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Dynamic Simulation of Wind Turbine Power Generation Using Modified P&O-ANFIS Based MPPT Control

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A B S T R A CT

This paper presents the modeling, simulation, and performance analysis of a smart Maximum Power Point Tracking (MPPT) control system integrated with a DC–DC converter for Wind Turbine (WT) power generation. Existing research remains limited in addressing hybrid MPPT controllers that merge conventional and intelligent techniques, are validated under varying wind and load conditions, and are integrated with wide-range high-voltage DC–DC converters with thorough dynamic performance assessment. The proposed intelligent MPPT scheme combines the conventional Perturb and Observe (P&O) algorithm with an Adaptive Neuro-Fuzzy Inference System (ANFIS) to enhance accuracy and dynamic response in extracting the maximum available power under varying wind and load conditions. The hybrid P&O–ANFIS-based controller adaptively adjusts the converter's duty cycle to ensure optimal energy harvesting and efficient power transfer to the load. A boost converter is employed to step up the WT output voltage from 150 V to a range of 230–600 V. Simulation results confirm that the modified P&O–ANFIS MPPT controller achieves superior tracking capability, exhibiting reduced steady-state oscillations and improved transient response compared to conventional MPPT methods. Moreover, the system demonstrates stable voltage regulation and reliable power continuity to the load. The overall average efficiency achieved by the proposed controller is approximately 90%, the average rise time, settling time and steady state time of the system are 0.023 s, 0.14 s, and 0.196 s, respectively. The findings emphasize the importance of adaptive intelligent control in optimizing and improving the overall performance of modern WT-based power generation systems.

Keywords: Wind Turbine Power Generation; P&O-ANFIS MPPT algorithm; Boost Converter

1. Introduction

The global demand for electrical energy has been steadily increasing due to the rapid growth in the use of household electrical devices, particularly Direct Current (DC) appliances. These devices are designed to simplify human tasks and improve operational efficiency, resulting in higher energy consumption across residential and industrial sectors. Consequently, the number of power generation systems must continuously increase to meet this growing energy demand. In this regard, Renewable Energy (RE) sources such as Photovoltaic (PV) systems, Wind Turbines (WT), Fuel Cells, Supercapacitors, and Ultracapacitors have emerged as promising alternatives to conventional fossil-based energy sources. Most of these renewable sources inherently produce DC power, making them compatible with modern DC microgrid systems.

However, RE sources are strongly influenced by environmental and climatic variations, which cause fluctuations and intermittency in electrical power generation. The unpredictable nature of RE output presents a major challenge in maintaining the stability and reliability of modern power systems.

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Therefore, accurate forecasting and optimal control of RE power generation are crucial to ensure smooth integration with the grid and efficient utilization of renewable resources [1], [2]. In tropical regions such as Indonesia, wind and solar energy availability vary significantly between seasons. During the rainy season, solar radiation decreases to around 400 W/m², leading to lower PV system output. Conversely, during the dry season, average wind speeds can reach 10 m/s, enabling WT systems to produce more power compared to PV systems. Offshore wind turbine topologies, operating within an average wind speed range of 5–10 m/s, are commonly applied in coastal regions.

Among various renewable technologies, wind energy is considered one of the most efficient and clean sources of electrical power. Wind Turbines (WTs) are easy to operate, environmentally friendly, and require minimal supervision, although they still demand periodic mechanical maintenance. The electrical output of a WT depends primarily on wind speed variations, which directly influence the mechanical torque applied to the turbine blades. Consequently, the WT exhibits a nonlinear power–voltage (P–V) characteristic curve, containing a specific Maximum Power Point (MPP) that represents the optimal operating condition. To continuously operate at this point, a Maximum Power Point Tracking (MPPT) algorithm is required.

Several conventional and intelligent MPPT algorithms have been proposed to enhance the efficiency of renewable energy systems. Conventional methods include Perturb and Observe (P&O) [3], Incremental Conductance (Inc) [4], and Hill Climbing (HC), while intelligent control methods such as Artificial Neural Networks (ANN), Fuzzy Logic Control (FLC)[5], Adaptive Neuro-Fuzzy Inference System (ANFIS)[6], Particle Swarm Optimization (PSO) [7], and Artificial Bee Colony (ABC) [8] have shown improved performance under dynamic environmental conditions. In WT applications, the electrical power generated is typically connected to a DC bus through a DC–DC converter, either in single or multi-stage configuration, to regulate voltage and enhance power transfer efficiency. Wind Turbine Generators (WTGs) are particularly advantageous for remote and coastal areas due to their high reliability and mechanical robustness[9], [10], [11]. Nevertheless, the inherently sporadic nature of wind makes power generation from WTs difficult to predict and control effectively. The Permanent Magnet Synchronous Generator (PMSG) is preferred in WT systems due to its high efficiency, compact design, and minimal maintenance requirements [12], [13], [14].

To extract maximum power from wind energy, several MPPT algorithms such as Tip Speed Ratio (TSR), Power Signal Feedback (PSF), and Perturb and Observe (P&O) have been implemented in WT systems [15], [16]. However, the intermittent nature of wind and the nonlinear characteristics of WT systems often result in reduced energy conversion efficiency[17], [18]. Recent studies have proposed various advanced control strategies to address this issue. For instance, the combination of Fuzzy Logic Control with Fractional Order Proportional-Integral-Derivative (FO-PID) controllers has been explored for hybrid energy systems [19], while Finite-Set Model Predictive Control (FSMPC) has been applied to DC microgrids integrating PV, wind, and battery systems to ensure smooth power delivery[20], [21]. Model Predictive Control (MPC) techniques have also been used to optimize energy flow between renewable sources, storage units, and loads [22], [23]. Similarly, Proportional-Integral (PI) controllers have been applied to regulate voltage and minimize Total Harmonic Distortion (THD) in hybrid PV–wind–biomass systems [24][25].

Despite extensive research on MPPT techniques for wind turbine systems, several limitations remain, particularly in addressing simultaneous wind speed and load variations, transient performance evaluation, and wide-range voltage regulation. Conventional MPPT methods are still prone to tracking oscillations, while intelligent-based approaches generally involve higher computational complexity. Moreover, the integration of hybrid intelligent MPPT controllers with wide-range high-voltage DC–DC converters has not been sufficiently explored. Therefore, a clear research gap exists in the development

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and comprehensive evaluation of a hybrid MPPT control scheme that combines conventional and intelligent methods under dynamic wind and load conditions. Moreover, limited attention has been given to control strategies that improve dynamic response and power stability under rapidly fluctuating wind conditions.

Therefore, this study proposes the development and analysis of a modified P&O–ANFIS-based MPPT control system for a PMSG-based wind turbine generator. The proposed hybrid control system combines the simplicity of the P&O algorithm with the adaptive learning and reasoning capabilities of ANFIS to achieve faster convergence, reduced oscillations, and improved tracking efficiency under varying wind conditions. The main contributions of this paper are as follows:

1. Design and modeling of a PMSG-based wind power generation system integrated with a modified P&O–ANFIS intelligent MPPT controller.
2. Simulation and performance analysis of the proposed control configuration under various wind speed conditions.
3. Comparative evaluation of the proposed system against conventional MPPT algorithms in terms of tracking speed, efficiency, and output stability.

The results of this research are expected to enhance the performance of small-scale wind energy systems and contribute to the advancement of intelligent control strategies for renewable energy applications, particularly in DC microgrids and remote coastal areas.

The remainder of this paper is organized as follows: Section II presents the overall configuration of the proposed wind energy conversion system, including the main components and their functional interconnections. Section III describes the detailed modeling of the system and the design of the proposed P&O–ANFIS-based MPPT control strategy. Section IV discusses the simulation setup, performance evaluation, and analysis of the obtained results under various wind conditions. Finally, Section V concludes the paper by summarizing the key findings and highlighting potential directions for future research.

2. Wind Power System

2.1. *Modelling Wind Power Generations*

Figure 1 illustrates the configuration of a wind turbine power generation system. The system converts the kinetic energy of the wind into electrical energy through an electromechanical conversion process. The wind turbine captures wind energy and transforms it into mechanical rotational energy, which is transmitted to the Permanent Magnet Synchronous Generator (PMSG). The PMSG is commonly used due to its high efficiency, reliability, and capability to operate without the need for an external excitation source. The generated three-phase alternating current (AC) from the PMSG is then rectified using a diode bridge rectifier, producing a direct current (DC) output voltage (Vdc). This DC output can subsequently be regulated or conditioned through power electronic converters for various applications, such as grid connection, standalone loads, or hybrid renewable energy systems.

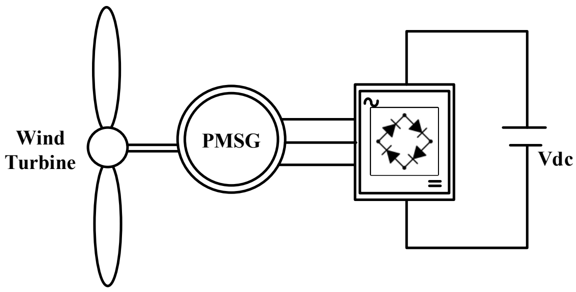

Fig.1. Show model of wind turbine power

The kinetic energy of a wind and power of wind are influenced by mass m: $\rho A v t$ (kg) and velocity of wind v (m/s), as shown in (1) and (2). Where E_k is wind's kinetic energy, ρ is the air density, the area

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across which the wind blows is $A{:}\pi R^2$, R is the radius of the wind turbine, P_w: E_k/t is the potentially power of wind that can used, t is the time

$$E_k = \frac{1}{2}mv^2 = \frac{1}{2}\rho A v^3 t \tag{1}$$

$$P_w = \frac{1}{2}\rho A v^3 \tag{2}$$

Equation (2) expression of wind power only depicts the wind's highest potential power. Actually, the wind turbine can only convert a portion of this potential energy into electricity depend on the power coefficient C_p. it is the ratio of the wind's power and the mechanical power P_m which can be generated by turbine. Based on The Betz's limit, the highest value of the output coefficient, is 59.26%; nevertheless, it actually exists in the range of roughly 25 to 45%[26]. Power coefficient can be expressed as (3).

$$C_p = \frac{P_m}{P_w} \tag{3}$$

$$C_p(\lambda, \beta) = c_1\left(c_2\frac{1}{\lambda_1} - c_3\beta - c_4\right)e^{-\frac{c_5}{\lambda_i}}$$

$$\frac{1}{\lambda_i} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{\beta^3 + 1}$$

$$\lambda = \frac{\omega \mathrm{x} R}{v}$$

Where Pm is the output mechanical power of wind turbine, λ is the tip speed ratio, $\omega(rad/s)=2\pi f$ is rotor tip angular velocity, β is the blade pitch angle, c1=0.5, c2=116, c3=0.4, c4=5 and c5=21. Equations (1) and (2) can be used to express the mechanical energy of a wind turbine that can be obtained from the wind, as shown (4).

$$P_m = \frac{1}{2}\rho\pi R^2 C_p(\lambda, \beta)v^3 \tag{4}$$

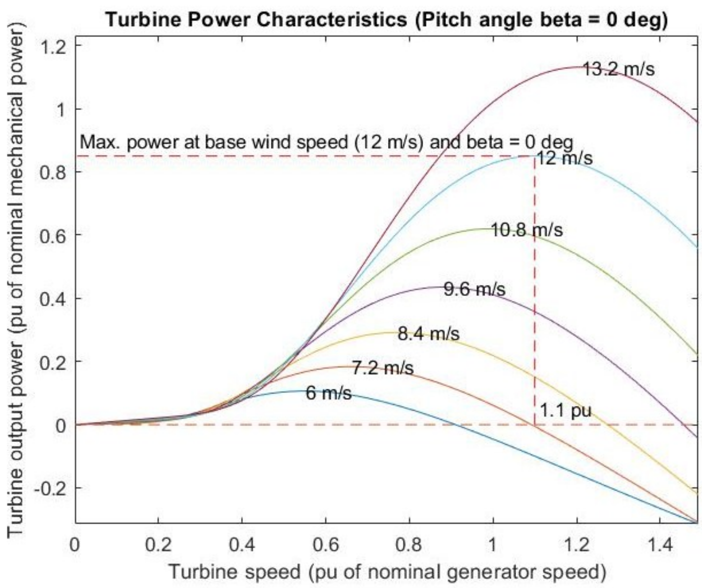

Fig. 2. The output mechanical power of wind turbine according to the turbine speed or the rotor rotation speed

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Figure 2. The figure presents the turbine power characteristics showing the relationship between the turbine's mechanical output power and rotor speed under various wind velocities. Each curve illustrates that the power increases with rotor speed up to the Maximum Power Point (MPP) and then decreases due to aerodynamic and mechanical losses. The rated mechanical power (≈1.1 pu) is achieved at a base wind speed of 12 m/s, while higher speeds activate the pitch control system to prevent overloading. These characteristics form the basis for the Maximum Power Point Tracking (MPPT) strategy to maintain optimal energy extraction.

The maximum mechanical power output of wind turbine may be shown to vary with wind speed. In the other hand, the mechanical power of wind turbine influenced by wind power turbine's mechanical torque T_m and wind turbine power turbine's rotation speed of turbine ω_m, can be expressed in (5).

$$P_m = T_m \omega_m \tag{5}$$
$$T_m = \frac{\rho \pi R^2 C_p(\lambda, \beta) v^3}{2\omega_m}$$

In this proposed system, the generator model used to convert mechanical energy into electrical energy is the Permanent Magnet Synchronous Generator (PMSG) model. In [15], [21], [23], [25], the PMSG model has been illustrated. In 3-phase systems, the currents and voltages are typically depicted in dq frame via dq transformation. As illustrated in Fig. 3 the electrical elements in synchronously spinning coordinate axis are transformed according to the stator's three-phase current, d axis is set as the generator rotor's N pole and q axis is perpendicular to the electrical angles.

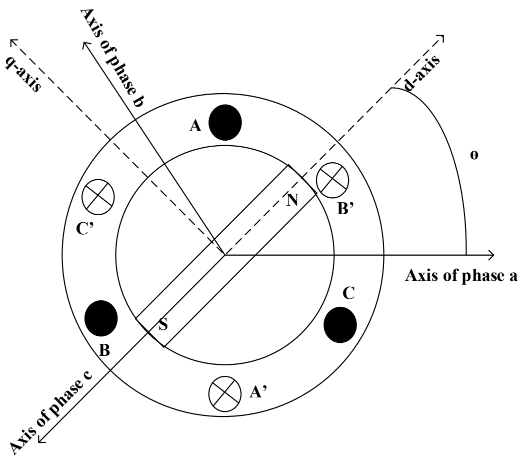

Fig.3. the electrical elements in synchronously spinning coordinate axis

The formula of PMSG is shown in eq. 6.

$$\frac{di_d}{dt} = -\frac{R_{st}}{L} i_d + P\omega_m i_q + \frac{1}{L} u_d \tag{6}$$
$$\frac{di_q}{dt} = -\frac{R_{st}}{L} i_q - P\omega_m i_d + \frac{1}{L} P\Psi_m \omega_m + \frac{1}{L} u_q$$

Where i_d is the d-axis current flow to the stator, iq is the q-axis current flowing to the stator, ud is the input voltage for the stator's d axis, u_q is the input voltage for the stator's q axis, ω_m is the generator's rotor speed, Rst is the resistance, L is the inductance, P is the number of pole pairs and ψ_m is the magnetic flux of the PMSG. The electromagnetic torque Te of the PMSG is expressed in (7)

$$T_e = \frac{3}{2} P\left(\psi_m i_q + \left(L_d - L_q\right) i_q i_d\right) \tag{7}$$

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If each axis' inductance is equal ($L = L_d = L_q$), Equation (6) can be reduced as follows in (8).

$$T_e = \frac{3}{2} P \psi_m i_q \tag{8}$$

2.2. *Modelling of MPPT Modified P&O-ANFIS*

The ANFIS control algorithm combines a neural network with a fuzzy logic controller. The MPPT system based on ANFIS intelligent control produces tracking with high accuracy and convergence speed, capable of optimal power tracking with zero oscillation around the MPP point. The advantage of ANFIS as MPPT intelligent control is that it is able to handle non-linear characteristics of RES sources. The ANFIS training data are obtained from simulation results using the Perturb and Observe (P&O) algorithm based on the Hill Climbing method. The P&O algorithm operates in two main stages. The first stage is the *perturbation* process, which functions to adjust the reference voltage, while the second stage is the *observation* process, which aims to monitor and compute the power change resulting from the previous perturbation action. The operational flow of the P&O algorithm is illustrated in the flowchart shown in Fig. 4. The input data in the form of output voltage and current from the rectifier circuit are used to calculate the power, power variation, and voltage variation. Subsequently, the current power $P(n)$is compared with the previous power $P(n-1)$, and the current voltage $V(n)$is compared with the previous voltage $V(n-1)$. The duty cycle is determined based on the comparison of power and voltage variations using a step size of 0.005. When the step size is positive, the duty cycle is decreased, whereas when it is negative, the duty cycle is increased. The output data generated by the P&O algorithm are used as training data for the ANFIS. The P&O method operates in two main stages, namely the *perturbation* stage, which is responsible for converting the reference voltage, and the *observation* stage, which is used to evaluate the power variation resulting from the action applied in the previous *perturbation* stage.

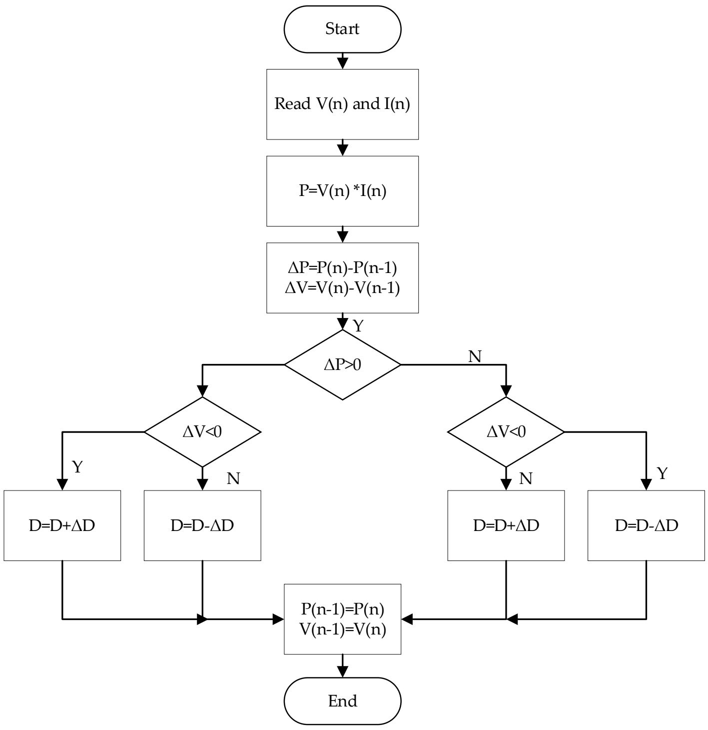

Fig. 4. Flowchart MPPT P&O

Fuzzy membership functions are trained by a neural network back propagation algorithm to form tuned membership parameters. Fuzzy logic control will change linguistic variables into numerical

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variables. ANFIS input and output training data is determined by considering the epoch used, while the inference rule-based system is determined based on variations in input and output. The learning based ANFIS controller will be implemented as an MPPT algorithm after the fuzzy membership parameters have been trained correctly. This research uses the Sugeno inference system with the back propagation optimization method and the least squares method. The structure of ANFIS based MPPT is shown in Fig.5. The ANFIS produces a set of inference rules based on adjusting the previously defined membership function until a small error rate is obtained and the desired output value is obtained. The member function values are adjusted until the smallest possible error value is obtained. This Membership function value will become a learning model in the MPPT control system when the membership function is set. The membership function value will be compared with the trained data. If an error occurs, the membership value will be adjusted so that the error is minimized. The ANFIS training configuration employs three membership functions for each input using triangular membership functions (Trimf). A hybrid learning model is adopted with a minimum error tolerance approaching zero and a total of 10 training epochs. The ANFIS system utilizes two inputs, namely voltage and current, where each input is assigned three membership functions, resulting in nine inference rules. These rules are then processed to produce a single output in the form of the duty cycle value.

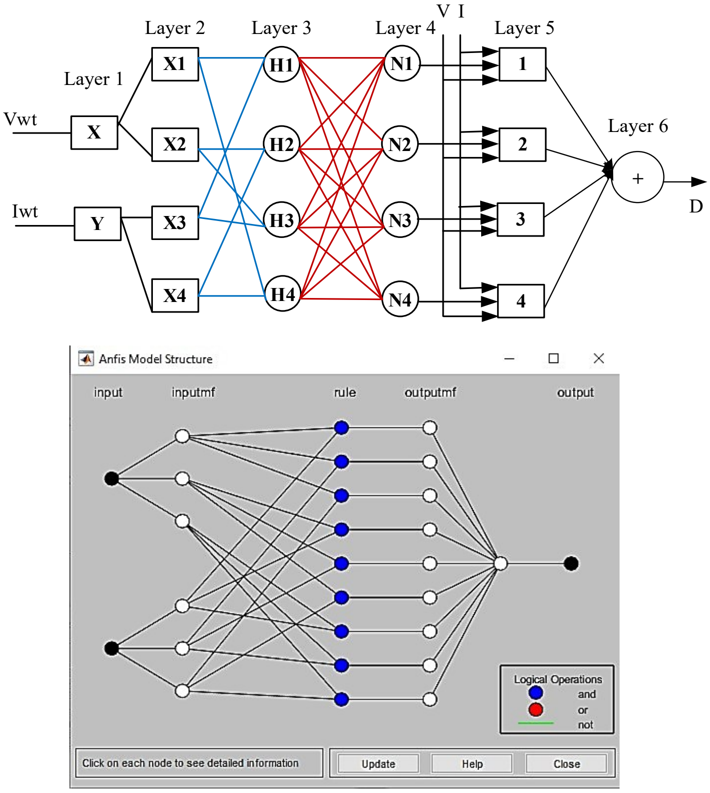

Fig. 5. The structure of ANFIS based MPPT

3. Method

In this research, the simulation design of the Maximum Power Point Tracking (MPPT) system was developed and implemented using a modified Perturb and Observe–Adaptive Neuro-Fuzzy Inference System (P&O-ANFIS) algorithm. This algorithm serves as a control strategy to determine the optimal duty cycle for the power converter. The proposed ANFIS-based MPPT controller utilizes the adaptive learning capability of the ANFIS structure, which requires a dataset consisting of input and output variables to build an accurate inference model. During the training stage, the ANFIS learns and generalizes the nonlinear mapping between the input and output data, improving the controller's

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precision in decision-making under different environmental and operational scenarios. The ANFIS model design and training processes were performed using the ANFIS Editor GUI in MATLAB, which supports the configuration of membership functions, generation of fuzzy rules, and performance assessment. The complete workflow of the proposed ANFIS-based MPPT implementation is presented in Figure 6.

The modified MPPT P&O-ANFIS functions as a controller to generate the output duty cycle. The ANFIS requires training data consisting of input and output datasets. The ANFIS process begins with the acquisition of input and output data from the P&O algorithm, where the input data are the output voltage and current of the rectifier circuit, while the output data correspond to the duty cycle values. These data are then used as input for the ANFIS training block. Subsequently, the ANFIS training parameters are configured, including the number of membership functions (MFs), the type of MFs, the optimization method, the error tolerance, and the number of epochs. After the parameter configuration and training process are completed, the maximum error value is evaluated. If the error does not satisfy the predefined tolerance limit, the training and parameter tuning processes are repeated. Once the maximum error meets the acceptance criteria, the next stage is to perform ANFIS testing on the converter system. In this study, 200.001 trained data with 10 iteration epochs was used, for the purpose of ANFIS training so 0.00000000075 training error is reduced.

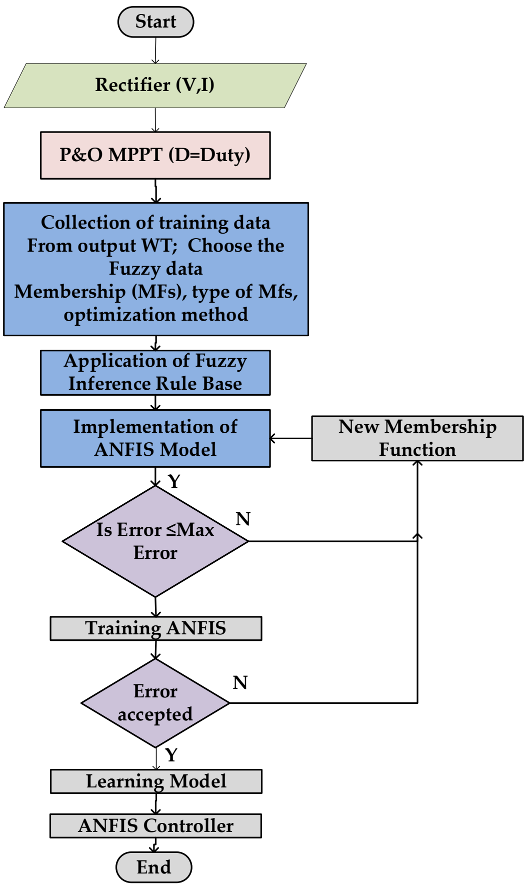

Fig. 6. The structure of ANFIS based MPPT

3.1. *Desain of DC-DC Converter for Wind Turbine*

In the proposed wind energy conversion system, the mechanical power generated by the wind turbine is rated at 2500 W. The turbine is mechanically coupled to a Permanent Magnet Synchronous Generator (PMSG), which converts the extracted mechanical energy into electrical power. The generated electrical output from the PMSG, also rated at 2500 W, is supplied to a three-phase rectifier circuit that converts the alternating current (AC) voltage into direct current (DC) voltage. After the rectification

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process, the DC electrical power obtained is approximately 2350 W, accounting for conversion and transmission losses within the system. This DC power output serves as the input source for the design and implementation of a high-efficiency boost converter within the wind turbine system.

The boost converter is employed to step up the rectified DC voltage from 155 V to 600 V shown in Figure 7, aligning with the required DC bus voltage of the overall power conversion system. Moreover, the boost converter is integrated with a Maximum Power Point Tracking (MPPT) controller to optimize the power extraction from the wind turbine under varying wind speed conditions. The MPPT ensures that the system continuously operates at the optimal power point, thereby enhancing energy conversion efficiency and stability. Table 1 presents the key parameters of the wind turbine and the PMSG system, while Table 2 summarizes the electrical and design parameters of the implemented boost converter. The DC–DC boost converter is designed to operate within an input voltage range of 62–155 V, corresponding to wind speed fluctuations of 5–12 m/s. The design specifications include a voltage ripple of 0.5%, a switching frequency of 5 kHz, a duty cycle of 75%, and an output power rating of 2300 W

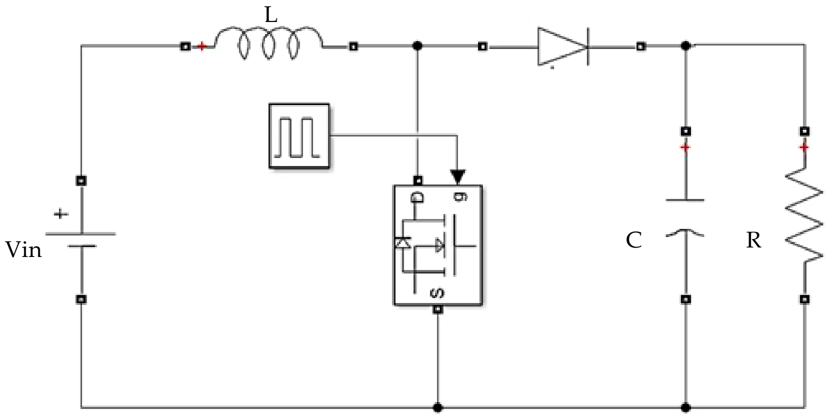

Fig. 7. DC-DC Boost Converter

Calculating of the inductor and capacitor DC-DC boost converter:

The output voltage converter:

$$V_o = \frac{1}{1\text{-}D} \times v_{in} \tag{9}$$

$$V_o = \frac{1}{1\text{-}0.75} \times 155$$

$$V_o = 618{,}4 \text{ volt}$$

Resistance (R)

$$R= \frac{V_o^2}{P} \tag{10}$$

$$R= \frac{618.4^{\ 2}}{2300}$$

$$R= 191{,}21 \text{ ohm}$$

Inductor current (IL)

$$IL= \frac{v_{in}}{(1\text{-}D)^2 \times R} \tag{11}$$

$$IL= \frac{155}{(1\text{-}0{,}75)^2 \times 191{,}21}$$

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$$IL= 12{,}94 \text{ A}$$

Ripple inductor current (ΔIL)

$$\Delta IL= 40\% \times IL \tag{12}$$
$$\Delta IL= 5{,}2 \text{ A}$$

Inductor (L)

$$L= \frac{D \times v_{in}}{\Delta IL \times f} \tag{13}$$
$$L= \frac{0{,}75 \times 155}{5{,}2 \times 5000}$$
$$L= 0.00448 \text{ H} \approx 4480{,}3\ \mu H$$

Minimum and maximum inductor current

$$ILmax=IL+\frac{\Delta IL}{2}=12{,}94+\frac{5{,}2}{2}=15{,}54 \text{ A} \tag{14}$$
$$ILmin=IL-\frac{\Delta IL}{2}=12{,}94-\frac{5{,}2}{2}=10{,}34 \text{ A}$$

Capacitor (C)

$$C\geq \frac{D}{R\times (\frac{\Delta V_o}{V_o})\times f} \tag{15}$$
$$C\geq \frac{0{,}75}{191{,}21\times 0{,}005\times 5000}$$
$$C\geq 0{,}0001569 \text{ F} \approx 156{,}9\ \mu\text{F}$$

Table 1. Parameter of WT System

Parameter	Values
Wind Power/Rated stator power (W)	2500
Electric Power (W)	2350
Electric power rectifier (W)	2350
Wind speed (m/s)	5-10
Angular velocity (rad/s)	102.31
Radius turbine (m)	0.95
Rate torque (N.m)	10-14.2
Rated rotation speed (rpm)	2300
Rectifier Voltage (Vdc)	160
Rectifier current (Idc)	10.2

Table 2. Parameter of DC-DC Boost Converter WT System

Parameter	Values
Input Voltage (V)	62-155
Output voltage (V)	230-600
Frequency (Hz)	5000
Inductor (H)	0.00448
Capacitor (F)	0.0001569

3.2. *Desain of System Configuration*

The proposed wind power generation system with a modified Perturb and Observe (P&O)–ANFIS-based control strategy is shown in Fig. 8. The system consists of a wind turbine, a Permanent Magnet

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Synchronous Generator (PMSG), a rectifier, and a DC–DC boost converter. The boost converter is a key component in stand-alone DC microgrid applications, as it regulates and steps up the rectified voltage to supply residential loads. The system is designed to convert variable wind energy into stable DC power, while the secondary control layer maintains a constant DC bus voltage under fluctuating input and load conditions. This autonomous DC microgrid configuration is suitable for electrification in remote coastal and island areas, such as Istanbul Island, Demak, Central Java, Indonesia, offering high efficiency, low converter cost, simplified control, and strong compatibility with renewable energy sources.

To ensure optimal power extraction, the wind turbine system is integrated with a Maximum Power Point Tracking (MPPT) mechanism. The proposed MPPT approach employs a modified P&O algorithm enhanced with an intelligent ANFIS-based controller. This hybrid control strategy effectively combines the simplicity of the conventional P&O method with the adaptive learning capability of ANFIS, thereby improving dynamic response and maximizing power conversion efficiency under varying wind and load conditions.

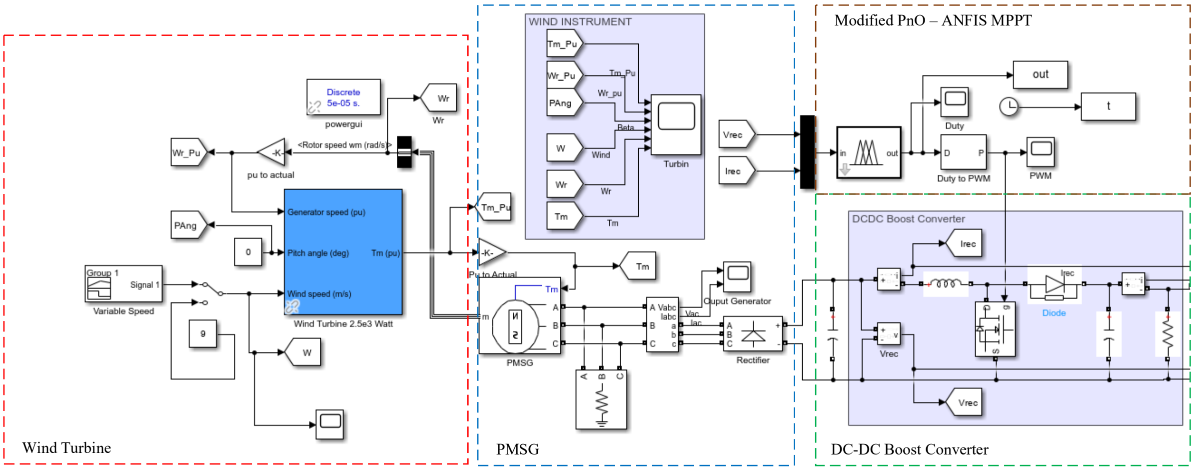

Fig. 8. Wind Turbine Power Generation integrated modified P&O-ANFIS MPPT system configuration

As illustrated in Fig. 8, the proposed system architecture consists of four main functional sections: the wind turbine (WT), Permanent Magnet Synchronous Generator (PMSG), rectifier, and DC–DC boost converter integrated with a modified P&O–ANFIS-based MPPT controller. The power conversion process begins with the WT, which captures the kinetic energy of the wind and converts it into mechanical torque. The generated torque drives the PMSG, which transforms the mechanical energy into three-phase AC electrical power. The generated AC power from the PMSG is then rectified through a three-phase diode rectifier to obtain a DC output. This DC voltage is subsequently processed by the DC–DC boost converter, which steps up and regulates the voltage to a constant level suitable for the DC microgrid bus. The boost converter's duty cycle is continuously adjusted based on the control signal provided by the modified P&O–ANFIS MPPT algorithm.

The modified P&O algorithm provides a fast response to changes in wind speed by perturbing the operating point and observing the corresponding variation in output power. However, to overcome the limitations of conventional P&O methods—such as steady-state oscillations and slow convergence—the proposed system incorporates the ANFIS-based intelligent controller. The ANFIS component adaptively tunes the control parameters by learning from input–output relationships between the reference voltage and the actual DC bus voltage, thereby enhancing tracking precision and overall stability

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4. Results and Discussion

In this study, the performance of the proposed wind turbine power generation system integrated with an intelligent Maximum Power Point Tracking (MPPT) control algorithm is validated through comprehensive MATLAB/Simulink simulations. The system is evaluated under various wind speed conditions to assess its dynamic response and adaptability to environmental variations. The primary objective of this technical analysis is to confirm the capability of the intelligent MPPT controller to optimize the power extraction efficiency of the wind turbine, thereby enhancing the overall performance and reliability of the renewable energy conversion system.

4.1. Characteristic of Wind Turbine Power Generation

The wind turbine characteristic test was performed to validate the consistency between the experimental results and the theoretical power output model of the turbine. The test was conducted under open-loop conditions by varying the wind speed from 5 m/s to 12 m/s, allowing for an in-depth evaluation of the turbine's electrical behavior under different aerodynamic inputs. As illustrated in Figure 9, the P–V (power–voltage) characteristics clearly demonstrate a nonlinear relationship between the generated power and terminal voltage at different wind velocities. The power output increases significantly with higher wind speeds due to the cubic dependency of wind power on velocity.

At a low wind speed of 5 m/s, the turbine produces approximately 399 W, indicating limited kinetic energy available for conversion. As the wind speed increases to 7 m/s, the output rises to around 847 W, while at 9 m/s, the power output reaches 1401 W. The maximum power of approximately 2350 W is achieved at 12 m/s, which closely aligns with the turbine's rated capacity. These results confirm that the wind turbine model accurately represents the expected aerodynamic and electrical performance characteristics. Furthermore, the distinct peak power points observed in each curve highlight the importance of implementing a Maximum Power Point Tracking (MPPT) control strategy to ensure optimal energy extraction under varying wind speed conditions.

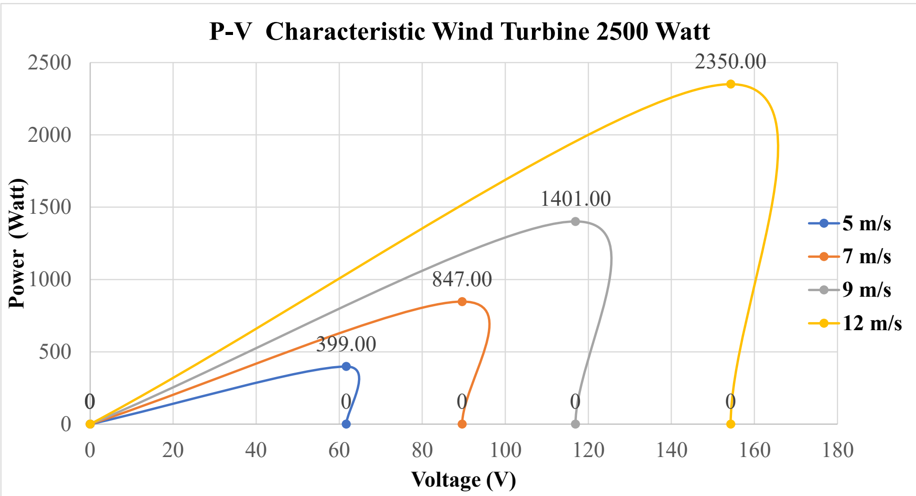

Fig. 9. The Characteristic of Wind Turbine Power Generation

4.2. MPPT Power Output of Wind Turbine Power Generation

In this section, the performance of the proposed Maximum Power Point Tracking (MPPT) control strategy based on the hybrid Perturb and Observe–Adaptive Neuro-Fuzzy Inference System (P&O–ANFIS) algorithm for the wind turbine (WT) system is evaluated under variable wind speed conditions. The wind speed fluctuates dynamically between 5 m/s and 12 m/s, as depicted in the upper plot of Figure 9, while the corresponding power responses for both the wind input power and the WT output power are shown in the lower plot.

The simulation results clearly demonstrate that the P&O–ANFIS algorithm effectively tracks the Maximum Power Point (MPP) of the WT under varying wind speeds without observable overshoot or

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oscillations. As illustrated in Figure 10, the generated power closely follows the changes in wind velocity with high precision and stability. When the wind speed ranges from 0 < t < 2 s (5 m/s), the WT generates approximately 400 W. As the wind speed increases to 10 m/s (2 < t < 4 s), the output power rises significantly to around 1,800 W. Subsequently, as the wind speed decreases to 8 m/s (4 < t < 6 s), the output power drops to about 1,200 W, and further declines to 850 W at 7 m/s (6 < t < 8 s). Finally, when the wind speed reaches 12 m/s (8 < t < 10 s), the WT system achieves its maximum output power of approximately 2,100 W.

At this point, the wind input power is measured at around 2,350 W, indicating that the P&O–ANFIS MPPT controller achieves an efficiency of approximately 90%. This high level of performance demonstrates the capability of the intelligent control system to extract nearly all the available energy from the wind resource, even under rapidly changing wind conditions. The results confirm that integrating the ANFIS component enhances the adaptability and convergence speed of the conventional P&O algorithm, resulting in smoother transient responses and superior tracking accuracy. Overall, the P&O–ANFIS-based MPPT control exhibits robust and efficient performance in maintaining optimal energy conversion throughout varying wind speed conditions.

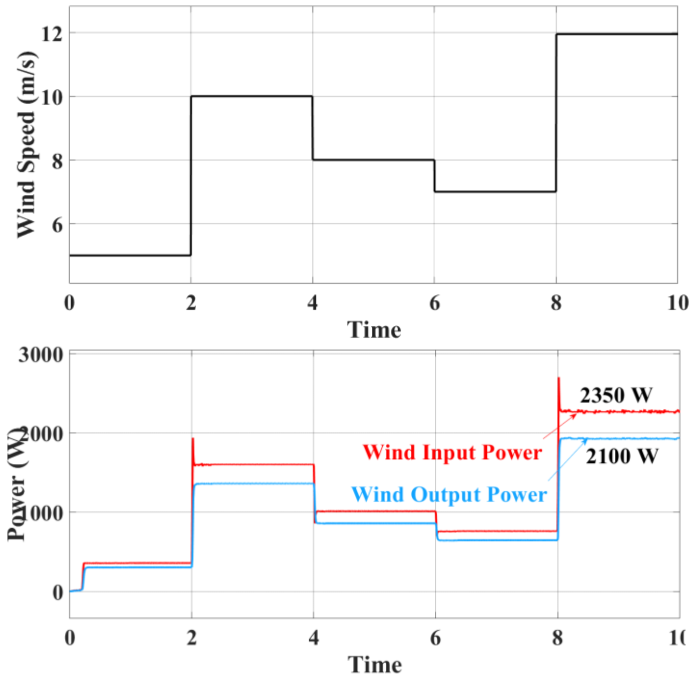

Fig.10. Wind Turbine Power Generation integrated modified P&O-ANFIS MPPT system configuration

4.3. Performance of Modified P&O-ANFIS MPPT system configuration when wind speed variation

The performance of the modified P&O-ANFIS–based MPPT control system was validated by testing the wind power generation under varying wind speed conditions. The evaluated dynamic performance parameters included steady-state time, rise time, settling time, and overshoot. The power response to

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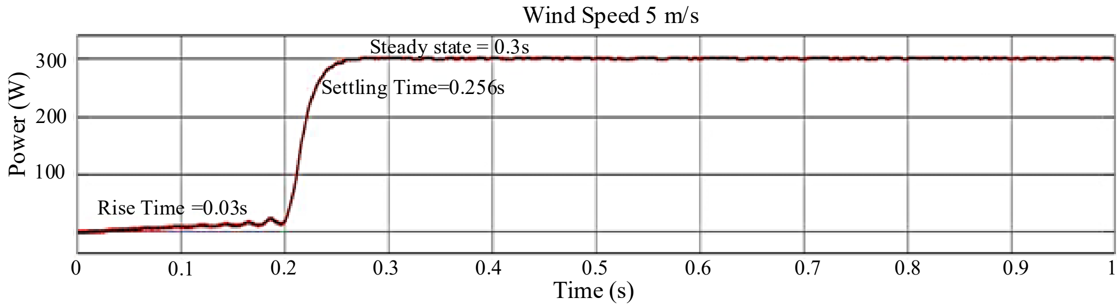
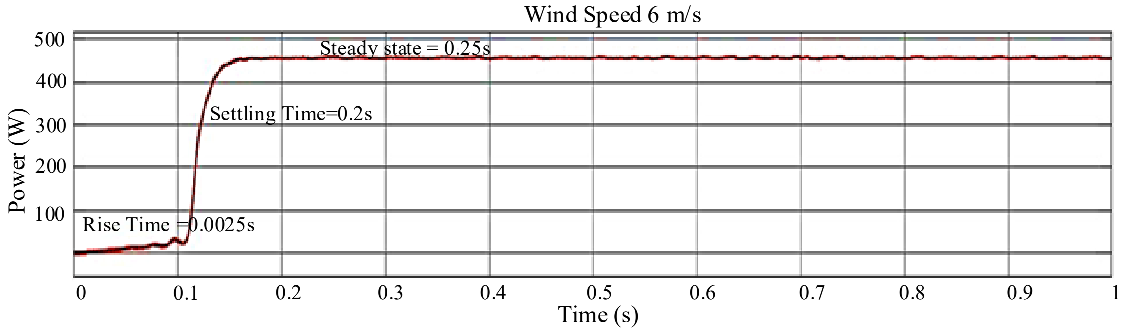
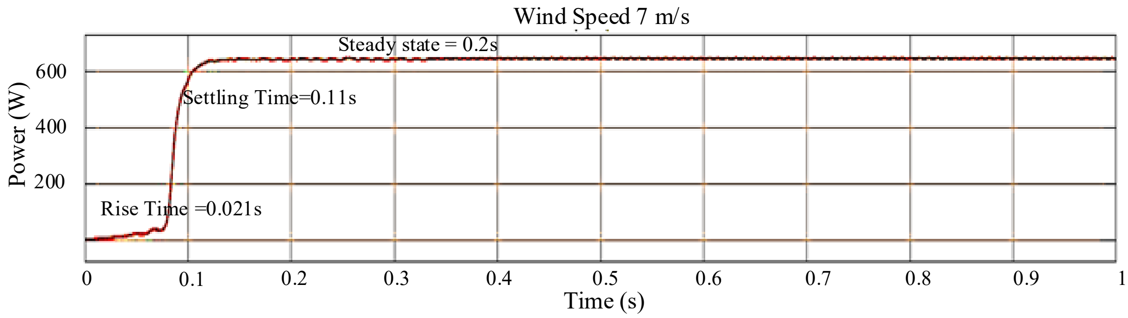
wind speed variations is presented in Fig. 11, where the wind speed was varied from 5 to 9 m/s.



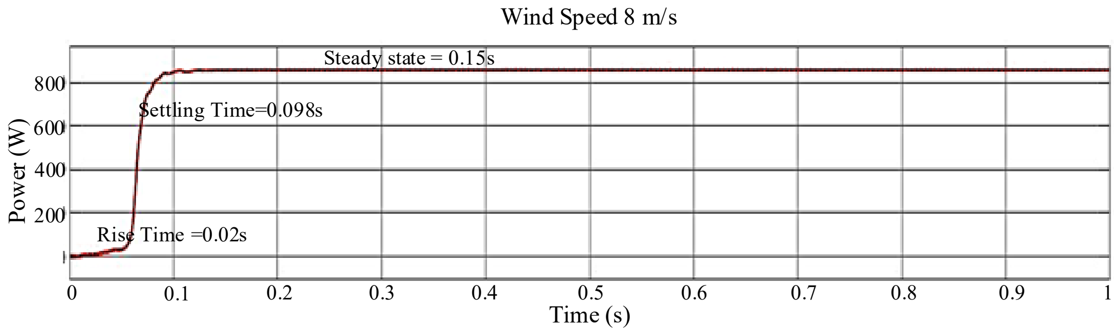
(a)



(b)



(c)



(d)

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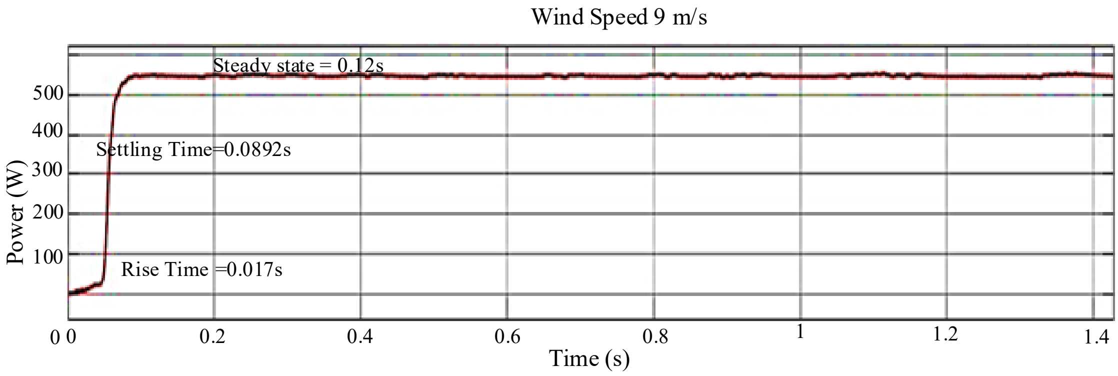

(e)

Fig.11. Wind Turbine Power Generation integrated modified P&O-ANFIS MPPT performance (a) v= 5 m/s, (b) v= 6 m/s, (c) v= 7 m/s, (d) v= 8 m/s and (e) v = 9 m/s.

The dynamic power response of the wind turbine system under various wind speed conditions is presented in Fig. 11. At a wind speed of 5 m/s, as shown in Fig. 11(a), the system exhibits a rise time of 0.033 s, a settling time of 0.256 s, and reaches steady state at 0.30 s with a maximum output power of 301.1 W. At 6 m/s, as depicted in Fig. 11(b), the rise time decreases to 0.025 s, the settling time to 0.20 s, and the steady-state time to 0.25 s, producing a peak power of 457.6 W. At a wind speed of 7 m/s, as shown in Fig. 11(c), the system achieves a rise time of 0.021 s, a settling time of 0.11 s, and reaches steady state at 0.20 s with a peak power of 642.1 W. Furthermore, Fig. 11(d) illustrates the system response at 8 m/s, where the rise time is 0.020 s, the settling time is 0.098 s, and the steady-state time is 0.15 s, resulting in a peak output power of 856.5 W. Finally, at the highest wind speed of 9 m/s, as presented in Fig. 11(e), the system demonstrates a rise time of 0.017 s, a settling time of 0.089 s, and reaches steady state at 0.08 s, delivering a maximum power of 1090 W. Overall, the average rise time, settling time and steady state time of the system are 0.023 s, 0.14 s, and 0.196 s, respectively. These results also indicate that increasing wind speed significantly reduces the time required for the system to reach the steady-state condition. The modified P&O–ANFIS achieves a significantly faster settling time than the conventional P&O method[12], reducing it from 0.5 s to 0.14 s, which corresponds to a 72% improvement in dynamic response

4.4. Performance of Wind Turbine Power Generation when load variation

The experimental test was conducted at a constant wind speed of 7 m/s, which represents the average daily wind speed in the Istanbul Island area of Demak, Central Java, Indonesia. At this wind velocity, the wind turbine (WT) demonstrated a rated power generation capacity of approximately 850 W. The system performance was evaluated under varying load conditions ranging from 700 W to 850 W to assess its operational efficiency and stability. As presented in Table 3, the input power (Pin) and output power (Pout) values were recorded for each load condition, with efficiency calculated as the ratio of Pout to Pin.

The results indicate that the WT system consistently maintains high efficiency across the tested load range. Specifically, at load conditions of 700 W, 750 W, 800 W, and 850 W, the corresponding efficiencies were 90%, 90%, 91%, and 92%, respectively. The efficiency is determined by comparing the output power with the input power of the wind turbine generation system under various load power variations. The average efficiency achieved throughout the experiment was approximately 90%, confirming the system's effective power conversion capability and minimal energy loss under typical wind conditions of the test location. These findings validate the suitability of the proposed WT system for local-scale renewable energy applications in coastal regions with moderate wind resources.

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Table 3. The Efficiency of WT System for load variation test

Pload (W)	Pin (W)	Pout (W)	Efficiency(%)
700	750	680	90
750	790	715	90
800	830	756	91
850	880	810	92

5. Conclusion

This simulation demonstrates the effectiveness of the modified P&O–ANFIS-based MPPT algorithm integrated with a DC–DC boost converter in enhancing the performance of a wind turbine (WT) power generation system. The modified P&O–ANFIS achieves a significantly faster settling time than the conventional P&O method, reducing it from 0.5 s to 0.14 s, which corresponds to a 72% improvement in dynamic response. The proposed control strategy successfully extracts the maximum available power from the WT under varying wind speed and load conditions, maintaining the system at its optimal operating point. The boost converter efficiently raises the WT output voltage from 150 V to a range of 230–600 V, enabling stable and efficient power delivery. The WT system achieves a maximum output power of 2,100 W with an average energy conversion efficiency of approximately 90%.

The results confirm that the modified P&O–ANFIS algorithm provides superior tracking accuracy and faster convergence compared to conventional MPPT methods. Future work may focus on further improving maximum power transfer capability through the integration with other artificial intelligence methods, extending the system implementation into a hybrid renewable energy configuration for microgrid implementation and include prototype implementation.

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