

Article

Performance Evaluation of Artificial Neural Network, Perturb and Observe, and Incremental Conductance MPPT Controllers for Wind Energy Conversion Systems

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Abstract

Reliable maximum power point tracking (MPPT) methods are essential in dynamic wind conditions to obtain maximum efficiency in wind energy conversion systems (WECSs). Conventional methods like incremental conductance (INC) and perturb and observe (P&O) are simple and robust but have drawbacks in terms of convergence and oscillations around the maximum power point (MPP) under dynamic conditions. In contrast, intelligent control methods such as artificial neural networks (ANNs) adapt more effectively. This paper presents a comparative analysis of ANN, P&O, and INC methods to obtain MPP for a WECS. A permanent magnet synchronous generator (PMSG) was coupled with a DC–DC boost converter to study the performance of the three MPPT methods under two different wind profiles. The ANN was trained with Bayesian regularization (BR) to estimate wind speed using rotor speed and computed mechanical power as inputs. The INC method achieved MPP using real-time power–voltage curves, while the P&O method perturbs the control variable, observes its results in output power, and adjusts the control variable accordingly. The three MPPT methods were compared in terms of power extraction, voltage stability, robustness, and dynamic response. The ANN achieved faster response, smoother output power and voltage, and reduced oscillation to dynamic conditions with higher output power compared to P&O and INC. On the other hand, the P&O and INC methods are less computationally intensive and do not require offline training.

Keywords: artificial neural network (ANN); incremental conductance (INC); maximum power point tracking (MPPT); perturb and observe (P&O); Bayesian regularization (BR); permanent magnet synchronous generator (PMSG); wind energy conversion system (WECS)

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1. Introduction

The global demand for electric power has surged in recent years, driven by population growth and rapid industrialization. Traditional power generation systems rely on fossil fuels. The utilization of wind power eliminates emissions of harmful waste from traditional fossil fuel power plants. Wind power has been growing tremendously over the past decades. In 2023, the global installed wind power capacity reached 1 TW, accounting for about 10% of global electricity production. Wind power is expected to take an even higher portion in power generation due to its rapid capacity expansion, cost competitiveness, and grid modernization [1]. In wind energy conversion systems (WECSs), wind turbines are

connected to a generator either directly or with a gearbox to generate electricity. In fixed-speed WECSs, the generator speed is constant, and no power converters are used. Variable speed wind turbines (VSWTs) are widely used in wind power systems, mainly based on doubly fed induction generators (DFIGs) and permanent magnet synchronous generators (PMSGs). DFIGs were historically dominant in wind power. Since 2010, more wind power systems have shifted to PMSGs due to their simpler structure, lower maintenance cost, and higher reliability. In addition, PMSG-based systems enhance system efficiency by removing the gearbox, leading to lighter and more cost-effective designs [2]. PMSGs have also become more cost-effective with the reduced cost of power electronics and improvements in wide-bandgap (WBG) semiconductors. PMSGs are connected to the grid via a machine-side converter (MSC) and a grid-side converter (GSC) [3]. On the machine side, the converters regulate the generator speed and torque and manage the reactive power and power factor. A DC-link capacitor stabilizes the voltage between MSC and GSC. The GSC is used to control the DC-link voltage and transfers the active power from the MSC to the grid. The MSC can be implemented using different topologies, such as a voltage source converter (VSC) or a rectifier connected to a boost converter [4]. A large amount of work has been done on the control of MSCs using VSC. However, less research has been conducted to study the control of MSC using a rectifier connected to a boost converter [5]. In comparison, the rectifier and boost converter topology has a simpler design and lower cost but does not provide reactive power control. Therefore, it is more often used for small-scale, off-grid systems [6].

The primary challenge of wind power is its fluctuation over time. To maximize efficiency, it is essential to operate the wind turbines at their optimal rotor speeds using MPPT under different wind speeds [7,8]. Conventional MPPT methods are generally categorized into direct power controllers (DPCs) and indirect power controllers (IPCs). IPCs obtain maximum mechanical power (P_m), whereas DPCs directly maximize the electrical output power (P_e). IPCs include tip speed ratio (TSR), power signal feedback (PSF), and optimal torque (OT) methods. DPCs include perturb and observe (P&O), incremental conductance (INC), and optimum relation-based (ORB) methods.

The P&O algorithm is one of the most widely adopted MPPT methods due to its simplicity and flexibility, but it has drawbacks during dynamic conditions due to oscillation around the operating point [9]. A variable step size is needed to obtain both speed and accuracy [10]. The INC algorithm is independent of turbine and generator specifications. It measures the incremental changes in current and voltage to determine if the operating point is at, before, or after the MPP. It has better accuracy than P&O and works well in moderately varying wind speeds. However, INC needs accurate measurement of the voltage and current, and real-time calculation of the derivative of the current; thus, it is susceptible to noise and oscillation around the MPP, especially in highly variable wind speeds, which increases power losses and results in system instability [9].

In recent years, artificial intelligence (AI), such as machine learning (ML)-based methods, has emerged as a powerful tool for modeling and control in complex engineering systems with nonlinear characteristics and uncertain operating conditions. Commonly used ML includes ANN, support vector machines, and ensemble learning methods with wide applications in signal estimation, system identification, and optimization tasks.

ANNs have been applied to signal prediction and estimation in control and power electronics due to their universal approximation capability. Prior studies have demonstrated that ANN-based estimators offer improved robustness to parameter shift and external disturbances. ANNs can estimate complex nonlinear signals more effectively compared to conventional estimation techniques.

ANNs are increasingly utilized for wind power MPPT [11,12]. They have self-learning capabilities and do not require exact mathematical models. The ANN can be trained offline with a diverse set of data to adapt to a wide range of operating conditions. It eliminates complex real-time calculations and wind speed sensors, and results in a simple and effective solution for MPPT [13–16]. When the wind turbines undergo major changes such as aging or environmental changes, the ANN can be retrained using updated data to continue achieving the MPP. Wind speed sensors increase costs and decrease reliability. When the sensors are under adverse weather conditions over long periods of time, they may fail prematurely. Time delays from the sensors may result in noise and reduce system performance. Wind speed estimation without sensors reduces cost and increases efficiency and reliability [14,17–19].

Different MPPT methods have been compared for their advantages and disadvantages [7]. However, there is a lack of detailed evaluation and comparison of the design and performance between conventional and AI-based MPPT. Less analysis has been conducted on standalone WECS using boost converters. In addition, data generation and training methods for MPPT using ANN in the literature are often briefly described.

To address these challenges, the main contribution of the paper is to provide a performance evaluation of derivative-based INC, perturbation-based P&O, and ANN-based MPPT methods in terms of design, implementation, and performance evaluation. The proposed ANN-based MPPT is compared against the two widely adopted methods for the same WECS under two dynamic wind profiles. In addition to the output power, the study uses metrics such as MPPT efficiency and steady-state ripple to provide a quantitative comparison. The study also considers an unseen turbulent wind profile and adds noise to address generalization concerns associated with ANN training using theoretical data.

The paper is organized as follows. Section 2 describes the modeling of wind turbines. Section 3 presents the three MPPT methods. P&O is described in Section 3.1, INC-based MPPT is presented in Section 3.2, followed by details on the design and training of ANN-based MPPT in Section 3.3. Simulation results of the three different control approaches are reported and compared in Section 4. All the symbols used in the paper are summarized and defined in Table 1 for clarity and consistency.

Table 1. Symbol definition table.

Symbol	Description	Units
V_w	wind speed	m/s
V_w^*	estimated wind speed	m/s
V_{w-in}	cut-in wind speed	m/s
V_{w-out}	cut-out wind speed	m/s
P_m	mechanical power	kW
ρ	air density	kg/m ³
A	cross-sectional area	m ²
$C_p(\lambda)$	power coefficient	-
λ	tip speed ratio	-
ω_t	turbine angular speed	rad/s
r	turbine radius	m
λ_{opt}	optimal tip speed ratio	-
ω_r	generator angular speed	rad/s

Table 1. Cont.

Symbol	Description	Units
P	generator poles	-
J	rotor and generator inertia	$\text{kg}\cdot\text{m}^2$
P_e	electrical output power	kW
η_g	generator efficiency	%
η_c	converter efficiency	%
ω_r^*	reference rotor speed	rad/s

2. System Modeling

Output power for a WECS is controlled to work within a specific range of wind speeds. There are typically four regions of operation based on the wind speed shown in Figure 1. The WECS operates more effectively in the speed range between the cut-in speed (V_{w-in}) and the cut-out speed (V_{w-out}). The wind turbine will not operate below (V_{w-in}) in region R1 to avoid low efficiency and will not operate above V_{w-out} in region R4 to protect the turbines from extreme weather conditions. In region R2, the output power increases with wind speed until the rated output power is reached. MPPT is used to extract the maximum amount of power, and the pitch angle is zero in this region. At the rated speed, a higher wind speed will not increase the output power. Pitch control is applied in region R3 to limit output power and prevent overload. In this paper, the system operates in region R2 with zero pitch angle to study MPPT.

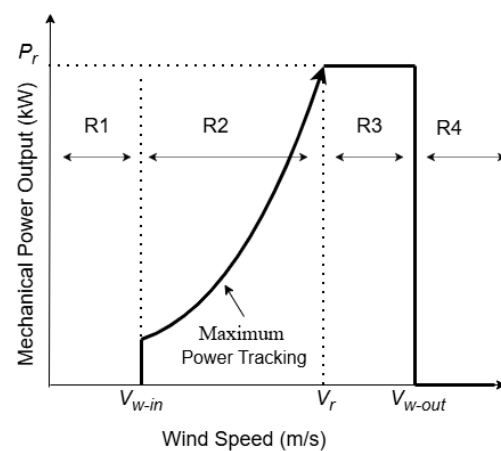


Figure 1. Wind turbine power curve.

The mechanical power extracted from the wind turbine is computed using the standard aerodynamic power expression shown in Equation (1),

$$P_m = \frac{1}{2} \rho A C_p(\lambda) V_w^3 \quad (1)$$

where P_m denotes the mechanical power extracted from the wind turbine, ρ is the air density (kg/m^3), A is the cross-sectional area (m^2), $C_p(\lambda)$ is the power coefficient, and V_w is the speed of wind (m/s).

The power coefficient $C_p(\lambda)$ is a variable that depends on the pitch angle and the tip speed ratio (TSR) of wind turbines. TSR, represented by λ , is shown in Equation (2).

$$\lambda = \frac{\omega_t r}{V_w} \quad (2)$$

where ω_t is the turbine angular speed, and r is the turbine radius (m).

The relationship between the optimal TSR and the turbine speed is determined by Equation (3).

$$\omega_t = K_1 V_w \quad (3)$$

where $K_1 = \frac{\lambda_{opt}}{r}$, and λ_{opt} is the optimal TSR.

The generator rotor angular speed and the electrical angular speed are related in Equation (4).

$$\omega_r = \frac{2}{P} \omega \quad (4)$$

where ω is the electrical angular speed, and P is the number of generator poles.

The mechanical power of the generator and turbine system is expressed in Equation (5).

$$P_m = J \omega_r \frac{d\omega_r}{dt} + P_e \quad (5)$$

where J is the combined rotor and generator inertia, P_e is the electrical output power, and ω_r is the generator rotor angular speed.

Electrical output power depends on both generator efficiency (η_g) and converter efficiency (η_c). Equation (6) shows the relationship between mechanical and electrical output power. The rotor speed plays a crucial role in achieving the maximum power. Hence, even after achieving maximum mechanical wind power, it is not guaranteed to get the maximum electrical power output if the desired rotor speed is not achieved [16].

$$P_e = P_m \eta_g \eta_c \quad (6)$$

In this paper, the parameters of WECS were defined using a physics-based model approach instead of experimental identification. Manufacturer specifications and commonly reported values from the literature were selected for turbine and generator parameters. The TSR and power coefficient characteristics were obtained from a standard C_p - λ model. To obtain optimal power extraction, the power coefficient should be maximized, which requires maintaining the TSR at its optimal value by operating the rotor at the corresponding speed. Figure 2 illustrates the relationship between $C_p(\lambda)$ and TSR. The value of the power coefficient $C_p(\lambda)$ reaches a maximum value of 0.48 when the TSR is equal to 8.1. Since the maximum power coefficient occurs at a certain TSR, control strategies aim to locate the optimal TSR to reach the MPP. The next section discusses three MPPT methods: P&O, INC, and ANN.

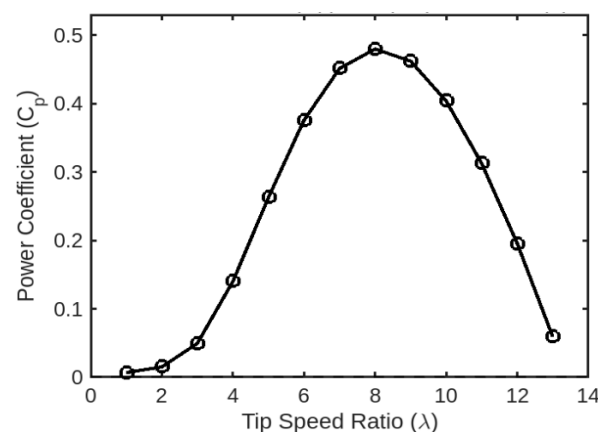


Figure 2. Power coefficient (C_p) vs. tip speed ratio (λ).

3. Methods of Maximum Power Point Tracking

The proposed standalone wind energy conversion system (WECS) uses a PMSG, a rectifier, and a boost converter. The block diagrams for P&O/INC- and ANN-based MPPT methods are shown in Figures 3 and 4, respectively. The rectifier converts the PMSG's AC output to DC. The boost converter adjusts the operating point of the PMSG to reach the MPP. The P&O-based MPPT perturbs the operating point and adjusts the duty cycle based on changes in the output power. The INC-based MPPT calculates the slope of the power–voltage curve and adjusts the duty cycle accordingly to reach the optimal operating point.

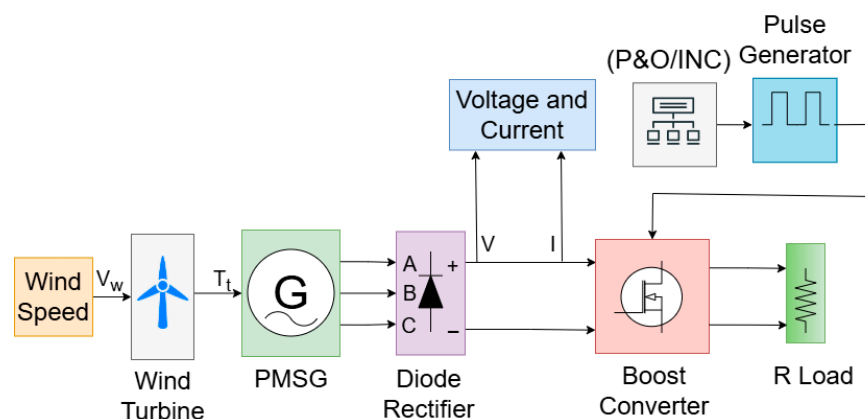


Figure 3. Block diagram of P&O- and INC-based MPPT.

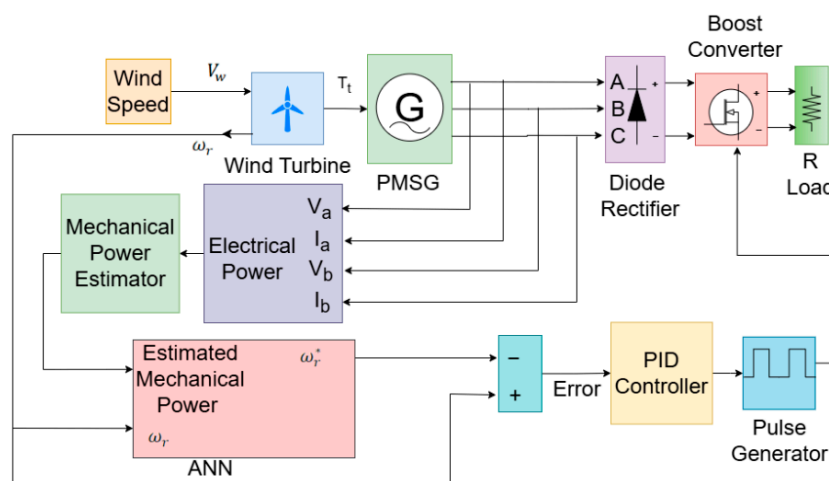


Figure 4. Block diagram of ANN-based MPPT.

3.1. Design of Perturb and Observe (P&O)-Based MPPT

The perturb and observe (P&O) algorithm is simple to implement and is extensively used for MPPT in both wind and solar power systems. This method compares the variation of power between consecutive intervals of the sampling periods to determine the direction to move the operating point. The duty cycle indirectly controls the output voltage of renewable energy sources. When the duty cycle increases, the output voltage decreases. If the duty cycle decreases, the output voltage increases.

The incremental changes of voltage (ΔV) and power (ΔP) at each sampling instant are computed in Equations (7) and (8).

$$\Delta V = V(k) - V(k-1) \quad (7)$$

$$\Delta P = P(k) - P(k-1) \quad (8)$$

A small perturbation of the duty cycle ΔD is applied, and ΔP and ΔV are measured. If the product of ΔP and ΔV is positive, the operating point is moving toward MPP, ΔD will continue in the same direction. On the other hand, if ΔP is negative, the operating point is moving away from MPP, ΔD will reverse the direction. The duty cycle is limited between the minimum duty cycle D_{min} and the maximum duty cycle D_{max} for stability and safe operation. The duty cycle is then updated by Equation (9). The flowchart of the P&O algorithm is shown in Figure 5.

$$D(k) = D(k-1) \pm \Delta D \quad (9)$$

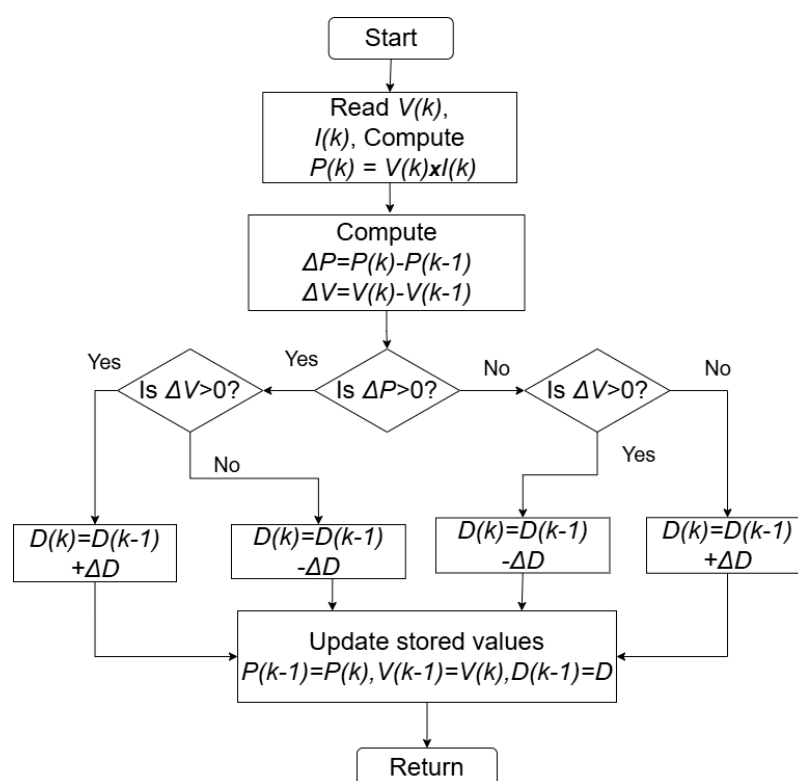


Figure 5. Perturb and observe (P&O) algorithm flowchart.

3.2. Design of Incremental Conductance (INC)-Based MPPT

The INC algorithm has been widely used for MPPT in solar PV systems and WECS. It does not require detailed specifications of the wind turbines or generators. This improves the system's reliability and reduces the overall cost. The MPP is determined by the instantaneous rate of change of power with respect to voltage, as expressed in Equation (10), where dP represents the change in output power, and dV represents the change in voltage. The MPP is reached when its derivative is equal to zero, as shown in (11). If $dP/dV > 0$, the operating point is to the left of the MPP, and the duty cycle will be decreased. On the other hand, if $dP/dV < 0$, the operating point is to the right of the MPP, and the duty cycle will be increased. When $dP/dV = 0$, the MPP is reached, and the duty cycle will remain the same. The power–voltage curve is shown in Figure 6, and the INC-based MPPT flowchart is shown in Figure 7.

$$\frac{dP}{dV} = I + V dI/dV \quad (10)$$

$$\frac{dI}{dV} = -I/V \quad (11)$$

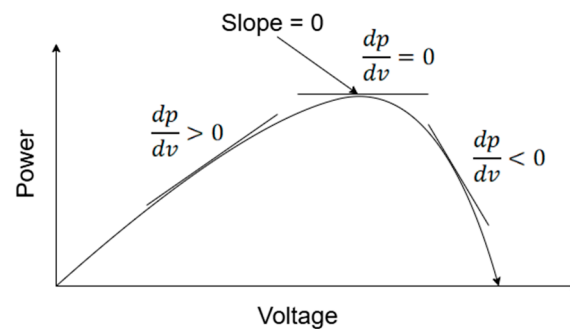


Figure 6. Power–voltage curve.

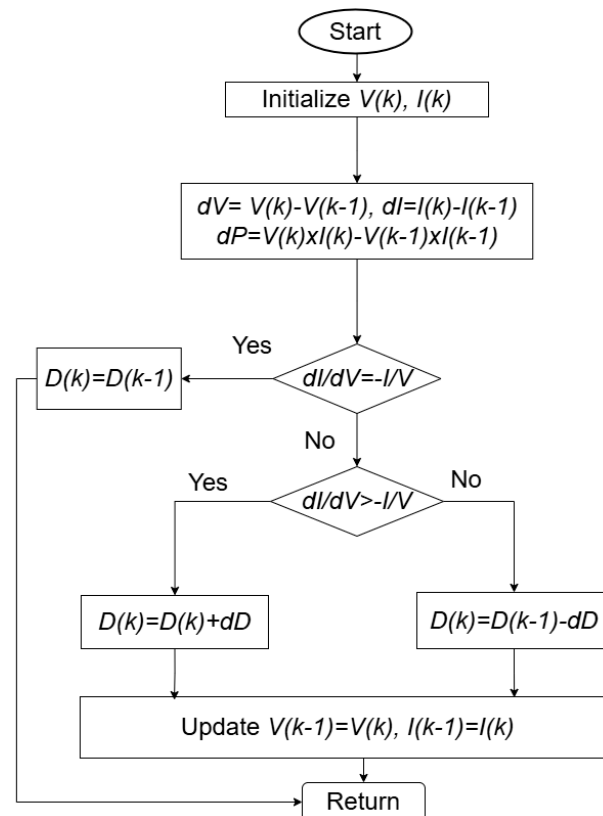


Figure 7. Incremental conductance (INC) algorithm flowchart.

3.3. Design of ANN-Based MPPT

A control strategy based on an ANN is developed to extract the maximum power for the WECS under a range of wind conditions. The ANN model is trained using computed mechanical power (P_m) and generator rotor speed (ω_r) as input variables to estimate the wind speed (V_w^*). The method was first presented in [14]. From the estimated wind speed, reference of the rotor speed (ω_r^*) is obtained and compared with the actual rotor speed to calculate the error signal. A PID controller then determines the duty cycle of the boost converter based on the error. The training scheme and control strategy are illustrated in Figures 8 and 9, respectively. The reference rotor speed is expressed as a function of the estimated wind speed in Equation (12).

$$\omega_r^* = K_2 V_w^* \quad (12)$$

where $K_2 = (\lambda_{opt}/r)$, λ_{opt} is the optimal TSR, r is the radius of the turbine, and V_w^* is the estimated wind speed.

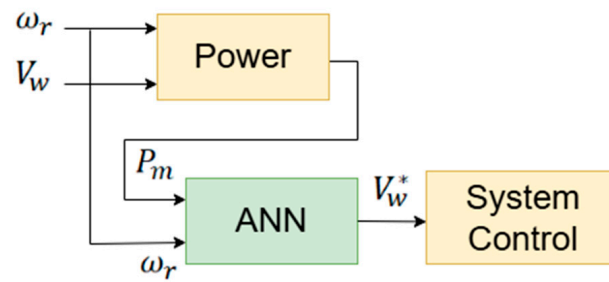


Figure 8. ANN training scheme.

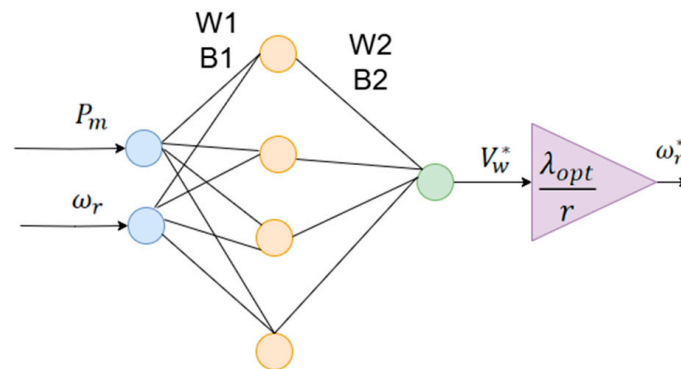


Figure 9. ANN control strategy.

The ANN is trained using a curve-fitting regression model with the Bayesian regularization (BR) algorithm. There are two main approaches to training an ANN: MATLAB 2024 code or the Simulink tool. Training with MATLAB code has greater flexibility in algorithm selection and custom preprocessing. In contrast, the Simulink ANN tool provides a simpler graphical interface for direct deployment and quick integration into Simulink models, but with very limited flexibility. We experimented with several training algorithms, including Levenberg–Marquardt (LM), scaled conjugate gradient (SCG), and Bayesian regularization (BR) to evaluate estimation accuracy, generalization performance, and convergence speed. Table 2 shows the comparison of three training methods, where BR has the highest number of epochs, the highest correlation coefficient that is close to unity, and the highest accuracy with the lowest RMSE. BR minimizes the cost function that balances the magnitude and training error of the network weights. It enhances prediction accuracy and reduces overfitting, especially when measurement uncertainties are present in the training data. On the other hand, LM and SCG converged faster than BR but have higher RMSE. We selected BR because of its stable convergence and the lowest RMSE with strong generalization.

Table 2. Comparison of different ANN training algorithms for wind speed estimation.

Method	Epochs	Accuracy(R)-All	RMSE (All)
Bayesian Regularization	1253	≈ 1.00000	5.26×10^{-7}
Levenberg–Marquardt	654	≈ 1.00000	1.25×10^{-6}
Scaled Conjugate Gradient	135	≈ 0.99997	7.92×10^{-3}

The topology of the ANN was selected based on model accuracy, sustainability, computational complexity, and implementation efficiency. A feedforward multilayer perceptron (MLP) structure was adopted. The number of hidden neurons was empirically selected using preliminary training tests, which reduce computational complexity and prevent overfitting to ensure accurate convergence. The input layer has two features, namely

computed mechanical power (P_m) and rotor speed (ω_r). The hidden layer uses a sigmoid activation function, and the output layer uses a linear activation function to estimate the wind speed. From Figure 9, W1 and B1 indicate the weight matrix from input to hidden layer and the bias vector for hidden layer neurons, respectively, whereas W2 and B2 represent the weight matrix from hidden to output layer and the bias vector for output layer neurons, respectively.

To generate data for training, the mechanical power (P_m) is computed using the equations of the aerodynamic wind turbine model, which is a function of rotor speed and turbine parameters in Equation (1). The rotor speed (ω_r) is determined from the system Equation (2). The training data were generated by computing over a wide range of operating conditions and wind speeds ranging from 5 m/s to 17 m/s. For each operating point, computed mechanical power (P_m) and the corresponding rotor speed (ω_r) were recorded as inputs to the ANN, whereas the wind speed was used as the target output. Both input and output were normalized to enhance numerical stability and convergence throughout the learning process. This approach allows the ANN to learn the nonlinear mapping between the variables of wind speed, rotor speed, and mechanical power to ensure accurate estimation. The ANN is trained offline, whereas the simulation results are obtained from the dynamic system under varying wind profiles. The mechanical power is not measured directly in the simulation; instead, it is calculated from the generator electrical power and rotor speed dynamics from Equations (4) and (5).

The proposed method is similar to the MPPT presented in [14], where an ANN estimates the wind speed using rotor speed and mechanical power to eliminate the need for mechanical sensors and determine the optimal TSR (λ_{opt}) through the rotor speed reference ω_r^* . While [14] primarily focuses on ANN models to avoid time-consuming calculations and physical wind sensors, our work emphasizes a comparative analysis between ANN trained with Bayesian regularization, INC, and P&O methods under two wind profiles and details on how to train ANNs. Unlike [14], our study further evaluates ANN performance by comparing AC output powers, voltage stability, and noise sensitivity of the three MPPT methods.

The regression results in Figure 10 show that the correlation coefficient is closest to unity across training and test data with a normalized RMSE of 5.26×10^{-7} . Figure 11 shows that the mean squared error (MSE) of 2.81×10^{-13} was reached at epoch 1253 shown by the blue dot, which indicates that there is negligible deviation between the predicted and target values. Although the correlation coefficient indicates a perfect fit to the training data generated, real-world generalization may not be guaranteed. Therefore, additional robustness tests were implemented in Section 4 with measurement noise and an unseen turbulent wind profile to observe the robustness and generalization capability of the ANN. Under these conditions, the ANN estimator can generalize beyond nominal operating points, as it is trained over a wide range of conditions by mapping the disturbed input signals to the respective output signal. Under moderate disturbances, the estimated wind speed has smooth transients and stable performance, which enables the reliable operation of MPPT.

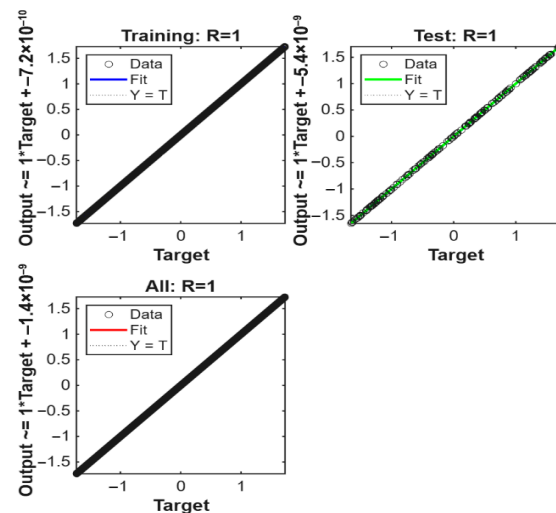


Figure 10. Regression plots for ANN.

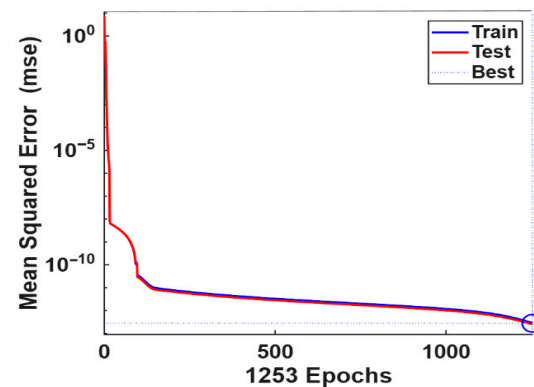


Figure 11. Mean squared error.

4. Results

The wind turbine in the Simulink simulation has a nominal mechanical output power of 12.3 kW, a base wind speed of 12 m/s, a turbine radius of 1.3 m, and an optimal TSR (λ_{opt}) of 8.1. The PMSG has a per-phase resistance of 0.0485 Ω , phase inductance of 0.395 mH, and flux linkage $\psi = 0.1194$ V·s. The simulations were run for 80 s. The INC, P&O, and ANN controllers were compared for wind profile 1 (Figure 12) and wind profile 2 (Figure 13). The average power was measured by the simulation scope using its averaging method and rounded to two decimal places.

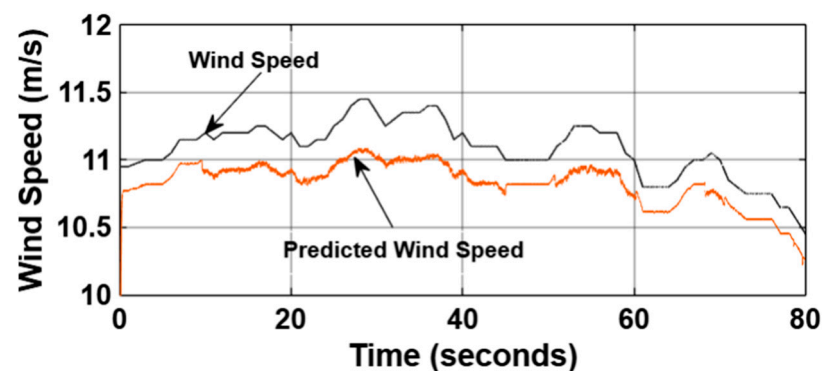


Figure 12. Wind profile 1.

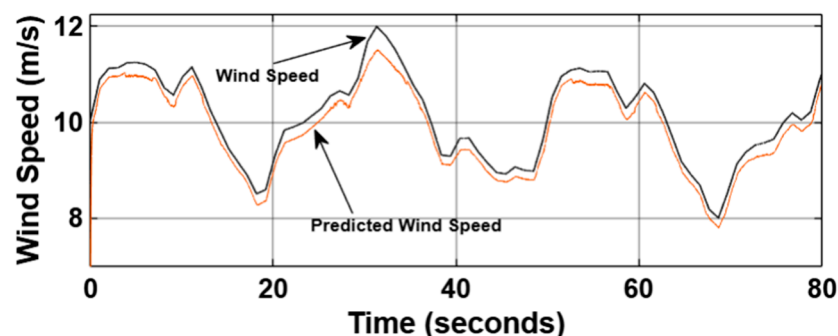


Figure 13. Wind profile 2.

4.1. Performance Analysis for Wind Profile 1

In wind profile 1 shown in Figure 12, the wind speed varies smoothly between 10.4 and 11.5 m/s. The ANN accurately estimated the wind speed shown in Figure 12 with an estimation error below 0.4 m/s (Figure 14). The AC output power and DC output voltage obtained using the ANN controller are presented in Figures 15 and 16, respectively, and those obtained using the P&O controller are shown in Figures 17 and 18, while the corresponding results using the INC controller are shown in Figures 19 and 20. It can be observed that both the output power and output voltage obtained using the ANN controller are more stable, with less noise compared with the results obtained using the P&O and INC controllers. The average output power using the ANN, P&O, and INC is 5.78 kW, 4.54 kW, and 4.69 kW, respectively.

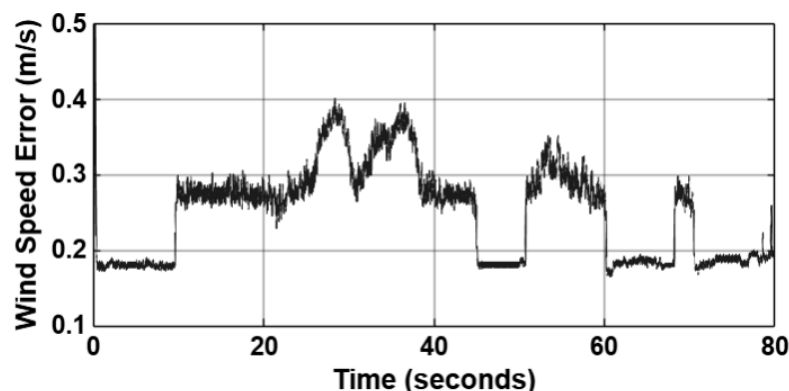


Figure 14. Wind speed estimation error—wind profile 1.

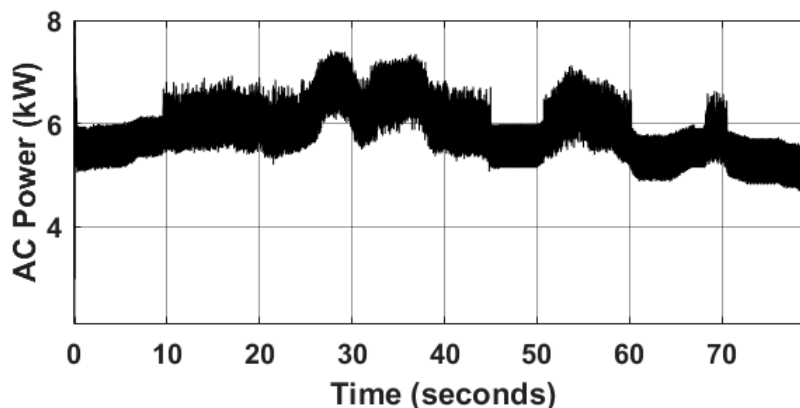


Figure 15. AC output power for ANN—wind profile 1.

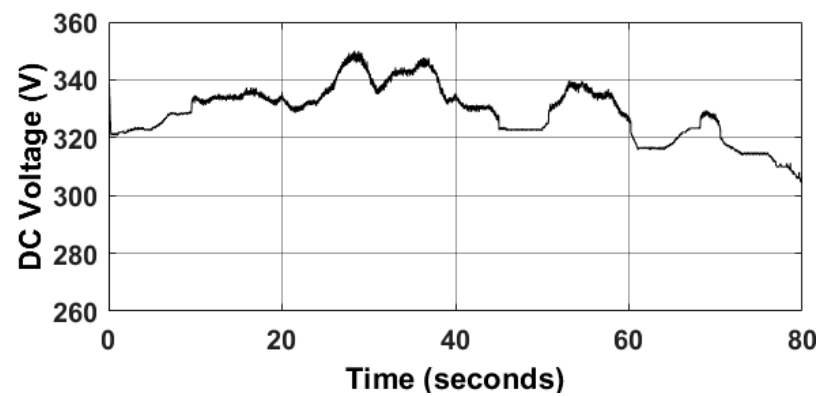


Figure 16. DC output voltage for ANN—wind profile 1.

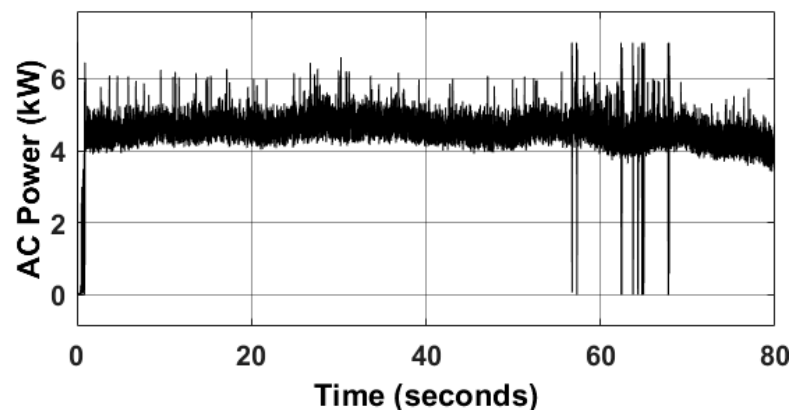


Figure 17. AC output power for P&O—wind profile 1.

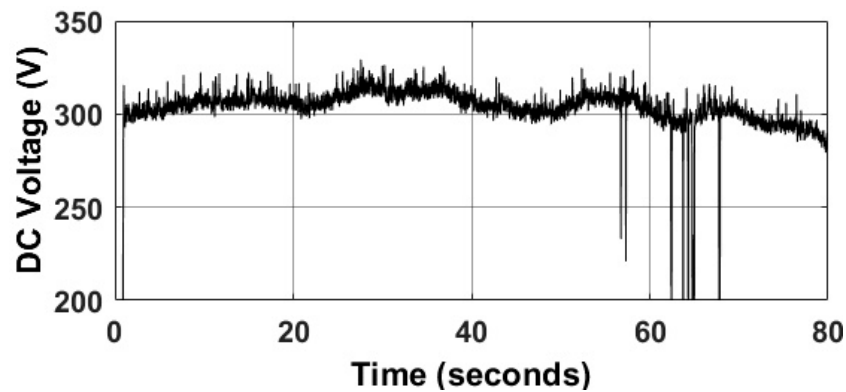


Figure 18. DC output voltage for P&O—wind profile 1.

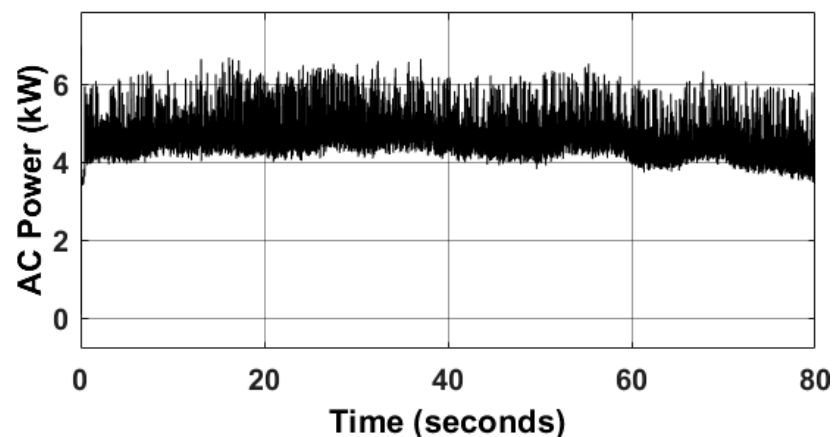


Figure 19. AC output power for INC—wind profile 1.

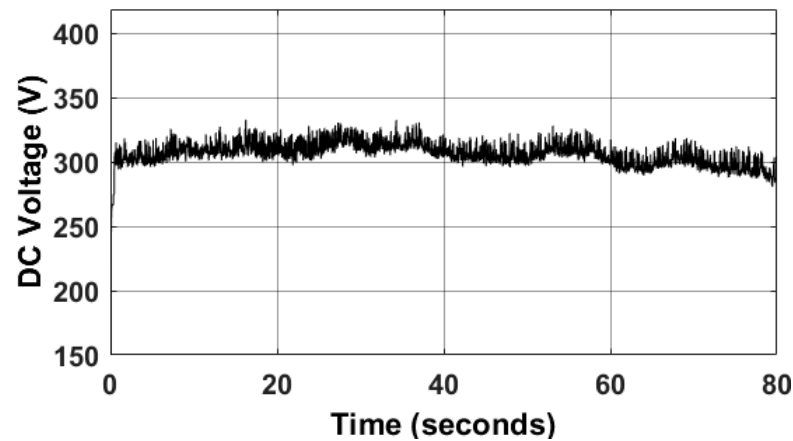


Figure 20. DC output voltage for INC—wind profile 1.

4.2. Performance Analysis for Wind Profile 2

In wind profile 2 (Figure 13), the wind speed varies more abruptly between 8 and 12 m/s. The ANN accurately estimated the wind speed with an estimation error below 0.3 m/s, as shown in Figure 21. The AC output power and DC output voltage obtained using the ANN controller are presented in Figures 22 and 23, respectively. The results from P&O are shown in Figures 24 and 25, and the results using the INC controller are shown in Figures 26 and 27. It can be observed that, similar to wind profile 1, both the output power and output voltage obtained using the ANN controller are more stable, with less noise, compared with the results obtained using the P&O and INC controllers for wind profile 2. The average power using the ANN, P&O, and INC controllers is 4.66 kW, 3.10 kW, and 3.89 kW, respectively. Table 3 summarizes the comparison of output power using ANN- and P&O-based MPPT for the WECS, whereas Table 4 summarizes output power for ANN- and INC-based MPPT.

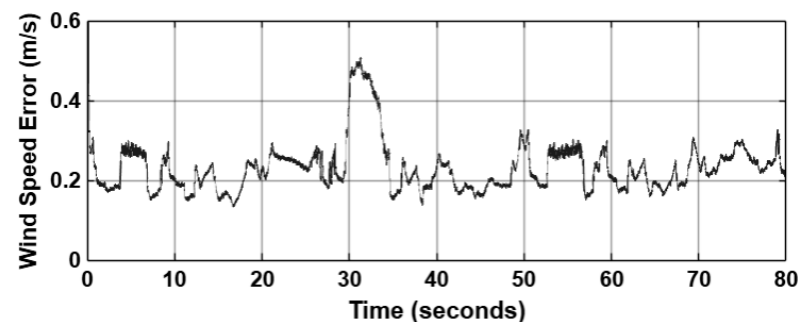


Figure 21. Wind speed estimation error—wind profile 2.

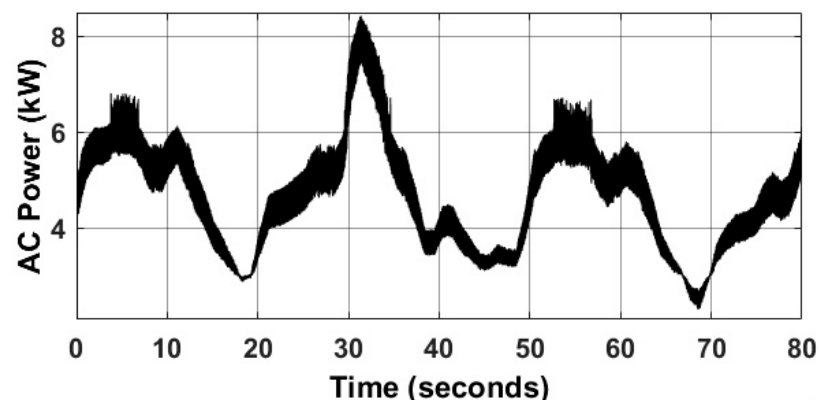


Figure 22. AC output power for ANN—wind profile 2.

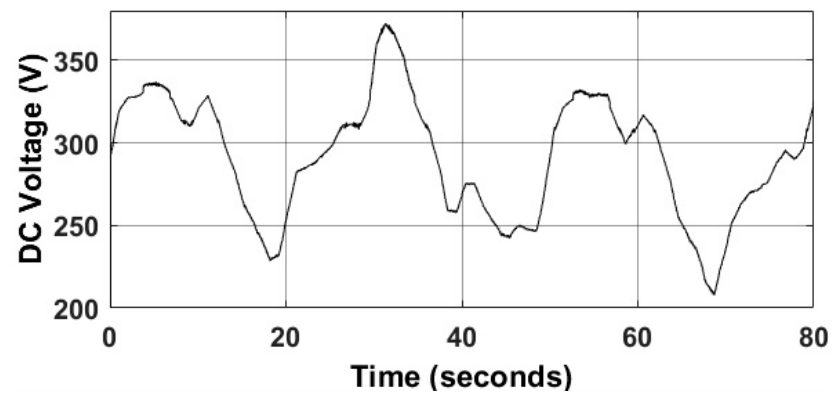


Figure 23. DC output voltage for ANN—wind profile 2.

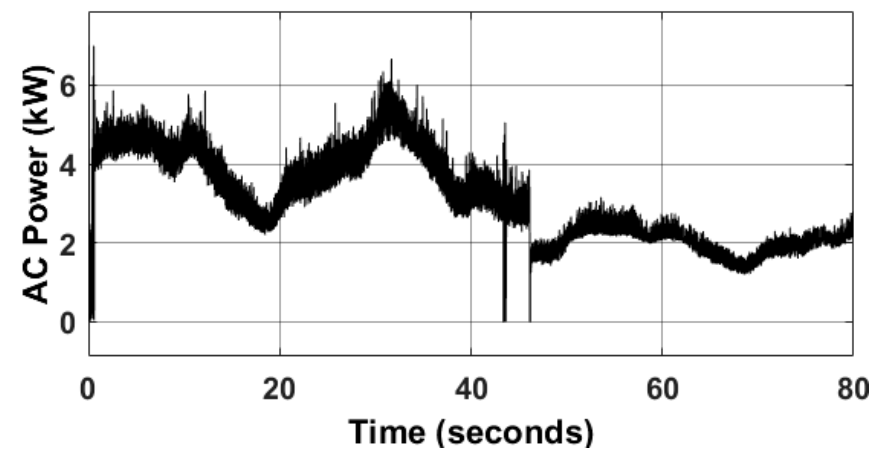


Figure 24. AC output power for P&O—wind profile 2.

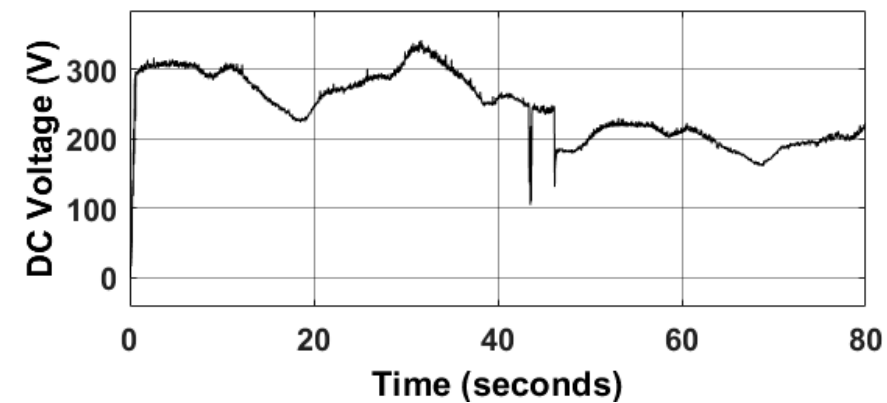


Figure 25. DC output voltage for P&O—wind profile 2.

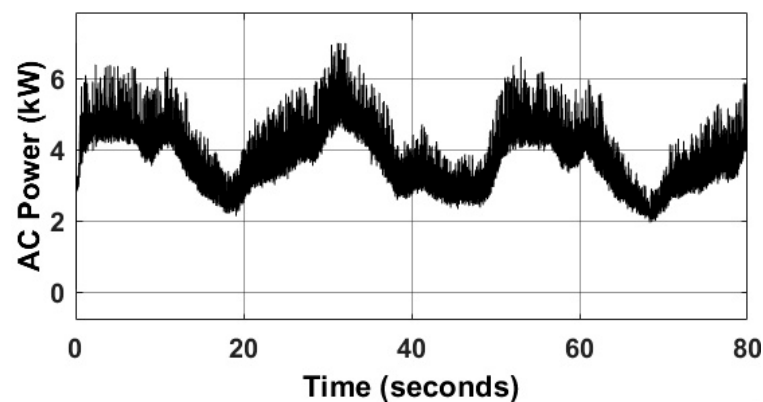


Figure 26. AC output power for INC—wind profile 2.

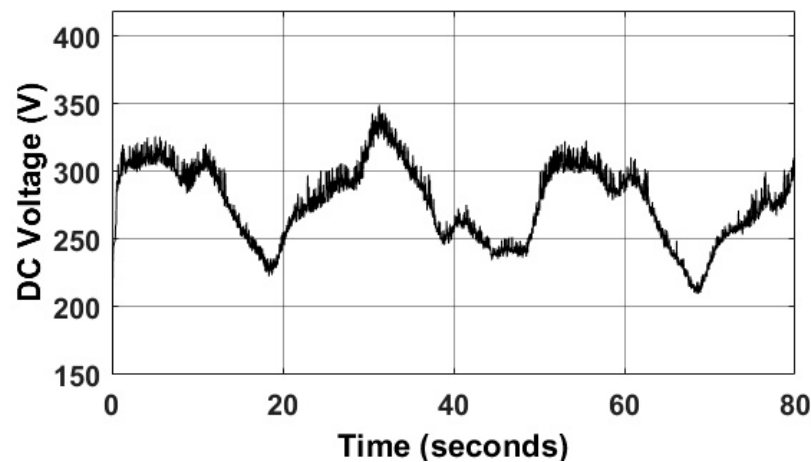


Figure 27. DC output voltage for INC—wind profile 2.

Table 3. Comparison of ANN- and P&O-based MPPT.

Parameter	P&O	ANN	Improvement with ANN
Mean AC Power (kW)—Wind Profile 1	4.54	5.78	27.31%
Mean AC Power (kW)—Wind Profile 2	3.10	4.66	50.32%

Table 4. Comparison of ANN- and INC-based MPPT.

Parameter	INC	ANN	Improvement with ANN
Mean AC Power (kW)—Wind Profile 1	4.69	5.78	23.24%
Mean AC Power (kW)—Wind Profile 2	3.89	4.66	19.79%

4.3. Robustness and Generalization Tests

The robustness and generalization capability of the proposed ANN-based MPPT method were evaluated under measurement noise conditions and using an unseen turbulent wind profile shown in Figure 28. Measurement noise was modeled in Simulink using band-limited white noise with a 2% noise level for wind profile 2. The performance metrics of MPPT tracking efficiency (%) and steady-state ripple (%) for the unseen wind profile and the measurement noise were evaluated from the simulation and reported in Tables 5 and 6. The results indicate that ANN-based MPPT achieved higher tracking efficiency and lower steady state ripple under measurement noise and turbulent wind conditions, which demonstrates strong generalization capability and robustness to disturbances. The INC-based MPPT performance is moderate with higher ripple, whereas P&O-based MPPT has the lowest tracking efficiency, indicating less adaptability to dynamic and noisy conditions.

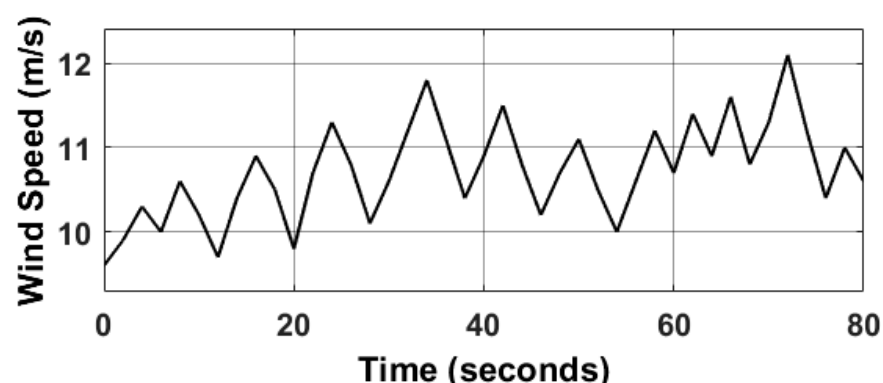


Figure 28. Unseen turbulent wind profile.

Table 5. Generalization tests under the unseen turbulent wind profile.

Method	MPPT Tracking Efficiency (%)	Peak-to-Peak Steady-State Ripple (%)
ANN	70.45	30.31
INC	56.90	42.92
P&O	30.06	29.01

Table 6. Robustness tests under measurement noise with a noise level of 2% of the measurement value for wind profile 2.

Method	MPPT Tracking Efficiency (%)	Peak-to-Peak Steady-State Ripple (%)
ANN	70.02	34.43
INC	56.52	50.91
P&O	55.88	49.98

5. Conclusions

ANN, P&O, and INC-based MPPT methods were studied for WECS under two dynamic wind profiles, one with a steadier wind speed and the other with a wider range of wind speeds. The ANN was designed and trained offline using the MATLAB code with data computed from the system model. Simulation results show that the ANN-based MPPT achieved 23.24% higher output power for wind profile 1 and 19.79% higher output power for wind profile 2 compared to INC-based MPPT, whereas 27.31% and 50.32% higher output power compared to P&O-based MPPT for wind profile 1 and wind profile 2, respectively. In addition, the ANN-based MPPT resulted in smoother voltage regulation and less oscillation around the operating point. The P&O- and INC-based MPPT methods have drawbacks in terms of noise sensitivity and oscillations. However, their real-time computations are less intensive. Future work will focus on combining both INC and ANN methods to implement a hybrid control method to improve the performance of intelligent control methods and the simplicity of traditional methods.

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