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Comparative Analysis of MPPT Techniques for PMSG-Based Wind Energy Systems Using ANN and P&O Algorithms

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Abstract – This paper presents a comprehensive comparative study of Maximum Power Point Tracking (MPPT) techniques for wind energy systems utilizing a Permanent Magnet Synchronous Generator (PMSG). The objective is to enhance energy harvesting efficiency in fluctuating wind conditions through improved MPPT strategies. Traditional Perturb and Observe (P&O) algorithms, known for their simplicity and low computational requirements, are evaluated against Artificial Neural Network (ANN)-based MPPT controllers, which leverage machine learning to adaptively optimize power output. Using MATLAB/Simulink, a detailed simulation model incorporating wind turbine aerodynamics, PMSG dynamics, full-bridge rectification, and double boost DC-DC conversion was developed. The P&O method exhibited notable power oscillations and slower response to wind speed changes. In contrast, the ANN-based MPPT, trained on real meteorological data, demonstrated superior performance with faster convergence, higher tracking accuracy, and reduced ripple. The hybrid integration of P&O and ANN approaches further balanced computational complexity with efficiency. Additionally, a stationary battery storage system with a bidirectional DC-DC converter was implemented to assess energy storage capability for electric vehicle charging. Simulation results validate the ANN-based controller's effectiveness under variable wind profiles, making it a viable candidate for real-time wind power applications. This study highlights the transformative potential of AI in renewable energy systems and emphasizes the importance of integrating smart control algorithms for optimal wind energy conversion. Future work will focus on real-world implementation and economic evaluation under diverse atmospheric conditions.

Keywords – Wind Energy, MPPT, PMSG, Artificial Neural Networks, Perturb and Observe, MATLAB/Simulink, Energy Storage.

I. INTRODUCTION

The global shift to renewable energy has established wind power as a prime source of sustainable power generation. Among wind energy conversion systems (WECS), the Permanent Magnet Synchronous Generator (PMSG) has been the center of attention due to its small size, high torque-to-weight ratio, and minimal mechanical losses. However, the fluctuating nature of wind speed is a primary concern in maximum power extraction. To address this, Maximum Power Point Tracking (MPPT) methods are employed to ensure that the system operates at maximum efficiency in different conditions [1]. Conventional MPPT methods such as Perturb and Observe (P&O) remain popular due to their ease of implementation and minimal computational requirements.

Despite numerous advantageous traits, they exhibit notable drawbacks in the form of persistent oscillations at the maximum point (MPP) and sluggish convergence during sudden changes in wind. Modern advances in computational intelligence have introduced Artificial Neural Networks (ANNs) as a potential substitute, leveraging their ability to map intricate nonlinear relationships and learn in uncertain environments. Compared to traditional approaches, ANN-based MPPT has the potential to predict optimal operating points with better accuracy, reducing energy loss and improving transient response [2],[3].

The use of artificial intelligence (AI) in wind energy systems has opened new horizons towards optimizing MPPT efficiency. AI-based techniques, such as ANNs, offer instant adaptation to changes in the surroundings, with better efficiency compared to the conventional method. While P&O is a popular reference because of its simplicity in implementation, its lack of capability to deal with rapidly changing conditions supports the need for advanced solutions [4].

This paper presents comparative simulation analysis of P&O and ANN-based MPPT approaches for a PMSG-based WECS through simulations in MATLAB/Simulink, comparing their performance based on tracking precision, dynamic behavior, and energy harvesting. The research contributes towards ongoing improvement of wind turbine control systems.

II. MATERIALS AND METHOD

A. Wind Energy System Modeling

The wind turbine model considers three inputs pitch angle, wind velocity, and generator speed with wind speed and pitch angle fixed at 12 m/s and 0 degrees, respectively. The generator operates as a motor when mechanical torque is positive and as a generator when torque is negative. The generator speed is converted to per unit (PU) by dividing by the base value $\frac{8.1\times 12}{1.3}$,while the turbine torque ($T=\frac{p}{w}$) in PU is scaled to its real value before being fed into the PMSG. The generator's AC output is rectified using a MATLAB universal bridge, followed by a double boost converter to increase the DC voltage, where voltage and current measurements determine power output. A P&O MPPT algorithm generates switching signals for the boost converter, comparing them with a repetitive sequence for optimal control [14].

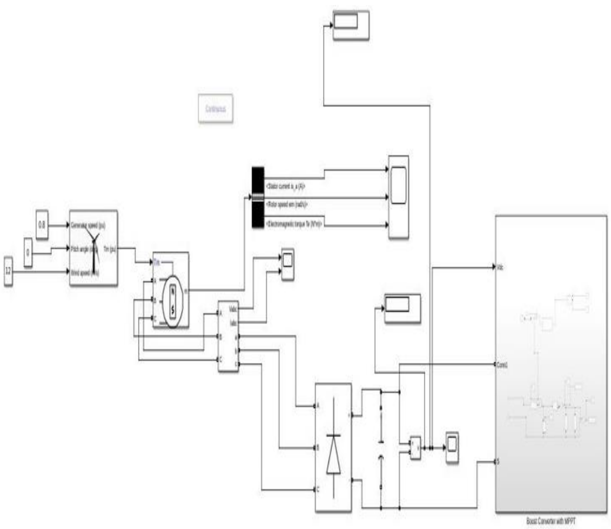

Figure 1 wind power generation simulink

Figure 1 illustrates the Simulink model representing both the mechanical and electrical components of the wind power generation system implemented in MATLAB.

B. PMSG Wind Modeling

As seen from Figure 1, The wind turbine model considers three inputs—pitch angle, wind velocity, and generator speed—with wind speed and pitch angle fixed at 12 m/s and 0 degrees, respectively. The generator operates as a motor when mechanical torque is positive and as a generator when torque is negative. The generator speed is converted to per unit (PU) by dividing by the base value.

$w_{pu} = \frac{w_g}{w_{base}}$= (8.1×12)/1.3 = 74.77rad/s

while the turbine torque $Tm,\ actual = Tm,pu \cdot Tbase$ in PU is scaled to its real value before being fed into the PMSG. The generator's AC output is rectified using a MATLAB universal bridge, followed by a double boost converter to increase the DC voltage, where voltage and current measurements determine power output $p_{dc} = v_{dc} \cdot i_{dc}$ A P&O MPPT algorithm generates switching signals for the boost converter, comparing them with a repetitive sequence for optimal control.

1) *Aerodynamic of a WT Modelling*

The WT transforms energy of wind into mechanical energy, as seen in equation (1) [6].

$$P_m = \frac{1}{2} C_p(\lambda, \beta) A \rho v^3$$

Furthermore, when the pitch angle is constant, the available turbine mechanical torque (Tm) should simply be represented as equation (2):

$$T_m = \frac{\frac{1}{2} C_p(\lambda) A \rho v^3}{\omega_m}$$

Where is the pitch angle in degrees, v is the wind speed (m/s), the WT power coefficient, is the air density (usually 1.225 kg/m3), and A is the swept area of the rotor blades (m2). The tip velocity ratio is given elsewhere as below [7].

$$\lambda = \frac{W_m \cdot R}{v} \qquad (3)$$

Where the W is turbine's rotating speed, and R is the rotor blade's radius.

C. MPPT Technique

The wind energy variability is caused by varying wind speeds. The following analysis takes into account a WT system with three inputs: pitch angle (maintained at 0°), wind speed (maintained constant at 12 m/s), and generator speed. The latter is derived from a Permanent Magnet Synchronous Generator (PMSG), which operates as a generator when negative mechanical torque is applied and as a motor when positive torque is applied. The generator speed, initially in rad/s, is converted to per unit (PU) on the basis of a base value of (8.1×12)/1.3(8.1×12)/1.3. The turbine mechanical torque (Tm) in PU is divided by its base value to determine the actual torque to be given to the PMSG. The PMSG produces a three-phase AC output where voltage, current, and power are measured. This AC output is converted by a universal bridge and further processed by a double boost converter (DBC) for DC voltage stepping up [8].

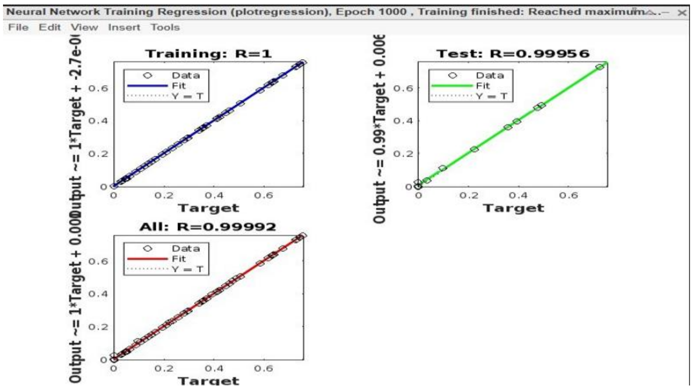

Figure 2 Performance plot of regression analysis for the training, testing, and validation datasets.

Figure 2 demonstrates the regression analysis for the training, testing, and validation datasets. This plot highlights the accuracy of the NN in predicting the duty cycle adjustments, ensuring that the wind power system operates at maximum efficiency.

D. P&O algorithm

The WT is established in this segment, together with P&O controlling methodologies employing DBC and it is modeled in Matlab program. The network has three inputs and one output, which can be seen in Figure 9. The rotor's measurement of the generator's velocity is the initial input. Pitch angle is determined in °, and we'll employ 0 degrees in this experiment. The velocity of wind in meters per second is the 3rd parameter, which has been adjusted for the constant (12 m/s) simulated conditions. The WT output is mechanical torque, which is passed through an LPF (low pass filter) as seen in figure 12. After that, the turbine is linked to the PMSG generator.

To examine the effectiveness assessment of P&O MPPT, comparison research on WT is performed employing MATLAB/Simulation. Modeling the system to feed a DC load at 220V while maintaining the air velocity consistent at 12 m/s.

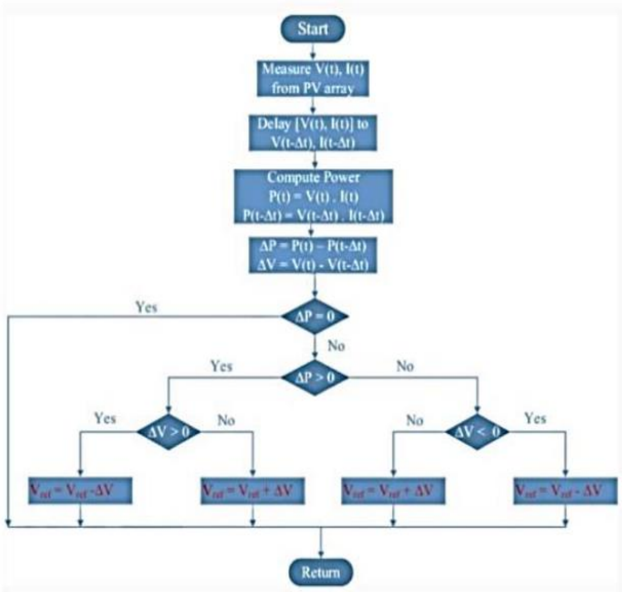

Figure 3: Flow diagram of P&O algorithm

E. Converter

Modelling The boost converter is being employed to generate a significant sustained output voltage that exceeds the input voltage. To accomplish the appropriate voltage, a DBC can be employed. A single switch controls the basic classic DC/DC converter, Boost. A boost converter which comprises of a capacitor, a switch, a diode, and an inductor. The diode seems to become reverse biased when the circuit is powered on, boosting current and charges the inductor, which is maintained by a capacitor. The diode becomes forward biased when the machine is powered off, [9], [10]

And the current in inductor decreases; the charge of capacitor rises; and the & DC source inductor sustain the load & the capacitor. The DBC is modeled as follows [11].

$$V_o = \frac{V_i}{1 - D}$$

Where Vo signifies output voltage while the Vi denote the input voltages, correspondingly. The duty cycle is denoted by the letter D. The DBC's capacitor and inductor are estimated by:

$$L = \frac{V_{i,min}}{\Delta I_L \cdot f_s} \cdot D$$

2) *Stationary Storage with Bidirectional DC-DC Boost Converter*

Bidirectional DC-DC converters are commonly used to enable energy storage in battery systems. These converters are generally categorized into two types: isolated and non-isolated configurations. In this study, the electrical power generated by the wind turbine is stored in a stationary battery system, which is subsequently used to charge an electric vehicle (EV) battery during nighttime hours. At 240 V, 40 Ah lithium-ion battery is selected as the stationary storage medium. [12]

The equivalent circuit diagram of the DC-DC boost converter utilized in the system is illustrated in Figure 5.

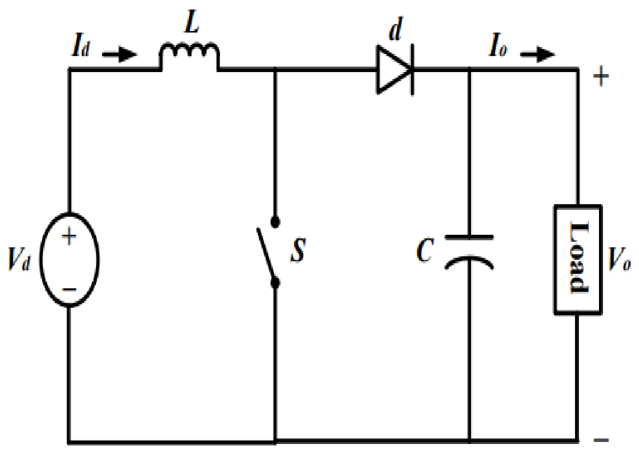

Figure 5: Equivalent circuit diagram of the DC-DC boost converter.

Table 1

PARAMETERS OF THE WIND TURBINE	
RATED POWER	5.3 KW
CP	0.45
RADIUS	0.5 M
SWEPT AREA	3000.3 ㎡
CUT-IN WINDSPEED	3.0 M/S
RATED WINDSPEED	12.0 M/S
CUT-OUT WINDSPEED	25.0 M/S
AIR DENSITY	1.225 KG/M³
RATED FREQUENCY	50 HZ

Table 2 Parameters Of The Training Wheather

DATE	WIND SPEED (M/S)	TEMPERATURE (°C)	PRESSURE (HPA)
2023-03-01	5.0	25.0	1015
2023-03-02	5.5	24.8	1016
2023-03-03	6.0	24.5	1017
2023-03-04	6.5	24.2	1018
2023-03-05	7.0	24.0	1019
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2023-04-30	35.5	20.0	1025

Table 3

PARAMETERS OF THE PHYSICAL WT	
BLADERS	3 --14*21
GENERATOR	BLDC
VOLTMETER	DIGITAL
RECTIFIER	FULL BRIDGE

III. RESULTS AND DISCUSSION

This study integrates a dual approach for wind power optimization using both Simulink-based system modeling and Artificial Neural Networks (ANN). The Simulink model simulates the wind turbine dynamics, PMSG generation, rectification, and DC-DC conversion using MPPT control. Key control logic includes Perturb & Observe (P&O;) MPPT algorithms and Boost converter modulation. ANN is applied to forecast power generation based on meteorological variables including wind speed, pressure, and temperature. Data is normalized using z-scores before training. The ANN has two hidden layers (64 and 32 neurons) and is trained using 80% of collected data.

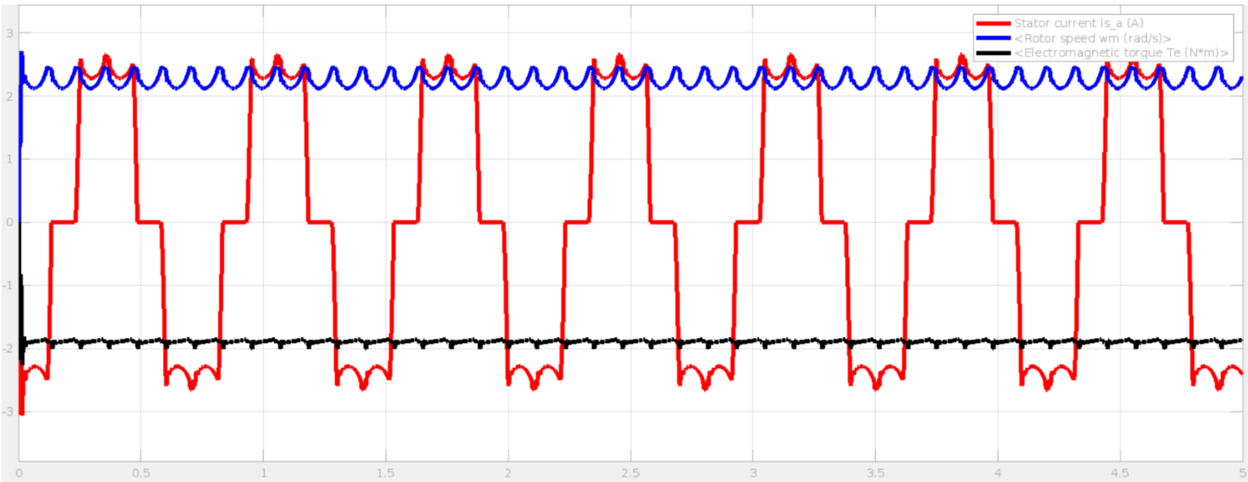
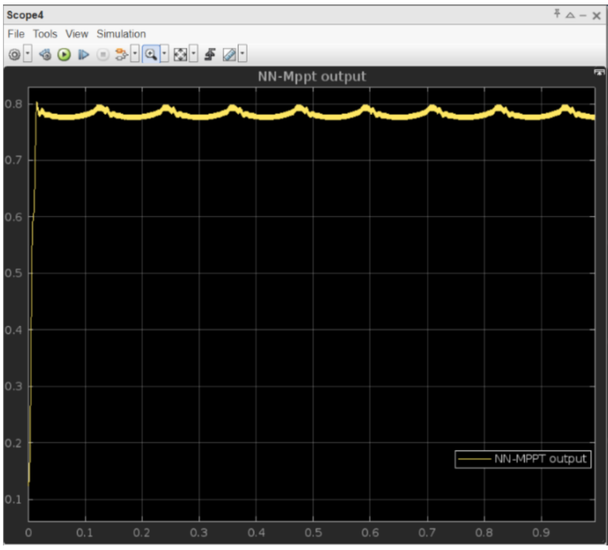


Figure 6. Stator Current, Rotor Speed, and Torque in PMSG

Figure 6 shows the stator current (red), rotor speed (blue), and electromagnetic torque (black) of a simulated Permanent Magnet Synchronous Generator (PMSG) under MATLAB. The machine is evaluated on AI-based MPPT algorithms: Perturb and Observe (P&O) and Neural Network (NN). Stator current captures evident switching nature, while rotor speed is generally constant with some ripple, indicating successful power harvesting. The electromagnetic torque remains constant at -2 Nm, with focus on steady performance. The dynamics of the waveform suggest that NN-based MPPT exhibits smoother dynamics and convergence than P&O and hence is more appropriately suited for application in real-time adaptive control.

These graphs 7 & 8 is a comparison of NN-MPPT (left) and P&O MPPT (right) controller outputs of a PMSG-based system. The Neural Network (NN) MPPT responds faster and to a higher level, settling to 0.8 with lower oscillation. This indicates superior tracking capability and dynamic response towards irradiance change. In contrast, the P&O algorithm converges at 0.6 and demonstrates larger fluctuation and slower settling tendency, meaning lower tracking efficiency and disturbance sensitivity. In general, the NN-based MPPT possesses better performance in speed, stability, and accuracy and hence is more suitable for real-time and variable operating conditions.



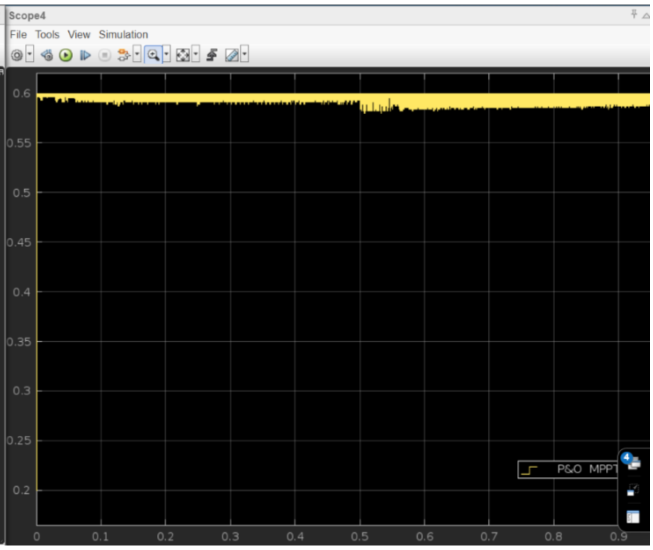


Figure 7.NN-MPPT OUTPUT

Figure 8. P&O MPPT OUTPUT

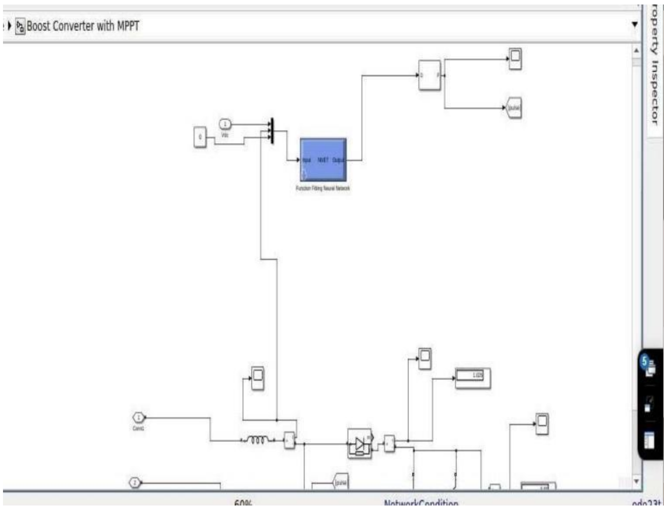


Figure 10: ANN-MPPT

Figure 11: PROTOTIP WIND TURBINE

IV. CONCLUSION

This paper emphasizes the need for MPPT algorithm optimization to get the maximum energy harvesting from PMSG-based wind power systems. While conventional P&O is a convenient option due to its simplicity and minimal computational load, drawbacks are that there is resonance near the maximum power point along with a less-than-optimal dynamic performance during sudden wind gusts. ANN-based MPPT controllers overcome these issues satisfactorily by modeling nonlinear relations and adapting in real time to changing environmental conditions, leading to faster stabilization and reduced power oscillation. Hybrid MPPT techniques enhance performance further by merging the strengths of both methods. Despite the added computational requirements of ANN techniques, their established gains in energy output and tracking precision make them well worth implementing in modern wind systems. Future studies must focus on comprehensive economic analyses and experimentation under extreme turbulence to assess in full the real-world practical benefits of ANN-based MPPT.

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