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A COMPARATIVE ANALYSIS OF CONVENTIONAL AND ANN-BASED MPPT ALGORITHMS FOR WIND ENERGY CONVERSION SYSTEMS

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Abstract- This paper focuses on the development of improve Wind Energy Conversion Systems (WECS) efficiency using advanced Maximum Power Point Tracking (MPPT) algorithms. Traditional methods like Perturb and Observe (P&O) and Incremental Conductance (InC) are simple but have drawbacks, such as oscillations and slow response under dynamic wind conditions. The research explores Artificial Neural Network (ANN)-based MPPT algorithms, including Levenberg-Marquardt (LM), Bayesian Regularization (BR), and Scaled Conjugate Gradient (SCG), for their ability to handle nonlinearities and adapt to variable wind profiles. MATLAB Simulink simulations evaluate these algorithms on metrics like efficiency, response time, and stability. Results show ANN algorithms outperform conventional methods, with BR achieving the highest power output, SCG excelling in speed-efficiency balance, and LM ensuring fast, accurate tracking.

Keywords: ANN, MPPT, P&O, MLI, DC to DC boost converter.

1. INTRODUCTION

Renewable energy sources (RES) have become increasingly important as alternatives to conventional energy generation, offering clean and sustainable solutions. Among these, wind energy has gained significant attention due to growing concerns about fossil fuel depletion, global warming, greenhouse gas emissions, and environmental pollution. Wind energy systems require efficient techniques to maximize power extraction under varying conditions, and Artificial Intelligence (AI)-based models provide a promising approach to achieve this. The advantage of AI-based models, particularly Artificial Neural Networks (ANN), lies in their ability to approximate the Maximum Power Point (MPP) without solving complex mathematical equations. ANNs are a key component of AI, capable of approximating any continuous nonlinear function through a multilayer network with one or more hidden layers. Their parallel design and simple structure, composed of interconnected processing elements, allow for fast and efficient computation. An ANN-based MPPT system can quickly and accurately identify the MPP under changing environmental conditions. Unlike conventional methods, ANN algorithms generalize learning experiences, enabling them to make predictions even for unseen data. This reduces online learning time and improves system efficiency. Additionally, ANNs can adapt to dynamic wind profiles, ensuring stable and precise power tracking. The proposed ANN-based MPPT system achieves fast and stable responses for real power control, outperforming conventional techniques. It ensures maximum power extraction with enhanced stability, precision, and dynamic performance under variable wind speeds. MATLAB Simulink simulations demonstrate the effectiveness of the ANN-based approach, highlighting its superior tracking efficiency and adaptability compared to traditional methods. Overall, this study emphasizes the advantages of ANN-based MPPT controllers in Wind Energy Conversion Systems (WECS), showcasing their ability to enhance power generation, optimize system performance, and contribute to the development of sustainable energy solutions.

2. DYNAMIC MODELING OF WIND TURBINE MODEL

This section outlines the modeling and control principles of the wind turbine, along with its characteristics. The power P_{wind} (in watts) extracted from the wind is given as:

$$P_{wind} = \frac{1}{2}\rho A v^3 C_p(\lambda, \theta) \tag{2.1}$$

Where ρ is the air density in kg/m^3, A is the area swept by the rotor blades in m^2, v is the wind velocity in m/s. C_p is called the power coefficient or the rotor efficiency and is function of tip speed ratio (TSR) and pitch angle (θ). The power accessible in the air which is changed into mechanical energy through wind turbine is mathematically given as

$$P = \frac{1}{2}\rho A v_w^3 \tag{2.2}$$

The effectiveness of wind energy conversion system is virtually 60 %. It preserve be analyzed at the same time as a part of kinetic energy is delivered to the rotating part and the respite of energy is wasted. The total energy changed can be scientifically interrelated to power coefficient (*Cp*). The power coefficient *Cp* is the ratio of total power changed into mechanical energy to the total power received by the wind turbine. This is shown as mathematically below

$$C_p = \frac{P_{total}}{1/2\rho A v_w^3} \tag{2.3}$$

Where P_{total} is the total power received by the wind turbine as of wind at connection. It is the maximum value of the power coefficient in wind energy conversion system. Again the power coefficient is a function of many further components such as blade arrangement, rotor blades and setting etc. hence optimized Cp is obtained by precision and accurate pact of these factors. Numerous different report of power coefficient has been worn. The accurate mathematical method for power coefficient is given as

$$C_p(\lambda,\beta) = 0.5\left(116\frac{1}{\lambda_1} - 0.4\beta - 5\right)e^{-\left(\frac{21}{\lambda_1}\right)} \tag{2.4}$$

$$\frac{1}{\lambda_1} = \frac{1}{\lambda + 0.08\beta} - \frac{0.035}{1+\beta^3} \tag{2.5}$$

In this model, the value of the pitch angle of the wind turbine is assumed as zero. The attribute of power coefficient is a role of tip speed ratio, thrust force and the rotor torque obligatory by rotor blades. The $Cp-\lambda$ characteristic shows the rotor presentation irrespective of rotor dimension and position parameters. The maximum rotor efficiency C_p is achieved at a particular TSR, which is specific to the aerodynamic design of a given turbine. Groups of C_p–curves with pitch angle as the parameter obtained by measurement or by computation can be represented as a nonlinear function. The following function is used.

$$C_p = C_1(C_2 - C_3\theta - C_4)\exp(-C_5) \tag{2.6}$$

where θ is the pitch angle.

Proper adjustment of the coefficients C_1– C_5 would result in a close simulation of a specific turbine under consideration. The values for C_1– C_5 used in this study are listed in Table 2.1. The $C_{p\text{-}\lambda}$ characteristic curves at different pitch angles are plotted, we can observe that when pitch angle is equal to 2 degrees, the tip speed ratio has a wide range and a maximum C_p value of 0.35, suitable for wind turbines designed to operate over a wide range of wind speeds. With an increase in the pitch angle, the range of TSR and the maximum value of power coefficient decrease considerably.

Table-2.1 Parameter Values for C_1 – C_5

C_1	0.5
C_2	116/kθ
C_3	0.4
C_4	5
C_5	21/ Kθ

kθ in Table 2.1 used to calculate C_2 and C_5 is determined by λ and θ:

$$k_\theta = \left[\frac{1}{\lambda + 0.08\theta} - \frac{0.035}{\theta^3 + 1}\right]^{-1} \tag{2.7}$$

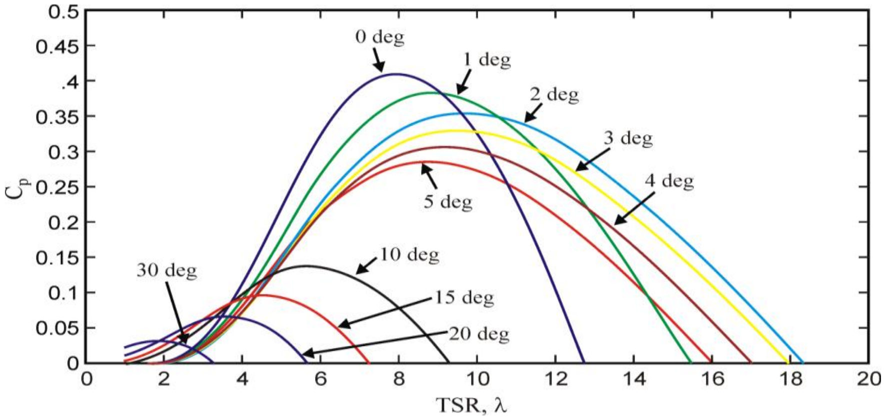

Fig. 2.1 C_p-λCharacteristics at Different Pitch Angles (θ)

From Fig. 2.1, it is plain that power coefficient increases with augment in tip speed ratio. Except when tip speed ratio increases further afar the optimized value, power coefficient starts to cry off at same slope. Hence there is only one optimized point where power extraction is maximum.

3. MODELING OF PROPOSED WIND ENERGY CONVERSION SYSTEM

In grid-connected wind power generation systems, Permanent Magnet Synchronous Generators (PMSGs) are commonly utilized due to their high efficiency and reliability. The block diagram of the ANN-based MPPT Controller for the Wind Energy Conversion System is presented in Fig. 3.1

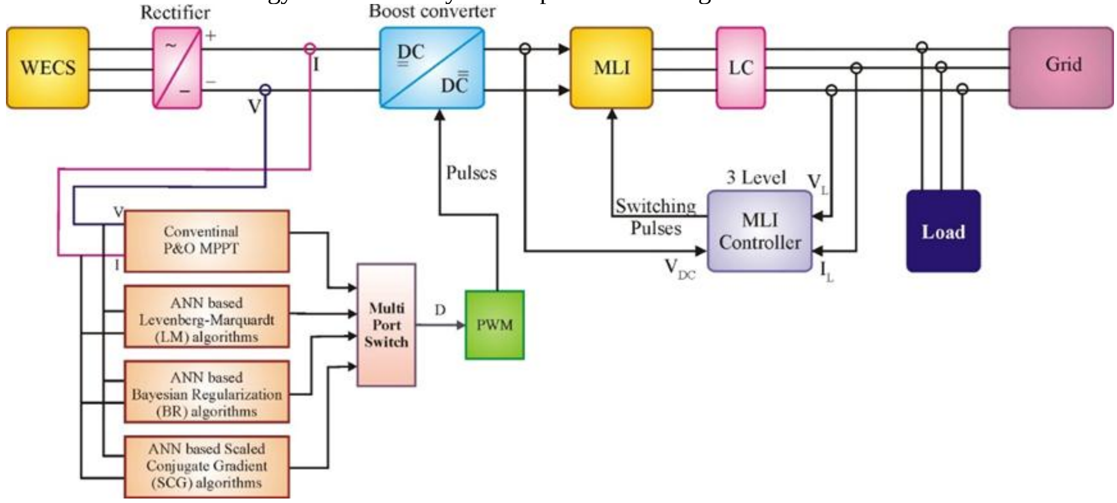

Fig. 3.1 Block Diagram of ANN MPPT Controller

Fig. 3.1 illustrates a block diagram of ANN-based MPPT Controller Wind Energy Conversion System. This system leverages renewable energy sources to provide continuous power by adapting to varying input conditions. The Wind Energy Conversion System (WECS) generates alternating current (AC) power using a Permanent Magnet Synchronous Generator (PMSG). This AC power is then converted into direct current (DC) via a rectifier, enabling the application of an Artificial Neural Network (ANN)-trained Maximum Power Point Tracking (MPPT) algorithm. To maximize power extraction, a boost converter is employed to regulate the rectified DC voltage. The ANN-trained MPPT algorithm dynamically adjusts the boost converter's duty cycle, ensuring optimal power generation even under fluctuating wind conditions. The regulated DC voltage is then supplied to a DC bus, which acts as a central power distribution hub. This DC bus efficiently powers connected loads.

The DC bus is integrated with a multilevel inverter (MLI), which converts the DC power back into AC for transmission and utilization. The MLI output is synchronized with the grid frequency to ensure seamless integration. A 2 kW fixed load is connected to the transmission line, demonstrating the system’s ability to deliver consistent power under steady-state operating conditions. Driven by variable wind speeds, the wind turbine generates AC power, which is processed by the AC-to-DC converter for compatibility with the DC bus. The use of the ANN-trained MPPT algorithm enhances the system’s efficiency and performance, even under dynamic wind profiles. This design ensures effective interfacing between the wind turbine's power output and load demands, highlighting the reliability and robustness of the proposed control strategy. Block Diagram of ANN based MPPT controller scheme is shown in Figure 3.1 and Figure 3.2 shows the architecture of the ANN based MPPT for WECS.

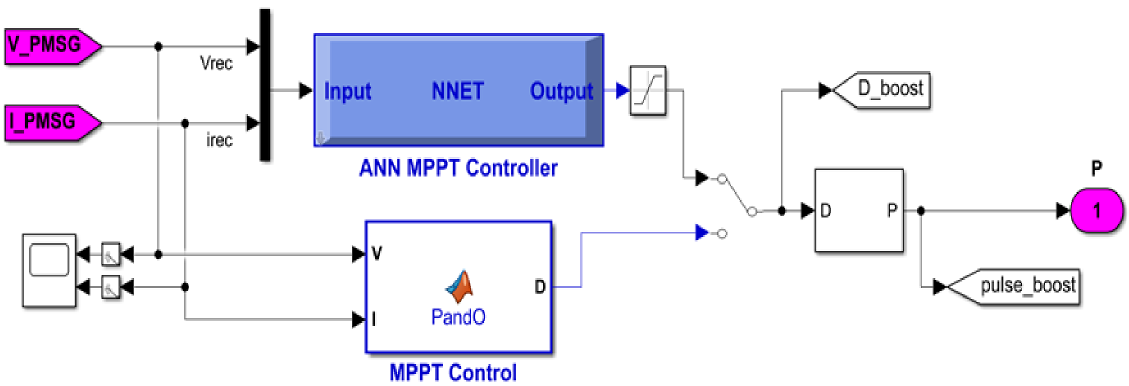

Fig. 3.2 Simulink block diagram of ANN based MPPT for WECS

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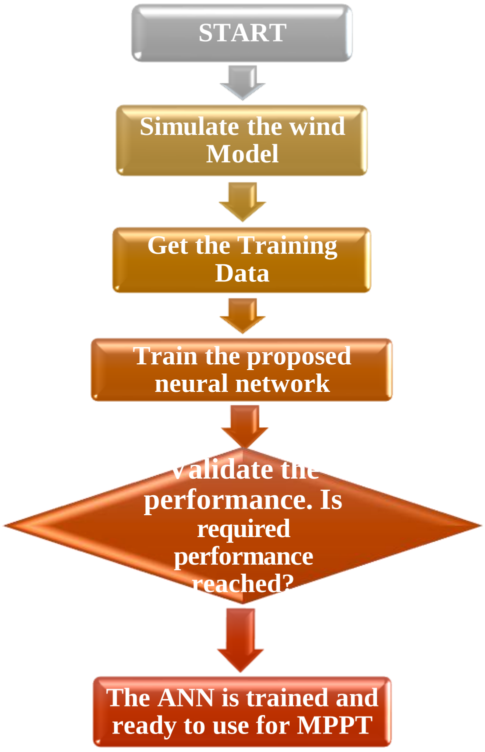

Fig. 3.3 Flow chart for Training Procedure of ANN based MPPT for WECS

To extract the maximum power from wind system, artificial neural network based MPPT is proposed. The basic architecture of ANN consists of three layers as an input layer, hidden layer and output layer. The basic architecture of ANN is shown in Figure. 3.4.

ANNs are used in MPPT system as it can provide accurate and fast response for different input and output conditions.

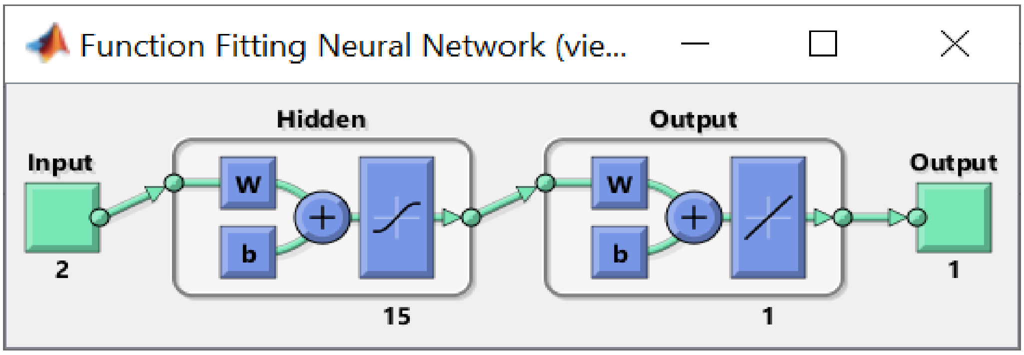

Fig. 3.4 Architecture of ANN

4. SIMULINK RESULT OF ANN BASED MPPT CONTROLLER FOR WECS

This paper presents a comparative analysis of simulation results for wind energy conversion systems (WECS) using different MPPT (Maximum Power Point Tracking) algorithms. The focus is on comparing Artificial Neural Network (ANN)-based MPPT algorithms—Levenberg-Marquardt, Bayesian Regularization, and Scaled Conjugate Gradient (SCG)—with the conventional Perturb and Observe (P&O) MPPT algorithm. The simulations, performed in MATLAB/Simulink, evaluate the performance of these algorithms under various wind conditions. Key parameters such as system stability, reliability, and efficiency are analyzed to highlight the advantages and limitations of each MPPT approach. This study aims to provide insights into the effectiveness of ANN-based MPPT algorithms compared to conventional methods for optimizing the power output of WECS in diverse operating conditions.

4.1 Simulation Result for Comparative simulation results of ANN and P&O MPPT algorithm during step change in wind speed from 8-12-8m/s

In this case, the wind speed undergoes step changes from 12 m/s to 8 m/s and then back to 12 m/s at 0-7-14-20 seconds, the comparative simulation results highlight several key performance metrics. Initially, at 12 m/s wind speed from 0 to 7 seconds, the Permanent Magnet Synchronous Generator (PMSG) rotor speed stabilizes around

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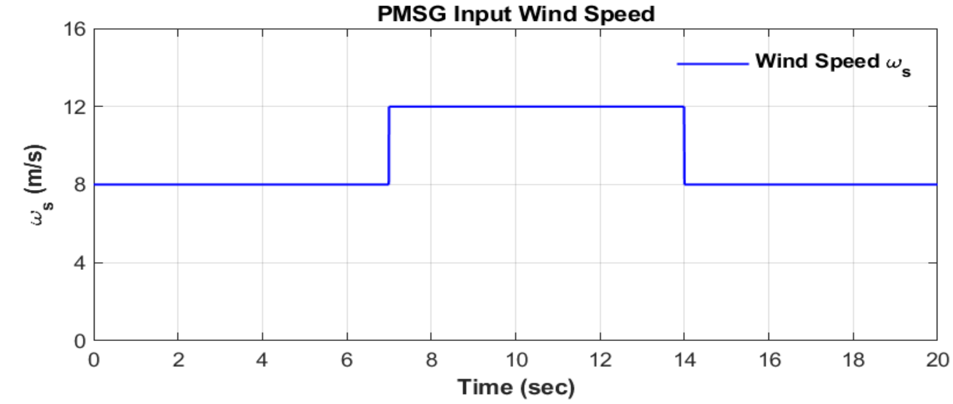
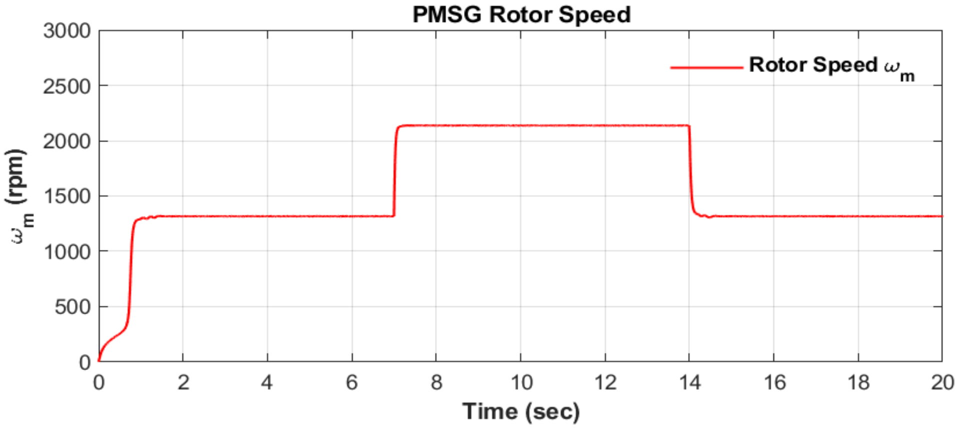
2200 rpm as shown in figure 4.1 (a) & (b). As shown in figure 4.2 (a) & (b), the PMSG phase-to-phase voltage and current show minimal variation across the different Maximum Power Point Tracking (MPPT) algorithms, indicating stable operation, respectively. At 8 m/s wind speed, from 7 to 14 seconds, the PMSG rotor speed drops to around 1350 rpm, as shown in figure 4.1 (a) & (b). The phase-to-phase voltage and current respond according to the wind speed changes, as shown in figure 4.2 (a) & (b).

When the wind speed returns to 12 m/s from 14 to 20 seconds, the PMSG rotor speed stabilizes again at around 2200 rpm. The phase-to-phase voltage and current remain consistent with the previous steady-state conditions.

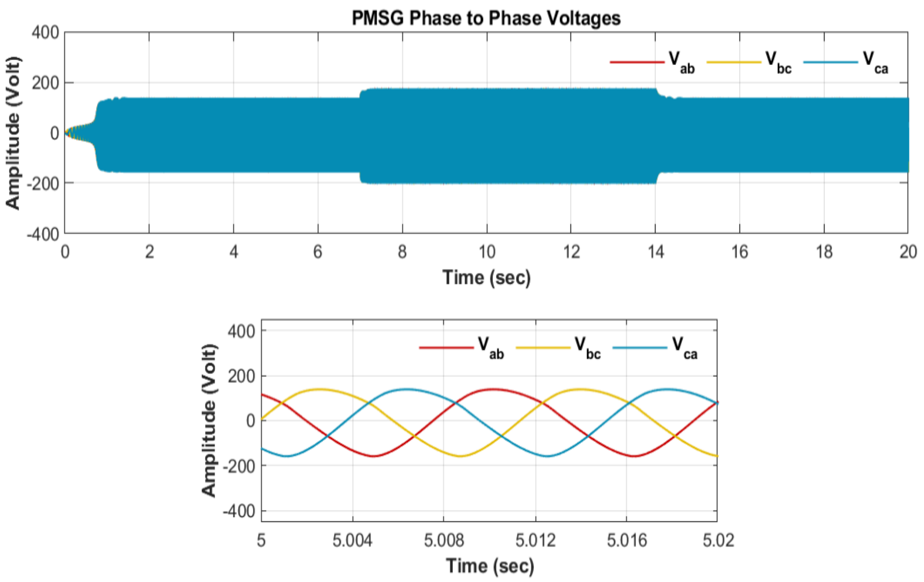


(a)



(b)

Fig. 4.1 Simulation results of PMSG, (a) input wind speed and, (b) rotor speed



(a)

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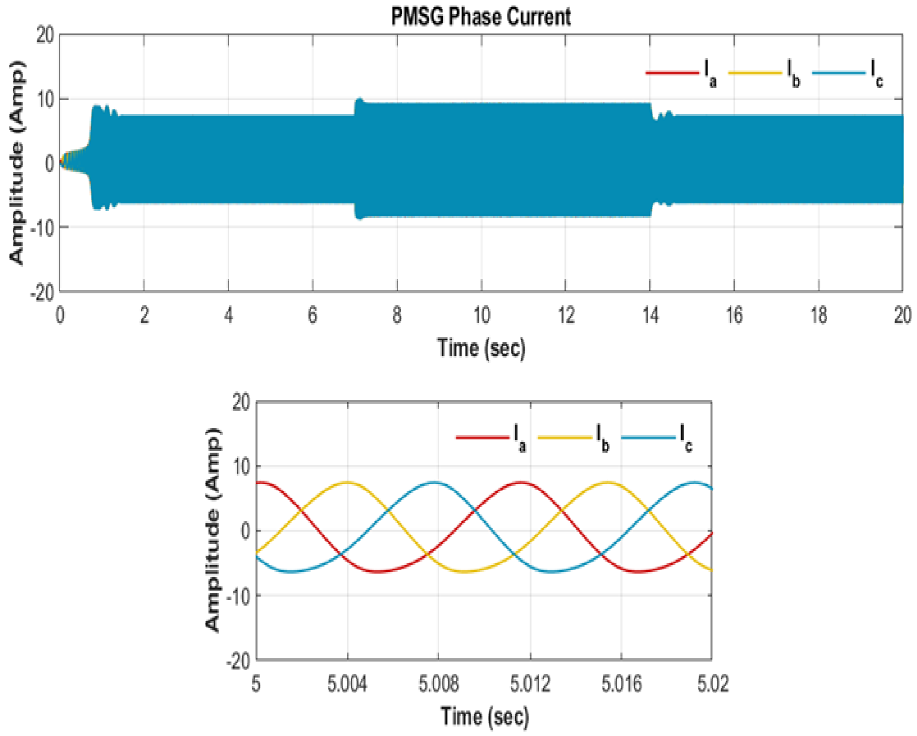
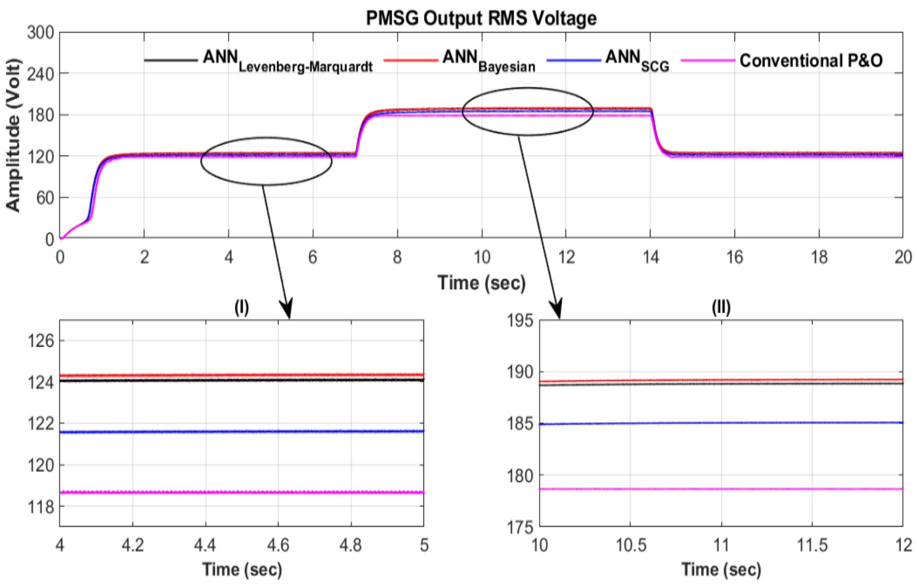


(b)

Fig. 4.2 Simulation results PMSG, (a) phase-phase voltage and, (b) phase current

As shown in figure 4.3 (a) & (b), at 12 m/s wind speed from 0 to 7 seconds, the RMS voltage (V_{RMS}) values are: Bayesian Regularization (189.2 V), SCG (185.1 V), Levenberg-Marquardt (188.9 V), and P&O (178.6 V). The RMS current (I_{RMS}) values are: Bayesian Regularization (8.362 A), SCG (8.274 A), Levenberg-Marquardt (8.375 A), and P&O (7.36 A), respectively. At 8 m/s wind speed, from 7 to 14 seconds, The RMS voltage (V_{RMS}) values show: Bayesian Regularization (124.4 V), SCG (121.6 V), Levenberg-Marquardt (124 V), and P&O (118.6 V). The RMS current (I_{RMS}) values are: Bayesian Regularization (5.549 A), SCG (5.49 A), Levenberg-Marquardt (5.542 A), and P&O (4.829 A).

When the wind speed returns to 12 m/s from 14 to 20 seconds, the RMS voltage (V_{RMS}) values are: Bayesian Regularization (189.2 V), SCG (185.1 V), Levenberg-Marquardt (188.9 V), and P&O (178.6 V). The RMS current (I_{RMS}) values are: Bayesian Regularization (8.362 A), SCG (8.274 A), Levenberg-Marquardt (8.375 A), and P&O (7.36 A).



(a)

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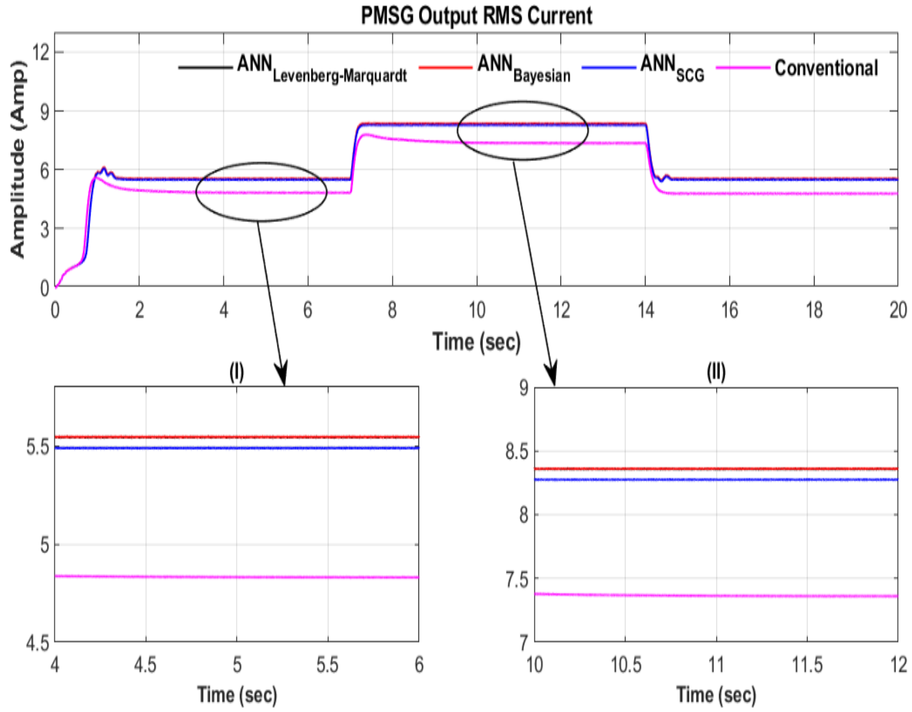

(b)

Fig. 4.3 Simulation results PMSG, (a) RMS voltage and, (b) RMS current

When considering the PMSG power output as shown in Figure 4.4, Bayesian Regularization achieves the highest power output at 1139 W at 8 m/s wind speed from 7-14 sec, followed closely by Levenberg-Marquardt at 1141 W, SCG at 1128 W, and P&O at 1040 W. The same trend is observed at 12 m/s wind speed from 0-7 sec & 14-20 sec, with Bayesian Regularization still showing the highest power output at 2588 W, followed by SCG at 2560 W, Levenberg-Marquardt at 2587 W, and P&O at 2408 W. These findings highlight the superior performance of the ANN-based MPPT algorithms in terms of power extraction efficiency and stability across varying wind speeds.

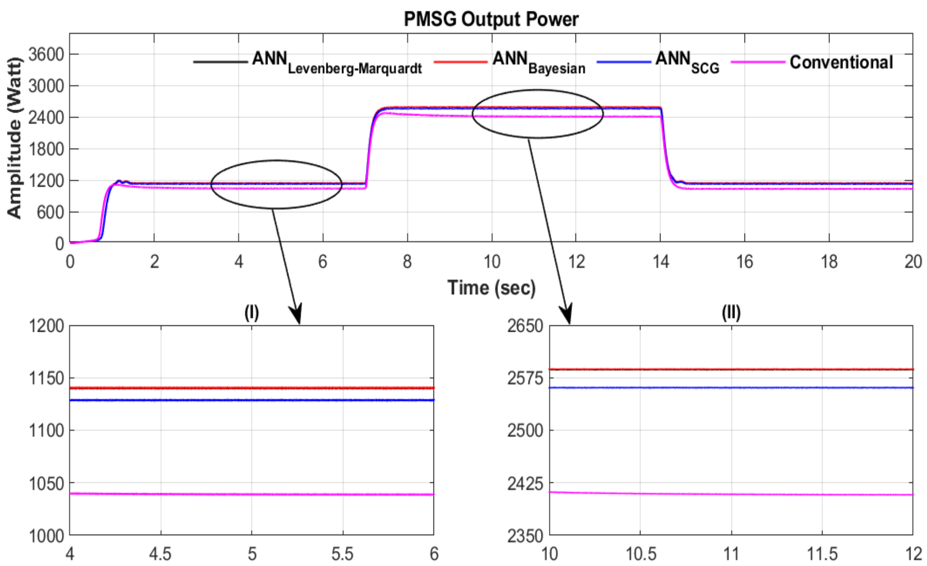

Fig. 4.4 Simulation results PMSG output power

These findings underscore the effectiveness of ANN-based MPPT algorithms in adapting to fluctuating wind conditions, optimizing power extraction, and maintaining a consistent maximum power point tracking performance, which is critical for the efficient operation of the wind energy conversion system.

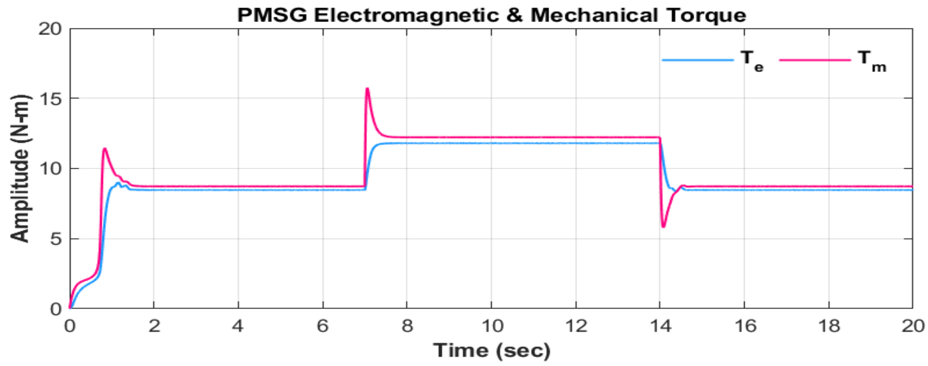

Fig. 4.5 Simulation results PMSG electromagnetic and mechanical torque

Figures 4.5 and 4.6 show the waveforms of the PMSG electromagnetic torque (T_e) and mechanical torque (T_m), which changes according to PMSG rotor speed, and the boost converter duty cycle generated by all MPPT algorithms, respectively. The duty cycle generated by the ANN algorithms (Levenberg-Marquardt, Bayesian Regularization, and SCG) is almost identical, maintaining an amplitude around 0.7. In contrast, the duty cycle generated by the P&O method is around 0.1 amplitude.

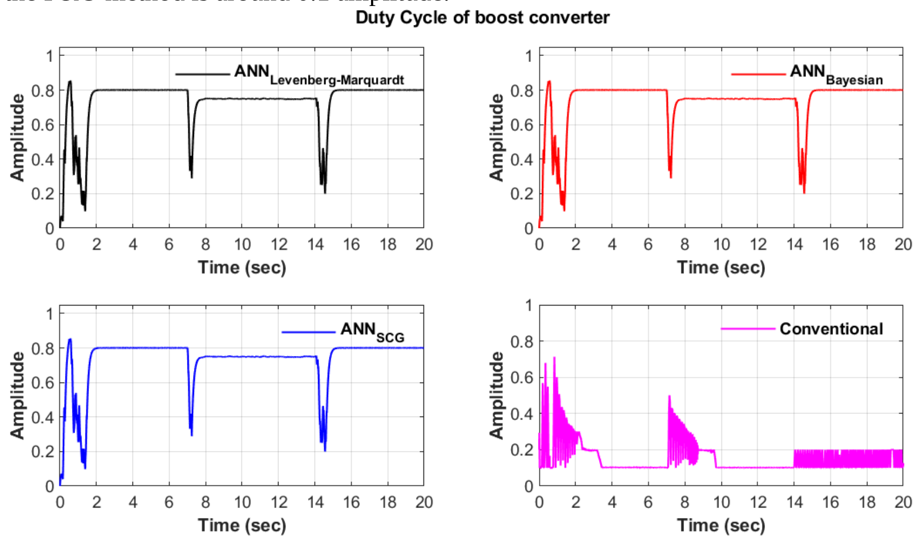

Fig. 4.6 Simulation results of Boost converter duty cycle

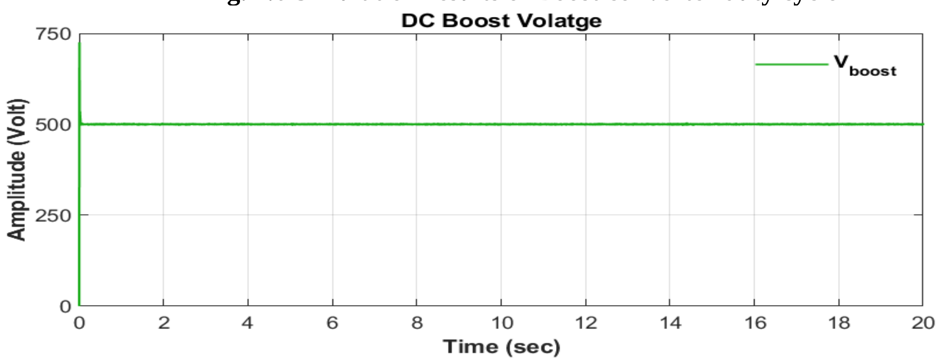

Fig. 4.7 Simulation results boost converter DC voltage

Figure 4.7 displays the waveform of the DC boost voltage, which is approximately 500 V for all the MPPT algorithms. The performance of various MPPT algorithms was evaluated under wind speed variations from 8 m/s to 12 m/s and back to 8 m/s at different intervals. A comparative analysis was conducted on the PMSG output power generated by ANN-based MPPT algorithms—Bayesian Regularization, SCG, and Levenberg-Marquardt—and the conventional Perturb and Observe (P&O) algorithm. The results demonstrate that, at every wind speed interval, the output power generated by ANN-based MPPT algorithms consistently exceeds that of the P&O algorithm. Among the ANN approaches, Bayesian Regularization achieves the highest power output, followed by SCG and Levenberg-Marquardt, while the P&O algorithm delivers the lowest output. This analysis underscores the superior efficiency and reliability of ANN-based MPPT algorithms, particularly Bayesian Regularization, in optimizing power extraction from the PMSG under dynamic wind conditions.

CONCLUSION

This paper aims to develop an ANN-based MPPT algorithm for a PMSG-based wind energy conversion system (WECS) integrated with a grid model and simulate it using MATLAB/Simulink. The system is analyzed under various wind speed profiles, demonstrating that the rotor speed of the PMSG dynamically adapts to changing wind conditions, leading to variations in electrical parameters such as voltage and current. ANN-based MPPT algorithms, particularly Bayesian Regularization, outperform the conventional P&O algorithm, achieving higher power output and better stability, especially at higher wind speeds. These algorithms ensure precise control of electromagnetic torque and boost converter duty cycles, maintaining system stability and a steady DC voltage of approximately 500V. The proposed approach enhances system performance under steady-state, transient, and dynamic conditions, offering efficient, stable, and adaptive power extraction. Overall, ANN-based MPPT algorithms significantly improve power tracking and system stability in variable wind environments compared to conventional methods.

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