## **ORIGINAL**



# **Improving Photovoltaic System Performance with Artificial Neural Network Control**

## **Mejora del rendimiento de los sistemas fotovoltaicos mediante el control por redes neuronales artificiales**

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## **ABSTRACT**

Photovoltaic systems play a pivotal role in renewable energy initiatives. To enhance the efficiency of solar panels amid changing environmental conditions, effective Maximum Power Point Tracking (MPPT) is essential. This study introduces an innovative control approach based on an Artificial Neural Network (ANN) controller tailored for photovoltaic systems. The aim is to elevate the precision and adaptability of MPPT, thereby improving solar energy harvesting. This research integrated an ANN controller into a photovoltaic system in order dynamically optimize the operating point of solar panels in response to environmental changes. The performance of the ANN controller was compared with traditional MPPT approaches using simulation in Simulink/Matlab. The results of the simulation showed that the ANN controller performed better than the traditional MPPT techniques, highlighting the effectiveness of this method for dynamically changing solar panel performance. The ANN particularly demonstrates higher precision and adaptability when environmental conditions vary. The strategy consistently achieves and maintains the maximum power point, enhancing overall energy harvesting efficiency. The integration of an ANN controller marks a significant advance in solar energy control. The study highlights the superiority of the ANN controller through rigorous simulations, demonstrating increased accuracy and adaptability. This approach not only proves effective, but also has the potential to outperform other MPPT strategies in terms of stability and responsiveness.

**Keywords:** Photovoltaic System; Artificial Neural Network; Maximum Power Point Tracking; Artificial Intelligence.

#### **RESUMEN**

Los sistemas fotovoltaicos desempeñan un papel fundamental en las iniciativas de energías renovables. Para mejorar la eficiencia de los paneles solares en condiciones ambientales cambiantes, es esencial un seguimiento eficaz del punto de máxima potencia (MPPT). Este estudio introduce un innovador enfoque de control basado en un controlador de Red Neuronal Artificial (RNA) adaptado a los sistemas fotovoltaicos. El objetivo es elevar la precisión y adaptabilidad del MPPT, mejorando así la captación de energía solar. Esta investigación integró un controlador RNA en un sistema fotovoltaico con el fin de optimizar dinámicamente el punto de funcionamiento de los paneles solares en respuesta a los cambios ambientales. El rendimiento del controlador RNA se comparó con los enfoques MPPT tradicionales mediante simulación en Simulink/ Matlab. Los resultados de la simulación mostraron que el controlador RNA funcionaba mejor que las técnicas MPPT tradicionales, destacando la eficacia de este método para modificar dinámicamente el rendimiento de los paneles solares. En particular, la RNA demuestra una mayor precisión y adaptabilidad cuando varían las condiciones ambientales. La estrategia alcanza y mantiene sistemáticamente el punto de máxima potencia, mejorando la eficiencia global de la captación de energía. La integración de un controlador RNA supone un avance significativo en el control de la energía solar. El estudio destaca la superioridad del controlador RNA

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mediante simulaciones rigurosas, demostrando una mayor precisión y adaptabilidad. Este enfoque no sólo demuestra su eficacia, sino que también tiene el potencial de superar a otras estrategias MPPT en términos de estabilidad y capacidad de respuesta.

**Palabras clave:** Sistema Fotovoltaico; Red Neuronal Artificial; Seguimiento del Punto de Máxima Potencia; Inteligencia Artificial.

#### **INTRODUCTION**

Renewable energy entails that the energy density is as high as that of fossil fuels, or even higher, and that clean energy does not emit pollutants such as nitrogen compounds, sulfate compounds, and dust.(1)

Numerous countries throughout the world have recently focused a great lot of effort on the development of renewable energy to prevent the imminent depletion of fossil fuels.<sup>(2)</sup>

As a result, the use of solar systems in a range of applications has increased in recent years, making the adoption of flaw-detection technology essential. Generating electricity from solar photovoltaic systems is one of the most environmentally friendly options and one of the most important sources of renewable energy.

In the constantly evolving environment of renewable energy, maximizing the performance of photovoltaic systems remains the highest priority. As solar energy takes a leading role in the global transition to sustainable energy sources, advanced and adaptive control systems become increasingly important.  $^{(3,4)}$ 

In order to fully realize the potential of solar energy, sophisticated control systems capable of establishing the inherent complexity of this technology are required.

Traditional techniques, which make use of rule-based algorithms and traditional proportional-integralderivative (PID) controllers, have limitations in properly regulating the complex, non-linear dynamics of PV systems. This has sparked a search for cutting-edge technology capable of pushing the limits of control and optimization in solar energy generation.<sup>(5)</sup>

The MPPT can improve the competence of the PV system because of its intrinsic non-linear substantial electrical features and connectivity. A popular technique for solar cell functions is the maximum power point tracker, which recovers converting competence based on the commission power of the matrix. In order to discover the maximum power position of a PV panel, artificial intelligence (AI) based methods using genetic algorithm (GA), (ANN), and PSO (particle swarm optimization) are employed as solutions in the MPPT controller. (6,7)

Amid this search, a particularly interesting path is emerging: the integration of artificial neural networks into photovoltaic control frameworks. ANNs represent a paradigm shift in the way we think about control mechanisms. These computational models are particularly effective at learning patterns from data, adapting to changing conditions, and managing the nonlinear interactions intrinsic to solar power generation.<sup>(8)</sup>

The combination of artificial intelligence, in the form of ANNs, and PV systems represents a ground-breaking combination capable of improving the efficiency, adaptability, and reliability of solar energy technology.(9) This integration not only fits in with the broader goals of sustainable energy but also opens up new possibilities for harnessing and optimizing the power of the sun.

In the field of renewable energy management, the integration of Artificial Neural Networks (ANNs) in controlling Photovoltaic (PV) systems is recognized as an innovative path. Since it is difficult for traditional fixed algorithms to adjust to changing environmental conditions, this literature review analyzes the most recent advances.<sup>(10)</sup>

Harish et al.<sup>(11)</sup> this article discusses the MPPT that solar power systems frequently use. These technologies comprise intelligence-based processes, predictive approaches, or predictive methodologies. The effectiveness of each of these methods is also briefly compared.

Mohamed et al.<sup>(12)</sup> focus on increasing power captured from PV systems, they introduce a new hybrid MPPT technique combining AI and traditional techniques, the technique accurately tracks the dynamic global maximum power under partial shading conditions, and it outperforms other MPPT techniques in terms of efficiency and waveform distortions. This hybrid technique combines Artificial Neural Network (ANN), Variable Step Perturb and Observe (VSP&O), and Fuzzy Logic Controller (FLC). The hybrid ANN-VSPO-FLC technique accurately tracks the Dynamic GMP. Efficiency ranges from 99,65 % to 99,995 %, and tracking speed ranges from 0,04s to 0,08s. The technique also performs well under normal irradiance and temperature changes.

Mahmoud et al.(13) propose two AI-based MPPT systems for grid connected photovoltaic units. The first design uses optimized fuzzy logic control with a genetic algorithm and particle swarm optimization, the second design uses a genetic algorithm-based artificial neural network. A combination of the two designs is introduced to maximize efficiency. The simulation results methods in terms of output DC power and tracking speed, highlighting their potential for maximizing the efficiency of photovoltaic systems, Mahmoud et al.<sup>(13)</sup> suggest

that the AI-based MPPT methods can be applied not only to grid-connected photovoltaic systems but also to stand-alone PV systems and other applications such as charging electric vehicles and irrigation purposes.

Moussa et al.<sup>(14)</sup> present an improved energy management and optimization system based on fuzzy logic technology for controlling hybrid electric energy sources, including solar panels, wind turbines, and energy storage systems, with the electric grid as a backup during adverse weather conditions. The system is implemented on an Arduino 2560 mega microcontroller, and simulations are conducted to characterize the system and ensure continuous accommodation at home. The effectiveness of the proposed system is confirmed by visualizing the output control signals from the electronic switches. The fuzzy logic smart controllers implemented in the system successfully manage the household hybrid energy system, and the FLSC Arduino output PWM signals directly excite the electronic switches to convey the available energy from the sources to the user.

Our research provides a revolutionary use of ANNs to dynamically control PV systems, overcoming existing fixed techniques. Using ANNs to optimize energy output in response to changing environmental conditions is distinctive. This study represents an important step toward reliable and effective renewable energy sources. The paper is divided into separate sections to comprehensively address various aspects of the research Section 2 delves into thorough analysis of PV system and the proposed method, Section 3 presents and analyzes the

Simulation and results, finally, in the concluding section, the research findings are summarized, presenting the main conclusions obtained from the study. .

## **METHODS**

## **Design of the proposed Photovoltaic System**

The proposed photovoltaic system contains a PV array, DC-DC boost converter, MPPT controller, and a load. (15,16)

## **Photovoltaic panel model**

A photovoltaic panel is a device that can transform solar energy into direct electrical current using semiconductor components that transmit photovoltaic radiation. In order to model a PV panel numerically, we use the fundamental equation of the PV panel's equivalent circuit as shown in figure 1, the current produced by the panel can be expressed as follows: (17)



**Figure 1.** Photovoltaic panel equivalent circuit

 $I=1$ ph−I0  $[(V+IRS)nKNsT-1]$ −Ish (1)

Iph is the photo-current is then given as,

Iph=[Isc+Ki (T-298)G/1000 (2)

Isc is the short circuit current. The reverse saturation current of the diode is given by,  $(18)$ 

 $Irs= Isc/(e^{(\alpha)}((q \text{ Voc})/(n \text{ K T Ns}))-1)$  (3)

Voc is the open-circuit voltage. The module's saturation current at any given temperature is given by,

 $I_0=Irs.(T/Tn)^3.e'((Eg0)/K.(1/Tn-1/T))$  (4)

Tn= 298 K; Eg0 is the bandgap energy.

#### **DC-DC BOOST converter**

A boost converter is a type of switching power supply that increases the output voltage level beyond the input voltage. It produces more voltage than it receives. It is a switching converter that functions on an ON-OFF cycle. A boost converter has an input voltage V\_in, an inductor L, and a controlled semiconductor switch (S) like MOSFET, IGBT, and BJT, a diode (D), and a capacitor (C\_out). The following equations determine how this converter operates<sup>(19)</sup>





 $V_0 = V/((1-\alpha))$  (5)

 $I_0 = |x(1-a)|$  (6)

The value of the input capacitor can be designed as follows.

 $C_1 \geq \alpha / (8 \times F^2 \geq L \times 0.01)$  (7)

Equation  $(8)$  can be used to find the inductor value, where r is between  $[0,3, 0,5]$ .

L $\geq$ ( $\alpha$ ×(1- $\alpha$ )<sup>2</sup>×R)/(r×F) (8)

The minimum value of the output capacitor can be determined by applying Equation.

C  $2≥α/(Fx0.02×R)$  (9)

Equation (10) is used to calculate the duty cycle for peak power transfer at STC (Standard Test Conditions).

 $\alpha = 1 - \sqrt{(17.04/(3.55 \times R))}$  (10)

#### **Maximum Power Point tracking**

Maximum Power Point Tracking is an approach of optimizing energy production used by photovoltaic cells and similar devices to achieve the highest level of control.<sup>(20)</sup>

Photovoltaic cells have a complex relationship between their operating conditions and the quantity of power they can generate. The power produced is primarily determined by sun irradiance and temperature. Due to the non-linear I-V characteristics, and knowing that output power changes with cell voltage, it is crucial to develop a technique that would harness the most available solar power at any given time.

A maximum operating point is obtained in each power-voltage or current-voltage curve of a solar panel, where the solar panel delivers the highest potential power to the load. The maximum power point (MPP) of a solar panel corresponds to this distinct position.

We can therefore deduce that the operating current and voltage that maximize energy production vary according to environmental conditions.<sup>(21)</sup>

MPP is affected by environmental factors such as irradiation, with different values of irradiation, there is a corresponding change in MPP values.(22) An MPPT algorithm must be applied that continuously tracks the MPP at each instant to deliver the maximum power, thus enhancing system efficiency. In many applications, the load demand may be greater than the power supplied by the photovoltaic system. Many methodologies are used to maximize the energy output of photovoltaic systems, ranging from simple parameter connections to complex time-based analyses.

Temperature is a further significant consideration that influences solar cell performance. The photon generation rate increases with temperature, causing the gap between the bands to narrow due to an increase in reverse saturation current.<sup>(23)</sup> This process results in an insignificant decrease in current but an important increase in voltage. There is a decreasing correlation between temperature and solar cell performance. Solar cells function better on cold and bright sunny days rather than on hot and bright sunny days. Solar panels are now made from non-silicon materials that are temperature-insensitive. As a result, they are used under settings that are constant or near the ambient temperature.

An MPPT controller is required to track this variation. Many MPPT control approaches have come into existence in the last century.

The Perturb and Observe (P&O) approach is frequently implemented in solar systems for MPPT.<sup>(24)</sup> This

method modifies the operational point of solar panels regularly, either by changing voltage or current, while assessing the influence on power output. The algorithm then calculates the direction of the power increase and continues to perturb until the system reaches the maximum power point, where it runs most effectively. While the P&O approach is simple and inexpensive to execute, its dependence on constant perturbations may cause oscillations around the MPP and make it sensitive to rapidly changing environmental conditions. Despite these limitations, its ease of use and low cost make it a popular choice for MPPT in a variety of solar energy applications.



**Figure 3.** Flowchart of P&O Method

Traditional Maximum Power Point Tracking approaches in solar systems, such as P&O, have several imperfections. These approaches are susceptible to oscillations around the MPP, especially in dynamic environments, resulting in inferior efficiency.<sup>(25)</sup> They may have difficulty rapidly adapting to variations in irradiance and temperature, causing tracking mistakes and transitory power losses. Their weaknesses are exacerbated by their sensitivity to system characteristics, limited effectiveness in partial shading conditions, and difficulties in dealing with complicated system dynamics. As a result, there is growing interest in sophisticated MPPT techniques, particularly artificial intelligence-based approaches such as neural network controllers, which aim to overcome these limits and improve the precision and adaptability of MPP tracking in a variety of operating settings.

There has been increasing interest in leveraging the capacity of artificial neural networks to get around the inherent limitations of conventional maximum power point tracking approaches in solar systems. Artificial neural networks are a promising solution for maximum power point tracking since they are more adaptive and clever.(26) Artificial neural networks, unlike traditional rule-based techniques, can learn complicated patterns from data, allowing them to navigate complex, non-linear interactions within the photovoltaic system. This versatility enables artificial neural networks to perform efficiently under a variety of environmental situations, minimizing difficulties such as oscillations, errors during transients, and difficulty in dealing with partial shading scenarios. The application of artificial neural networks in MPPT not only improves MPP tracking accuracy but also increases overall efficiency and robustness.

## **Artificial Neural Network Controller**

ANN is a simulation of the human nervous system which, like the brain, learns from the environment to process information.(27) The concept is gaining increasing recognition for its excellent accuracy and promising prospects. An ANN can be used for several tasks such as pattern recognition or data classification, each with its own algorithm and configuration. The act of learning from the environment is equivalent to modifying a set of weights called synaptic weights that connect distinct neurons. This is how the biological nervous system works,

and it's also how an ANN works.

Neural networks can extract meaningful observations from vast quantities of naturally difficult and imperfect data. They can produce excellent results when extracting patterns and identifying trends that other computer algorithms struggle to detect, and that are virtually impossible for humans to notice.(28) A neural network is trained on one set of comparable data before being used or evaluated on another set of data. The advantages of artificial neural networks result from their ability to model complex relationships and patterns in data, making them flexible tools for image identification, natural language processing, and system control. ANNs are good at modeling complex relationships because of their layered approach to learning, all of which contribute to their wide use in addressing complex issues in a variety of fields. Instead, the most popular type of ANN, a multilayer feed-forward ANN, is used to implement. There are three types of layers, with the first being an input layer and the last being an output layer. The multilayer feed forward contains several hidden layers between the two layers. Therefore the connection goes from the first layer through the next layer, and they only continue forward. Multilayer feed-forward ANNs are divided into two distinct phases:

The training phase is additionally referred to as the learning phase, this phase involves generating an outcome when given a specified input to the ANN, which is achieved through continual training on a set of training data.



Figure 4. A fully connected multilayer feed forward network with one hidden layer and bias neurons<sup>(29)</sup>

The execution phase. The network learns from labeled data during training by modifying internal parameters, which improves its ability to make correct predictions. The trained network is deployed in the execution phase to provide predictions or classifications on current and unseen data, using the learned models to make intelligent decisions.

Feed-Forward network can easily be used to transform an input into an output. The problem arises when we're working with a network whose connections point in all directions (like the brain) and we need to calculate an output from it.

In a multilayer feed-forward ANN all neurons in each layer paired to all neurons in the following layer as shown in figure 4. The network is known as a completely linked network. When the ANN is trained, two parameters need to be chosen, the first one is the weight that is assigned to the various inputs, while the second one is the value in the activation functions. Such a configuration is infeasible, and the system would be simpler to manipulate if only one parameter were changed. A bias neuron is created to solve this problem. The bias neuron consistently returns a result of 1. The bias neuron is not connected to the previous layer neurons, but only to the next layer neurons.

#### **RESULTS**

The performance of ANN based MPPT and P&O based MPPT algorithms in a PV Standalone system with a boost converter are compared using simulation in MATLAB/Simulink. The ANN is trained using data collected through the Perturb and Observe method on an assortment of system circumstances included in the data set.

#### **Architecture of the Artificial Neural Network Controller**

ANN is trained using PV array voltage and current, solar irradiance, and temperature. The Neural Network learns by changing the weights using the Feed-Forward back propagation Levenberg-Marquardt algorithm with PV voltage and PV current as inputs to the ANN.<sup>(30)</sup> The hidden layer includes fifteen neurons and generates hidden layer output using a tangent sigmoid activation function, whilst the output layer neurons produce

output layer output using a linear activation function.



**Figure 5.** Artificial Neural Network Controller Architecture

The primary advantage of the suggested approach is that it tracks MPP more quickly. Since the parameters of a photovoltaic array change over time, it is necessary to frequently retrain the neural network to ensure precise tracking of MPP. The temperature and irradiation signals varied in the following forms.



**Figure 6.** Irradiation and Temperature signals with time-varying

This simulation allows us to evaluate the effectiveness of the ANN control at different irradiance levels.











using P&O controller







**Figure11.** Output power of the photovoltaic system using artificial neural network controller



Output voltage, current and power of PV system obtained using P&O and ANN controller are compared in terms of performance based on efficiency.



Table 1 demonstrate the power output differences between the ANN- and P&O-based models, with the ANN Controller showing higher power output (468,3) than the P&O model (449,5). In terms of waveform characteristics, the ANN model produces fewer oscillations around the MPP than the P&O model. In addition, the ANN model has a higher efficiency of 93,66 %, while the P&O model achieves an efficiency of 89,9 %.

The results of using the MPPT technique based on Artificial Neural Networks (ANNs) are discussed in this section. A number of quantitative metrics are provided to provide a comprehensive understanding of the controller's behaviour, such as tracking accuracy, convergence speed, and overall system efficiency.

The ability of the ANN-based MPPT technique to accurately identify and maintain the optimal operating point of solar panels is demonstrated by its tracking accuracy, which is a crucial point. Results of simulations shows that the artificial neural network (ANN) continually outperforms the traditional perturbation and observation (P&O) technique, demonstrating its greater accuracy in dynamically adapting to changing environmental factors.

Another important parameter that shows how well the ANN-based MPPT technique achieves the maximum power point is convergence speed. Evaluations in comparison to the P&O approach highlight the ANN's precision and quickness in responding to variations, highlighting its capacity to respond quickly to variations in temperature and irradiation.

Total system efficiency is a comprehensive measure that takes into account both convergence speed and tracking accuracy. The results demonstrate the effectiveness of the ANN-based strategy in maximizing system efficiency and, consequently, the energy output of the photovoltaic system.

In addition, the illustrations provide information on the dynamic behaviour of the ANN-based control approach in various situations. These representations showed the robustness and flexibility of ANN-based control in simulated scenarios, demonstrating how the system reacts and adapts in real time. Comparing results using the P&O approach demonstrated an important difference, highlighting the ANN-based MPPT strategy's practical advantages and theoretical foundations. The findings provide important information for improving the practical application of intelligent control approaches in solar systems. The theoretical underpinning is supported by this research, which highlights the effectiveness of ANN-based control in improving solar system performance under dynamic real-world circumstances.

#### **CONCLUSION**

This study highlights benefits provided by the Artificial Neural Network technique for maximum power tracking in a stand-alone solar system with a DC-DC Boost converter, in comparison to the P&O approach. The ANN is robust against changing weather circumstances and irradiation environments, demonstrating accuracy in determining the maximum power point. The better dynamic performance of the ANN model in maximum power-point tracking is a crucial discovery. With its training and integrated knowledge of expected maximum power points that correspond with environmental inputs, the ANN outperforms the P&O technique. Because of its increased flexibility, the artificial neural network (ANN) can follow changes in the maximum power point more precisely and quickly. As a result, by confirming the useful advantages of using ANN-based approaches in standalone solar systems, this research advances the area. Because of its improved dynamic performance

and ability to precisely estimate the maximum power point, the ANN is a reliable and effective substitute for conventional approaches

## **REFERENCES**

1. Sedaghati F, Nahavandi A, Badamchizadeh MA, Ghaemi S, Abedinpour Fallah M. PV Maximum Power-Point Tracking by Using Artificial Neural Network. Mathematical Problems in Engineering. 2012; 2012:1–10.

2. A. Mossa M, Gam O, Bianchi N. Performance Enhancement of a Hybrid Renewable Energy System Accompanied with Energy Storage Unit Using Effective Control System. IJRCS. 2022 Feb 27;2(1):140–71

3. Pan Z, Quynh NV, Ali ZM, Dadfar S, Kashiwagi T. Enhancement of maximum power point tracking technique based on PV-Battery system using hybrid BAT algorithm and fuzzy controller. Journal of Cleaner Production. 2020 Nov;274:123719.

4. Saravanan S, Ramesh Babu N. Maximum power point tracking algorithms for photovoltaic system – A review. Renewable and Sustainable Energy Reviews. 2016 May;57:192–204.

5. AL-Rousan N, Isa NAM, Desa MKM. Advances in solar photovoltaic tracking systems: A review. Renewable and Sustainable Energy Reviews. 2018 Feb;82:2548–69.

6. Li J, Wu Y, Ma S, Chen M, Zhang B, Jiang B. Analysis of photovoltaic array maximum power point tracking under uniform environment and partial shading condition: A review. Energy Reports. 2022 Nov;8:13235–52.

7. Premkumar M, Kumar C, Sowmya R, Pradeep J. A novel salp swarm assisted hybrid maximum power point tracking algorithm for the solar photovoltaic power generation systems. Automatika. 2021 Jan 2;62(1):1–20.

8. Yang F, Cho H, Zhang H, Zhang J, Wu Y. Artificial neural network (ANN) based prediction and optimization of an organic Rankine cycle (ORC) for diesel engine waste heat recovery. Energy Conversion and Management. 2018 May;164:15–26.

9. Somwanshi PD, Chaware SM. A Review on: Advanced Artificial Neural Networks (ANN) approach for IDS by layered method. 2014;5.

10. Tao H, Ghahremani M, Ahmed FW, Jing W, Nazir MS, Ohshima K. A novel MPPT controller in PV systems with hybrid whale optimization-PS algorithm based ANFIS under different conditions. Control Engineering Practice. 2021 Jul;112:104809.

11. Harish Kumar V.C, Amala Shanthi S, Analysis of various MPPT techniques used in Z Source Inverters. 2020 International Conference on Inventive Computation Technologies (ICICT) 2020 DOI: 10.1109/IEEE Coimbatore, India.

12. Masry MZE, Mohammed A, Amer F, Mubarak R. New Hybrid MPPT Technique Including Artificial Intelligence and Traditional Techniques for Extracting the Global Maximum Power from Partially Shaded PV Systems. Sustainability. 2023 Jul 11;15(14):10884.

13. Ali MN, Mahmoud K, Lehtonen M, Darwish MMF. Promising MPPT Methods Combining Metaheuristic, Fuzzy-Logic and ANN Techniques for Grid-Connected Photovoltaic. Sensors. 2021 Feb 10;21(4):1244.

14. Ali Moussa M, Derrouazin A, Latroch M, Aillerie M. A hybrid renewable energy production system using a smart controller based on fuzzy logic. Electrical Engineering & Electromechanics. 2022 May 30;(3):46–50.µ

15. Benchikh S, JarouT, Nasri E, Roa L .Design of an adaptive neuro fuzzy inference system for photovoltaic system. In: Farhaoui, Y., Rocha, A., Brahmia, A., Bhushab, B. (eds.) Artificial Intelligence and Smart Environment, ICAISE 2022. Lecture Notes in Networks and Systems, vol 635. Springer, Cham. DOI: 10.1007/978-3-031-26254- 8\_50

16. Parvaneh MH, Khorasani PG. A new hybrid method based on Fuzzy Logic for maximum power point tracking of Photovoltaic Systems. Energy Reports. 2020 Nov; 6:1619–32.

17. Nuhel AK, Utsho MRAJ, Amin MA, Rafi FF, Sazid MM and Roy PH, Grid-tiled Rooftop Solar PV System with the Integration of Smart Metering Scheme, 2022 International Conference on Augmented Intelligence and Sustainable Systems (ICAISS), Trichy, India, 2022, pp. 1352-1358, doi: 10.1109/ICAISS55157.2022.10011020.

18. Moyo TP, Tabakov PY, Moyo S, Comparative Analysis of Different Computational Intelligence Techniques For Maximum Power Point Tracking of Pv Systems, Journal of Sustainable Energy Vol.13, No, 1, June,2022

19. Faraj K, Hussain J. Analysis and Comparison of DC-DC Boost Converter and Interleaved DC-DC Boost Converter. ETJ. 2020 May 25;38(5):622–35.

20. Saidi AS, Salah CB, Errachdi A, Azeem MF, Bhutto JK, Thafasal Ijyas VP. A novel approach in stand-alone photovoltaic system using MPPT controllers & NNE. Ain Shams Engineering Journal. 2021 Jun;12(2):1973–84.

21. Manna S, Singh DK, Akella AK, Kotb H, AboRas KM, Zawbaa HM, et al. Design and implementation of a new adaptive MPPT controller for solar PV systems. Energy Reports. 2023 Dec;9:1818–29.

22. Tey KS, Mekhilef S. Modified incremental conductance MPPT algorithm to mitigate inaccurate responses under fast-changing solar irradiation level. Solar Energy. 2014 Mar;101:333–42.

23. Fathi M, Parian JA. Intelligent MPPT for photovoltaic panels using a novel fuzzy logic and artificial neural networks based on evolutionary algorithms. Energy Reports. 2021 Nov 1;7:1338–48.

24. Yadav P, Tech B. MAXIMUM POWER POINT TRACKING BASED ARTIFICIAL NEURAL NETWORK APPROACH FOR SOLAR PHOTOVOLTAIC SYSTEM. International Journal Advanced Research Engineering and Technology. 2021 March: 12

25. Rezk H, Eltamaly AM. A comprehensive comparison of different MPPT techniques for photovoltaic systems. Solar Energy. 2015 Feb;112:1–11.

26. Kermadi M, Berkouk EM. Artificial intelligence-based maximum power point tracking controllers for Photovoltaic systems: Comparative study. Renewable and Sustainable Energy Reviews. 2017 Mar;69:369–86.

27. Villegas-Mier CG, Rodriguez-Resendiz J, Álvarez-Alvarado JM, Rodriguez-Resendiz H, Herrera-Navarro AM, Rodríguez-Abreo O. Artificial Neural Networks in MPPT Algorithms for Optimization of Photovoltaic Power Systems: A Review. Micromachines. 2021 Oct 17;12(10):1260.

28. Bourenane H, Berkani A, Negadi K, Marignetti F, Hebri K. Artificial Neural Networks Based Power Management for a Battery/Supercapacitor and Integrated Photovoltaic Hybrid Storage System for Electric Vehicles. JESA. 2023 Feb 28;56(1):139–51.

29. Somwanshi PD, Chaware SM. A Review on: Advanced Artificial Neural Networks (ANN) approach for IDS by layered method. International Journal of Computer Science and Information Technologies. 2014.

30. Arora A, Gaur P. Comparison of ANN and ANFIS based MPPT Controller for grid connected PV systems. 2015 Annual IEEE India Conference (INDICON), New Delhi, India. doi: 10.1109/INDICON.2015.7443568.

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#### **CONFLICT OF INTEREST**

None.

#### **AUTHORSHIP CONTRIBUTION**

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