Konya Mühendislik Bilimleri Dergisi, c. 11, s. 1, 71-86, 2023
Konya Journal of Engineering Sciences, v. 11, n. 1, 71-86, 2023
ISSN: 2667-8055 (Electronic)
DOI: 10.36306/konjes.1179030

COMPARATIVE PERFORMANCE ANALYSIS OF A FEED-FORWARD NEURAL NETWORK-BASED MPPT FOR RAPIDLY CHANGING CLIMATIC CONDITIONS

*Fuad ALHAJ OMAR

Zonguldak Bülent Ecevit University, Electric and Energy Department, Zonguldak, TÜRKİYE
fuad.a@beun.edu.tr

Highlights

- Introducing a Maximum Power Point Tracking (MPPT) system based on a feed-forward artificial neural network.
- Presenting MPPT technique to work under rapid and abrupt changes in climatic conditions.
- Validation of the proposed MPPT system performance by comparison against the incremental conductance (IC) and fuzzy logic (FL) methodologies.

Graphical Abstract

Flowchart of the proposed procedure

***Corresponding Author:** Fuad ALHAJ OMAR, fuad.a@beun.edu.tr

Konya Mühendislik Bilimleri Dergisi, c. 11, s. 1, 71-86, 2023
Konya Journal of Engineering Sciences, v. 11, n. 1, 71-86, 2023
ISSN: 2667-8055 (Electronic)
DOI: 10.36306/konjes.1179030

COMPARATIVE PERFORMANCE ANALYSIS OF A FEED-FORWARD NEURAL NETWORK-BASED MPPT FOR RAPIDLY CHANGING CLIMATIC CONDITIONS

***Fuad ALHAJ OMAR**

Zonguldak Bülent Ecevit University, Electric and Energy Department, Zonguldak, TÜRKİYE
fuad.a@beun.edu.tr

(Geliş/Received: 22.09.2022; Kabul/Accepted in Revised Form: 04.11.2022)

ABSTRACT: Rapid and abrupt changes in climatic conditions present a challenge to classical MPPT techniques as they drift from the MPP, resulting in loss of power. This paper presents a new MPPT technique based on a feed-forward artificial neural network (FFANN) and a direct control technique. In the proposed approach, FFAAN estimates the optimum value of the PV output voltage V_{MPP}, while the direct control technique achieves an optimal adjustment of the duty cycle making the operating point at MPP. To evaluate the performance of the proposed technique, the accurate electrical model of the system parts was built and simulated in MATLAB/Simulink environment. The simulation results are collected under rapidly changing climatic conditions. Simulation results show that the proposed MPPT technique achieves higher performance in terms of tracking efficiency and convergence speed compared to both the IC-based MPPT and FL-based MPPT systems. The results show that the proposed technique accurately estimates V_{MPP}, achieving a tracking efficiency of 99.9%, while the tracking efficiency is 94% when using FL-based MPPT and 91.5% when using IC-based MPPT. This demonstrates that the proposed technique exhibits superior performance under rapidly changing climatic conditions and increases energy production efficiency compared to classical techniques.

Keywords: *Photovoltaic, MPPT, Artificial Neural Network, Fuzzy Logic, Incremental Conductance*

1. INTRODUCTION

The electricity demand is increasing dramatically since it has become an essential factor for social welfare and economic development [1]. To meet this need, most traditional energy sources, such as fossil fuels, have been exhausted. Unfortunately, excessive use of fossil fuels has caused air pollution and global warming due to carbon dioxide emissions. For these reasons, most countries seek to switch to new forms of energy called "renewable energies", which are relatively efficient even though they are expensive. Since renewable energies come from natural resources such as sunlight, wind, geothermal heat, tides, etc., they can be regenerated naturally. Many remote and rural areas around the world use renewable energy sources to generate electricity. They use photovoltaic panels, wind turbines, geothermal energy, biomass, and others [2, 3]. The electricity generated from renewable energy systems is intermittent because it depends on climatic conditions and geographical location, so they are usually combined with a storage system to ensure the continuous availability of electricity [4, 5]. Among the renewable energy sources, solar energy has proven its efficiency because it is abundant, free and environment friendly. Therefore, solar PV systems have become an essential component and integral part of renewable energy networks [6-8].

In recent years, solar PV energy systems have experienced rapid growth and remarkable development. They are used in many applications such as rural water supply, light sources, traffic systems, water pumping, battery charging, meteorological systems, and satellite power systems [9, 10]. Although the widespread use of solar PV systems, they still face efficiency limitations. Many factors directly affect the performance of solar PV systems, such as nonlinear characteristics, irradiance, temperature, weather conditions, and properties of the solar cell material [11, 12]. Thus, to improve the PV systems' efficiency, control techniques called the

***Corresponding Author:** Fuad ALHAJ OMAR, fuad.a@beun.edu.tr

maximum power point tracking (MPPT) systems have been proposed. They are designed to extract the maximum available power from the PV panel under various atmospheric conditions [13, 14]. The basic working principle of the MPPT is that it generates an appropriate duty cycle to switch the DC-DC converter, which in turn matches the resistance of the solar panels with the resistance of the load, thus achieving maximum energy transfer from input to output [15, 16]. In recent years, many MPPT techniques have been proposed. The proposed MPPT techniques differ in many aspects such as working principle, efficiency, convergence speed, sensors requirements and implementation complexity [17, 18]. The MPPT techniques are divided into two main types [19, 20]: classic techniques, such as Hill Climbing (HC) [21], Perturbation and Observation (P&O) [22], Incremental Conductance (IC) [23], Fractional open-circuit voltage [24], and Fractional short-circuit current [25]; and artificial intelligence-based techniques, such as Fuzzy Logic Controller (FLC) and Artificial Neural Network (ANN) [26]. Classical techniques are widely used since they are simple, easy to implement, and cost-effective. However, their efficiency and convergence speed are low, and they suffer from oscillation around the MPP. Therefore, artificial intelligence-based techniques have been used to address these problems [27, 28]. The FL technique is attractive in PV systems because it does not require complex mathematics, its efficiency and convergence speed are higher than the classic techniques, and less oscillation around the MPP [29, 30]. However, this technique still suffers from the problem of drifting from the MPP under sudden changes in climatic conditions. This is due to the need for good knowledge of the solar systems in order to accurately determine the relationship function of the model [1].

Recently there has been a great interest in using ANN in PV systems, as many ANN-based MPPT controllers have been developed [2, 31]. The main advantages of ANN are that good knowledge of photovoltaic system parameters is not required for MPPT design, and it can handle complex nonlinear relationships without the need for an accurate mathematical model. However, the critical weak point of this technique in its training strategy when used as a prediction model [1].

The current study presents a new MPPT system based on the feed-forward artificial neural networks (FFANN) and a direct control method. The proposed technique improves the efficiency of solar PV systems under rapid climate changes. In this context, FFANN trained by a back-propagation algorithm was employed to estimate the optimum value of the PV output voltage VMPP. The irradiance and temperature are used as input variables for the proposed FFANN model, whilst the estimated voltage $\widehat{V_{MPP}}$ is the output. The direct control method was used to achieve the optimum adjustment of the duty cycle after comparing the estimated voltage value ($\widehat{V_{MPP}}$) with the theoretical voltage value (V_{MPP}). The duty cycle is converted into a signal to switch the DC-DC converter using a pulse-width modulation generator (PMW). The system model was built in the MATLAB/Simulink environment, where simulations were performed, and results were collected. The results showed that the proposed method has good dynamic performance, high convergence speed, and high accuracy in tracking the MPP under rapid climatic changes. For validation of the results, a comparison between the proposed MPPT system, fuzzy logic (FL)-based MPPT system, and the incremental conductance (IC)-based MPPT system, was performed in terms of the tracking efficiency, convergence speed, and performance. The results prove that the proposed technique performs better than the other techniques. Hence, the proposed FFANN-MPPT technique achieves the highest efficiency under rapid climatic changes.

The rest of this article is organized as follows: sections 2 and 3 present the structure and model of the proposed FFANN technique. Sections 4, 5 and 6 cover the principles of the direct control technique, fuzzy logic-based MPPT technique, and incremental conductance (IC)-based MPPT technique. Section 7 introduces the modelling of the system. In Section 8, the simulation results are provided and discussed. The last section contains the conclusion.

2. STRUCTURE OF THE PROPOSED FFANN

An artificial neural network (ANN) is a data processing system that simulates and resembles the neural networks in humans. An artificial neural network is similar to the human brain in that it acquires knowledge by training and retains it using neurons' connecting forces called synaptic weights. The weights link the neurons in each layer with all the neurons in the next layer. The network is trained to perform certain functions by adjusting the values of the synaptic weights.

The proposed FFANN architecture consists of three layers: an input layer, a hidden layer and an output layer, as shown in Figure 1. The input layer contains two input variables. The first variable is the solar irradiance G [W/m^2], while the second variable is the temperature of the solar cell T [^{o}C]. Whereas the output layer contains a single neuron representing the optimal PV output voltage (VMPP). The number of neurons in the hidden layer is determined during the training process.

To evaluate the accuracy of the proposed neural network in estimating the VMPP, we will rely on the performance index representing the mean squared error (MSE) and the correlation coefficient (R), which are given as follows:

$$MSE = \frac{1}{N}\sum_{K=1}^{N}\left(\tilde{V}_{MPP} - V_{MPP}\right)^2 \quad (1)$$

$$R = \sqrt{1 - \frac{\sum_{K=1}^{N}\left(V_{MPP} - \tilde{V}_{MPP}\right)^2}{\sum_{K=1}^{N}\left(V_{MPP} - \bar{V}_{MPP}\right)^2}} \quad (2)$$

V_{MPP}: represents the real values.
$\tilde{V}_{MPP}$: represents the estimated values generated from the neural model.

The ideal performance of a trained neural network corresponds to a minimum MSE value and an R-value close to 1.

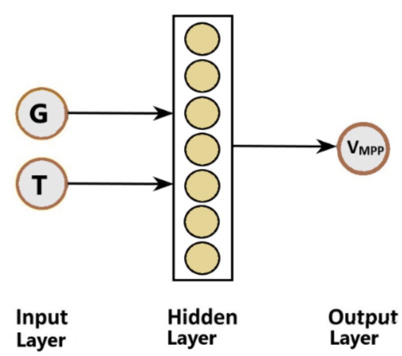

Figure 1. The general structure of the ANN

3. MODELLING THE PROPOSED FFANN

To model the proposed network in MATLAB, the following procedures were implemented:

1. The "newff" function was adopted for the proposed network modelling as it is used to model the FFANN networks.
2. Entering the input data representing different values of solar cell temperature ranging [0-60 ^{o}C] and solar irradiance ranging [300- 1000 W/m^2]. The input data size was 400 samples arranged in a matrix.

In addition, network output data representing VMPP has been extracted. Where the values of VMPP were obtained since they are considered solutions to the following equation:

$$At\ MPP: \quad \frac{dP_{PV}}{dV_{PV}} = 0 \qquad (3)$$

3. The entered data were randomly divided into three groups: the training set, the validation set and the testing set, with 70% for the training set and 15% for each of the validation and testing sets.
4. The training function "trainlm" representing the "Marquardt Levenberg" algorithm was chosen. This algorithm is widely used in training the FFANN because it has a high speed to reach the optimal solution. The "tansig" activation function in the hidden layer and the "purelin" linear activation function in the output layer are also adopted.
5. Determining the number of neurons in the hidden layer experimentally by changing the number of these neurons and training the network until the optimal performance index is obtained.

Three scenarios are adopted to build FFANN, all of which contain an input layer with two neurons and an output layer with one neuron, while the number of neurons in the hidden layer varies from two to three to four, as shown in Table 1. The values of MSE and R were also relied upon in the training, validation and testing phase to approve the final network architecture.

Table (1): the network training scenarios with MES and R values in the training, validation, and testing phases.

Network architecture (# of neurons in layers)	**Training phase**		**Validation phase**		**Testing phase**	
	R	**MSE**	**R**	**MSE**	**R**	**MSE**
2- 2- 1	0,99993	7,6812 $\times 10^{-4}$	0,99996	3,5487 $\times 10^{-4}$	0,99994	6,2407 $\times 10^{-4}$
2- 3- 1	0,99997	1,2547 $\times 10^{-5}$	0,99998	1,5025 $\times 10^{-5}$	0,99997	1,3964 $\times 10^{-5}$
2- 4- 1	1,000	1,9736 $\times 10^{-6}$	1,000	2,8671 $\times 10^{-6}$	1,000	3,0572 $\times 10^{-6}$

From Table 1, it is clear that increasing the number of hidden layer neurons minimizes the value of MSE but increases the size and complexity of the network, so the last scenario (4 neurons in the hidden layer) is adopted since it gives the optimal performance index. The figure 2 shows FFANN architecture used in the study.

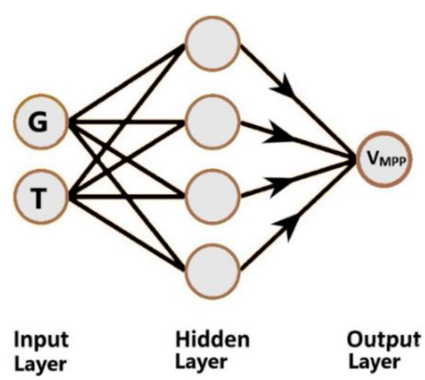

Figure 2. The proposed FFANN technique structure

Figure 3 shows the performance curve of the FFANN model corresponding to the approved training scenario. It includes the training process curve, validation process curve, testing process curve, and the best values curve. It is clear from Figure 3 that all the curves converged to the MSE value equal to (MSE=1.896×10^{-5}) under 1000 epochs.

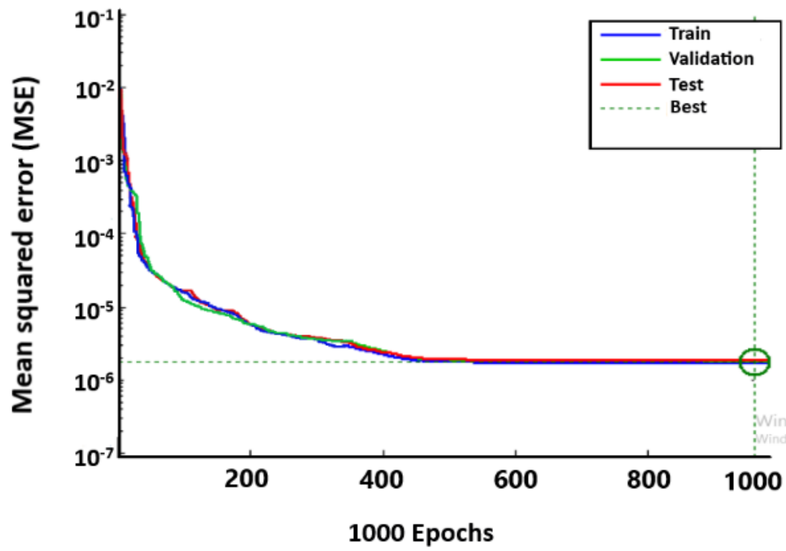

Figure 3. The neural network performance curve for the three groups (training-validation-testing).

Figure 4 shows the value of the correlation coefficients for the three groups (training-validation-testing) equal to one, which proves the accuracy of the proposed FFANN model.

After the training process and obtaining the optimal FFANN model, the weights and offsets obtained in training stage were adopted and used in the model simulation in the MATLAB/ Simulink environment. The final approved FFANN model is shown in Figure 5.

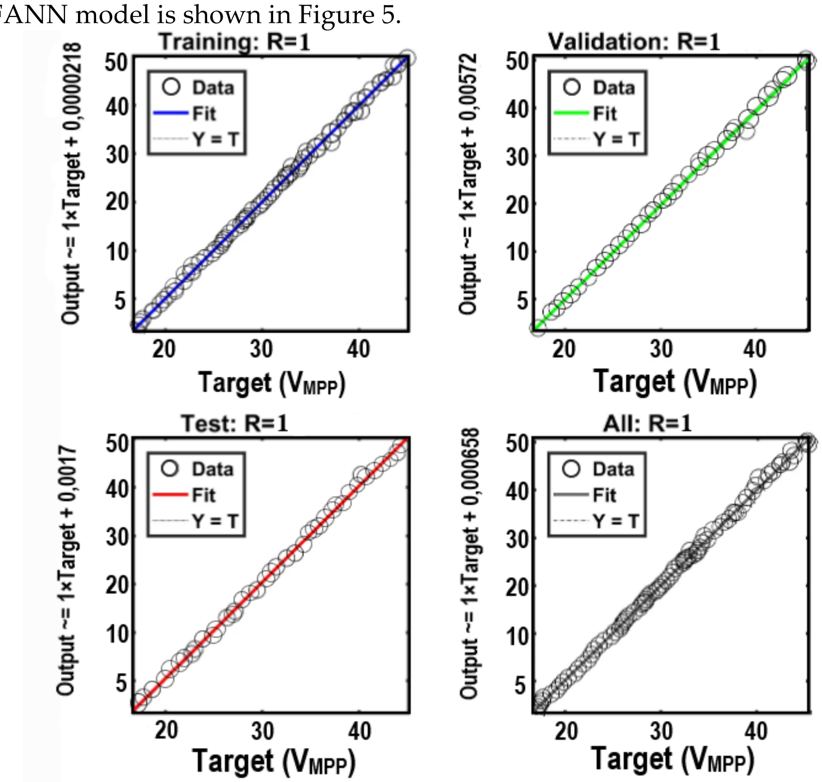

Figure 4. Correlation coefficients for the three groups (training-validation-testing).

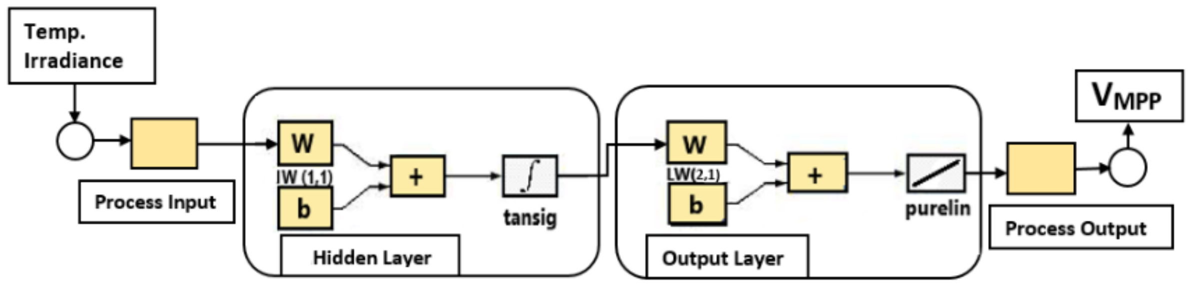

Figure 5. The FFANN model adopted in MATLAB

4. DIRECT CONTROL TECHNIQUE

To achieve the MPP under rapid climate changes, the duty cycle used to control the DC-DC converter must be precisely determined. For this purpose, the direct control technique is used to determine the optimal value of the duty cycle based on comparing the output voltage of the PV system (V_{PV}) with the optimum voltage produced by the FFANN model (V_{MPP}). Based on the difference between the two values, the duty cycle is changed, increasing or decreasing by a fixed step. Figure 6 shows the flowchart of this technique and its work principle.

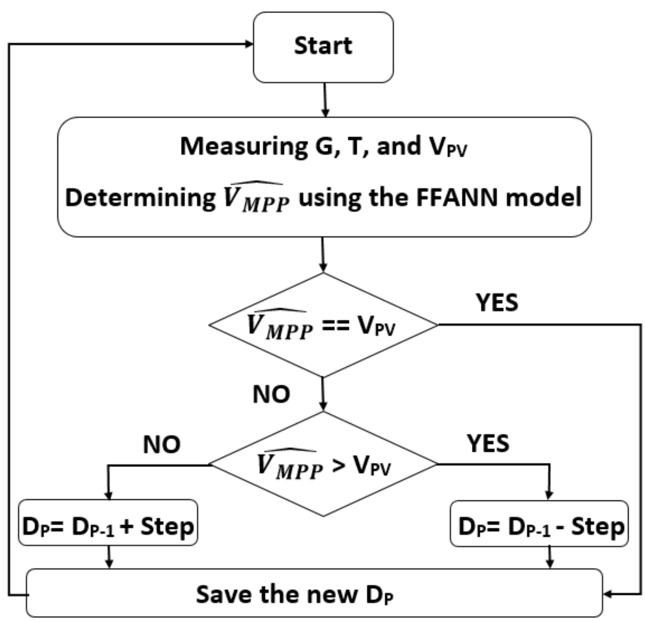

Figure 6. The flowchart of the direct control technique.

5. FUZZY LOGIC-BASED MPPT TECHNIQUE

This controller operates in three phases: fuzzification, rule base table lookup, and defuzzification [32-33]. In the fuzzification phase the numerical input variables are converted into linguistic variables based on a membership function, as shown in Figure 7. In this study, five fuzzy levels are used: PS (Positive Small), NS

(Negative Small), PB (Positive Big), NB (Negative Big), and ZE (Zero). To increase the accuracy, more fuzzy levels can be used, but this will increase the processing time.

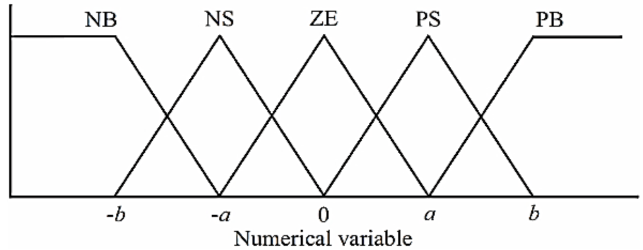

Figure 7. The Membership function for inputs and output of the fuzzy logic algorithm.

The a & b in Figure 7 represent the range of the numeric variables. The inputs of the fuzzy logic-based MPPT controller are error (E) and change in error (ΔE). Where E and ΔE are calculated based on expert experience.

$$E(n) = \frac{P(n) - P(n-1)}{V(n) - V(n-1)}$$

And

$$\Delta E = E(n) - E(n-1)$$

After calculating E and ΔE they will be converted into language variables. The changes in duty cycle ΔD which represent the output of the fuzzy controller can be obtained from the rule base shown in Table 2.

According to the knowledge of the user and converter used, the change in duty cycle ΔD is determined for the different combinations of E and E. Depending on the proposed membership function shown in Figure 7, the linguistic variables are converted into numerical variables during the defuzzification phase. The generated PWM signal will control the power converter to achieve the MPP.

Table (2): The fuzzy logic algorithm rule base.

E \ ΔE	NB	NS	ZE	PS	PB
NB	ZE	ZE	NB	NB	NB
NS	ZE	ZE	NS	NS	NS
ZE	NS	ZE	ZE	ZE	PS
PS	PS	PS	PS	ZE	ZE
PB	PB	PB	PB	ZE	ZE

6. INCREMENTAL CONDUCTANCE (IC)-BASED MPPT TECHNIQUE

The basic principle of this technique is based on the fact that the differential of the P_{PV} with respect to V_{PV} is zero at the MPP, negative on the right of the MPP, and positive on the left of the MPP, as follows: [34]

$$\frac{dP_{PV}}{dV_{PV}} = 0, \qquad at\ MPP.$$

$$\frac{dP_{PV}}{dV_{PV}} > 0, \qquad left\ of\ MPP.$$

$$\frac{dP_{PV}}{dV_{PV}} < 0, \qquad right\ of\ MPP.$$

By calculating the differential at different instants, the MPP can be achieved as shown in Figure 8.

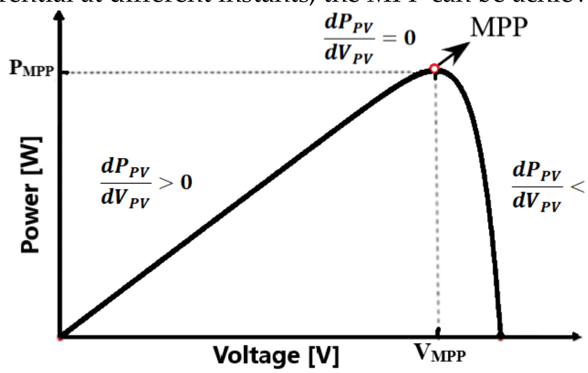

Figure 8. The work principle of IC algorithm

7. MODEL OF THE SYSTEM

The schematic diagram of the system to be modelled in the MATLAB environment is shown in Figure 9. The DC/DC boost converter is inserted between the PV modules and the load to perform an adaptation between them. By controlling the duty cycle of the switching elements, the operating point of the system can be kept at the MPP. The input-output equation of the DC-DC boost converter is:

$$V_{PV} = (1 - D) \times V_O$$

Here, V_{PV} is the PV panel output voltage, V_O is the DC-DC boost converter output voltage, and D is the duty cycle.

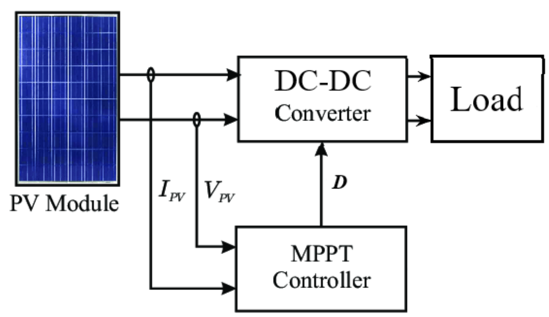

Figure 9. Schematic diagram of the MPPT system

Using the general mathematical equation for the photovoltaic cell, the photovoltaic panel was modelled in MATLAB/Simulink. The studied PV system consists of 74 solar cells connected in series. The maximum power generated by the PV system under standard climatic conditions (irradiance= 1000W/m^2 and Temperature = 25^{o}C) was 150 W. To test the proposed system under rapidly changing climatic conditions and compare it with IC-based MPPT and FL-based MPPT systems, the characteristics of the PV panel are drawn out in two cases. The first case is under constant temperature (25^{o}C) and variable irradiance levels (400, 600, 700, 800, 900, and 1000W/m^2), while the second case is under constant irradiance (850 W/m^2) and variable temperature levels (25, 35, 45, and 55^{o}C) as shown in Figures 10 and 11 respectively. The different levels of temperature and solar radiation were applied for 12 secs., as shown in Figures 12 and 13, respectively.

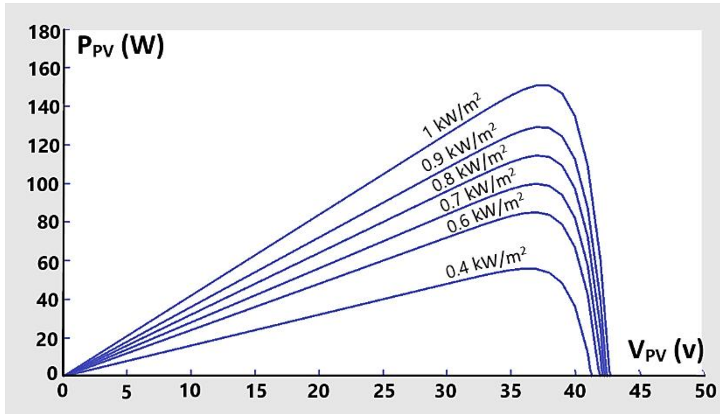

Figure 10. The P-V characteristics of the modelled PV panel under variable irradiance levels

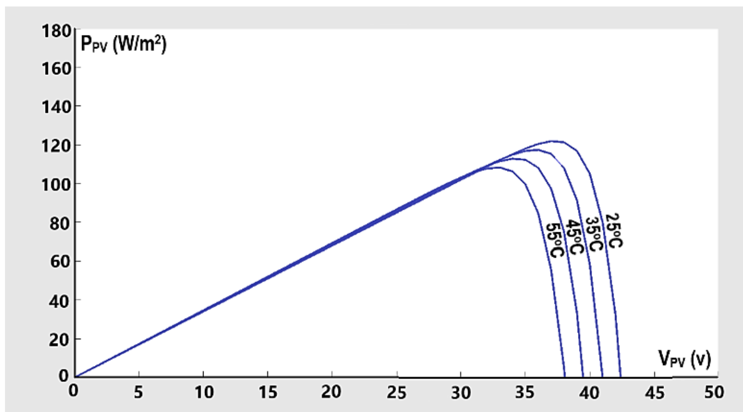

Figure 11. The P-V characteristics of the modelled PV panel under variable temperature levels

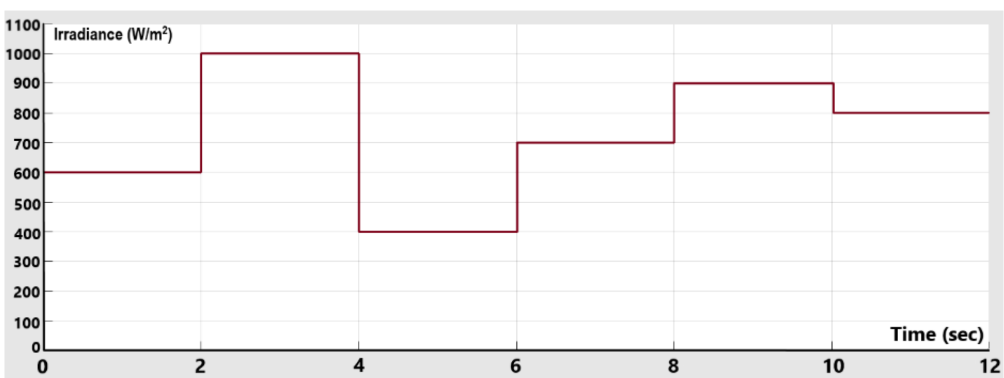

Figure 12. The applied different levels of solar irradiance.

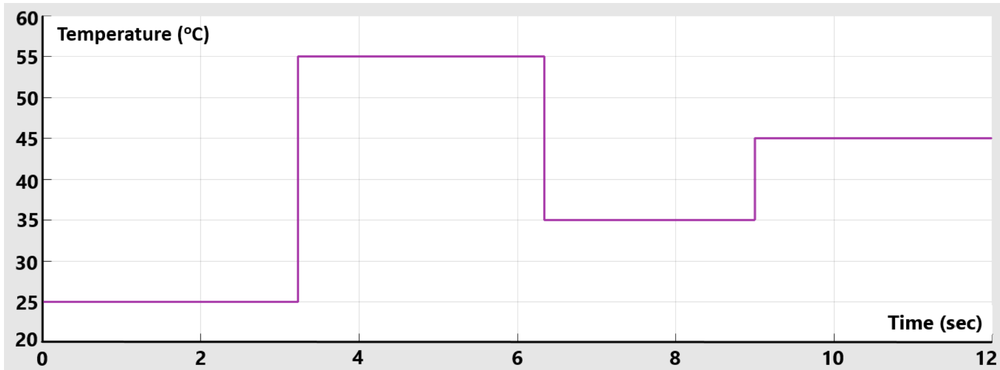

Figure 13. The applied different levels of temperature

The whole system was modelled and simulated using MATLAB/Simulink. In the simulation phase, the three MPPT techniques were tested and evaluated under the two cases mentioned.

8. SIMULATION RESULTS AND DISCUSSION

Before presenting the simulation results of the three controllers, the ability of the FFANN model to estimate the VMPP under rapidly changing climatic conditions will be introduced. The estimated voltage ($\widehat{V_{MPP}}$) was measured by the FFANN model and compared with the theoretical value (V_{MPP}), and then the MSE was calculated. Table 3 shows a comparison between the $\widehat{V_{MPP}}$ and the V_{MPP} under variable irradiance levels and constant temperature T= 25°C. While Table 4 shows the comparison under variable temperature and constant irradiance (850 W/m²). The results showed that the MSE values are close to zero, which means that the $\widehat{V_{MPP}}$ values measured by the FFANN model are almost identical to the theoretical values, which reflects the high accuracy of the FFAAN model in estimating the VMMP under rapid climate changes.

Table 3: Values of the $\widehat{V_{MPP}}$ and the V_{MPP} under variable irradiance levels and constant temperature (T= 25°C)

Irradiance (W/m²)	Theoretical values (V_{MPP})	Estimated values $\widehat{V_{MPP}}$	($\widehat{V_{MPP}}$ - V_{MPP})²
400	37.4051	37.3984	0.04489×10⁻³
600	37.3948	37.4014	0.04356×10⁻³
700	37.3929	37.3989	0.036×10⁻³
800	37.4102	37.4093	0.00081×10⁻³
900	37.3986	37.4016	0.009×10⁻³
1000	37.4026	37.3976	0.025×10⁻³
$MSE = \frac{1}{N}\sum_{1}^{N}(\widehat{V_{MPP}} - V_{MPP})^2 = 0.02654 \times 10^{-3}$			

Table 4: Values of the $\widehat{V_{MPP}}$ and the V_{MPP} under variable temperature and constant irradiance (850 W/m²)

Temperature (°C)	Theoretical values (V_{MPP})	Estimated values $\widehat{V_{MPP}}$	$(\widehat{V_{MPP}} - V_{MPP})^2$
25	37.4161	37.4019	0.20164×10^{-3}
35	36.3894	36.3906	0.00144×10^{-3}
45	35.2709	35.2651	0.03364×10^{-3}
55	34.1069	34.0948	0.14641×10^{-3}

$$MSE = \frac{1}{N}\sum_{1}^{N}(\widehat{V_{MPP}} - V_{MPP})^2 = 0.09578 \times 10^{-3}$$

The significant aim of this study is to investigate an efficient and high-performance MPPT system under rapid climate change to optimize the use of the solar energy system. To evaluate and analyze the proposed FFANN technique and compare it with IC-based MPPT and FL-based MPPT, an offline simulation was performed in MATLAB/Simulink for each technique.

Figure 14 shows the simulation results for the three systems under constant temperature (T = 25 °C) and different irradiance changes according to the following values (400, 600, 700, 800, 900, 1000 W/m²) for 12 seconds. It can be seen that the FFANN technique was able to detect and track MPP despite the instantaneous change in irradiance. In addition, the energy extracted from solar panels is greater when using FFANN than with other techniques. The simulation results indicate that the steady-state oscillation at the MPP was less when using the FFANN technique, resulting in lower energy loss and increased system efficiency. Furthermore, the proposed FFANN technique achieves better transient state behavior for the PV system, as its convergence speed to the MPP was higher compared to the IC-based MPPT and FL-based MPPT techniques. This is due to the accuracy and speed of the FFANN technique in determining an appropriate duty cycle as shown in Figure 15. This in turn leads to effective control of the DC-DC converter and making the operating point precisely at MPP regardless of rapid changes in irradiance.

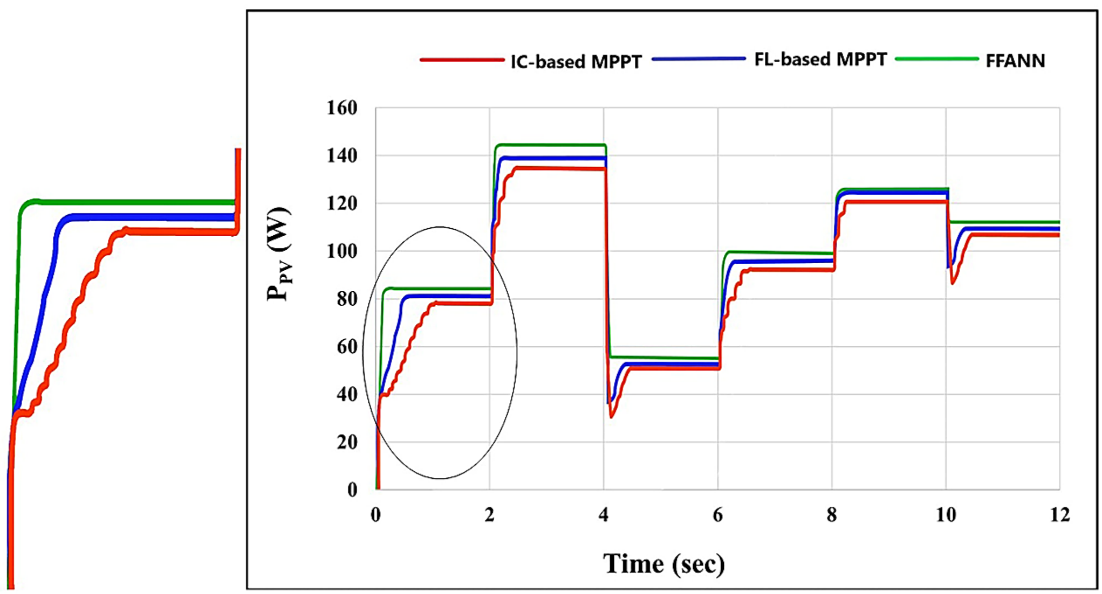

Figure 14. The produced power under variable irradiance levels and constant temperature (T = 25 °C).

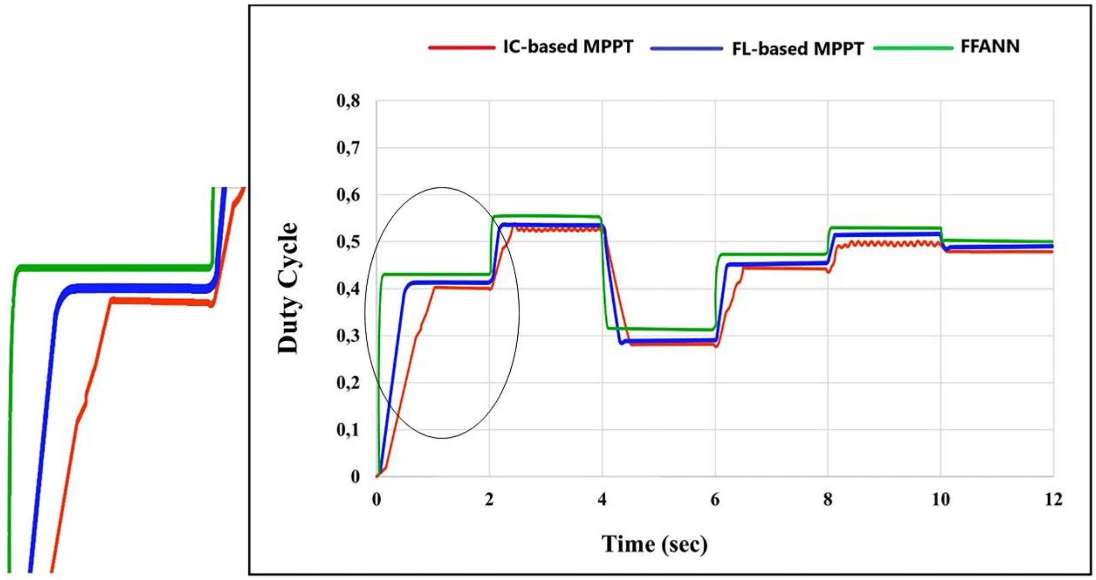

Figure 15. Changing the duty cycle under variable irradiance and constant temperature.

In other atmospheric conditions corresponding to the temperature changes of the solar cell according to the values (25, 35, 45, 55 °C) with constant irradiance (850 W/m²), as shown in Figure 16, the proposed FFAAN technique achieves better dynamic performance, as the working point converges to the MPP in less time compared to the IC-based MPPT and FL-based MPPT. Moreover, the proposed technique showed a better response speed to sudden changes in temperature and its ability to quickly achieve the optimum duty cycle, as shown in Figure 17.

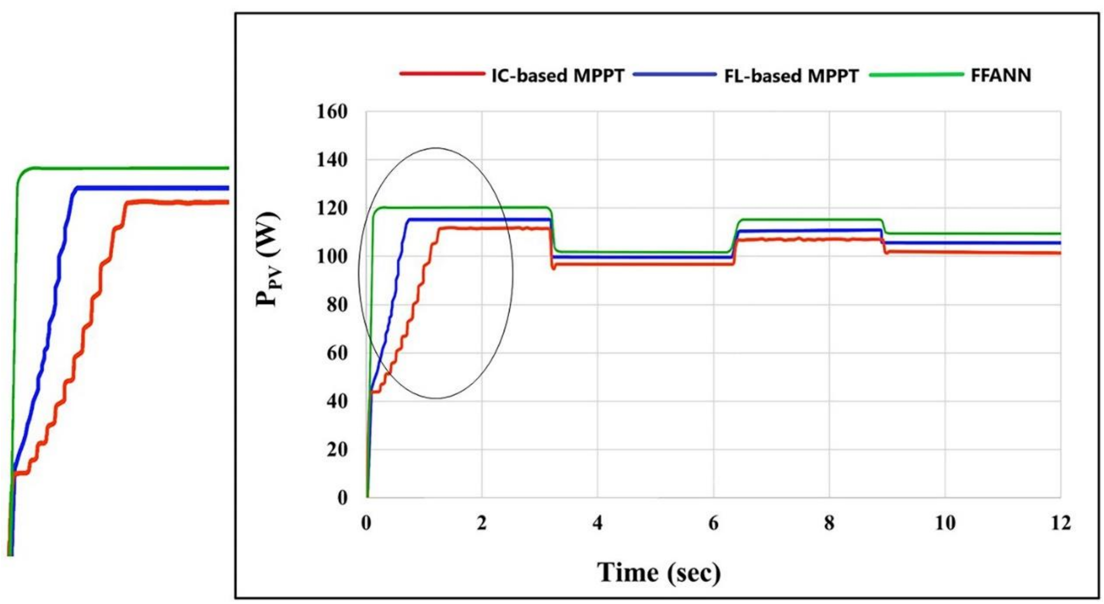

Figure 16. The produced power under variable temperature and constant irradiance (850 W/m²).

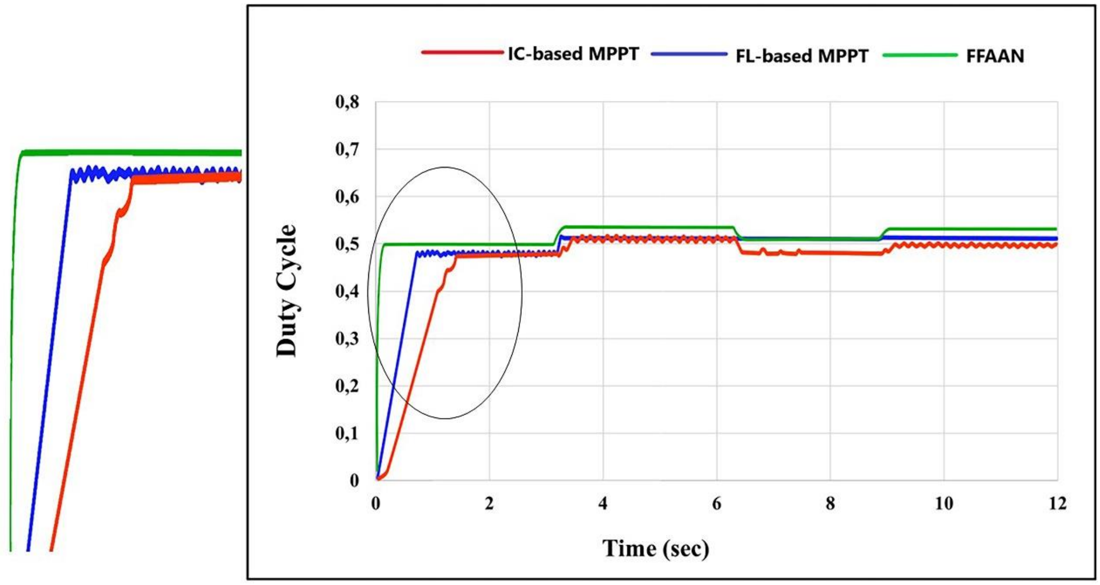

Figure 17. Changing the duty cycle under variable temperature and constant irradiance.

A comparison between the three techniques in terms of tracking efficiency and convergence speed is presented in Table 5. Where the proposed technique shows better results in terms of tracking efficiency and convergence speed.

Table 5: Comparison of the three techniques in terms of tracking efficiency and convergence speed.

Technique	**Tracking efficiency**	**Convergence speed**
FFANN	99.9 %	0.15 sec
Fuzzy logic	94 %	0.45 sec
Incremental conductance	91.5 %	1 sec

Finally, although the IC-based MPPT and FL-based MPPT techniques were somewhat capable of capturing and tracking MPP under variable atmospheric conditions, the results showed that the proposed FFANN technique has better performance in terms of tracking efficiency and convergence speed. In this regard, the oscillations present in the FFANN were also less than in the other techniques. Moreover, the response to the rapid changes in climatic conditions was better.

9. CONCLUSION

In this research work, a new MPPT technique based on a feed-forward artificial neural network (FFANN) and a direct control technique is proposed to predict and track the maximum power point of the PV panel under rapidly changing climatic conditions. Using the accurate element models, the system was simulated in MATLAB/Simulink environment and the results were collected. The FFANN model is trained to estimate the optimum value of the PV output voltage (V_{MPP}). Through the training, the FFANN model exhibited a high accuracy in predicting the V_{MPP}. Using The direct control technique, the optimal adjustment of the duty cycle was achieved, therefore, the dynamic performance of the MPPT system improved. The outcome indicates that the proposed method exhibited superiority in extracting the maximum available power from the PV panel. A comparison is made between the proposed method and the FL-based MPPT and IC-based MPPT methods. According to the obtained simulation results, the tracking accuracy of the FFANN technique was robust under different atmospheric conditions compared to conventional FL and IC methods. As a result, the tracking efficiency of the new method is 99.9%, while it is 94% and 91.5% for FL and IC methods, respectively. In addition, the converging speed of the proposed method has been enhanced compared to FL and IC methods. Finally, optimizations are proven to be easy to design. Future efforts will be directed towards experimental implementing of the proposed method. Experimental results will be obtained to demonstrate the accuracy and effectiveness of the new method to increase the efficiency and yield of the solar generation system.

Declaration of Ethical Standards

The author declares that the study complies with all applicable laws and regulations and meets ethical standards.

Credit Authorship Contribution Statement

The author contributed to the design and modelling of the system, the analysis of the results and the writing of the manuscript.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding / Acknowledgements

The author declares that he has no financial support.

Data Availability

Data will be made available on request.

REFERENCES

[1] S. D. Al-Majidi, M. F. Abbod, and H. S. Al-Raweshidy, "A particle swarm optimisation-trained feedforward neural network for predicting the maximum power point of a photovoltaic array," *Engineering Applications of Artificial Intelligence,* vol. 92, p. 103688, 2020.
[2] S. Messalti, A. Harrag, and A. Loukriz, "A new variable step size neural networks MPPT controller: Review, simulation and hardware implementation," *Renewable and Sustainable Energy Reviews,* vol. 68, pp. 221-233, 2017.
[3] M. H. Zafar *et al.*, "A novel meta-heuristic optimization algorithm based MPPT control technique for PV systems under complex partial shading condition," *Sustainable Energy Technologies and Assessments,* vol. 47, p. 101367, 2021.
[4] P. Bahrani and N. Jain, "Performance analysis of P&O and FLC method of MPPT for PV module based on five-parameter model," in *Proceedings of international conference on computational intelligence and emerging power system*, 2022, pp. 357-369: Springer.
[5] A. Kulaksız, G. Gökkuş, and F. Alhajomar, "Rapid control prototyping based on 32-Bit ARM Cortex-M3 microcontroller for photovoltaic MPPT algorithms," 2019.
[6] R.-M. Chao, S.-H. Ko, H.-K. Lin, and I.-K. Wang, "Evaluation of a distributed photovoltaic system in grid-connected and standalone applications by different MPPT algorithms," *Energies,* vol. 11, no. 6, p. 1484, 2018.

[7] M. B. Hayat, D. Ali, K. C. Monyake, L. Alagha, and N. Ahmed, "Solar energy—A look into power generation, challenges, and a solar-powered future," *International Journal of Energy Research,* vol. 43, no. 3, pp. 1049-1067, 2019.

[8] F. Alhaj Omar and A. A. Kulaksiz, "Experimental evaluation of a hybrid global maximum power tracking algorithm based on modified firefly and perturbation and observation algorithms," *Neural Computing and Applications,* vol. 33, no. 24, pp. 17185-17208, 2021.

[9] A. M. O. Anwer, F. A. Omar, and A. A. Kulaksiz, "Design of a fuzzy logic-based MPPT controller for a PV system employing sensorless control of MRAS-based PMSM," *International Journal of Control, Automation and Systems,* vol. 18, no. 11, pp. 2788-2797, 2020.

[10] M. H. Alsharif, K. Yahya, and Z. W. Geem, "Strategic market growth and policy recommendations for sustainable solar energy deployment in South Korea," *Journal of Electrical Engineering & Technology,* vol. 15, no. 2, pp. 803-815, 2020.

[11] V. Gupta, M. Sharma, R. K. Pachauri, and K. D. Babu, "Comprehensive review on effect of dust on solar photovoltaic system and mitigation techniques," *Solar Energy,* vol. 191, pp. 596-622, 2019.

[12] M. A. Basit, S. Dilshad, R. Badar, and S. M. Sami ur Rehman, "Limitations, challenges, and solution approaches in grid-connected renewable energy systems," *International Journal of Energy Research,* vol. 44, no. 6, pp. 4132-4162, 2020.

[13] Y. Wan, M. Mao, L. Zhou, Q. Zhang, X. Xi, and C. Zheng, "A novel nature-inspired maximum power point tracking (MPPT) controller based on SSA-GWO algorithm for partially shaded photovoltaic systems," *Electronics,* vol. 8, no. 6, p. 680, 2019.

[14] H. H. Ammar, A. T. Azar, R. Shalaby, and M. I. Mahmoud, "Metaheuristic optimization of fractional order incremental conductance (FO-INC) maximum power point tracking (MPPT)," *Complexity,* vol. 2019, 2019.

[15] F. AlhajOmar, G. Gökkuş, and A. Kulaksız, "Performance Evaluation of P&O, IC and FL Algorithms used in Maximum Power Point Tracking Systems," in *International Conference on Engineering Technologies (ICENTE'18), Konya, TÜRKİYE*, 2018, pp. 286-289.

[16] S. Motahhir, A. El Hammoumi, and A. El Ghzizal, "The most used MPPT algorithms: Review and the suitable low-cost embedded board for each algorithm," *Journal of cleaner production,* vol. 246, p. 118983, 2020.

[17] A. Harrag and S. Messalti, "Variable step size modified P&O MPPT algorithm using GA-based hybrid offline/online PID controller," *Renewable and Sustainable Energy Reviews,* vol. 49, pp. 1247-1260, 2015.

[18] I. Houssamo, F. Locment, and M. Sechilariu, "Experimental analysis of impact of MPPT methods on energy efficiency for photovoltaic power systems," *International Journal of Electrical Power & Energy Systems,* vol. 46, pp. 98-107, 2013.

[19] A. Mellit and S. A. Kalogirou, "MPPT-based artificial intelligence techniques for photovoltaic systems and its implementation into field programmable gate array chips: Review of current status and future perspectives," *Energy,* vol. 70, pp. 1-21, 2014.

[20] F. A. Omar, N. Pamuk, and A. A. KULAKSIZ, "A critical evaluation of maximum power point tracking techniques for PV systems working under partial shading conditions," *Turkish Journal of Engineering,* vol. 7, no. 1, pp. 73-81, 2023.

[21] V. Jately, B. Azzopardi, J. Joshi, A. Sharma, and S. Arora, "Experimental analysis of hill-climbing MPPT algorithms under low irradiance levels," *Renewable and Sustainable Energy Reviews,* vol. 150, p. 111467, 2021.

[22] M. Abdel-Salam, M.-T. El-Mohandes, and M. Goda, "An improved perturb-and-observe based MPPT method for PV systems under varying irradiation levels," *Solar Energy,* vol. 171, pp. 547-561, 2018.

[23] M. A. Bakar Siddique, A. Asad, R. M. Asif, A. U. Rehman, M. T. Sadiq, and I. Ullah, "Implementation of incremental conductance MPPT algorithm with integral regulator by using boost converter in grid-connected PV array," *IETE Journal of Research,* pp. 1-14, 2021.

[24] D. Baimel, S. Tapuchi, Y. Levron, and J. Belikov, "Improved fractional open circuit voltage MPPT methods for PV systems," *Electronics,* vol. 8, no. 3, p. 321, 2019.

[25] M. M. Shebani, T. Iqbal, and J. E. Quaicoe, "Comparing bisection numerical algorithm with fractional short circuit current and open circuit voltage methods for MPPT photovoltaic systems," in *2016 IEEE Electrical Power and Energy Conference (EPEC)*, 2016, pp. 1-5: IEEE.

[26] A. Gupta, P. Kumar, R. K. Pachauri, and Y. K. Chauhan, "Performance analysis of neural network and fuzzy logic based MPPT techniques for solar PV systems," in *2014 6th IEEE power India international conference (PIICON)*, 2014, pp. 1-6: IEEE.

[27] T. T. Yetayew, T. Jyothsna, and G. Kusuma, "Evaluation of Incremental conductance and Firefly algorithm for PV MPPT application under partial shade condition," in *2016 IEEE 6th International Conference on Power Systems (ICPS)*, 2016, pp. 1-6: IEEE.

[28] M. Mokhlis, M. Ferfra, H. A. Vall, C. C. Ahmed, and A. Taouni, "Comparative study between the different MPPT techniques," in *2020 5th International Conference on Renewable Energies for Developing Countries (REDEC)*, 2020, pp. 1-6: IEEE.

[29] C. B. Prasad, S. K. Sonam, B. R. G. Reddy, and P. Harika, "A fuzzy logic based MPPT method for solar power generation," in *2017 International Conference on Intelligent Computing and Control Systems (ICICCS)*, 2017, pp. 1182-1186: IEEE.

[30] S. Ozdemir, N. Altin, and I. Sefa, "Fuzzy logic based MPPT controller for high conversion ratio quadratic boost converter," *International Journal of Hydrogen Energy,* vol. 42, no. 28, pp. 17748-17759, 2017.

[31] S. A. Rizzo and G. Scelba, "ANN based MPPT method for rapidly variable shading conditions," *Applied Energy,* vol. 145, pp. 124-132, 2015.

[32] M. Kumar, S. Kapoor, R. Nagar, A. J. I. J. o. A. R. i. E. Verma, Electronics, and I. Engineering, "Comparison between IC and fuzzy logic MPPT algorithm based solar PV system using boost converter," vol. 4, no. 6, pp. 4927-4939, 2015.

[33] M. K. Al-Nussairi, R. Bayindir, and E. Hossain, "Fuzzy logic controller for Dc-Dc buck converter with constant power load," in *2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA)*, 2017, pp. 1175-1179: IEEE.

[34] A. Safari and S. J. I. t. o. i. e. Mekhilef, "Simulation and hardware implementation of incremental conductance MPPT with direct control method using cuk converter," vol. 58, no. 4, pp. 1154-1161, 2010.