Bulletin of Electrical Engineering and Informatics
Vol. 14, No. 6, December 2025, pp. 4161~4173
ISSN: 2302-9285, DOI: 10.11591/eei.v14i6.10050

Artificial neural network maximum power point tracking for mitigation photovoltaic harmonic distortion

Adel Bouledroua, Tarek Mesbah, Samia Kelaiaia
Department of Electrical Engineering, Faculty of Technology, Badji Mokhtar University, Annaba, Algeria

Article Info

Article history:

Received Feb 11, 2025
Revised Aug 30, 2025
Accepted Sep 11, 2025

Keywords:

Artificial neural network
Maximum power point tracking
Photovoltaic
Power quality
Total harmonic distortion

ABSTRACT

This study introduces a novel methodology aimed at minimising total harmonic distortion (THD) in grid-connected photovoltaic (PV) systems (GCPVs) through the implementation of a maximum power point tracking (MPPT) approach based on artificial neural networks (ANN). High THD levels in PV systems can lead to inefficiencies, power quality issues, and potential damage to the grid infrastructure. Although traditional MPPT methods effectively optimise the power output, they often fail to address harmonics. The proposed ANN-based MPPT algorithm improves PV power harvesting while actively minimising the harmonic distortions. The ANN was trained using a comprehensive dataset that included various environmental conditions, ensuring robust performance in diverse operational scenarios. Simulation results demonstrate that the ANN-based MPPT approach significantly reduces THD to below 1% across various irradiance levels, in contrast to the 1.18% to 2.72% observed with conventional methods such as perturb and observe (P&O), while simultaneously preserving optimal power output. Reducing harmonic distortion improves the power quality, system efficiency, and lifespan of grid-connected components. This study highlights ANN-based control strategies for addressing the challenge of maximising energy harvesting and maintaining power quality in modern PV systems, offering a solution for the sustainable integration of solar energy into the grid.

Corresponding Author:

Adel Bouledroua
Department of Electrical Engineering, Faculty of Technology, Badji Mokhtar University
B.P.12, Annaba, 23000 Algeria
Email: adel.bouledroua@univ-annaba.dz

1. INTRODUCTION

In order to fulfill the increasing global energy demand, the use of renewable energy sources has grown; among these sources, photovoltaic systems (PVs) have emerged as a viable and promising alternative to fossil fuels [1], [2]. PV systems based on PVs effect convert solar radiation directly into electrical power [3]. Total harmonic distortion (THD) in solar systems is a major and permanent challenge that affects the power quality and efficiency of the overall system [4]. THD levels can lead to the damage of electrical components, overheating, and shorter operating times, which can defeat the environmental and economic purposes of solar energy systems [5].

Despite significant advancements in PV technology, the issue of THD remains a critical concern, particularly within grid-connected PV (GCPV) systems, where the seamless integration of sustainable energy into existing power grids is imperative [6]. While conventional maximum power point tracking (MPPT) techniques are effective in optimising PV system power output, they often exhibit limitations in their capacity to regulate THD values effectively [7]. This intrinsic inefficiency underscores the necessity for innovative approaches that concurrently enhance energy extraction efficiency and reduce harmonic distortion.

Recently, expensive studies have investigated various approaches to reduce THD in PV systems. A comprehensive review of the THD reduction technology [8] was carried out, emphasizing the importance of inverter technology and control strategies for optimal performance. Researchers discovered that employing advanced modulation techniques and filtering methods can greatly enhance the quality of power supplied to the grid. Additionally, [9] has offered a three-phase inverter optimized control method that considerably lowers THD while maintaining PVs system stability. Similarly, [10] has studied an optimization-based technique for selective harmonic elimination in GCPVs, which has been shown to significantly improve power quality by effectively reducing harmonic distortion. Their results highlighted the importance of using evolved control approaches to increase the effectiveness of PV systems while ensuring compliance with grid standards. Moreover, [11] has presented an active harmonic dampening filter that is controlled by an Imperial competitive algorithm (ICA). This study presents a new method that improves the performance of GCPVs. It effectively reduces harmonic distortion and increases the system's ability to adjust to different load conditions. An enhanced multi-carrier pulse width modulation (PWM) technique was introduced by [12], which was designed to mitigate harmonics in solar PVs systems based on cascaded H-bridge configurations. This advancement represents a significant contribution to the continuous efforts aimed at enhancing the reliability and renewable energy systems efficiency. These studies show the ongoing attempts to improve GCPV's power quality of GCPV, focusing on the implementation of innovative control strategies and the application of harmonic mitigation techniques.

This study presents an advanced methodology for addressing THD. While preceding sections highlighted the critical need for solutions that improve power extraction efficiency and reduce harmonic distortion, this research specifically proposes an artificial neural network (ANN)-based MPPT technique. This novel approach is engineered to concurrently optimise power harvesting from PV systems and actively minimise harmonic distortions, thereby enhancing overall system performance and reliability. A robust training regimen for the ANN will involve the utilisation of a comprehensive dataset, integrating both historical operational data and real-time measurements. This rigorous training regimen is intended to facilitate the ANN effective adaptation to a range of variable environmental conditions and dynamic load requirements, thereby confirming its efficacy across diverse operational scenarios.

The comprehensive ANN framework of this study, which successfully tackles two important problems in PV systems increasing energy extraction and actively lowering THD encapsulates its innovative element. Unlike conventional MPPT techniques, which often give priority to energy extraction without a proper balance of content management, our proposed methodology offers a holistic solution. This integrated approach enhances our understanding of renewable energy systems by improving scientific quality and contributions. It also significantly influences the design and operation of more efficient PV systems, leading to increased reliability and performance. Ultimately, this study aims to advance sustainable energy solutions, facilitating their seamless integration with modern power grids and supporting the global shift towards cleaner energy future by effectively mitigating harmonic distortion.

2. PROPOSED SYSTEM CONFIGURATION AND CONTROL METHODOLOGY

As illustrated in Figure 1, the proposed system configuration comprises several basic components designed to enable efficient energy conversion and easy integration into the power grid. PVs panels convert sunlight into direct current (DC) and are the central components of the system. This DC power is then buffered by a DC link that maintains a stable voltage level before the energy is transferred to the inverter. The inverter plays a crucial role in converting DC into alternating current (AC), an essential process for feeding energy into the power grid. To enhance the output waveform quality and effectively mitigate harmonic distortion, an LCL passive filter is strategically positioned between the inverter and the grid interface. This comprehensive configuration is designed to enhance the performance of the PV system and ensure both high operational reliability and high-power quality management in order to successfully integrate the power grid.

2.1. Solar photovoltaic modelling

The PV cell is the fundamental component of PV systems. To generate the required power and voltage, multiple PV cells are interconnected in either a series or parallel configuration, thereby forming a complete PV array [13], [14]. A single diode model is typically employed to represent a PV cell, as visually presented in Figure 2. This equivalent circuit provides a mathematical representation of the operational behaviour of the solar cell. Within this model, a current source is arranged in parallel with a diode, along with a series resistor (R_s) and a shunt resistor (R_{sh}). The photogenerated current (I_{ph}) is directly proportional to the intensity of incident sunlight, while the diode effectively depicts the characteristics of the cell's p-n junction. Specifically, series resistance (R) is responsible for resistance losses in cell connections, while shunt resistance (R_{sh}) is the leakage current present in the cell. In (1) illustrates the relationship between the current (I) and the voltage (V) in the PV cell [15]-[17].

$$I = I_{ph} - I_D - I_{sh} \tag{1}$$

In this context, the photocurrent is denoted as I_{ph}, while the diode current is denoted by I_D, and the shunt current is indicated as I_{sh}. These parameters are defined as (2)-(6):

$$I_{ph} = \frac{G}{G_n}\left(I_{scn} + K_i(T_c - T_{cn})\right) \tag{2}$$

$$I_D = I_s\left(e^{\frac{q(V+IR_S)}{AKT_C}} - 1\right) \tag{3}$$

$$I_{sh} = \frac{V+IR_S}{R_{sh}} \tag{4}$$

$$I_s = I_{sn}\left(\frac{T_{cn}}{T_c}\right)^3 e^{\left(\frac{qE_g}{AK}\left(\frac{1}{T_{cn}}-\frac{1}{T_C}\right)\right)} \tag{5}$$

$$I_{sn} = \frac{I_{scn}}{e^{\left(\frac{qV_{ocn}}{AKT_{cn}}\right)}-1} \tag{6}$$

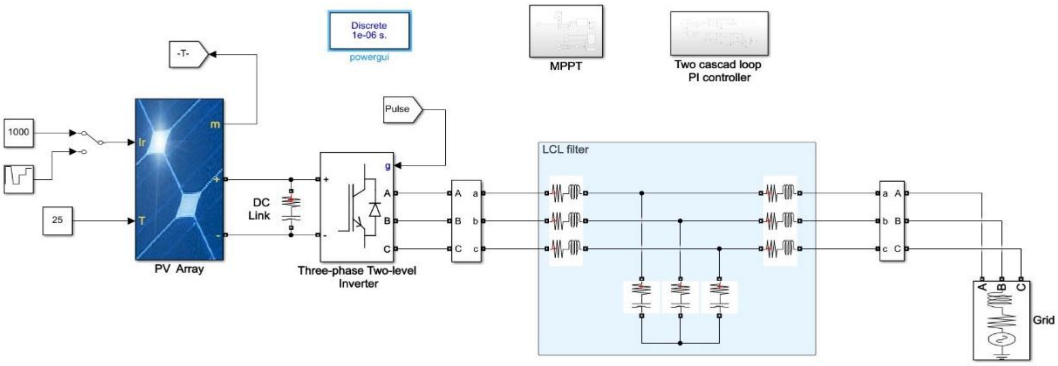


Figure 1. The proposed model was implemented in MATLAB/Simulink

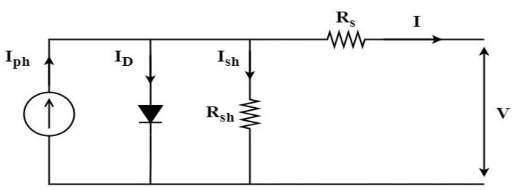
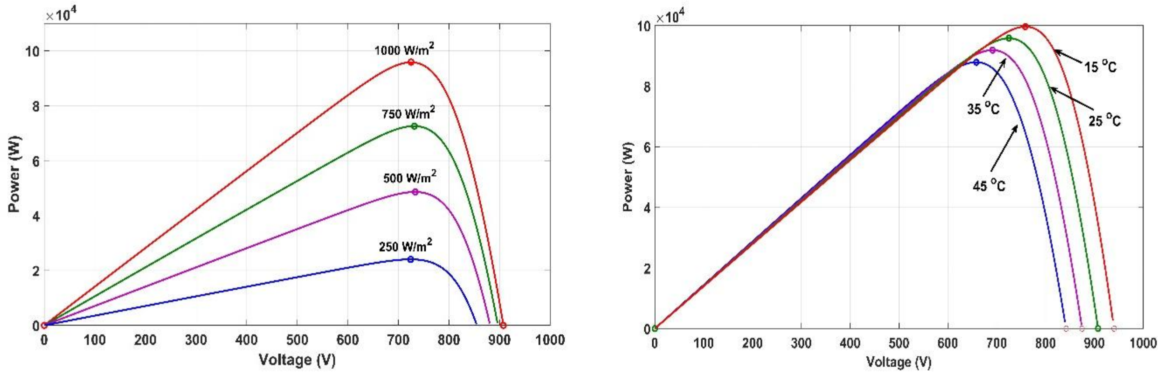


Figure 2. Single diode model of PV cell

Where I_{scn} represents the short-circuit current of a PV cell measured in amperes (A), while G denotes the solar irradiance expressed in watts per square meter (W/m²). The Boltzmann constant is indicated by K, measured in joules per kelvin ($J{\cdot}K^{-1}$), and T_c refers to the PV cell temperature in kelvins (K). The reference temperature is represented by T_{cn}, also in kelvins (K). The PV cell series resistance R_s is measured in ohms (Ω), and the shunt resistance R_{sh} is also measured in ohms (Ω). In voltage (V) the V_{ocn} shows the PV cell open circuit voltage. The band gap energy is denoted by Eg in joules (J), while K again refers to the Boltzmann constant. The ideality factor is represented by A, and the charge of an electron is indicated by q. The scenario characterized by standard testing conditions, wherein G_n is equal to 1000 W/m² and T_{cn} is 25 °C, is represented by the subscript "n."

Figure 3 shows how variations in solar irradiance and temperature impact the performance of PV systems. In particular, Figure 3(a) shows the effect of different irradiation levels on the P-V curve at constant temperature and Figure 3(b) shows the effect of the change in temperature at constant irradiation. These visual relationships clearly indicate that optimal operating points that deliver maximum power output change considerably with environmental changes. Therefore, accurate MPPT approaches must be implemented to adapt to these changes continuously and ensure that PV systems provide maximum performance. This study utilized the 1Soltech ISTH-215-P solar module and provided its electrical characteristics under standard testing conditions (STC), which are set at a solar irradiation of 1000 W/m² and a temperature of 25 °C, as detailed in Table 1.



(a) (b)

Figure 3. P-V curve: (a) effect of irradiance (T=25 °C) and (b) effect of temperature G=1000 W/m^2

Table 1. Specifications of 1Soltech ISTH-215-P PV module

Specification	Value
Power at STC	215 W
Voltage at MPP Vmp	29 V
Current at MPP Imp	7.35 A
Open circuit voltage Voc	36.3 V
Short circuit current Isc	7.84 A
Open circuit voltage temp coefficient β	-0.361 %/°C
Short circuit current temp coefficient α	0.102 %/°C

2.2. Maximum power point tracking technique

MPPT techniques are indispensable in PV applications, as they actively optimise the energy harvested from solar panels. This optimisation is essential given the inherent fluctuations in environmental conditions. By continuously adjusting the operating point, MPPT ensures the PV system consistently delivers its maximum power output, thereby adapting to variations in temperature and solar irradiation and consequently improving the entire system's efficiency [18].

2.2.1. Perturb and observe technique

Figure 4 illustrates the flowchart of the perturb and observe (P&O) algorithm, a popular method for MPPT commonly utilized in PV systems. Its widespread adoption is largely attributed to its inherent simplicity and proven effectiveness across diverse environmental conditions. The basic operation of the P&O method consists of iteratively adjusting the voltage of the PV array and carefully monitoring the corresponding changes in the energy output. This adaptation mechanism enables the system to continuously progress towards its maximum power point (MPP) [19], [20]. The operating cycle starts with the measurement of the instantaneous voltage, V(k), and the instantaneous current, I(k), of the PV panel, from which the current output, P(k), is calculated. The algorithm then calculates the change in power (ΔP) and voltage (ΔV) in relation to the previous measurement (k-1). Based on these computed variations, the system enacts specific control adjustments:

- If a zero change in power (ΔP is zero) is observed concurrently with a positive voltage perturbation (ΔV is positive), the algorithm decreases the voltage to search for a potentially superior power point.
- Should power output show an increase (ΔP is positive), the voltage is typically augmented to advance towards the MPP, irrespective of the prior voltage change direction.

– Furthermore, if a positive voltage change (V is positive) is recorded, the voltage decreases, which constitutes the standard exploration step of the algorithm's mechanism for navigation of the power-voltage characteristic curve.
– After each adjustment, historical voltage and current data are updated with the latest values to prepare the system for the next iteration. This continuous iterative process ensures that the system's operational point is optimised continuously, thus maximising the energy recovery from PV panels.

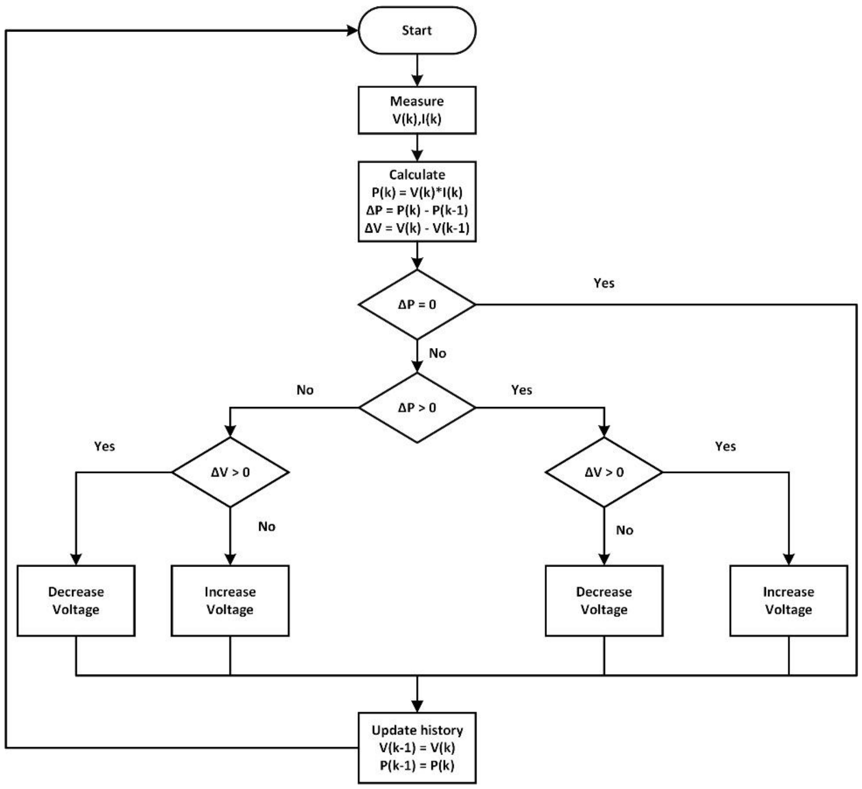


Figure 4. Flowchart of P&O algorithm

2.2.2. Proposed artificial neural network based maximum power point tracking technique approach

ANN is a complex computational framework that is inspired by the complex structure and functions of the human brain. ANN is comprised interconnected processing units called neurons, which cooperate to receive, process, and transmit information. As shown in Figure 5, a typical ANN architecture has three main layers: the input layer captures data, one or more hidden layers that handle complex calculations and information processing, and the output layer generates final results. These networks have special abilities in learning data and discovering complex nonlinear relationships without explicit mathematical models, making them particularly valuable for the analysis of complex systems [21], [22].

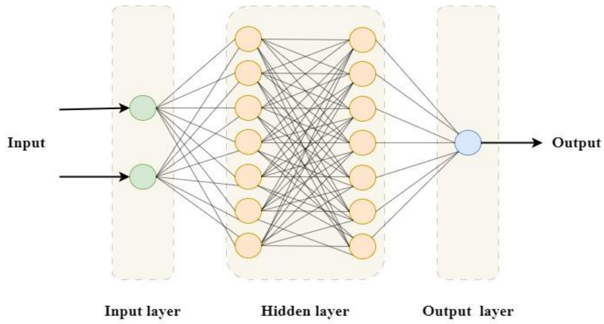


Figure 5. Structure of an ANN

ANNs provide a practical solution for MPPT in PV systems [23]. Their particular suitability is due to their inherent ability to model and identify complex non-linear relationships that are commonly encountered in PV systems, mainly due to the dynamic and variable nature of the environment, such as solar radiation and temperature [24]. The systematic design of an ANN for MPPT encompasses several critical stages: problem definition, meticulous data collection and preprocessing, precise network architecture design, robust model training and validation, and subsequent system implementation and iterative refinement. Each of these phases is indispensable for ensuring the ANN's optimal performance in maximising power extraction from PV systems [25], [26].

In this study, the development of ANN based MPPT started with the aim of maximizing power output of PV modules under different environmental conditions and thus improving the overall efficiency of the system. These environmental parameters are considered fundamental inputs to the ANN model because PV panel power output is intrinsically linked to panel temperature T and solar radiation G. The (7) and (8) were explicitly used to generate a wide range of temperature and radiation values, which were the main inputs to the ANN model. Subsequently, the corresponding maximum power point (MPP) voltage V_{mp}, current I_{mp}, and power P_{mp} were calculated using (9) to (11) under these simulated conditions. The designed ANN's output was explicitly defined as the optimal voltage to be generated by the solar panel, corresponding to the MPP.

The maximum (G_{max}) and minimum (G_{min}) radiation values were set at 1000 and 0 W/m^2, respectively, and the minimum (T_{min}) and maximum (T_{max}) temperature values were set at 15 and 35 °C, respectively. Standard solar radiation (G_s) was defined as 1000 W/m², and standard temperature (Ts) as 25 °C. Table 1 gives the voltage and current temperature coefficients, α and β. The following is an explicit formulation of these relationships:

$$G = [(G_{max} - G_{min}\ ) \times rand] + G_{min} \tag{7}$$

$$T = [(T_{max} - T_{min}) \times rand] + T_{min} \tag{8}$$

$$V_{mp} = V_{oc} + \left(\beta(T - T_s)\right) \tag{9}$$

$$I_{mp} = I_{sc} \times \left(\frac{G}{Gs}\right) + \left(1 + (\alpha(T - T_s))\right) \tag{10}$$

$$P_{mp} = I_{mp} \times V_{mp} \tag{11}$$

For this study, a feedforward ANN architecture was employed to model the intricate relationship between solar irradiance and temperature as input variables, and the desired optimal voltage output. The network's structure comprised an input layer, a single hidden layer containing 10 neurons that utilised a sigmoid activation function, and an output layer. To ensure robust training and evaluation, the overall dataset comprising 1000 data points of solar irradiance, temperature, and corresponding maximum power voltages was systematically partitioned into three distinct subsets. The training set, which made up 70% of the total data, was used to optimize the weights and biases of the ANN. A validation set, which made up 15% of the data, was essential for adjusting hyperparameters and reducing overfitting while training the model. The last 15% of the data was set aside as a test set to accurately evaluate how well the model performs on previously unseen data. This rigorous partitioning ensures that the ANN effectively tracks the MPP across various environmental conditions and exhibits strong generalisation capabilities for novel scenarios [27].

Levenberg-Marquardt (LM) algorithm has been chosen to train ANN models, mainly because of its proven effectiveness in solving non-linear problems of least squares [28]. This algorithm judiciously combines aspects of both steepest descent and Gauss–Newton methods, offering fast convergence, especially when estimated values are close to the final solution. The LM algorithm iteratively adjusts the network's weights and biases by approximating the Hessian matrix using the Jacobian, aiming to minimise the error function. During training, the network prediction accuracy was quantified using the MSE loss function, which measures the average square difference between the optimal ANN prediction voltage and the actual target MPP voltage [29]. The purpose of the LM algorithm is to minimize this MSE, thus optimizing the network's ability to identify the best operational points and maximize energy extraction efficiency.

Several key performance indicators and graphical representations were used to evaluate the ANN trained model, in particular for the LM algorithm, which consistently demonstrated superior performance in terms of gradients and overall efficiency. The regression plot visually depicts the correlation between the actual target values and the ANN model's predicted outputs. A regression coefficient (R) of 1, as reported for the LM algorithm in this study and in line with extensive literature, represents a perfect, nearly linear relationship and predictive power between observed and predicted values [30]. The error histogram is a plot of the prediction errors showing the difference between the predicted and actual values in training, validation, and test datasets. This histogram aids in verifying the overall accuracy and consistency of the model's predictions, with ideal performance indicated by errors clustered near zero [30]. The performance plot tracks critical metrics like mean squared error (MSE) and R-squared values across various training epochs, offering insights into the convergence behaviour and efficacy of the LM algorithm in optimising the ANN for precise MPPT predictions [31]. It's typically observed that training loss decreases with each epoch (a complete pass through the training dataset), while increasing test loss may signal overfitting. In addition, the Training States plot shows the MSE, gradients, and validation scores over time, illustrating how the LM algorithm learns from the dataset, with validation performance monitored to avoid overfitting and gradient values going to zero (indicating convergence) and a validation performance near zero indicating a low error in MPPT prediction.

The application of ANN in MPPT solar PV systems is widely appreciated for its superior precision, inherent flexibility and fast response times, often surpassing traditional methods [32], [33]. However, the effectiveness of ANN-based MPPT depends mainly on the quality and completeness of the training data sets and requires a large number of computing and data resources for optimal performance. A potential disadvantage is the risk of overfitting, which may compromise the generalisation capability of the model if not properly controlled during training. Consequently, the introduction of systems based on ANNs may entail higher upfront costs due to the need for complex hardware and software components [34].

3. RESULTS AND DISCUSSION

This section provides a summary and discussion of the key findings of this study. The simulation employs the proposed ANN-MPPT methodology to establish a correlation with 1000 input data points, specifically solar irradiance and temperature, pertaining to the PV array. To facilitate optimal analysis, a discrete simulation methodology is utilized in place of a continuous simulation approach.

As shown in Figure 6, the proposed ANN has an ideal predictive capability as confirmed by the R-regression coefficient (R) of 1. The result demonstrates high accuracy of the prediction power based on the input data and establishes a strong correlation between the output voltage produced and the target voltage required by the PV selected. Moreover, the regression chart in Figure 6 clearly shows that the data are trained carefully, which leads to negligible errors and a close match between the ANN output and the target value.

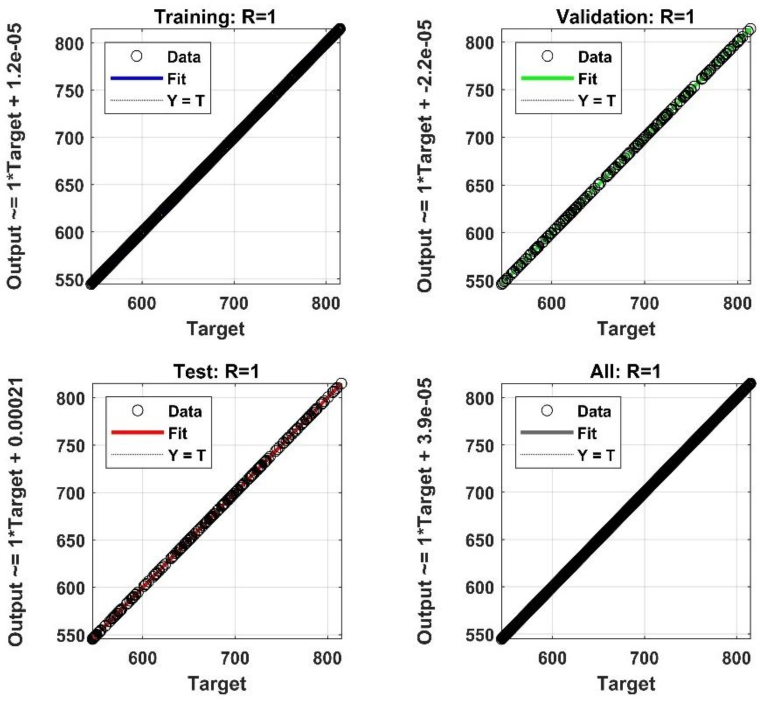


Figure 6. Regression plot of the proposed ANN approach

The error histogram presented in Figure 7 illustrates the absence of error throughout the training, validation, and testing phases of data matching, thereby affirming the effectiveness of the employed methodology. The histogram comprises a total of 20 vertical bars, each representing the number of samples from the selected dataset that correspond to specific error ranges. The total ANN error spans from -0.0027, located in the leftmost bin, to 0.002221, situated in the rightmost bin. This error range has been divided into 20 smaller bins, each possessing a width of 0.00025. Notably, a bin with an error value of -0.00011 is positioned at the midpoint of the histogram. The culmination of the error histogram reveals that all 20 bins register zero error, thereby underscoring the appropriateness of the ANN for MPPT.

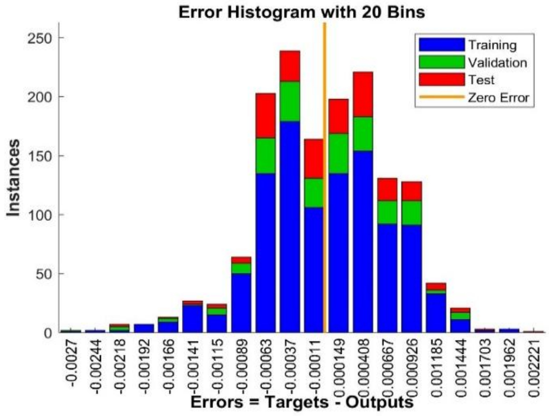


Figure 7. Error histogram

For processing the selected dataset, Figures 8 and 9 show the training status and performance test of the suggested approach. Figure 8 shows the validation assessment of the training dataset at 1000 epochs along with the gradient and momentum parameter (Mu). Using a minimum loss function, the simulation shows that the gradient at 1000 epochs is 0.0035294, indicating low variance in the trained data. The simulation results show that a zero output decision and an average per input vector define the cumulative error. The suitability of the LM algorithm for MPPT is supported by the small value of Mu, in conjunction with the gradient and validation assessments of the trained dataset. The mean squared error, illustrated in Figure 9, indicates that the samples from the trained dataset converge towards the optimal training outcome after 1000 epochs. At 1000 epochs, the training data set has ideal validation performance. The simulation results attached at 1000 epochs show that the ideal validation performance is 0.00000049248. When using the LM algorithm, the validation performance close to zero indicates a very small error in MPPT prediction.

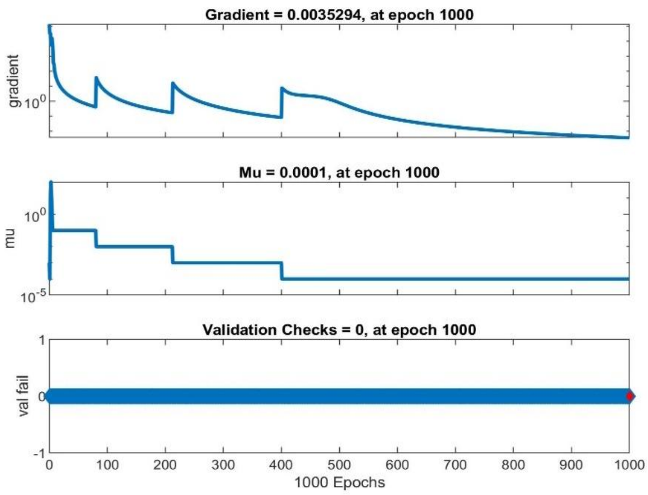


Figure 8. Training state

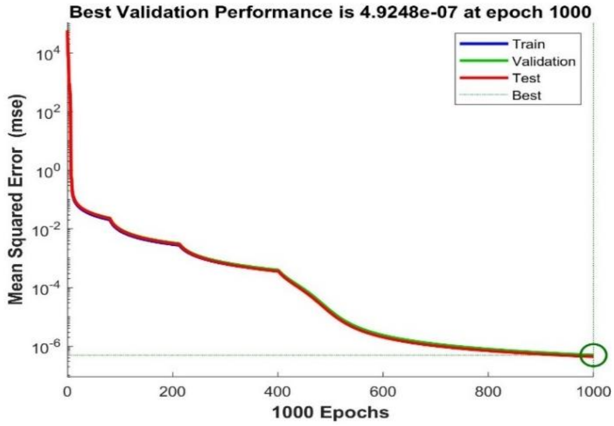


Figure 9. Performance test

This study aims to illustrate the effectiveness of the proposed ANN-MPPT method in minimizing THD compared to the traditional and commonly used P&O technique. The model, as depicted in Figure 1, was executed utilizing the MATLAB/Simulink software. The parameters utilized for the simulation are enumerated in Table 2. Various levels of solar irradiance were employed to evaluate the robustness and efficiency of the proposed methodology.

Table 2. Specifications values for the proposed model

Specification	Value
Rated power of PV array (Ppv)	95.92 Kw
PV array open-voltage circuit (Voc)	907.6 V
DC-link capacitor (Cdc)	1000 µF
Frequency switch (Fsw)	10 Khz
Inverter side inductor in LCL filter (Li)	500 µH
Capacitor in LCL filter (Ci)	100 µF
Grid side inductor in LCL filter (Lg)	500 µH
Grid voltage (VLL)	400 V
Grid frequency (fg)	50 Hz

Figure 10 illustrates a dynamic solar irradiance profile employed in the simulation study aimed at assessing the performance of the PV system under rapidly fluctuating weather conditions. The profile initiates with standard test conditions (STC: 1000 W/m² and 25 °C) from 0 to 0.35 seconds, during which four distinct irradiation levels are presented, characterized by abrupt transitions. Subsequently, the irradiance gradually diminishes to 750 W/m² until 0.7 seconds, followed by a further reduction to 500 W/m² until 1.05 seconds, concluding with an increase to 950 W/m² until the simulation terminates at 1.3 seconds. This profile is specifically designed to assess the system's dynamic responsiveness, MPPT efficiency, and power quality characteristics in the face of sudden irradiance variations, thereby simulating real-world conditions. The abrupt conditions to study the ability of the control system to maintain continuous operation and fluctuations in irradiance are used to evaluate the power converter's performance under difficult atmospheric conditions.

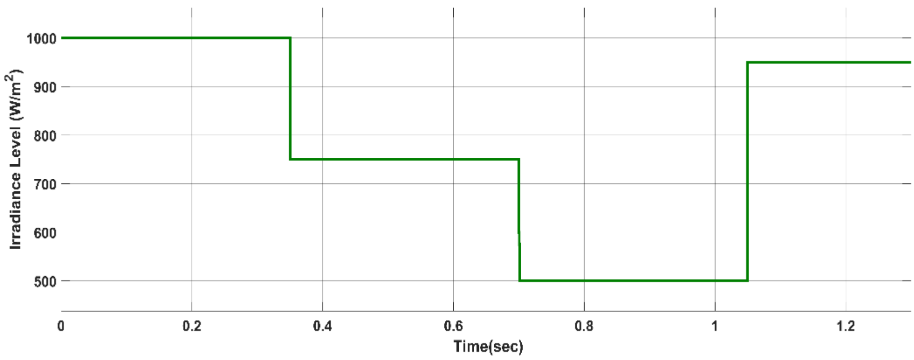


Figure 10. Solar irradiance level profile

Figure 11 presents an analysis of the THD associated with the current supplied to the grid, utilizing P&O-MPPT methodology. This analysis was conducted under different solar irradiance conditions of 1000, 750, 500, and 950 W/m². At the outset, the fundamental current operating at 50 Hz under 1000 W/m² stands at 195.5 A, accompanied by a THD of 1.18%, indicating a minimal level of harmonic distortion. As the radiation level diminishes to 750 W/m², the fundamental current decreases to 148.3 A. However, the THD rises to 1.65%, which means a slight deterioration in power quality. The fundamental current reaches 99.49 A at a reduced irradiance of 500 W/m², which corresponds to the THD of 2.72%, showing that low irradiance values increase the harmonic distortion in the system. The fundamental current rises to 186 A at 950 W/m² along with a THD of 1.29%, indicating a change in current quality. The P&O method shows a trend of increasing THD with decreasing irradiance by producing different THD values at different irradiance levels. This suggests that the P&O MPPT approach, while effective in tracking maximum power, may produce more harmonic content when irradiance varies, requiring additional filtering or compensation strategies for grid compliance.

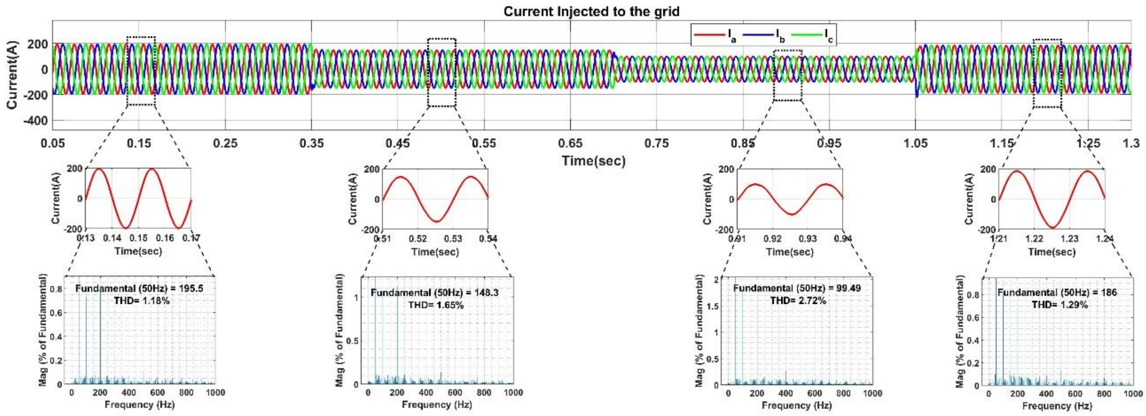


Figure 11. THD analysis of current injected into the grid using the P&O-MPPT method

Utilizing ANN-based MPPT approach, Figure 12 illustrates the current that is introduced into the grid under varying solar irradiance conditions of 1000, 750, 500, and 950 W/m². Furthermore, the THD is assessed for each of these scenarios. The current waveform shows a clear sinusoidal shape at each irradiation level, with accompanying THD values well below 1%, demonstrating effective harmonic reduction and consistent grid compatibility. The fundamental current is 195.4 A with a THD of 0.29%; the fundamental current was reduced to 148.1 A with a THD of 0.35%; the fundamental was reduced to 99.43 A with a THD of 0.57%; and the fundamental increases to 186 A with a THD of 0.29% at an irradiance of 950 W/m². Variations in irradiance demonstrate that the low THD values observed across different irradiance levels signify the efficacy of the ANN-based MPPT approach in accurately identifying the maximum power. This capability not only ensures minimal harmonic distortion but also enhances the quality of the power supplied into the grid. Consequently, the performance of the GCPVs is optimized.

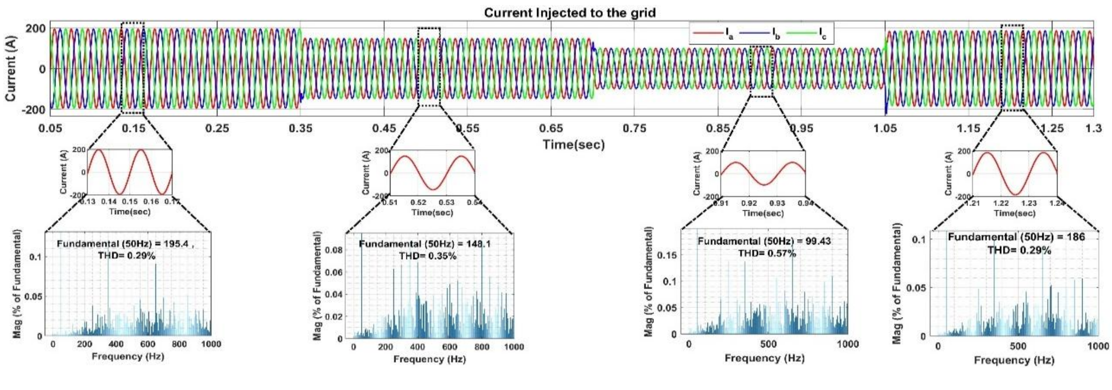


Figure 12. THD analysis of current injected into the grid using the ANN-MPPT approach

4. CONCLUSION

In this study, a novel ANN-based MPPT approach was proposed and tested to overcome the dual challenge of maximum energy harvesting and THD minimisation in GCPV systems, which are commonly faced by traditional MPPT methods. This research was driven by the fact that the traditional MPPT methods cannot effectively reduce THD, which will lead to low-quality power and the difficulty of grid integration. The simulation results indicated that the proposed ANN-MPPT can achieve more than 99% energy harvesting. The THD values are much lower than 1% at all the different solar irradiance levels and rapidly changing irradiance conditions, which is superior to the conventional P&O method. The THD values of the ANN-MPPT are much lower than those of the P&O method, which will increase as the irradiance decreases. These results suggest that the ANN-based MPPT approach can improve the maximum energy harvest and maintain the THD values below 1%, fulfilling strict grid THD requirements and solar power quality. However, there are specific inherent properties of ANN-based systems that need to be recognized. The performance of ANN-based systems is highly dependent on the quality and volume of the training dataset, which often requires a large amount of computational and data resources. It may be prone to overfitting under certain conditions, which could affect generalization in completely new settings, increasing the initial cost of implementation, as the hardware and software can be complex. For future research, testing the real-time implementation of this ANN-based MPPT algorithm in more complex environments, such as partial shading, would further confirm its robustness and flexibility. In addition, research into the integration of reinforcement learning algorithms to improve MPPT control or the development of hybrid control strategies combining multiple AI techniques offer promising avenues to further increase the efficiency and performance of the overall system. The model is applicable in a wide range of areas, including stand alone and grid-connected PV systems, as well as specialised applications in military equipment, telecommunications and space satellites.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Adel Bouledroua	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	✓
Tarek Mesbah	✓	✓				✓		✓	✓	✓	✓	✓		
Samia Kelaiaia	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

This paper does not involve any new data creation or analysis, so data availability is not relevant.

REFERENCES

[1] Y. A. Jieb, and E. Hossain, *Photovoltaic Systems: Fundamentals and Applications*. Cham: Springer International Publishing, 2022, doi: 10.1007/978-3-030-89780-2.
[2] B. Adel, M. Tarek, and K. Samia, "Evaluation of pulse width modulation techniques to reduce total harmonic distortion in grid-connected PV systems," *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 16, no. 1, pp. 564–574, 2025, doi: 10.11591/ijpeds.v16.i1.pp564-574.
[3] N. H. Achmad, A. Sudarmadji, and W. Nugroho, "Effect of Temperature and Solar Radiation on Electrical Power Generated by 50WP Monocrystalline Photovoltaic Panels at the South Tangerang Climatology Station," *Journal of Physics: Conference Series*,

8th International Conference on Engineering and Applied Science (ICEAT),Yogyakarta, Indonesia, 2024, vol. 2989, doi: 10.1088/1742-6596/2989/1/012005.
[4] S. Neku and S. P. Koko, “A Recent Review of Passive Filters as Used in Solar Photovoltaic-Based Systems to Mitigate Harmonics,” *2025 15th International Renewable Energy Congress (IREC)*, Hammamet, Tunisia, 2025, pp. 1-6, doi: 10.1109/IREC64614.2025.10926746.
[5] S. Adak and H. Cangi, “The quality problems at low irradiance in the grid-connected photovoltaic systems,” *Electrical Engineering*, vol. 106, no. 5, pp. 6185–6197, 2024, doi: 10.1007/s00202-024-02351-6.
[6] C. Ma, Q. Duan, W. Sheng, J. Qin, G. Sha, and Y. Qiu, “An AC/DC Dedicated Collection Network-Based Grid Integration Method of Autonomous PV Inverters to County Distribution Networks,” *2023 IEEE International Conference on Power Science and Technology (ICPST)*, Kunming, China, 2023, pp. 252-257, doi: 10.1109/ICPST56889.2023.10165127.
[7] S. A. Krim, F. Krim, H. Afghoul, and F. Abdelmalek, “An improved perturb and observe MPPT for photovoltaic systems using fuzzy step size,” *WSEAS Transactions on Power Systems*, vol. 19, pp. 105–114, 2024, doi: 10.37394/232016.2024.19.13.
[8] L. Alhafadhi and J. Teh, “Advances in reduction of total harmonic distortion in solar photovoltaic systems: A literature review,” *International Journal of Energy Research*, vol. 44, no. 4, pp. 2455–2470, Mar. 2020, doi: 10.1002/ER.5075.
[9] L. Abdelhak, B. Anas, B. Jamal, and E. O. Mostafa, “Optimized control of three-phase inverters to minimize total harmonic distortion in a grid-connected photovoltaic system,” *International Journal of Power Electronics and Drive Systems (IJPEDS)*, vol. 13, no. 4, pp. 2255–2268, 2022, doi: 10.11591/ijpeds.v13.i4.pp2255-2268.
[10] M. D. Raj, V. Thiyagarajan, N. B. M. Selvan, and D. S. Vanaja, “Amelioration of power quality in a solar PV fed grid-connected system using optimization-based selective harmonic elimination,” *Electrical Engineering*, vol. 104, no. 4, pp. 2775–2792, 2022, doi: 10.1007/s00202-022-01556-x.
[11] H. A. Hadi, A. Kassem, H. Amoud, S. Nadweh, N. M. Ghazaly, and N. Moubayed, “Using Active Filter Controlled by Imperialist Competitive Algorithm ICA for Harmonic Mitigation in Grid-Connected PV Systems,” *International Journal of Robotics and Control Systems*, vol. 4, no. 2, pp. 581–605, 2024, doi: 10.31763/ijrcs.v4i2.1365.
[12] S. K. Yadav, N. Mishra, and B. Singh, “An Improved Multicarrier PWM Technique for Harmonic Reduction in Cascaded H-Bridge Based Solar Photovoltaic System,” *IEEE Transactions on Industrial Informatics*, vol. 20, no. 7, pp. 9205-9214, July 2024, doi: 10.1109/TII.2024.3381796.
[13] S. R. Pendem, S. Mikkili, S. S. Rangarajan, S. Avv, R. E. Collins, and T. Senjyu, “Optimal hybrid PV array topologies to maximize the power output by reducing the effect of non-uniform operating conditions,” *Electronics*, vol. 10, no. 23, pp. 1-25, 2021, doi: 10.3390/electronics10233014.
[14] A. Sharma *et al.*, “Performance investigation of state-of-the-art metaheuristic techniques for parameter extraction of solar cells/module,” *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-37824-4.
[15] M. N. Ali, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, “Promising MPPT Methods Combining Metaheuristic, Fuzzy-Logic and ANN Techniques for Grid-Connected Photovoltaic,” *Sensors*, vol. 21, no. 4, p. 1244, 2021, doi: 10.3390/s21041244.
[16] B. Saleh, A. M. Yousef, F. K. Abo-Elyousr, M. Mohamed, S. A. M. Abdelwahab, and A. Elnozahy, “Performance Analysis of Maximum Power Point Tracking for Two Techniques with Direct Control of Photovoltaic Grid -Connected Systems,” *Energy Sources, Part A: Recovery, Utilization, and Environmental Effects*, vol. 44, no. 1, pp. 413–434, 2022, doi: 10.1080/15567036.2021.1898496.
[17] J. Li, C. Qin, C. Yang, B. Ai, and Y. Zhou, “Extraction of single diode model parameters of solar cells and PV modules by combining an intelligent optimization algorithm with simplified explicit equation,” *Energies*, vol. 16, no. 14, pp. 1-23, 2023, doi: 10.3390/en16145425.
[18] A. Mousa, “Maximum Power Point Tracking Achievements and Challenges in Photovoltaic Systems,” *International Journal of Engineering Science and Application*, vol. 7, no. 2, pp. 40–47, 2023, doi: 10.47709/brilliance.v3i2.2385.
[19] A. Sadick, *Maximum power point tracking simulation for photovoltaic systems using perturb and observe algorithm*, Solar Radiation-Enabling Technologies, Recent Innovations, and Advancements for Energy Transition, 2023, doi: 10.5772/intechopen.111632.
[20] N. B. Malla and V. Parajuli, “Comparison of Incremental Conductance and Perturb and Observe Techniques of Maximum Power Point Tracking for PV Systems,” *International Journal of Research in Science & Engineering*, no. 41, pp. 13–21, 2023, doi: 10.55529/ijrise.41.13.21.
[21] N. Boutasseta, M. S. Bouakkaz, I. Attoui, N. Fergani, A. Bouraiou, and A. Necaibia, “Implementation of MPPT Methods for improving the Performance of Photovoltaic Systems,” *2021 International Conference on Recent Advances in Mathematics and Informatics (ICRAMI)*, Tebessa, Algeria, 2021, pp. 1-4, doi: 10.1109/ICRAMI52622.2021.9585933.
[22] A. G. Olabi *et al.*, “Artificial neural networks applications in partially shaded PV systems,” *Thermal Science and Engineering Progress*, vol. 37, p. 101612, 2023, doi: 10.1016/j.tsep.2022.101612.
[23] V. Boscaino *et al.*, “Grid-connected photovoltaic inverters: Grid codes, topologies and control techniques,” *Renewable and Sustainable Energy Reviews*, vol. 189, p. 113903, 2024, doi: 10.1016/j.rser.2023.113903.
[24] A. V. Teja, W. R. Sultana, and S. R. Salkuti, “Performance explorations of a PMS motor drive using an ANN-based MPPT controller for solar-battery powered electric vehicles,” *Designs*, vol. 7, no. 3, pp. 1-18, doi: 10.3390/designs7030079.
[25] S. D. Al-Majidi, M. F. Abbod and H. S. Al-Raweshidy, “Design of an intelligent MPPT based on ANN using a real photovoltaic system data,” *2019 54th International Universities Power Engineering Conference (UPEC)*, Bucharest, Romania, 2019, pp. 1-6, doi: 10.1109/UPEC.2019.8893638.
[26] M. T. Hussain, A. Sarwar, M. Tariq, S. Urooj, A. BaQais, and Md. A. Hossain, “An Evaluation of ANN Algorithm Performance for MPPT Energy Harvesting in Solar PV Systems,” *Sustainability*, vol. 15, no. 14, p. 11144, 2023, doi: 10.3390/su151411144.
[27] M. Jlidi, O. Barambones, F. Hamidi, and M. Aoun, “ANN for Temperature and Irradiation Prediction and Maximum Power Point Tracking Using MRP-SMC,” *Energies (Basel)*, vol. 17, no. 12, p. 2802, 2024, doi: 10.3390/en17122802.
[28] F. Dubuisson, S. Dhaou, A. Chandra, M. Rezkallah, and H. Ibrahim, “Implementation of an Optimal Control based on ANN and LADRC for Two-Stage Single-Phase Photovoltaic Grid-Connected Inverter,” in *2022 IEEE Industry Applications Society Annual Meeting (IAS)*, IEEE, 2022, pp. 1–5, doi: 10.1109/IAS54023.2022.9940139.
[29] M. S, P. E, R. V, and D. P, “Integrating MPPT and Artificial Neural Networks for Efficient DC-DC and DC-AC Conversion in Photovoltaic Applications,” *International Journal of Electrical and Electronics Engineering*, vol. 10, no. 8, pp. 51–61, 2023, doi: 10.14445/23488379/IJEEE-V10I8P105.
[30] F. Bano, S. H. Serbaya, A. Rizwan, M. Shabaz, F. Hasan, and H. S. Khalifa, “An artificial neural network and Levenberg-Marquardt training algorithm-based mathematical model for performance prediction,” *Applied Mathematics in Science and Engineering*, vol. 32, no. 1, p. 2375529, 2024, doi: 10.1080/27690911.2024.2375529.

[31] R. B. Roy *et al.*, "A Comparative Performance Analysis of ANN Algorithms for MPPT Energy Harvesting in Solar PV System," *IEEE Access*, vol. 9, pp. 102137–102152, 2021, doi: 10.1109/ACCESS.2021.3096864.
[32] P. C, D. R, A. K. S, D. Y, H. R, and V. M, "A Novel Comparative Analysis of Solar P&O, ANN-based MPPT Controller under Different Irradiance Condition," *EAI Endorsed Transactions on Energy Web*, vol. 11, 2024, doi: 10.4108/ew.4942.
[33] B. Gautam, "Analysis of Artificial Intelligence Based MPPT in PV Grid Connected System," *Journal of Electrical Systems*, vol. 20, no. 7s, pp. 1016–1023, 2024, doi: 10.52783/jes.3482.
[34] S. M. A. Motakabber, K. Akter, A. H. M. Z. Alam, and S. H. Yusoff, "Design and Evaluation of a High-Performance Extensible DC-DC Converter Integrated with ANN Based MPPT Controller," *2023 9th International Conference on Computer and Communication Engineering (ICCCE)*, 2023, pp. 75–79, doi: 10.1109/ICCCE58854.2023.10246093.

BIOGRAPHIES OF AUTHORS

Adel Bouledroua was born in Annaba (Algeria), on March 4, 1982. He graduated the University of Badji Mokhtar, Department of Electromechanical Engineering (Algeria), in 2005. He received the degree of Magister in electromechanical Engineering from the University of Badji Mokhtar Annaba in 2008, and he is currently pursuing his Ph.D. from Badji Mokhtar University. His research interests include the field of renewable energy, photovoltaic power system, wind application, power electronics, motor drives, and artificial intelligence. He can be contacted at email: adel.bouledroua@univ-annaba.dz.

Tarek Mesbah received his B.E. degree, Master and Ph.D. Degrees in Electrical Engineering from Badji Mokhtar University of Annaba, Algeria. Currently he is a professor in the Badji Mokhtar University of Annaba. His research interests include the field of power grid, smart grid, power system optimization, and renewable energy. He can be contacted at email: tarek.mesbah@univ-annaba.dz.

Samia Kelaiaia received her B.E. degree, Master and Ph.D. Degree in Electrical Engineering from Badji Mokhtar University of Annaba, Algeria. Currently she is an assistant professor with the Badji Mokhtar University of Annaba. Her current research interests include power electronics, renewable energy, and renewable energy integration to power grid. She can be contacted at email: samia.kelaiaia@univ-annaba.dz.