Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Per Unit-Based Neural Network Control for MPPT of Wind Turbines: Reducing Data Needs and Enhancing Generalization

Berbara Djilali, Meharrar Aoued, Sahnoune Ahmed
Laboratory of Electrical Engineering, Computer Science, and Applied Mathematics
Sciences and Technology Department
Faculty of Science and Technology
Tissemsilt University- AHMED BEN YAHIA ELWANCHARISSI - Algeria

ARTICLE INFO

Received: 18 Nov 2024

Revised: 10 Jan 2025

Accepted: 26 Jan 2025

ABSTRACT

Artificial Neural Networks (ANNs) offer a highly adaptive and precise approach to tracking the Maximum Power Point (MPPT) of wind turbines. Despite their advantages, achieving effective generalization with ANNs often requires significant computational resources—especially when dealing with large datasets—and depends critically on the careful selection of input and output variables to ensure optimal performance.

In this study, we developed an ANN-based MPPT controller for wind energy conversion systems. The proposed network uses wind speed, mechanical power, and turbine rotational speed as input variables, while the output is the rotational speed expressed in Per Unit (PU). This PU-based representation not only simplifies the training process but also enhances the learning efficiency and generalization capability of the network across different wind turbine configurations.

Simulation results demonstrate that the proposed ANN controller provides accurate and robust performance in tracking the maximum power point, highlighting its potential as an effective solution for intelligent wind energy management.

Keywords: ANN, MPPT, wind turbine, Per Unit, Big Data.

1. INTRODUCTION

Given the increasingly alarming environmental consequences associated with the continued reliance on fossil fuels—such as greenhouse gas emissions, global warming, and air pollution—the transition toward renewable energy sources has emerged not only as a strategic choice but also as an unavoidable necessity. Renewable energy systems offer a sustainable alternative by producing electricity without emitting carbon dioxide or other harmful atmospheric pollutants. Their utilization significantly contributes to reducing the ecological footprint of energy production and supports the global effort to combat climate change. Furthermore, the ongoing development and integration of renewable energy technologies into national and international energy portfolios play a pivotal role in facilitating the ecological transition, ensuring energy security, and preserving the environment for future generations [1–3].

Among the wide array of renewable energy sources, wind energy has gained considerable attention due to its abundance, renewability, and inherently eco-friendly characteristics. It presents a clean, efficient, and economically viable solution for electricity generation. The harnessing of wind energy involves a conversion chain that transforms the kinetic energy of the wind into mechanical energy through the rotation of turbine blades, which is subsequently converted into electrical energy by an electric generator. This process, while conceptually straightforward, is subject to several technical challenges that must be addressed to optimize energy extraction.

One of the critical challenges in wind energy systems lies in the inherently nonlinear nature of the mechanical power output of wind turbines, which varies with wind speed and turbine characteristics [4]. This nonlinearity necessitates the implementation of maximum power point tracking (MPPT) techniques to ensure that the turbine operates at its optimal power point under varying wind conditions. Several MPPT algorithms have been developed and applied in this context, among which the Perturb and Observe (P&O) [5–13] and Incremental Conductance (INC) [14–21]

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

methods are widely used due to their conceptual simplicity and ease of implementation. However, these traditional methods are often accompanied by drawbacks such as oscillations around the maximum power point during steady-state operation, which can lead to efficiency losses and mechanical stress on system components.

In light of these limitations, this study explores a more advanced and adaptive solution based on artificial intelligence. Specifically, we propose the implementation of an MPPT system that leverages the capabilities of artificial neural networks (ANNs) to enhance the efficiency and responsiveness of wind energy conversion systems. The ANN-based MPPT controller is designed to process multiple input parameters—including wind speed, mechanical power, and turbine rotational speed—and output the optimal rotational speed in per unit (PU) to achieve maximum power extraction.

Through detailed simulations, we demonstrate that the developed neural controller exhibits superior performance in terms of robustness, accuracy, and responsiveness compared to conventional MPPT methods. The results confirm that the proposed ANN-based MPPT approach is highly effective in maximizing wind energy extraction while minimizing steady-state oscillations, thereby contributing to the advancement of intelligent and sustainable wind energy systems.

2. TURBINE MODEL

The mechanical power extracted by the wind turbine is expressed as follows [22-24]:

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

Where:

ρ: Air density (Kg/m3).

A: Area swept by the rotor blades (m2).

v: Wind speed (m/s).

C_p: Power coefficient.

The following relation expresses the differential equation of the rotational speed of the turbine [25-26]:

$$J\frac{d\Omega}{dt} = T_m - T_{em} - f\Omega \tag{2}$$

Where:

J : Inertia of turbine and generator (Kg.m2).

f : friction coefficient (N.m.s.rad-1).

T_m: Electromagnetic torque (N.m).

Tem: mechanical torque (N.m).

In this work, we use a three-blade horizontal wind turbine. The curve representing the mechanical power recovered from the turbine as a function of the rotational speed, for different wind speeds, is shown in Figure 1. The values of the corresponding simulation parameters are presented in Table 1.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

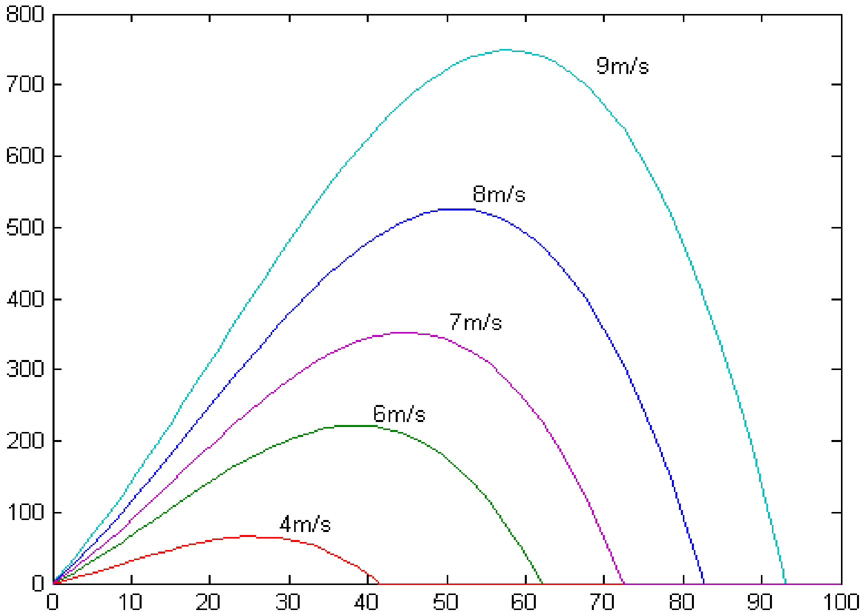

Figure 1. Mechanical power/speed characteristic.

Table 1: Wind turbine parameters

neters	:
l power	/
l wind speed	ı/s
ɔer of blades	
swept by the rotor blades	ı²

3. ARTIFICIAL NEURON MODEL

Artificial neural networks (ANNs) are computational models inspired by the functioning of biological neurons [127-28]. They are widely used in artificial intelligence and machine learning to solve complex problems such as image recognition, trend prediction, and natural language processing.

An artificial neural network consists of a set of neurons, where each neuron (see Figure 2) receives a variable number of inputs from neurons located upstream. Each of these inputs is associated with a weight W, which represents the strength of the synaptic connection between the neurons [29-39].

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

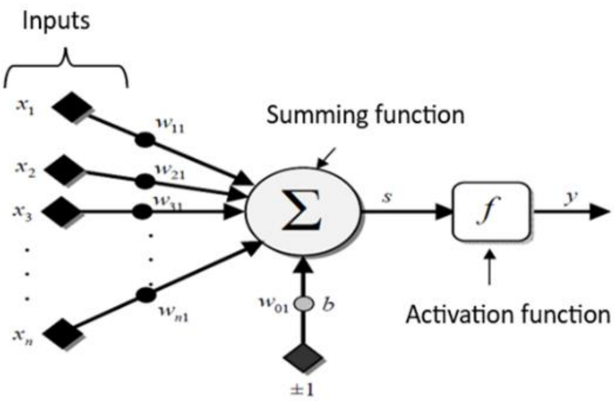

Figure 2. Artificial Neuron model.

The activation function determines whether a neuron should be activated. Without it, the network would behave like a simple linear model.

The connections between neurons, characterized by their respective weights, play a crucial role in the learning process and the overall performance of the network. By adjusting these weights using learning algorithms such as backpropagation [40-42], the neural network can optimize its ability to solve complex problems like image recognition, machine translation, or data prediction.

In summary, artificial neural networks mimic the functioning of the human brain, enabling the processing and analysis of large amounts of data with remarkable efficiency.

4. PROPOSED ARTIFICIAL NEURAL NETWORK

The choice of inputs and outputs in an artificial neural network (ANN) plays a crucial role in its efficiency [43-46], performance, and generalization capability. Poor selection can lead to slow convergence and insufficient accuracy.

In this work, to optimize the learning of the ANN, we developed a neural network (see Fig. 3) using wind speed, mechanical power P, and rotational speed Ω of the turbine as input variables. The output variable of the model is the rotational speed in per unit (PU), defined as the ratio of the measured rotational speed to the maximum rotational speed, as given by the following equation:

$$\Omega_{PU} = \frac{\Omega_{mes}}{\Omega_{Max}} \tag{3}$$

This ratio is between 0 and 1, thus facilitating analysis and use in control models or machine learning [47-52].

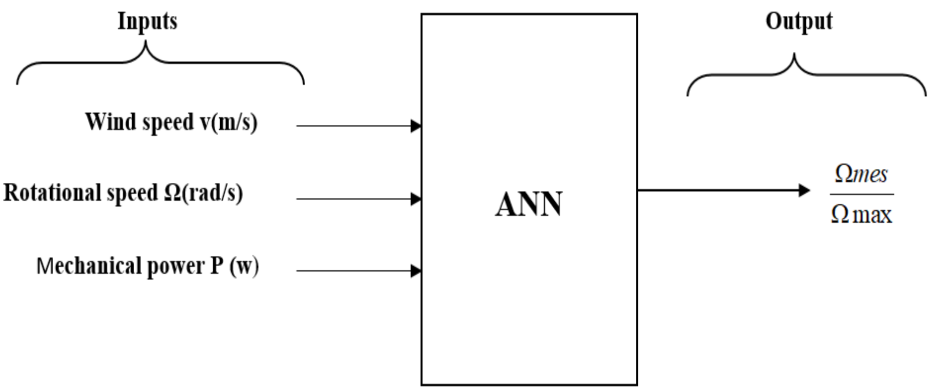

Figure 3. Developed neural network model.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

From the rotational speed expressed in per unit, the optimal rotational speed can be calculated using the following equation [40-42]:

$$\frac{\Omega op}{\Omega \max} = 0.63 \tag{4}$$

Figure 4 below illustrates the neural network used:

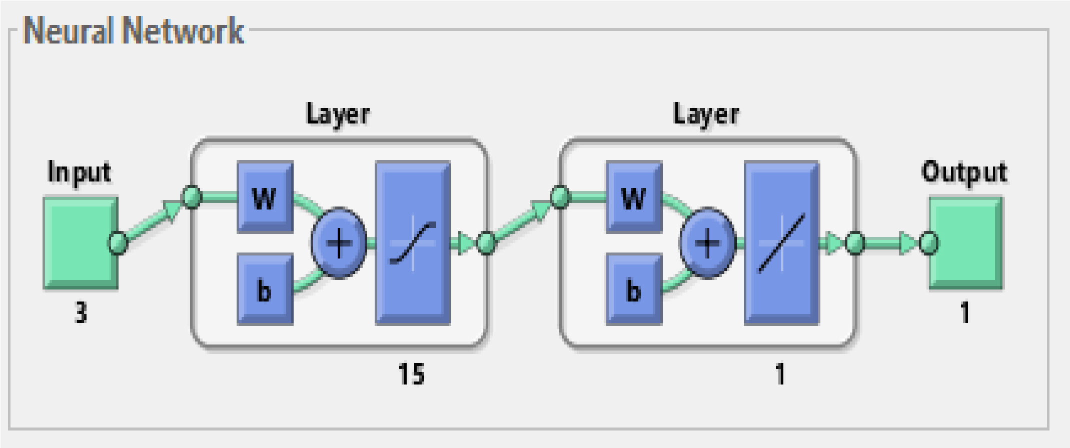

Figure 4. The architecture of the proposed neural network.

Figure 5 illustrates the mean squared error between the outputs of the artificial neural network (ANN) and their target values as a function of the number of iterations (epochs). The final error obtained is 6.6403*10-7.

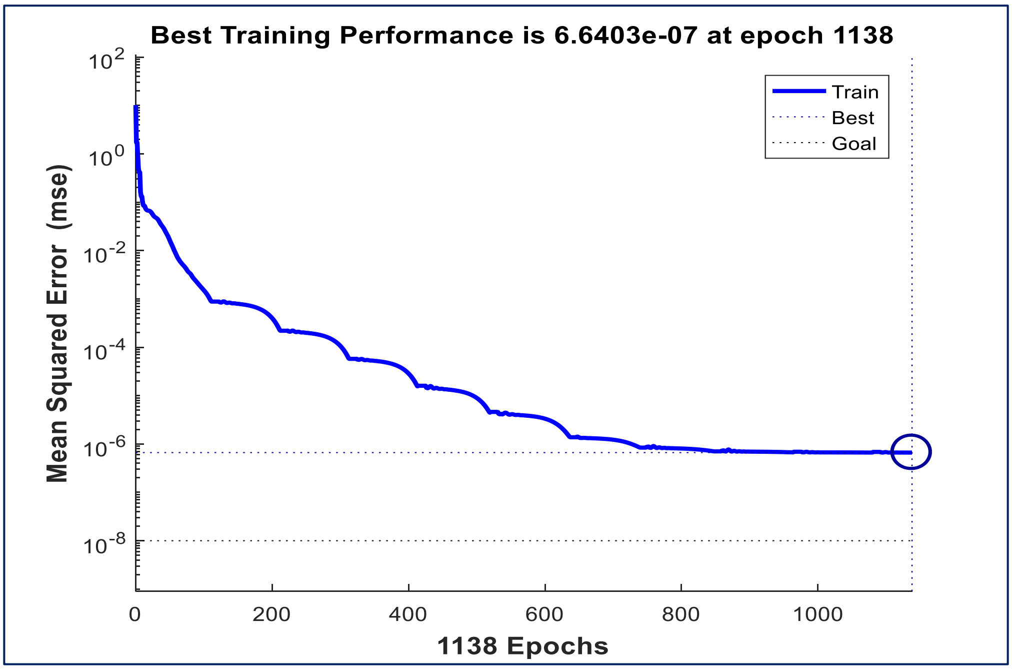

Figure 5. Evolution of the mean squared error during training.

For a scenario involving rapid variations in wind speed (as illustrated in Figure 6), Figure 7 presents the rotational speed response of the wind turbine optimized by the proposed neural network-based MPPT controller. This response is compared against the optimal rotational speed curve derived from the turbine's power characteristic as a function

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/
Research Article

of its rotational speed. Furthermore, Figure 8 depicts the corresponding variation in the turbine's mechanical power when regulated by the MPPT controller, highlighting its capability to ensure efficient energy extraction under dynamic wind conditions.

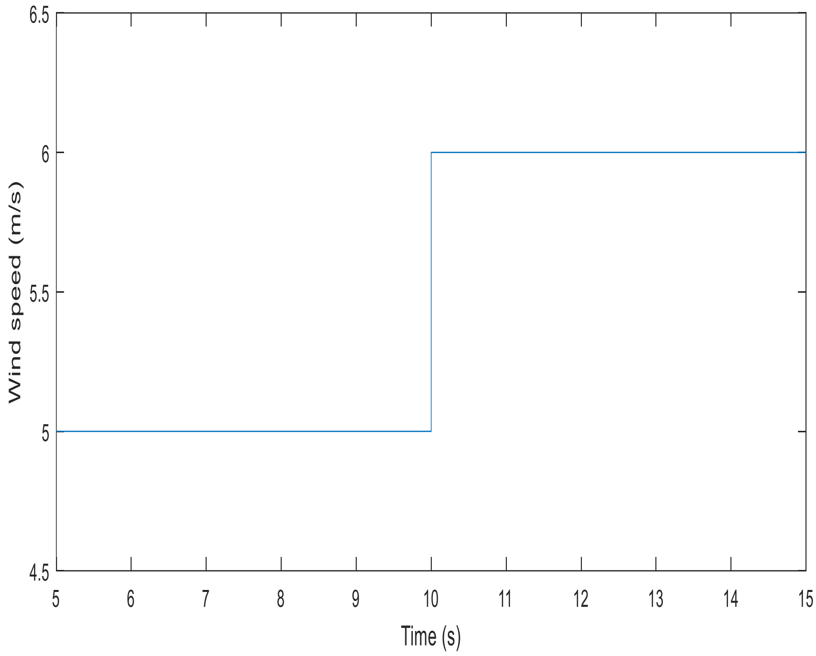

Figure 6. Wind speed

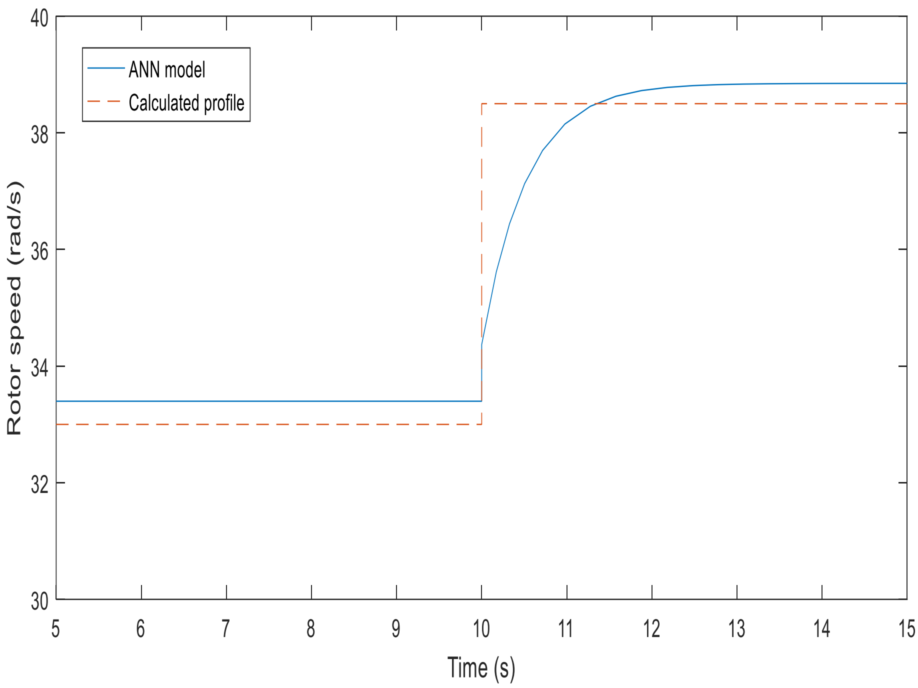

Figure 7. Rotor speed

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

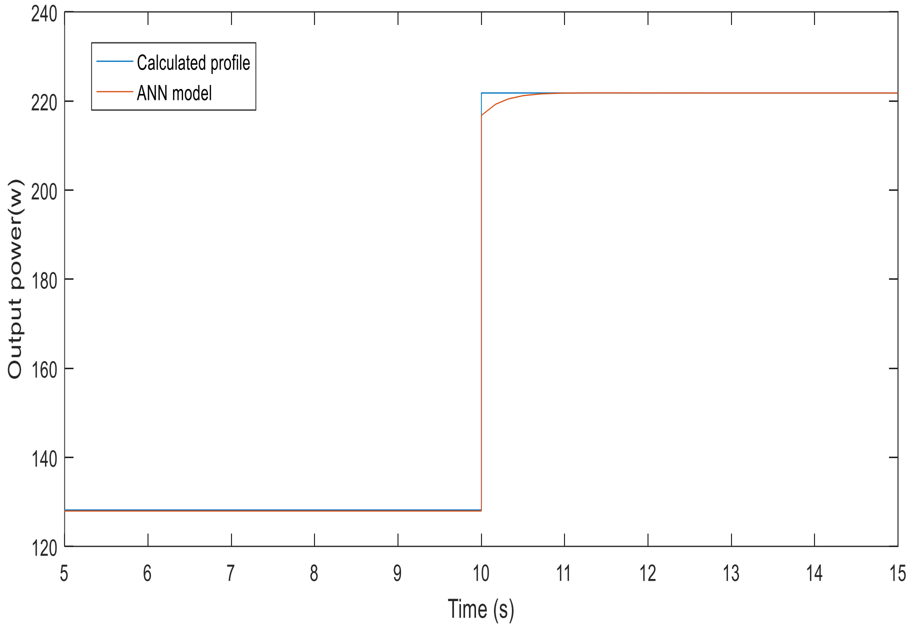

Figure 8. The mechanical power of the wind turbine

The analysis of the simulation results, as illustrated in the preceding figures, clearly highlights the robustness and effectiveness of the proposed neural network-based MPPT controller under dynamic wind conditions. One of the key aspects contributing to this performance is the strategic use of Per Unit (PU) normalization in the preparation of input and output data for the neural network. This normalization technique plays a crucial role in improving the learning efficiency of the ANN by scaling input variables to a consistent range, typically between 0 and 1. As a result, it eliminates disparities in magnitude between variables, which often hinder the training process in conventional neural networks. This uniform scaling facilitates faster convergence during training, reduces the likelihood of local minima entrapment, and leads to more stable and accurate model optimization.

In addition to accelerating the training process, PU normalization significantly enhances the generalization capability of the neural model. By removing the dimensional dependencies tied to specific turbine parameters and absolute values, the trained ANN becomes more adaptable across various wind turbine designs and system configurations. This allows the developed controller to maintain optimal performance even when deployed on turbines with different ratings or characteristics, without requiring retraining or extensive model adjustments. Such adaptability is particularly advantageous in real-world applications, where turbine models and operating conditions vary widely.

Furthermore, the use of PU-based data mitigates the risk of the ANN overfitting to the specificities of raw input data. Raw data often contain system-specific characteristics or anomalies that do not generalize well. PU normalization abstracts these specifics, allowing the ANN to learn the underlying physical relationships rather than memorizing details irrelevant to broader application contexts. Consequently, the dependency on massive datasets—commonly referred to as Big Data—is significantly reduced. Unlike traditional approaches that may require vast quantities of diverse training data to ensure reliable generalization, the proposed method achieves high accuracy and robustness using a relatively smaller and more compact dataset. This reduction in data requirements translates to lower computational load and reduced storage demands, which is particularly important for embedded systems and real-time applications where resources are limited.

Overall, the integration of PU-based data in ANN training presents a multifaceted advantage. It not only improves model training dynamics and performance but also ensures scalability, transferability, and computational efficiency. These benefits collectively position the proposed ANN-based MPPT controller as a viable and intelligent solution for modern wind energy systems, supporting the advancement of clean and efficient renewable energy technologies.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

5. CONCLUSION

In this study, we have developed and implemented a maximum power point tracking (MPPT) controller based on artificial neural network (ANN) techniques, specifically designed to predict the rotational speed in per unit (PU) of a wind turbine. This predicted speed is then used to determine the optimal operating point, thereby maximizing the extraction of available wind energy under varying wind conditions.

The simulation results confirm the effectiveness and robustness of the proposed ANN-based controller. Compared to conventional MPPT methods, the neural controller significantly enhances tracking performance, particularly by reducing oscillations around the maximum power point and ensuring faster dynamic response. Moreover, the use of per unit (PU) normalization improves the learning efficiency of the neural network, making it more suitable for generalization across various wind turbine models and system configurations.

Overall, the proposed approach offers a promising solution for intelligent control in wind energy systems. Its adaptability, predictive capability, and improved performance make it a valuable contribution to the ongoing development of more efficient and resilient renewable energy technologies. Future work may involve experimental validation and real-time implementation of the proposed controller on physical wind energy systems.

REFRENCES

[1] M. A. Abdullah, A. H. M. Yatim, C. W. Tan, and R. Saidur, “A review of maximum power point tracking algorithms for wind energy systems,” Renewable and Sustainable Energy Reviews, vol. 16, no. 5, pp. 3220–3227, 2012, doi: 10.1016/j.rser.2012.02.016.

[2] G. Hua and X. Dewei, “Stability analysis and improvements for variable-speed multipole permanent magnet synchronous generator-based wind energy conversion system,” IEEE Transactions on Sustainable Energy, vol. 2, no. 4, pp. 459–467, Oct. 2011, doi: 10.1109/TSTE.2011.2148691.

[3] P. Lu, L. Ye, Y. Tang, C. Zhang, W. Zhong, B. Sun, B. Zhai, Y. Qu, and X. Liu, “Multi-time scale active power optimal dispatch in wind power cluster based on model predictive control,” Proceedings of the CSEE, vol. 39, no. 19, pp. 6572–6582, 2019, doi: 10.13334/j.0258-8013.pcsee.190188.

[4] A. Meharrar, M. Tioursi, M. Hatti, and A. B. Stambouli, “A variable speed wind generator maximum power tracking based on adaptive neuro-fuzzy inference system,” Expert Systems with Applications, vol. 38, no. 6, pp. 7659–7664, Jun. 2011, doi: 10.1016/j.eswa.2010.12.123.

[5] M. Karabacak, “A new perturb and observe based higher order sliding mode MPPT control of wind turbines eliminating the rotor inertial effect,” Renewable Energy, vol. 133, pp. 807–827, Apr. 2019, doi: 10.1016/j.renene.2018.10.071.

[6] H. Ramadan, A. R. Youssef, H. H. H. Mousa, and E. E. M. Mohamed, “An efficient variable-step P&O maximum power point tracking technique for grid-connected wind energy conversion system,” SN Applied Sciences, vol. 1, no. 12, p. 1658, Dec. 2019, doi: 10.1007/s42452-019-1716-5.

[7] R. M. Linus and P. Damodharan, “Maximum power point tracking method using a modified perturb and observe algorithm for grid connected wind energy conversion systems,” IET Renewable Power Generation, vol. 9, no. 6, pp. 682–689, Sep. 2015, doi: 10.1049/iet-rpg.2014.0070.

[8] H. H. H. Mousa, A. R. Youssef, and E. E. M. Mohamed, “Hybrid and adaptive sectors P&O MPPT algorithm based wind generation system,” Renewable Energy, vol. 145, pp. 1412–1429, Jan. 2020, doi: 10.1016/j.renene.2019.06.078.

[9] K. N. Yu and C. K. Liao, “Applying novel fractional order incremental conductance algorithm to design and study the maximum power tracking of small wind power systems,” Journal of Applied Research and Technology, vol. 13, no. 2, pp. 238–244, Apr. 2015, doi: 10.1016/j.jart.2015.06.004.

[10] M. Guermoui, K. Gairaa, A. Rabehi, D. Djafer, and S. Benkaciali, “Estimation of the daily global solar radiation based on the Gaussian process regression methodology in the Saharan climate,” The European Physical Journal Plus, vol. 133, no. 6, p. 211, Jun. 2018, doi: 10.1140/epjp/i2018-12029-7.

[11] M. Guermoui, J. Boland, and A. Rabehi, “On the use of BRL model for daily and hourly solar radiation components assessment in a semiarid climate,” The European Physical Journal Plus, vol. 135, no. 2, p. 214, Feb. 2020, doi: 10.1140/epjp/s13360-019-00085-0.

[12] A. Rabehi, M. Guermoui, and D. Lalmi, “Hybrid models for global solar radiation prediction: a case study,” International Journal of Ambient Energy, vol. 41, no. 1, pp. 31–40, Jan. 2020, doi: 10.1080/01430750.2018.1443498.
[13] Abdelhalim Rabehi, A. Rabehi, and M. Guermoui, “Evaluation of Different Models for Global Solar Radiation Components Assessment,” Applied Solar Energy, vol. 57, no. 1, pp. 81–92, Jan. 2021, doi: 10.3103/S0003701X21010060.
[14] R. Khelifi, M. Guermoui, A. Rabehi, and D. Lalmi, “Multi-step-ahead forecasting of daily solar radiation components in the Saharan climate,” International Journal of Ambient Energy, vol. 41, no. 6, pp. 707–715, May 2020, doi: 10.1080/01430750.2018.1490349.
[15] M. Guermoui and A. Rabehi, “Soft computing for solar radiation potential assessment in Algeria,” International Journal of Ambient Energy, vol. 41, no. 13, pp. 1524–1533, Nov. 2020, doi: 10.1080/01430750.2018.1517686.
[16] M. Hamdani, M. Youcefi, A. Rabehi, B. Nail, and A. Douara, “Design and Implementation of a Medical TeleMonitoring System based on IoT,” Engineering, Technology & Applied Science Research, vol. 12, no. 4, pp. 8949–8953, Aug. 2022, doi: 10.48084/etasr.5040.
[17] M. Guermoui, R. Abdelaziz, K. Gairaa, L. Djemoui, and S. Benkaciali, “New temperature-based predicting model for global solar radiation using support vector regression,” International Journal of Ambient Energy, vol. 43, no. 1, pp. 1397–1407, Dec. 2022, doi: 10.1080/01430750.2019.1708792.
[18] M. Guermoui et al., “An analysis of case studies for advancing photovoltaic power forecasting through multi-scale fusion techniques,” Sci Rep, vol. 14, no. 1, p. 6653, Mar. 2024, doi: 10.1038/s41598-024-57398-z.
[19] A. Rabehi et al., “Simulation and Experimental Studies of Illumination Effects on the Current Transport of Nitridated GaAs Schottky Diode,” Semiconductors, vol. 52, no. 16, pp. 1998–2006, Dec. 2018, doi: 10.1134/S106378261816025X.
[20] N. E. Zakzouk, M. A. Elsaharty, A. K. Abdelsalam, A. A. Helal, and B. W. Williams, “Improved performance low-cost incremental conductance PV MPPT technique,” IET Renewable Power Generation, vol. 10, no. 4, pp. 561–574, Apr. 2016, doi: 10.1049/iet-rpg.2015.0072.
[21] A. R. Youssef, H. H. H. Mousa, and E. E. M. Mohamed, “Development of self-adaptive P&O MPPT algorithm for wind generation systems with concentrated search area,” Renewable Energy, vol. 154, pp. 875–893, Jul. 2020, doi: 10.1016/j.renene.2020.03.052.
[22] G. B. A. K. Shivashankar, “Optimal power point tracking of solar and wind energy in a hybrid wind solar energy system,” International Journal of Energy and Environmental Engineering, vol. 13, no. 1, pp. 77–103, Mar. 2022, doi: 10.1007/s40095-021-00425-1.
[23] Y. Errami, M. Ouassaid, and M. Maaroufi, “Modelling and optimal power control for permanent magnet synchronous generator wind turbine system connected to utility grid with fault conditions,” World Journal of Modelling and Simulation, vol. 11, no. 2, pp. 123–135, 2015.
[24] S. Heier, “Wind energy conversion systems,” in Grid Integration of Wind Energy Conversion Systems, Chichester, UK: John Wiley & Sons Ltd., 1998, pp. 34–36.
[25] M. Narayana, G. A. Putrus, M. Jovanovic, P. S. Leung, and S. McDonald, “Generic maximum power point tracking controller for small-scale wind turbines,” Renewable Energy, vol. 44, pp. 72–79, Aug. 2012, doi: 10.1016/j.renene.2012.01.087.
[26] A. Rabehi et al., “Current–Voltage, Capacitance–Voltage–Temperature, and DLTS Studies of Ni|6H-SiC Schottky Diode,” Semiconductors, vol. 55, no. 4, pp. 446–454, Apr. 2021, doi: 10.1134/S1063782621040138.
[27] I. E. Tibermacine et al., “Enhanced Performance of Microstrip Antenna Arrays through Concave Modifications and Cut-Corner Techniques,” ITEGAM- Journal of Engineering and Technology for Industrial Applications (ITEGAM-JETIA, vol. 11, no. 51, 2025, doi: 10.5935/jetia.v11i51.1414.
[28] A. Rabehi, M. Guermoui, R. Khelifi, and M. L. Mekhalfi, “Decomposing global solar radiation into its diffuse and direct normal radiation,” International Journal of Ambient Energy, vol. 41, no. 7, pp. 738–743, Jun. 2020, doi: 10.1080/01430750.2018.1492445.
[29] A. Rabehi, M. Amrani, Z. Benamara, B. Akkal, and A. H. Kacha, “Electrical and photoelectrical characteristics of Au/GaN/GaAs Schottky diode,” Optik (Stuttg), vol. 127, no. 16, pp. 6412–6418, Aug. 2016, doi: 10.1016/j.ijleo.2016.04.113.

[30] A. Ziane et al., "Numerical investigation of G-V measurements of metal - A nitride GaAs junction," Revista Mexicana de Fisica, vol. 70, no. 6, pp. 1–7, Nov. 2024, doi: 10.31349/RevMexFis.70.061604.
[31] A. Douara, A. Rabehi, and O. Baitiche, "Impact of AlN interlayer on the electronic and I-V characteristics of In0.17Al0.83N/GaN HEMTs devices," Revista Mexicana de Fisica, vol. 69, no. 3, 2023, doi: 10.31349/RevMexFis.69.031602.
[32] A. Douara, A. Rabehi, O. Baitiche, and M. Hamdani, "Improved electrical characteristics of Alx Ga1-xN/GaN High Electron Mobility Transistor by effect of physical and geometrical parameters," Revista Mexicana de Fisica, vol. 69, no. 4, Jul. 2023, doi: 10.31349/RevMexFis.69.041001.
[33] H. Bentegri et al., "Assessment of compressive strength of eco-concrete reinforced using machine learning tools," Sci Rep, vol. 15, no. 1, p. 5017, Feb. 2025, doi: 10.1038/s41598-025-89530-y.
[34] A. Douara, A. Rabehi, M. Guermoui, R. Daha, and I. E. Tibermacine, "Impact of AlN Buffer Layer Thickness on Electronic and Electrical Characteristics of In0.17Al0.83N/GaN High-Electron-Mobility Transistor," Physics of the Solid State, vol. 66, no. 6, pp. 157–164, Jun. 2024, doi: 10.1134/S1063783424600766.
[35] A. Ziane et al., "Frequency Dependent Capacitance and Conductance–Voltage Characteristics of Nitride GaAs Schottky Diode," Semiconductors, vol. 55, no. 1, pp. 51–55, Jan. 2021, doi: 10.1134/S1063782621010206.
[36] A. Douara, A. Rabehi, M. Guermoui, R. Daha, and I. E. Tibermacine, "Simulation-based optimization of barrier and spacer layers in InAlN/GaN HEMTs for improved 2DEG density," Micro and Nanostructures, vol. 195, Nov. 2024, doi: 10.1016/j.micrna.2024.207950.
[37] F. Mekaret et al., "A comparative study of Schottky barrier heights and charge transport mechanisms in 3C, 4H, and 6H silicon carbide polytypes," AIP Adv, vol. 14, no. 11, Nov. 2024, doi: 10.1063/5.0240123.
[38] A. Rabehi et al., "Accurate parameter estimation of Au/GaN/GaAs schottky diode model using grey wolf optimization," Revista Mexicana de Fisica, vol. 70, no. 2, pp. 1–8, 2024, doi: 10.31349/RevMexFis.70.021004.
[39] R. Khelifi et al., "Short-Term PV Power Forecasting Using a Hybrid TVF-EMD-ELM Strategy," International Transactions on Electrical Energy Systems, vol. 2023, 2023, doi: 10.1155/2023/6413716.
[40] M. Guermoui, A. Rabehi, K. Gairaa, and S. Benkaciali, "Support vector regression methodology for estimating global solar radiation in Algeria," The European Physical Journal Plus, vol. 133, no. 1, p. 22, Jan. 2018, doi: 10.1140/epjp/i2018-11845-y.
[41] M. Guermoui, A. Rabehi, S. Benkaciali, and D. Djafer, "Leonardo Electronic Journal of Practices and Technologies Daily global solar radiation modelling using multi-layer perceptron neural networks in semi-arid region", [Online]. Available: http://lejpt.academicdirect.org
[42] A. Rabehi et al., "Optimal Estimation of Schottky Diode Parameters Using Advanced Swarm Intelligence Algorithms," Semiconductors, vol. 54, no. 11, pp. 1398–1405, Nov. 2020, doi: 10.1134/S1063782620110214.
[43] A. Mehallou et al., "Optimal multiobjective design of an autonomous hybrid renewable energy system in the Adrar Region, Algeria," Sci Rep, vol. 15, no. 1, p. 4173, Feb. 2025, doi: 10.1038/s41598-025-88438-x.
[44] R. Khelifi et al., "Comparative performance analysis of hemispherical solar stills using date and olive kernels as heat storage material," Sci Rep, vol. 15, no. 1, p. 7128, Feb. 2025, doi: 10.1038/s41598-025-87448-z.
[45] A. Chennana et al., "Vibration signal analysis for rolling bearings faults diagnosis based on deep-shallow features fusion," Sci Rep, vol. 15, no. 1, p. 9270, Mar. 2025, doi: 10.1038/s41598-025-93133-y.
[46] M. Guermoui, F. Melgani, and C. Danilo, "Multi-step ahead forecasting of daily global and direct solar radiation: A review and case study of Ghardaia region," J Clean Prod, vol. 201, pp. 716–734, Nov. 2018, doi: 10.1016/j.jclepro.2018.08.006.
[47] B. Ladjal et al., "Hybrid deep learning CNN-LSTM model for forecasting direct normal irradiance: a study on solar potential in Ghardaia, Algeria," Sci Rep, vol. 15, no. 1, p. 15404, May 2025, doi: 10.1038/s41598-025-94239-z.
[48] J. Taghinezhad and S. Sheidaei, "Prediction of operating parameters and output power of ducted wind turbine using artificial neural networks," Energy Reports, vol. 8, pp. 3085–3095, Nov. 2022, doi: 10.1016/j.egyr.2022.02.159.
[49] L. Xia, Z. Ma, G. Kokogiannakis, Z. Wang, and S. Wang, "Model-based design optimization strategy for ground source heat pump systems with integrated photovoltaic thermal collectors," Applied Energy, vol. 214, pp. 178–190, Mar. 2018, doi: 10.1016/j.apenergy.2018.01.058.

Journal of Information Systems Engineering and Management
2025, 10(4)
e-ISSN: 2468-4376
https://www.jisem-journal.com/ **Research Article**

[50] M. Fan, J. Hu, R. Cao, W. Ruan, and X. Wei, "A review on experimental design for pollutants removal in water treatment with the aid of artificial intelligence," Chemosphere, vol. 200, pp. 330–343, Feb. 2018, doi: 10.1016/j.chemosphere.2018.02.094.
[51] M. Ding, L. Wang, and R. BiAn, "ANN-based approach for forecasting the power output of photovoltaic system," Procedia Environmental Sciences, vol. 11, pp. 1308–1315, 2011, doi: 10.1016/j.proenv.2011.12.197.
[52] A. Meharrar and M. Hatti, "Wind maximum power point prediction and tracking using artificial neural network and maximum rotation speed method," in International Conference in Artificial Intelligence in Renewable Energetic Systems, 2017, pp. 326–336.