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RESEARCH ARTICLE

Maximum Power Point Tracking in A Photovoltaic System Based on Artificial Neurons

Amel Ourici[1]*, **Bahi Abderaouf**[2]

1 Badji Mokhtar University Of Annaba, BP 12 Annaba, 23000, Algeria
2 Chadli Bendjedid University, El Taref, Algeria

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* **Corresponding author**.

amel.ourici@hotmail.com

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Abstract

Objectives: This study seeks to assess the efficacy of an approach utilizing artificial neural networks for tracking the maximum power point (MPP) in photovoltaic systems. The main objective is to compare this method with the traditional perturb and observe technique, evaluating its effectiveness, particularly when faced with changing weather conditions. **Methods:** An artificial neural network was employed to model the relationship between the weather conditions such as irradiation and temperature and the maximum power point of the 100 Kw photovoltaic system. They collected data from the installation, including performance measurements and corresponding environmental conditions. The artificial neural network was trained using this dataset to accurately estimate and track the MPP. In our study we have only one input variable which is the power of the photo voltaic generator and a single output which is the cyclic ratio' D', we collected these data from the solar panel simulation with perturb and observe control. The network we built has an input layer with two neurons, a hidden layer with 15 neurons and an output layer with one neuron, we performed a learning on 100 data using Matlab software, we trained and tested this neural network until we obtained a very small quadratic error compared with similar researches. Compared with a P&O method , the maximum power was riched. **Findings:** The deep learning model exhibited enhanced efficiency in extracting the maximum power point ;particularly ; in the presence of climatic variations. It successfully captured the complex relationships between weather conditions and the MPP, leading to improved power generation and minimized energy losses. The maximum power reached with perturb and observe method (P&O) is 95 kw for a response time of 0.1752 s, on the other hand the neural method is faster with a response time of 0.1567 s and at the same time the maximum power of 100 kw has been reached. **Novelty:** This study is unique in a way that it employed an artificial neural network for MPP extraction in photovoltaic installations. The neural network we used to simulate our photocoltaic installation produced excellent results: we can clearly see that the PV output voltage remained constant and PV maximum power reached 100 kw despite climatic variations.

Keywords: Solar Pannel; Maximum Power Tracking; Artificial Neurons; Quadratic Error; Climatic Variations.

1 Introduction

The increasing demand for renewable energy sources has propelled the rapid development of photovoltaic (PV) systems, which harness solar energy to generate electricity. However, the performance of these systems is influenced by various factors, including temperature, irradiance, and shading. These factors can significantly impact the efficiency and power output of PV installations. To optimize the power generation potential of PV systems, maximum power point tracking (MPPT) techniques are employed. The primary objective of MPPT is to identify the operating point at which the PV system generates the maximum power output.

Traditional MPPT methods, such as Perturb and Observe (P&O) and Incremental Conductance (IC), have been widely adopted due to their simplicity and cost-effectiveness. However, these methods have certain limitations, including slow response times and reduced accuracy in tracking the maximum power point. Recognizing the need for more efficient and accurate MPPT techniques, researchers have turned to artificial intelligence[1–3]. Artificial intelligence, particularly neural networks (NN), has demonstrated immense potential for enhancing the MPPT process in PV systems. By leveraging the capabilities of neural networks[4–7], it becomes possible to model the complex relationships between the various environmental factors and the maximum power point[8–10].

In the subsequent sections, we will delve into the methods employed in this study, present the findings obtained, and highlight the novelty and potential implications of utilizing neural networks for MPPT in PV systems[11–13]. By understanding the advancements and benefits offered by AI-based MPPT techniques, we can pave the way for the integration of intelligent solutions in the field of photovoltaics, thereby maximizing the utilization of solar energy and fostering sustainable development.

2 Methodology

The innovative aspect of our research lies in the robustness and reliability of the neural network approach. The neural network's ability to learn and generalize from diverse weather patterns allows it to outperform conventional methods that may struggle to adapt effectively.

We first simulated the perturb and observe method in order to collect data of our Pv system , which are the power and the cyclic ratio 'D' , then we built a neural network as shown in section 2.2, we performed a learning on 100 data using Matlab software.

2.1 SPhotovoltaic generator studied

We worked on a 100 kw PV array made from modules of the type SunPower SPR-305-WHT , that consists of 96 cells , number of series-connected modules per string is 5, and number of parallel strings is 66. This PV array is associated with a boost chopper, with a perturb and observe maximum power point tracking control, as a first approach., which is illustrate on Figure 1.

A real array consists of multiple connected PV cells, and to observe properties at the terminals of the PV array, additional parameters must be included in the basic equations[14,15].

$$I = I_{PV} - I_0 \left(exp\left(\frac{V+R_5 I}{V_t a}\right) - 1 \right] - \frac{V+R_5 I}{R_P} \quad (1)$$

Where I_{PV} and I_0 are the PV current and saturation currents, respectively, of the array and

Vt =NskT/q is the thermal voltage of the array with *Ns* cells connected in series. *Rs* is the equivalent series resistance of the array and *Rp* is the equivalent parallel resistance.

The maximum output will fluctuate due to changes in ambient temperature and amount of solar radiation. Real-time peak power point trackers are an integral part of a solar system because the maximum power available from a solar system varies continuously with atmospheric conditions. The maximum power point tracking MPPT schemes [16] proposed in the literature can be classified into three different categories [17] direct method, intelligent method and indirect method.

The direct method, also known as the truth-seeking method, the MPPT is searched by continuous disturbances of the operating point of the PV generator. Under this category, scheme perturbations and observations P&O [18], hill climbing HC [19], and incremental conductance INC [20] have been widely applied to PV systems. In the P&O method, the working voltage of the PV array is perturbed to reach the MPPT. Similar to the P&O method, the hill-climbing method perturbs the duty cycle of the DC/DC interface converter.

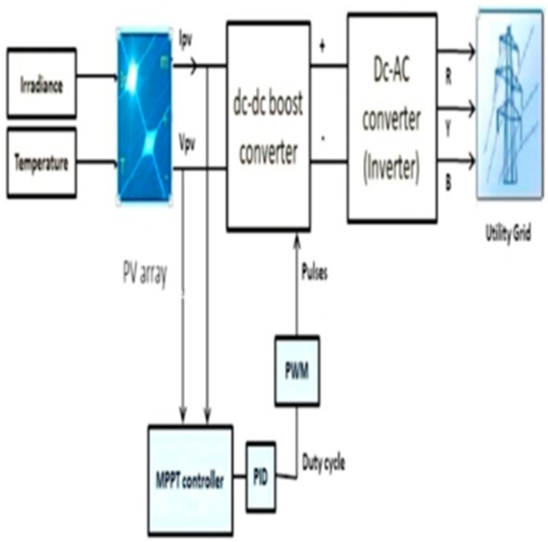

Fig 1. Schemeof photovoltaic generator studied

First we simulated the perturb and observe method for our system, imposing the variations shown on the Figure 2, irradiation and ambient temperature, and we got the results shown on Figure 3.

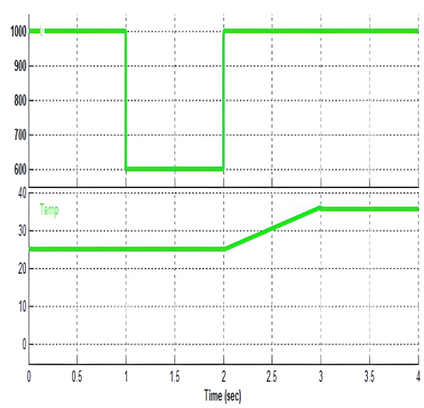

Fig 2. Required variations in irradiation and temperature

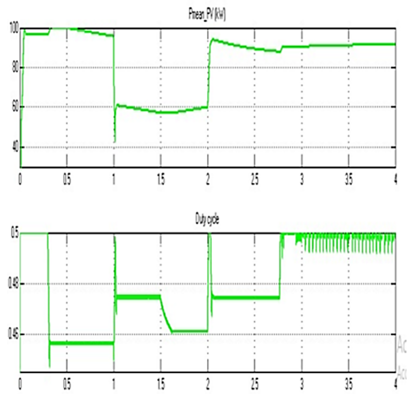

Fig 3. Output power of the PV array and the duty cycle with the P&O method

2.2 Design of the adapted artificial neural network

The proven potential of machine learning techniques in pattern matching and computer vision has prompted researchers to use these techniques to predict solar cell efficiency[(21)] [(22)]. The research work performed to date demonstrates the applications of these techniques for optimal efficiency prediction, best-suited design and materials for fabricating dye-sensitive solar cells (DSSCs). The network we used, is a fully connected back propagation one as shown on the Figure 4.

The process of designing our neural network can be summarized in these steps:

- The collection of a database: this data constitutes the input of the neural network, and therefore it determines both the size of the network and the performance of the system. In our study we have only one input variable which is the power of the photovoltaic generator and a single output which is the cyclic ratio' D', we collected these data from the solar panel simulation with perturb and observe control..
- We built a network of multilayer neurons with: an input layer with two neurons, a hidden layer with 15 neurons and an output layer with one neuron. We opted for 15 neurons and no more to not have a big retropagation error.

For the input and output layer transfer function and the hidden layer, the sigmoidal function was used.

- Training of the network of neurons on the bases of learning and validation, We carried out machine learning until obtaining a very small quadratic error.
- Measurement of neural network performance on the test basis.

The calculation stages of the neural network can be resumed like this

a- The output of the latent layer

$$y_i = f_j^c \left(\sum_{t=1}^{n} w_{ji}^c x_t + b_j^c \right) \tag{2}$$

b- The outputs of the output layer

$$o_k = f_k^s \left(\sum_{j=1}^{m} w_{kj}^s y_j + b_k^s \right) \tag{3}$$

c- The error terms of the output units

$$\delta_k^s = (tk - ok) f_k^{s'} \left(\sum_{t-1}^{m} w_{kj}^5 yj + b_k^* \right) \tag{4}$$

e- Weight and bias adjustment of the output layer

$$\begin{aligned} w_{kj}^s(t+1) &= w_{kj}^s(t) + \eta \delta_k^s y_j \\ b_k(t+1) &= b_k(t) + \eta \delta_k \end{aligned} \tag{5}$$

The input of the neural network is the power released by the photovoltaic generator, and the output is the cyclic ratio D (obtained during the previous simulation). We performed a learning on 100 data using Matlab software as shown on Figure 5, until a very small quadratic error, show in Figure 6.

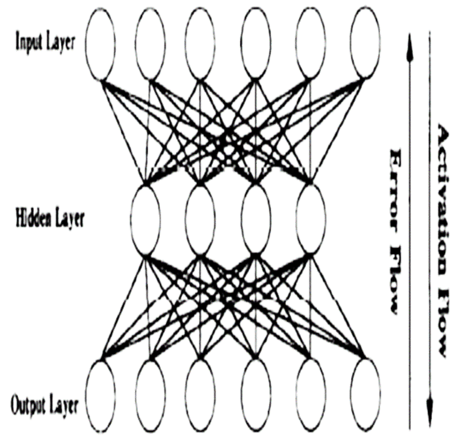

Fig 4. A fully connected backpropagation network, with the direction of activation and error flow indicated

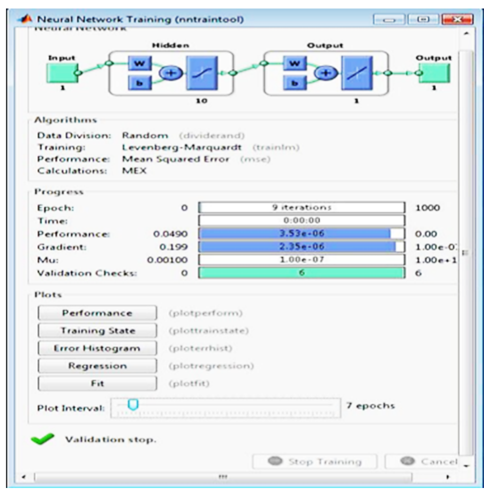

Fig 5. Neural network built with Matlab

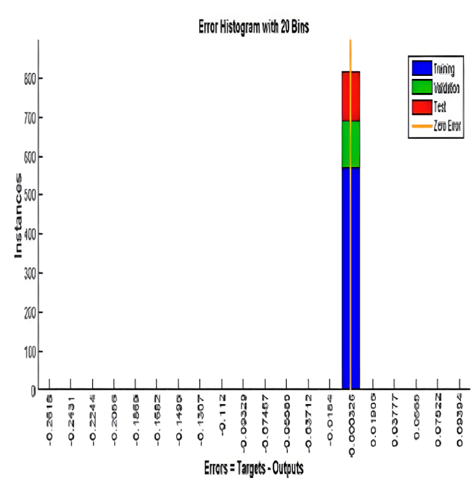

Fig 6. Quadratic error calculation

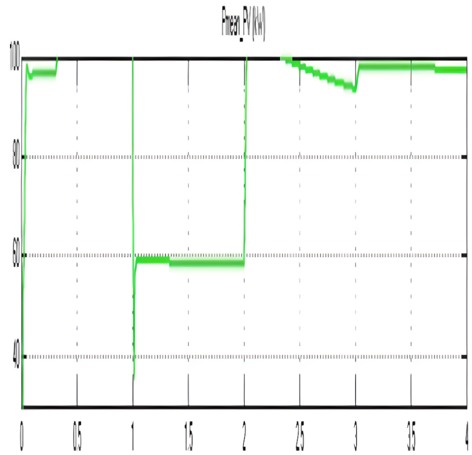

Fig 7. Output PV powerwith ANN method

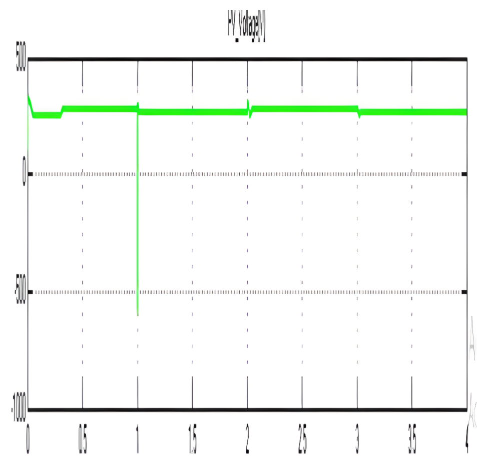

Fig 8. Output PV voltage with ANN method

Table 1. Comparison between the two methods

Comparison criteria	ANN method	P&O method
Response time	0.1567	0.1752
Extracted power	100 kw	95kw
convergence	+++	+

3 Results and Discussion

Despite the same variations in irradiation and ambient temperature, the results of the simulation of the power output of the photovoltaic generator, Figures 3 and 7, clearly show, that the maximum power has been reached by the artificial neural networks method , in an impeccable way, which minimizes excessive power loss. The output voltage of the PV array is also kept constant by the latter method. We can say that the neural networks method is very robust compared to the Perturb and observe method, and since the power loss is very minimal for the neural networks method, it can be said that the solar generator yield is much better than the P&O method. Our artificial neural network built with an input layer with two neurons, a hidden layer with 15 neurons and an output layer with one neuron , has demonstrated the accuracy of the results compared to the other research cited above. We can now implement it practically and have very good results.

4 Conclusion

In this article, we simulated a PV array of 100 Kw, with mppt controle , first, with a conventional P&O method, in which, the maximum power of 100Kw was not achieved with climate change, it is clear from the simulation results that the maximum power that was delivered with this method is 95 Kw and in severe climate change, the maximum power recorded was 90 Kw., but with a neural network method , the maximum power was clearly reached especially with the severe climatic changes (time from 3s to 4s), we can see that the power reached 100 kw, as desired. The simulation results obtained are very promising and in general, the performance of the MPPT based on artificiel neural network ANN, in terms of stability, accuracy and speed in the continuation of the maximum power point MPP are much better than the controller based on conventional MPPT method (P&O).

In conclusion, our research on the application of neural networks in photovoltaic installations represents a significant contribution to the field. By demonstrating the superiority of the neural network-based method for maximum power point tracking (MPPT), especially in the presence of climatic variations, we have highlighted the immense potential of artificial intelligence in optimizing the efficiency and performance of solar power systems. Our work showcases the adaptability and accuracy of neural networks in capturing the complex relationships between weather conditions and the maximum power point. Indeed , our neural network has demonstrated its effectiveness in comparison with the references cited in this article, thanks to its accuracy and the number of neurons used, which have given excellent results in the pursuit of maximum power of our PV system. By leveraging the power of deep learning, our research has overcome the limitations of traditional MPPT techniques and paved the way for more efficient and reliable energy generation from photovoltaic systems.

References

1) Phan BC, Lai YC, Lin CE. A Deep Reinforcement Learning-Based MPPT Control for PV Systems under Partial Shading Condition. *Sensors*. 2020;20(11):3039. Available from: https://doi.org/10.3390/s20113039.
2) Ruhi S, Shafayet CS, Farihal A, Mujibur RK. Implementation of an MPPT technique of a solar module with supervised machine learning. *Frontiers in Energy Research*. 2022;10. Available from: https://doi.org/10.3389/fenrg.2022.932653.
3) Akruri M, Farhat M, Barambones O, Ramos-Hernanz JA, Turkieh MJ, Badawi M, et al. Maximum Power Point Tracking of PV System Based on Machine Learning. *Energies*. 2020;13(3):692. Available from: https://doi.org/10.3390/en13030692.
4) Takruri M, Farhat M, Barambones O, Ramos-Hernanz JA, Turkieh MJ, Badawi M, et al. Maximum Power Point Tracking of PV System Based on Machine Learning. *Energies*. 2020;13(3):692–692. Available from: https://doi.org/10.3390/en13030692.
5) Falama SRZ, Gamzat H, Bakari A, Dadjé V, Dumbrava S, Makloufi F, et al. Maximum Power Point Tracking of Photovoltaic Energy Systems Based on Multidirectional Search Optimization Algorithm. *International journal of renewable energy research*. 2021;11:2021. Available from: https://dorl.net/dor/20.1001.1.13090127.2021.11.2.5.4.
6) Mossad MIaOAE, Al-Ahmar MA, Banakher FA. MMPT of PV system Based Cuckoo Search Algorithm; review and comparison. *Energy Procedia*. 2020. Available from: https://doi.org/10.1016/j.egypro.2019.04.013.
7) Amadou BA, Alphousseyni N, Mbaye NEH, Senghane M. Power optimization of a photovoltaic system with artificial intelligence algorithms over two seasons in tropical area. 2023. Available from: https://doi.org/10.1016/j.mex.2022.101959.
8) Shoaib A, Burhan M, Chen Q, Oh SJ. An artificial neural network-based performance model of triple-junction InGaP/InGaAs/Ge cells for the production estimation of concentrated photovoltaic systems. *Frontiers in Energy Research*. 2023;11. Available from: https://doi.org/10.3389/fenrg.2023.1067623.
9) Rai KB, Kumar N, Singh A. Design and analysis of Hermite function-based artificial neural network controller for performance enhancement of photovoltaic-integrated grid system. 2023. Available from: https://doi.org/10.1002/cta.3486.
10) Abdelkader E, Hassan R, Hicham M, Hicham B. Solar Power Output Forecasting Using Artificial Neural Network. 2021. Available from: https://www.researchgate.net/publication/356565720_Solar_Power_Output_Forecasting_Using_Artificial_Neural_Network.
11) Tatabhatla VMR, Agarwal A, Kanumuri T. Performance Improvement by Mitigating the Effects of Moving Cloud Conditions. 2021. Available from: https://doi.org/10.1109/TPEL.2020.3020807.
12) Panigrahi R, Mishra SK, Srivastava SC. Grid Integration of Small-Scale Photovoltaic Systems-A Review. *2018 IEEE Industry Applications Society Annual Meeting (IAS)*. 2018. Available from: https://doi.org/10.1109/TIA.2020.2979789.
13) Ma C, Dasenbrock J, Tobermann JC, Braun M. A novel indicator for evaluation of the impact of distributed generations on the energy losses of low voltage distribution grids. 2019. Available from: https://doi.org/10.1016/j.apenergy.2019.03.090.
14) Berrezzek F, Khelil K, Bouadjila T. Efficient MPPT scheme for a photovoltaic generator using neural network. 2020. Available from: https://doi.org/10.1109/CCSSP49278.2020.9151551.
15) Wang F, Xuan Z, Zhen Z, Li K, Wang T, Shi M. A day-ahead PV power forecasting method based on LSTM-RNN model and time correlation modification under partial daily pattern prediction framework. *Energy Conversion and Management*. 2020;212:112766. Available from: https://doi.org/10.1016/j.enconman.2020.112766.
16) Dong N, Chang JF, Wu AG, Gao ZK. A novel convolutional neural network framework based solar irradiance prediction method. *International Journal of Electrical Power & Energy Systems*. 2020;114:105411. Available from: https://doi.org/10.1016/j.ijepes.2019.105411.
17) Wang H, Liu Y, Zhou B, Li C, Cao G, Voropai N, et al. Taxonomy research of artificial intelligence for deterministic solar power forecasting. *Energy Conversion and Management*. 2020;214:112909. Available from: https://doi.org/10.1016/j.enconman.2020.112909.
18) Zang H, Cheng L, Ding T, Cheung KW, Wang M, Wei Z, et al. Estimation and validation of daily global solar radiation by day of the year-based models for different climates in China. *Renewable Energy*. 2019;135:984–1003. Available from: https://doi.org/10.1016/j.renene.2018.12.065.
19) Liu Y, Zhou Y, Chen Y, Wang D, Wang Y, Zhu Y. Comparison of support vector machine and copula-based nonlinear quantile regression for estimating the daily diffuse solar radiation: A case study in China. *Renewable Energy*. 2020;146:1101–1112. Available from: https://doi.org/10.1016/j.renene.2019.07.053.

20) Mghouchi YE, Chham E, Zemmouri EM, Bouardi AE. Assessment of different combinations of meteorological parameters for predicting daily global solar radiation using artificial neural networks. *Building and Environment*. 2019;149:607–622. Available from: https://doi.org/10.1016/j.buildenv.2018.12.055.
21) Ponce P, Pérez C, Fayek AR, Molina A. Solar Energy Implementation in Manufacturing Industry Using Multi-Criteria Decision-Making Fuzzy TOPSIS and S4 Framework. *Energies*. 2022;15(23):8838. Available from: https://doi.org/10.3390/en15238838.
22) Sarkodie WO, Ofosu EA, Ampimah BC. Decision Optimization Techniques for Evaluating Renewable Energy Resources for Power Generation in Ghana: Mcdm Approach. *SSRN Electronic Journal*. 2022;8:13504–13513. Available from: http://dx.doi.org/10.2139/ssrn.4178873.