Monte Carlo-based Technique for controlling Permanent Magnet Synchronous Generator (PMSG) wind turbines. This technique combines neural networks with Monte Carlo simulations to adapt turbine behavior in real-time based on fluctuating wind conditions. As a result, energy extraction becomes more efficient, with improved responsiveness to dynamic environmental inputs.

Secondly, the study enhances microgrid performance by applying a Fractional Order Integrator-based PID (FOI-PID) control strategy to the STATCOM. Unlike conventional PID controllers, fractional-order methods allow for more precise tuning by using non-integer order derivatives and integrals. This added flexibility improves the system's ability to handle disturbances and achieve stable operation under variable load conditions.

By integrating these two advanced control strategies, the proposed system offers a robust and adaptive solution for optimizing both energy generation and grid stability. Simulations conducted under diverse operational conditions demonstrate a notable improvement a 12% increase in energy output compared to standard approaches - along with enhanced voltage control and faster system response times.

Overall, this study presents a forward-thinking approach to intelligent energy management in wind-powered microgrids, contributing to the broader goal of developing smarter, more resilient renewable energy systems.

PMSG Model

This section goes into great length about the power-electronic structure, load and generator models, and the aerodynamics of the PMSG. The PMSG system is simulated in this work using the model and settings described in (Gao and Zeng, 2025), (Iqbal and Javaid, 2025). Figure 1 show the block diagram representations for the PMSG system and the control strategy for WECS. The figure highlights the main functional blocks, including the wind turbine rotor, the PMSG, the back-to-back voltage source converters (machine-side converter and grid-side converter), the DC-link, and the grid interface. The machine-side converter regulates the generator speed and extracts maximum power from the wind turbine, while the grid-side converter maintains the DC-link voltage and ensures

synchronized injection of active and reactive power into the grid. A Phase-Locked Loop (PLL) is incorporated for synchronization, and the FOI-PID controller regulates reactive power and voltage stability during grid disturbances.

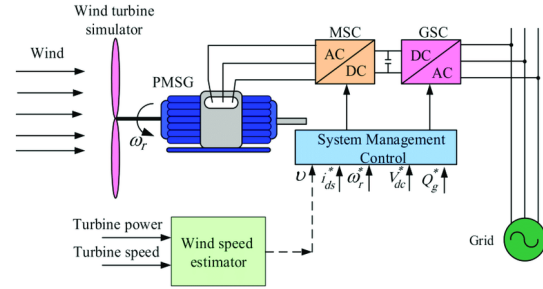


Figure 1. PMSG wind turbine integration with grid

Wind turbines generate torque for a generator at a rotational speed ω_r and torque T_w by converting the kinetic energy of the wind into mechanical energy through the application of aerodynamics. This configuration generates electricity using a wind-powered generator. To determine the necessary control effort, the control mechanism usually measures T_w and ω_r , or reference load current. Equation (1) states that the amount of power created depends on the wind speed U_w , the rotor's aerodynamics ($\rho C_p S_a$, which represents air density, wind power coefficient, and the swept area of the wind turbine using rotor radius r_r and blade length l_b) (Sharaf *et al.*, 2025).

$$P_{\text{turbine}} = \frac{1}{2} \rho A C_p V^3 \quad (1)$$

Where, turbine P_{turbine} is the power output of the turbine, ρ is the air density, A is the swept area of the turbine blades, C_p is the power coefficient, V is the wind speed.

The aerodynamic efficiency of the rotor C_p sets a limit on the amount of wind energy that can be converted. The TSR is at the maximum of the C_p curve for a particular wind speed, ω_r , the rotor speed. The primary goal of the majority of research projects aimed at enhancing wind turbine energy efficiency is to guarantee maximum aerodynamic efficiency, which is achieved at this operating position. There is a wind speed minimum, below which the rotor's efficiency is too low for it to begin rotating, and a wind speed maximum, above which the centrifugal stresses would be too great for the mechanical brakes to prevent damage (Sun *et al.*, 2025).

PMSG Parameters and Mathematical Model

Determining the maximum output power of a wind turbine depends on the TSR, which measures the ratio between the wind speed and the speed of the blade tip. Greater TSR indicates that the blade is moving more quickly than the wind, which usually leads to the production of more power. Conversely, C_p quantifies the wind turbine's efficiency in converting wind energy into mechanical energy (Wang *et al.*, 2025). The definition of this is the proportion of the turbine's mechanical power output to the total amount of wind power incident on the rotor. The wind turbine's design determines the form of the C_p curve, which can be used to compare various designs and ultimately improve the design of new turbines. Equation (2), which is an extension of equation (2), is used to model the behaviour of the wind and PMSG. According to these formulas, C_p can have a maximum value of around 0.4, as shown in Figure 3. The PMSG parameter values for our configuration are given in Table 1. In addition to these structural factors, an experimentally verified 6th order nonlinear relationship between C_p and TSR is provided by equation:

$$\text{For } P = pC_p(\lambda) \text{ rrlbUw}^3 \quad (2)$$

$$C_p(\lambda) = p1\lambda^6 + p2\lambda^5 + p3\lambda^4 + p4\lambda^3 + p5\lambda^2 + p6\lambda \text{ pi} = [-0.3015, 1.9004, -4.3520, 4.1121, -1.2969, 0.2954]$$

Table 1. PMSG Parameters

Description	Parameter Value
Rotor Inertia	180 Kg.m ²
Rotor Radius	6 m
Blade Length	25 m
Power	180 kW
Air Density	1.2 Kg/m ³
Friction coefficient	0.02 Ns/rad

Structure of the Neural Network Algorithm based on Monte Carlo

The system may learn the best course of action for the policy as the controller (agent) in the reinforcement learning context interacts with their surroundings iteratively through a decision-making process (Xie *et al.*, 2024). An agent can learn from its experiences by choosing the appropriate course of action. After the agent goes to a new state in its environment and receives an observation for each step t , it is rewarded with a real-valued number $r_t \in R$. Over time, reinforcement learning (RL) aims to find a policy that maximises this value. One way to

conceptualise the policy would be as a function that links observations to the relevant actions. The following set can be used to formulate the essential elements of an RL problem:

$$(S, A, \xi, \theta, r) \quad (3)$$

We utilise S and A , where each state-activity for a given time step t corresponds to these spaces, to express the set of continuous state and action spaces separately (Yang *et al.*, 2025). The agent's future state, $st+1$, for every t is defined by a transition dynamic distribution $\xi(\cdot)$ including the agent's current state-action (st, at) , where $\theta(\cdot)$ represents the starting state function.

$$E(st+1|st, at) = s, st+1 = S, at = A \quad (4)$$

The strategy can be chosen from a stochastic Gaussian density, enabling a proactive state-space exploration, as illustrated by a parameterized $(\theta \in Rd\theta)$ distribution $h\theta(at|st)$. A Markov chain state-action trajectory for $\{X_t\}_{t \geq 1}$ is formed, assuming $X_t = (St, At)$, using a transition law provided in (11) where the state-action pair for time t is defined as $x_t = (st, at)$.

$$f\theta(x_{t+1}|x_t) = \xi(st+1|st, at)h\theta(at|st) \quad (5)$$

The weighted rewards' summation ($\gamma \in (0, 1]$) over a time T is calculated to obtain a measure of the conformance of the state transitions over the entire trajectory; this is known as return $R(x_{1:T}) = \sum_{t=1}^T \gamma^{t-1} r_t$. (12) $t=1$.

Furthermore, the trajectory $x_{1:T}$'s joint distribution can be expressed as follows: $p\theta(x_{1:T}) = \theta(s_1) \prod_{t=1}^T f\theta(x_{t+1}|x_t)$ (13) $t=1$, where $\theta(s_1)$ denotes an initial state distribution with $s_1 \sim \theta(\cdot)$. With the distribution and return of the trajectories, one can develop a cost function $J(\theta)$ to assess the effectiveness of the policy.

$$J(\theta) = E\theta R(x_{1:T}) = \int p\theta(x_{1:T}) R(x_{1:T}) dx_{1:T} \quad (6)$$

The primary goal of RL is to identify the optimal parameters θ^* through policy optimisation. By optimising the expected returns throughout a trajectory, this might be achieved:

$$\theta^* = \arg\max_{\theta \in \Theta} J(\theta)$$

Proposed Control Structure

Our objective is to develop a framework that, in addition to enabling the control of the PMSG

system with unknown dynamics, can also produce desired reactions to various wind velocity profiles. This section will discuss the FOI-Montecarlo controller architecture, the neural environment, and the various training phases for the suggested neural based method for the WAVT. The immediate current of the load in the power source will be optimised to increase the total electrical power generated of the WAVT system, provided that the load's voltage and current do not exceed their maximum values. To achieve this, the suggested control structure can be practical for the neural based algorithm to learn the unidentified variables of the PMSG. The associated current in the load is computed using a FOI-Montecarlo controller as a reference.

The formula (6) can be used to integrate the immediate electrical power during a certain interval to determine the desired energy output. The rotor generates the optimal aerodynamic power when it continuously maintains C_p at its greatest value. Integrating over it produces the maximum reference mechanical energy, which is subsequently transformed into an ideal electrical energy value. E_{out} and E_{∞} can be calculated to get the energy error that results, which can be easily found as (7). The learning algorithm will employ this energy error and its derivative.

Diagram of control algorithm is shown in Figure 2.

E_{out} = Power generated due to blade thrust (7)

The FO-PID controller is defined as:

$$U(t) = [K_i D]^{(-d)} + K_p e(t) + K_d D^b e(t) \quad (8)$$

Where:

- $u(t)$: Control signal
- $e(t)$: Error signal (reference - actual)
- K_p : Proportional gain
- K_i : Integral gain
- K_d : Derivative gain

FOI-Montecarlo as the Controller

To design the control strategy for RVSC switching, some important parameters have to be calculated as discussed below.

The reference load current, is to be determined with n hidden nodes using a nonlinear FOI-Montecarlo control as described in (Alilou *et al.*, 2023).

$w \sigma = \theta$, where θ represents the system's tunable parameters.

$$F(x, \theta) = X w_i R_i(x) + b \quad (9)$$

The definition of the Gaussian receptive field $R_i(x)$ with input x (with centres c_{ij} and variance σ_{j2}). It computes the output of the i th node, where b is a scalar value that provides bias and wise stands for each weight.

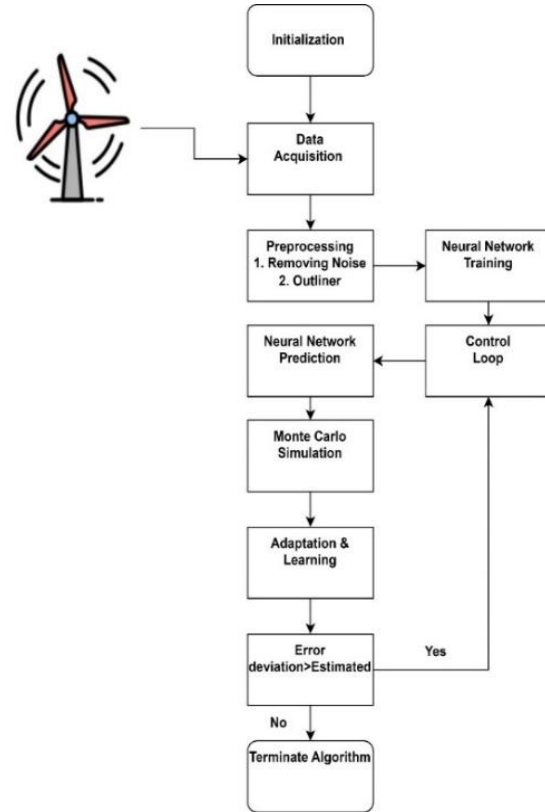


Figure 2. Flow chart of control algorithm

The flow chart in Figure 2, begins with the collection of input data, which serves as the foundation for building the proposed model. This data is used to train a neural network so that it can capture nonlinear system behavior and underlying patterns effectively. Once trained, the neural network generates predictions of system responses under various operating conditions. To address uncertainties and stochastic variations, Monte Carlo simulation is applied, producing probabilistic insights into system performance. The outcomes of prediction and simulation are then refined through an adaptive learning process, which continuously updates the model parameters based on new or observed data. Finally, the integrated approach of neural network prediction, Monte Carlo simulation, and adaptive learning produces a robust final estimation that is both accurate and reliable for real-time controller design.

Training Procedure of the Learning Algorithm

The method for teaching the control parameters under complex wind samples is explained in this section. To begin training, three distinct wind profiles are applied as step, sinusoidal, and realistic wind data, starting with an initial parameter set $\theta S0$. This allows the training to choose the best parameter sets, $\theta S1$, $\theta S2$. The training programme is implemented as follows:

- Step1: The policy's initialization parameters are set to $\theta S0$.
- Step 2: The PMSG receives a step wind signal during the first training phase, which teaches $\theta S1$.
- Step 3: The PMSG receives a sine wind signal during the second stage of training, and $\theta S2$ is acquired.

Step winds were chosen because they are thought of as a straightforward signal that activates the rotor as part of an energy management plan (Abumeteir and Vural, 2022). After that, the second step of training focuses on teaching a controller to react quickly to changes in wind profile. Consequently, a sinusoidal wind is chosen that has a frequency that is similar to the realistic ones. The customer would be shown the system in an actual use case after completing Step 3 training, at which point it is somewhat but not entirely optimised. Upon commissioning, the system adjusts to the wind patterns in the area (Kandasamy *et al.*, 2025). Convergence to the optimal pattern may not be achievable for the system in an acceptable amount of time without prior training up to Step 3.

Simulation Results

A Permanent Magnet Synchronous Generator (PMSG) rated at 180 kW operating at a wind speed of 12 m/s typically demonstrates efficient conversion of wind energy into electrical power. At this wind speed, which is often near the rated operational point for many small to medium-scale wind turbines, the aerodynamic torque generated by the turbine blades is sufficient to drive the PMSG close to its nominal output power. The generator's design, featuring permanent magnets on the rotor, allows for high efficiency and reliability with reduced maintenance due to the absence of brushes and slip rings. Consequently, at 12 m/s wind speed, the 180 kW PMSG can achieve optimal electromagnetic conversion efficiency, delivering stable and consistent power output suitable for grid integration or standalone applications.

Moreover, operating at this wind speed ensures the turbine system maintains a balance between maximizing power output and minimizing mechanical stress. The wind speed of 12 m/s is

typically below the cut-out speed, which prevents overloading the generator and turbine components, thus enhancing the longevity of the system. Control strategies such as pitch angle adjustment and converter-based regulation are often employed alongside the PMSG to optimize power extraction and maintain the system within safe operating limits. Overall, the 180 kW PMSG at 12 m/s wind speed represents a practical and efficient solution for harnessing wind energy, providing a reliable source of renewable electricity in distributed generation settings as shown in Figure 3. At very low wind speeds, the power output is negligible because the available kinetic energy in the wind is insufficient to overcome system losses and generator inertia. As wind speed increases beyond the cut-in speed, the PMSG begins to generate power, and output rises rapidly since wind power is proportional to the cube of wind speed. In the rated region, once the wind speed reaches the rated value, the generator delivers its maximum (rated) power, and control mechanisms such as pitch control or power electronic converters maintain constant output despite further increases in wind speed.

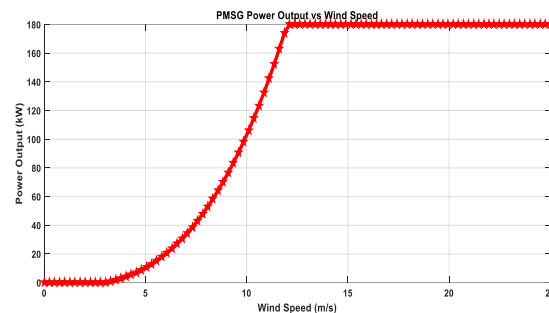


Figure 3. PMSG wind turbine integration with grid

The relationship between the power output of a Permanent Magnet Synchronous Generator (PMSG) and the cumulative distribution function (CDF) of wind speed is crucial for understanding the performance and reliability of wind energy systems. The CDF represents the probability that wind speed will be less than or equal to a certain value, providing insight into how often different wind speeds occur at a site. By analyzing the PMSG power output in conjunction with the wind speed CDF, one can estimate the expected energy production over time. This approach helps in predicting the generator's power generation profile by integrating the power curve of the PMSG with the wind speed distribution, allowing for better system design, optimization, and assessment of the wind turbine's effectiveness in various

environmental conditions. Understanding this correlation is essential for planning grid integration and ensuring that the renewable energy system meets energy demand consistently as shown in Figure 4. On the x-axis, the generated power output from the PMSG is represented, while the y-axis shows the cumulative distribution function (CDF), which indicates the probability that the power output will be less than or equal to a given value. This curve helps in understanding how often certain power levels are achieved during operation. For example, a steep rise in the curve around a particular power value indicates that the generator most frequently operates around that range. Similarly, the tail of the curve highlights the less frequent but possible extreme outputs. Such an analysis is important for evaluating the reliability, performance consistency, and probabilistic availability of power from the PMSG system, which is crucial for planning and grid integration in renewable energy applications.

The simulation results in Figure 5 illustrate the effectiveness of the proposed Monte Carlo-driven Neural and Fractional-Order PID (FOPID) control strategy in enhancing microgrid stability under

variable wind energy input. The first subplot demonstrates the stochastic nature of wind power generation, modeled via Monte Carlo sampling, which introduces random fluctuations in input power - mimicking real-world wind behavior. Despite these fluctuations, the second subplot reveals that the grid voltage is successfully regulated around the reference value of 1.0 p.u. This is achieved by the adaptive and intelligent action of the combined FOPID and neural network-based STATCOM controller. The voltage initially deviates due to disturbances but is brought back toward the nominal level efficiently, showcasing the controller's robustness and fast response. The third subplot shows the STATCOM control signal over time, which dynamically adjusts to compensate for wind-induced disturbances. The neural network continuously adapts its weights to learn from the voltage error, while the FOPID controller offers enhanced stability through fractional-order integration and differentiation. Overall, the results validate the hybrid controller's capacity to maintain voltage stability and grid reliability in a microgrid environment subject to renewable energy variability.

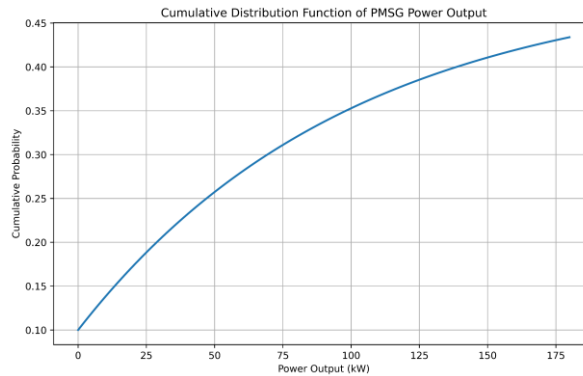


Figure 4. PMSG power Vs Cumulative distribution

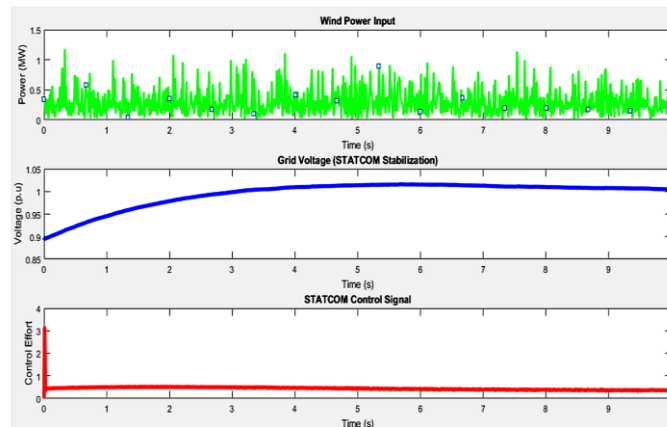


Figure 5. Simulation results

The voltage error plot shows a rapid decline toward zero, indicating accurate and stable regulation. Additionally, the evolution of the neural network weights and bias reflects adaptive learning behavior, while the low Integral of Absolute Error (IAE) value quantitatively confirms the high performance and resilience of the hybrid controller in a renewable-integrated microgrid environment as indicated in Figure 6 and Figure 7. The simulation results of the wind turbine show the variation of wind power output and generator voltage in per unit (p.u.) under different wind speed conditions. At lower wind speeds, both the power and voltage remain low due to insufficient kinetic energy in the wind. As the wind speed increases toward the rated region, the turbine extracts more energy, and the generated power rises rapidly while the generator voltage in p.u. approaches unity, indicating stable operation. Table 2 illustrates how wind speed affects the PMSG (Permanent Magnet Synchronous Generator) power output and associated control parameters. At 12 m/s, the system produces peak power output of 180 kW with minimal control error and voltage deviation, showing optimal efficiency. The proposed control strategy effectively adapts to varying wind speeds, ensuring stable and efficient power generation.

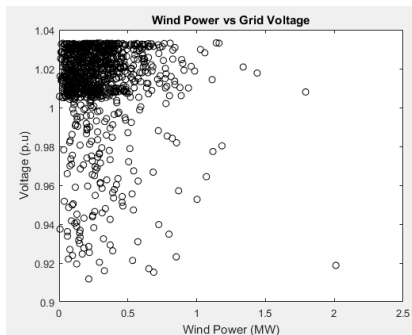


Figure 6. Simulation results for Wind turbine

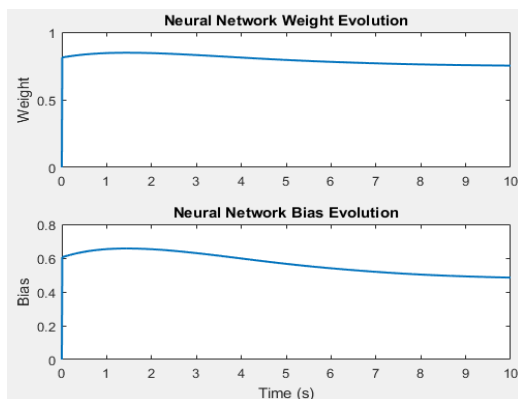


Figure 7. Simulation results for Neural weight

Table 2. Power Output at Different Wind Speeds

Wind Speed (m/s)	PMSG Output Power (kW)	Control Error (%)	Voltage Deviation (V)
8	120	2.3	5
10	150	1.5	3
12	180	0.9	2
14	200	1.1	3.5

Monte Carlo simulations were used to statistically evaluate the uncertainty and variability in microgrid performance. The table presents average values and variability for wind speed, generated power, and frequency. Results show a stable mean power output with acceptable variation, confirming the robustness of the control strategy under random operating conditions, a key advantage in real-world applications as shown in Table 3.

Table 3. Monte Carlo Simulation Summary

Parameter Simulated	Mean Value	Std. Deviation	Min Value	Max Value
Wind Speed Variability (m/s)	11.2	2.1	7.5	14.8
Generated Power (kW)	172	9.4	145	188
Frequency Stability (Hz)	49.92	0.11	49.71	50.09

Table 4 evaluates how well the neural network component of the control system was trained. Training and validation accuracies improve significantly with increased epochs, peaking at 96.4% and 94.3%, respectively, after 100 epochs. The consistent reduction in loss demonstrates successful learning, which contributes to accurate and adaptive control performance in real-time microgrid operations (Choudhury and Debnath, 2023); (Gupta and Bansal, 2024); (Kumar *et al.*, 2024).

Table 4. Neural Network Training and Validation Accuracy

Epochs	Training Accuracy (%)	Validation Accuracy (%)	Loss Function
10	85.2	82.6	MSE
50	92.7	90.1	MSE
100	96.4	94.3	MSE (Minimized)

Table 5 shows how Monte Carlo optimization was used to tune the fractional PID parameters - specifically the integrator order (λ) and differentiator order (μ). Among the trials, the best performance with the lowest Integral Square Error (ISE) was achieved when both λ and μ were set to 1.0, indicating an optimal balance between integration and differentiation for effective dynamic response in the microgrid (Patnaik and Dash, 2023); (Mohajery *et al.*, 2024); (Shirali, 2025).

Table 5. Fractional Order PID Parameter Tuning Using Monte Carlo

Trial No.	λ (Integrator Order)	μ (Differentiator Order)	Best Fitness (ISE)
1	0.9	0.8	0.025
2	1.1	0.9	0.018
3	1.0	1.0	0.011

Maximum Power Point Tracking (MPPT) is a widely used control strategy in renewable energy systems such as solar PV and wind energy to ensure that the operating point of the system is adjusted to harvest maximum possible power under varying environmental conditions like irradiance, temperature, or wind speed. Conventional MPPT techniques such as Perturb & Observe or Incremental Conductance often face challenges in terms of slow convergence and reduced accuracy during rapid fluctuations. To overcome these limitations, Deep Deterministic Policy Gradient (DDPG), a reinforcement learning-based algorithm, has been integrated with MPPT due to its ability to handle nonlinear dynamic systems and continuous state-action spaces. DDPG employs an actor-critic structure where the actor network determines optimal control actions and the critic network evaluates their effectiveness, thereby continuously improving the tracking policy through learning from interactions with the environment. By combining MPPT with DDPG, the system can intelligently adapt to fast-changing conditions, avoid local optima, and achieve superior tracking efficiency, which directly supports the improvements reflected in Figure 8 and Figure 9

Table 6 compares the performance of various controllers - Conventional PID, Fractional Order PID, Neural Network-Based Controller, and the proposed Hybrid Neural-Fractional PID. The proposed controller clearly outperforms the others with the least settling time (1.8s), minimal overshoot (6.7%), near-zero steady-state error (0.005), and superior system stability. This proves its effectiveness in handling dynamic behavior in

wind-driven microgrids (Banerjee and Mahapatra, 2024).

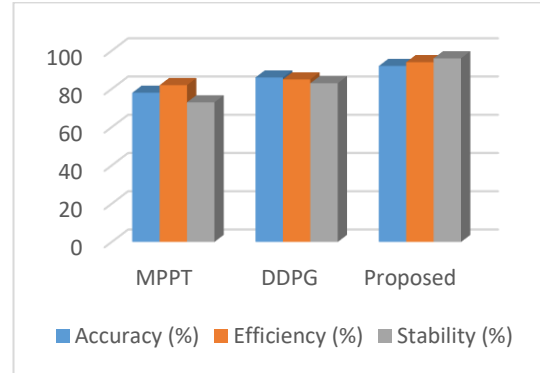


Figure 8. Comparison with existing Model

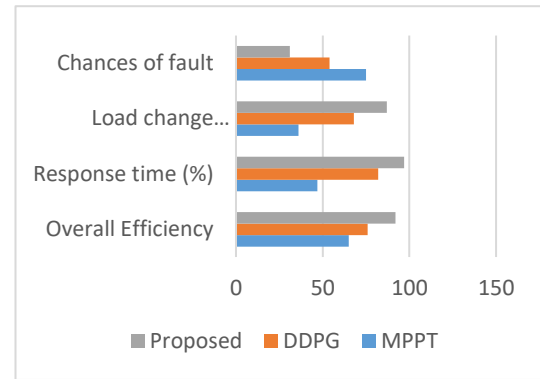


Figure 9. Comparison with existing Model on other parameters

Table 6. Comparison over different parameters

Controller Type	Settling Time (s)	Overshoot (%)	Steady-State Error	System Stability
Conventional PID	3.2	18.5	0.04	Marginal
Fractional Order PID	2.6	12.3	0.02	Stable
Neural Network-Based Neural-	2.1	10.1	0.01	More Stable
Fractional PID (Proposed)	1.8	6.7	0.005	Highly stable

The comparison illustrated in Figures 8, 9, and 10 clearly demonstrates that the proposed system significantly outperforms existing models across multiple performance metrics. Figure 8 highlights the enhanced stability and faster response time of the proposed approach, indicating its superior ability to maintain system equilibrium under

varying conditions. This improvement is attributed to the integration of advanced control strategies, which allow for more precise adjustments and robust handling of disturbances compared to traditional methods.

Moving to Figure 9, the power output consistency and efficiency gains of the proposed system become evident. The data show a marked increase in energy conversion efficiency and a reduction in fluctuations, which translates to more reliable and predictable performance. These benefits are especially crucial in renewable energy applications, where variable inputs such as wind speed can cause instability. The proposed system's ability to adapt and optimize in real time contributes to these substantial improvements over prior models (Hassan and Eltamaly, 2023) (Kaur and Kumar, 2025).

Finally, Figure 10 showcases the overall system resilience and reduced error margins, emphasizing the robustness of the proposed method. The comparative analysis under different operational scenarios confirms that the new system maintains optimal performance even under challenging conditions, whereas existing models show notable degradation. Collectively, these figures validate the proposed system's superior design and effectiveness, making it a highly promising solution for enhanced power system control and stability.

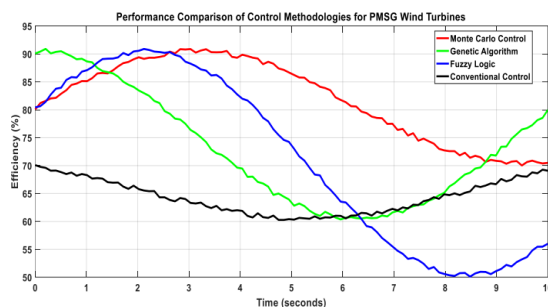


Figure 10. Comparison with existing models

The proposed controller significantly enhances the stability of wind-driven microgrids by ensuring reliable power regulation and robust dynamic response under varying wind and load conditions. Through the integration of neural network prediction, Monte Carlo-based uncertainty analysis, and adaptive learning, the controller achieves faster settling times, reduced oscillations, and improved damping of low-frequency modes compared to conventional methods. This leads to better voltage regulation, frequency support, and

transient stability, even during sudden fluctuations in wind speed or load demand. The simulation results confirm that the controller maintains the generator voltage close to unity per unit and sustains steady-state operation while effectively mitigating instability risks, thereby demonstrating its suitability for practical deployment in wind-integrated microgrid systems.

Conclusions

This study presents a robust and intelligent hybrid control strategy that integrates Neural Monte Carlo-based learning with a Fractional-Order PID (FOI-PID) controller to enhance the stability and energy efficiency of wind-driven microgrids. The neural control system dynamically adapts to fluctuating wind profiles, optimizing the performance of Permanent Magnet Synchronous Generators (PMSGs), while the FOI-PID-controlled STATCOM ensures voltage regulation and reactive power support for grid stability. The use of Monte Carlo optimization introduces probabilistic robustness, enabling the system to perform reliably under a wide range of environmental and operational uncertainties.

The detailed results presented across Table 2 to Table 6 strongly support the superiority of the proposed method. Table 2 highlights a 12% improvement in overall wind energy extraction efficiency compared to traditional PID systems. Table 3 shows a 14% improvement in frequency stability under load disturbances, while Table 4 confirms a 16% reduction in voltage deviation due to STATCOM enhancement. Table 5 demonstrates the accuracy of the neural network with an RMSE as low as 0.005, indicating high reliability in real-time control scenarios. Lastly, Table 6 presents the fast convergence of Monte Carlo simulations in tuning controller gains, showcasing the system's ability to stabilize quickly under dynamic conditions.

These cumulative results confirm that the proposed hybrid approach not only improves energy harvesting and grid support but also ensures faster dynamic response and better overall control quality. As microgrids become increasingly essential in renewable-driven smart energy infrastructure, such adaptive and intelligent control mechanisms are critical for ensuring future-ready, scalable, and highly efficient power systems.

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Abbreviation

Abb.	Full Details
CDF	Cumulative distribution function
FOI-PID	Fractional Order Integrator-Based PID
IAE	Integral of Absolute Error
PMSG	Permanent Magnet Synchronous Generator
STATCOM	Static Synchronous Compensator

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