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Conventional and artificial intelligence based maximum power point tracking techniques for efficient solar power generation

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Abstract

The increasing global need for renewable energy sources, driven by environmental concerns and the limited availability of traditional energy, highlights the significance of solar energy. However, weather fluctuations challenge the efficiency of solar systems, making maximum power point tracking (MPPT) systems crucial for optimal energy harvesting. This study compares ten MPPT approaches, including both conventional and artificial intelligence (AI)-based techniques. These controllers were designed and implemented using MATLAB Simulink, and their performance was evaluated under real environmental conditions with fluctuating irradiance and temperature. The results demonstrate that conventional techniques, such as incremental conductance (INC), Perturb and Observe (P&O), Incremental conductance and Particle Swam Optimization (INC-PSO), Fuzzy Logic Control and Particle Swam Optimization (FLC-PSO), and Perturb and Observe and Particle Swam Optimization (P&O-PSO), achieved accuracies of 94%, 97.6%, 98.9%, 98.7%, and 99.3% respectively. In contrast, AI-based intelligent techniques, including Artificial Neural Network (ANN), Artificial Neural Fuzzy Interference System (ANFIS), Fuzzy Logic Control (FLC), Particle Swam Optimization (PSO), and Artificial Neural Network and Particle Swam Optimization (ANN-PSO), outperform achieving higher accuracies of 97.8%, 99.9%, 98.9%, 99.2%, and 99%, respectively. Compared to available research, which often reports lower accuracies for conventional techniques, our study highlights the enhanced performance of AI-based methods. This study provides a comprehensive comparative analysis, delivering critical analysis and practical guidance for engineers and researchers in selecting the most effective MPPT controller optimized to specific environmental conditions. By improving the efficiency and reliability of solar power systems, our research supports the advancement of sustainable energy solutions.

KEYWORDS

artificial intelligence, machine learning, MPPT techniques, smart grid, solar power generation

1 | INTRODUCTION

Climate change is now recognized as the greatest threat to humanity. As a result of challenges including global warming, fossil fuel shortages, and political unpredictability in the major fuel-supplying nations the globe has switched from using fossil fuels to renewable energy technologies (RETs).[1] Renewable energy systems harness natural resources like solar, wind, water, and geothermal energy, which can be naturally replenished over time. These technologies may be used to produce power, heat residences and commercial buildings, and supply energy for transportation. By diversifying the energy mix and reducing reliance on imported fossil fuels, RET enhance the energy security of numerous nations. Consequently, this leads to decreased vulnerability to price fluctuations and geopolitical tensions associated with fossil fuel imports.[2] RET has numerous environmental benefits. The designs, uses, and best utilization of RET have become the primary concerns of electricity producers. Due to the significant growth in renewable energy technologies (RETs), it is crucial to continue formulating and executing plans to boost their efficiency.[3] RETs are gaining popularity as a sustainable alternative to fossil fuels, helping to mitigate harmful climate change.[4] Future energy generation is expected to heavily rely on solar energy since it is a clean energy source that requires less maintenance, costs less, and occupies less space than other RETs. The solar panels are used to harness solar energy, transforming sunlight into electricity.[5] Both residential and commercial buildings as well as large-scale power generation for power networks can be supplied by solar panels.[6] The efficiency of solar energy capture is primarily influenced by atmospheric conditions, dust, temperature, cloud cover, and geographic location.[7] Partial shadowing is one of the most significant elements influencing solar photovoltaic (PV) efficiency. When parts of a solar PV module or array receive less sunlight than others, this is known as partial shadowing. Uneven cloud cover or shadows cast by trees, buildings, or other objects may cause partial shading. Under partial shading conditions, the PV panels or array will not produce as much power as they would under uniform sunlight.[8] The degree of shade and the PV system's architecture will determine how much power is lost. The maximum power point tracking (MPPT), controller approach is a method to reduce the impact of partial shadowing on solar PV systems. The point of operation of a PV system is modified automatically by MPPT controllers to boost power output. This is important when there is partial shading since the optimal operating point may change depending on how the shading is spread.[9] When the power output in the PV system hits the maximum power point (MPP), the amount of energy extracted from the PV module is at its maximum. Consequently, MPPT algorithms must be used to continuously track MPP. Solar panels' voltage and current are adjusted using MPPT controllers to make sure they are working at the MPP.[10] This has the potential to greatly boost the power generated by solar panels. Although MPPT controllers are often more expensive than pulse width modulation (PWM) controllers, they have several advantages, including the ability to expand the working range, enhance efficiency, and boost solar panel power output by up to 30%. Additionally, MPPT controllers are more dependable across a range of circumstances.[11,12] In this research comparative study of ten conventional and artificial intelligence (AI) based intelligent controllers is modeled using MATLAB Simulink. The controllers conventional include: Incremental conductance (INC), Perturb and Observe (P&O), Incremental conductance and Particle Swam Optimization (INC-PSO), Perturb and Observe and Particle Swam Optimization (P&O-PSO). The AI-based controllers include Artificial Neural Network (ANN), Fuzzy Logic Control (FLC), Artificial Neural Fuzzy Interference System (ANFIS), Particle Swam Optimization (PSO), Artificial Neural Network and Particle Swam Optimization (ANN-PSO) and Fuzzy Logic Control and Particle Swam Optimization (FLC-PSO). The results of this study can help engineers, researchers, and business professionals to choose the best MPPT algorithms based on performance, cost-effectiveness, and adaptability to changing environmental conditions (ECs), ultimately increasing the efficiency and dependability of solar power generation systems installed in a variety of environments.

The arbitrary nature of solar energy, influenced by weather conditions and climate change, often results in irregular energy production and diminished overall system efficiency.[13] To address this challenge, the utilization of an appropriate MPPT technique becomes imperative. An effective MPPT technique enhances power generation irrespective of weather conditions. Traditional MPPT methods are commonly used to control PV systems and optimize power generation. These techniques utilize iterative algorithms to adjust the PV system's operating point, consistently aiming to find the MPP. Despite their effectiveness, these conventional approaches may face challenges in rapidly changing ECs, which can limit their efficiency in capturing solar energy.[14] On the other hand, intelligent MPPT techniques represent a paradigm shift in MPPT control strategies. These techniques using advanced computational methods, including AI algorithms such as neural networks, fuzzy logic, and evolutionary algorithms. By employing AI, intelligent MPPT Techniques demonstrate superior adaptability and efficiency to track the MPP under varying environmental scenarios, such as, temperature fluctuations partial shading, and solar irradiance variations. This enhanced adaptability ensures precise alignment with the MPP, leading to optimized energy extraction and improved overall system performance. Therefore, the effective selection and deployment of suitable MPPT techniques, whether traditional or intelligent, are key to mitigating the challenges posed by the fluctuating nature of solar energy. While many MPPT methods have been suggested in the academic literature, there is still a shortage of comprehensive comparative analyses of these approaches. Additionally, the majority of studies assess these techniques in idealized ECs, failing to capture the complexities of real-world scenarios.[15] Our study is motivated by the imperative need to address these gaps in existing research. By conducting a detailed comparative analysis of ten conventional and AI-based MPPT controllers including INC, INC-PSO, P&O, and P&O-PSO. The AI-based controllers including ANN, PSO, ANN-PSO, FLC, ANFIS, and FLC-PSO are designed and investigated in this proposed work to identify optimal control algorithms. We aim to provide engineers, researchers, and professionals with the necessary tools to make informed decisions about the selection and application of MPPT algorithms. Furthermore, by evaluating these controllers under real ECs using MATLAB Simulink, we seek to offer more realistic and valuable insights into their performance. Ultimately, the goal of our study is to contribute to the progress of solar power systems and control algorithms, leading to a more sustainable and efficient energy future.

Conventional control techniques such as INC, INC-PSO, P&O, and P&O-PSO. The INC algorithm fine-tunes the terminal voltage of the PV panel to align with the MPP voltage by evaluating the ratio of INC ($\Delta I/\Delta V$) against the instantaneous conductance (I/V).[16] It stabilizes once the MPP is reached, preventing further oscillations. The P&O algorithm determines power using voltage and current sensors, compares it to previous cycle power, and adjusts the voltage accordingly to oscillate around the MPP.[17] It increases or decreases voltage based on the power differential to maintain optimal extraction. The hybrid INC-PSO method combines the rapid MPP tracking of INC with the fine-tuning capability of PSO. PSO optimizes the duty cycle derived from INC, reducing power oscillations and improving accuracy. Similarly, P&O-PSO combines P&O's simplicity with PSO's optimization capabilities.[18] The summed outputs from both controllers are fed into a PWM generator, enhancing performance under varying conditions. The FLC-PSO method integrates FLC's intelligent decision-making with PSO's global optimization, improving tracking speed and accuracy under fluctuating conditions.[19,20]

AI-based intelligent techniques include ANN, PSO, ANN-PSO, FLC, ANFIS, and FLC-PSO. ANN-based MPPT involves data collection (inputs and outputs), network training using algorithms like Levenberg Marquardt back-propagation, and deploying the trained model in Simulink to predict optimal operating points based on real-time environmental inputs.[21] ANFIS combines strengths of neural networks and fuzzy logic rules, forming a hybrid system that adapts to changes in temperature and irradiance, optimizing the MPP tracking process. The ANN-PSO hybrid method leverages ANN's predictive power and PSO's adaptive optimization, providing robust performance under dynamic conditions by combining the strengths of both techniques.[22] PSO uses a population of particles to explore the solution space and find the global MPP, adjusting particles' positions based on cognitive and social coefficients to efficiently converge on the optimal solution.[23] FLC-based MPPT employs fuzzy logic principles to handle uncertainties and non-linearities in the PV system, adjusting the duty cycle based on linguistic rules derived from expert knowledge.[24]

Various studies have proposed different conventional and AI-based MPPT methods for efficient power extraction, a comprehensive comparative analysis between these techniques is often lacking. Additionally, many studies assess the performance of techniques in standard ECs, overlooking the complexities of real-world scenarios. Our study bridges several critical research gaps in the field of solar power generation systems and their control algorithms. Firstly, we provide a comprehensive comparative analysis of ten distinct MPPT controllers, encompassing both conventional and advanced AI-based techniques. This fills a significant void in the literature, where previous studies often focused on individual methods without offering a holistic comparison with the AI-based MPPT controllers. Additionally, our research addresses the need for realistic evaluation by implementing and testing these controllers in actual ECs using MATLAB Simulink. By doing so, we provide valuable insights into their performance under fluctuating irradiance and temperature conditions, which is often lacking in theoretical or simplified simulation studies. Furthermore, our study offers analytical guidance for practical implementation by evaluating key parameters such as system stability, design complexity, and adaptability to changing ECs. This guidance fills a crucial gap in the literature, empowering engineers, researchers, and professionals to select and optimize MPPT algorithms for improved solar energy harvesting. Lastly, by including advanced AI techniques alongside conventional methods, we demonstrate the superiority of these approaches in enhancing MPPT performance, thereby contributing to the ongoing advancement of solar energy technology. Through these contributions, our research significantly advances the understanding and application of MPPT techniques, driving the transition towards sustainable and renewable energy sources.

The objective of this work is to the domain of solar energy systems and control algorithms. Specifically, it involves the development of a sophisticated PV model within the MATLAB Simulink environment. We focus on the design and detailed evaluation of ten distinct MPPT controllers, encompassing both conventional algorithms like INC, P&O,

INC-PSO, P&O-PSO, and AI-driven approaches such as ANN, FLC, ANFIS, PSO, ANN-PSO, and FLC-PSO. The core of our contribution is a comprehensive comparative analysis of these controllers, assessing vital performance parameters such as maximum output voltage, extracted maximum power, time response, design complexity, and system stability. This research ultimately aims to guide the scientific community in the selection and optimization of MPPT algorithms for improved solar energy harvesting. MPPT systems are essential for optimizing energy extraction from solar panels, especially under varying weather conditions. These systems ensure that the PV panels operate at MPP, where the product of current and voltage is maximized. MPPT techniques can be broadly categorized into conventional and AI-based methods.

Following are the detailed objectives and the main contributions of the proposed study.

1.1 | Objectives

1. To design and implement ten conventional and AI-based MPPT controllers using MATLAB Simulink, enabling a comprehensive evaluation under real ECs.
2. To assess the effectiveness of each MPPT controller in terms of accuracy, response time, and adaptability under varying real environmental irradiance and temperature conditions.
3. To compare ten different MPPT controllers, including both conventional and AI-based intelligent approaches, for their efficiency in solar energy harvesting.
4. To provide analytical guidance for researchers, engineers, and professionals by choosing the most effective MPPT algorithm based on performance, cost-effectiveness, and environmental adaptability.

The paper is organized into six sections: Section 1 describes the study significance, problems and objectives. Section 2 presented the state of the art literature review on MPPT techniques. Section 3 covers the development of conventional and AI-based MPPT techniques on MATLAB and complete system configuration is discussed. The simulation and experimental result analysis are done in Section 4 and detailed discussion is given in Section 5. The conclusion of the proposed work is shown in Section 6.

2 | LITERATURE REVIEW

The quest for maximizing the efficiency of solar power generation has led to significant advancements in MPPT techniques. These techniques are crucial for optimizing the power output of PV systems under varying ECs. Over the years, researchers have developed and refined both conventional and AI-based MPPT methods to address the inherent challenges associated with fluctuating irradiance and temperature. This section reviews notable contributions in the field, highlighting the evolution of MPPT strategies and their respective performances in enhancing solar energy harvesting.

A recent study[25] proposes an enhanced INC MPPT strategy to improve PV system performance, especially for off-grid applications in remote areas. Traditional INC methods face challenges like a trade-off between fluctuation and convergence speed and drift phenomena. The proposed enhancement uses an adaptive step magnitude, adjusting perturbation steps based on variations in power, voltage, and current, and includes a drift avoidance mechanism for robustness. The strategy was tested in an off-grid PV system supplying batteries, using MATLAB/Simulink simulations and experimental tests with a dSPACE DS1104 card. Results showed that the enhanced INC method significantly improves tracking precision, reduces fluctuation, speeds up convergence, minimizes power loss, and increases tracking efficiency. It achieved the lowest tracking time (<0.012 s) and the highest average tracking efficiency (97.84%) compared to recent MPPT techniques.

Another study[26] highlights the importance of MPPT controllers for optimizing the performance of solar energy generation. The authors present a novel MPPT method that combines the INC algorithm with Hysteresis control was applied to a standalone PV system. This hybrid approach leverages INC for MPP search while Hysteresis control enhances tracking accuracy, quickly adapting to severe weather changes without oscillations around the MPP. The system employs a five-level S-Packed U Cells (SPUC5) inverter to convert Direct Current (DC) to Alternating Current (AC) voltage, utilizing a minimal number of switches and a single DC source voltage. Capacitor voltage balancing is managed through PWM. Simulated in MATLAB/Simulink under various irradiance conditions, the proposed system demonstrated superior performance compared to INC-PWM and INC-PI methods, validating the effectiveness of both the MPPT algorithm and the SPUC5 inverter.

In PV systems, employing MPPT techniques is crucial for optimizing efficiency and performance. The rapid growth of the PV industry has led to the development of diverse MPPT strategies. Notably, the INC method is recognized for its fast convergence to the MPP, though it experiences considerable ripple under consistent radiation. On the other hand, the PSO method, despite its slower convergence relative to INC, results in lower ripple in the output power. To harness the advantages of both methods, a novel approach integrating the principles of INC and PSO has been proposed by this study. This innovative strategy aims to capitalize on the rapid convergence of the INC controller in response to radiation changes and the stability and precision of the PSO method under continuous irradiation conditions. By synergistically combining these techniques, the proposed approach seeks to enhance MPPT performance in PV systems, leading to increased overall efficiency and stability.[27]

The continuous advancement of MPPT algorithms is crucial for efficiently capturing the global MPP, especially in scenarios involving partial shading of PV arrays, thereby enhancing the overall efficiency of PV systems. Among these algorithms, PSO stands out as a notable soft computing strategy, offering hardware simplicity and independence from specific PV system configurations. However, determining optimal PSO parameters for successful global MPP extraction remains a challenge in practical deployment. To address this challenge, recent research offers a structured approach to parameter selection, factoring in solar panel layout, DC–DC converter architecture, and battery specifics. Additionally, an innovative method for optimizing the sample period has been introduced, aimed at maximizing digital MPPT controller performance. The modified PSO algorithm, equipped with custom parameters, represents a substantial improvement in the efficacy of MPPT control for PV systems.[28]

PSO has emerged as a prominent MPPT control algorithm for PV systems, ensuring maximum power extraction across varying climatic conditions. While classical MPPT algorithms like P&O, and PSO, are effective, they often suffer from instability, high oscillation, and slower convergence to the MPP. Addressing these limitations, recent research introduces a novel MPPT controller based on a modified heterogeneous multi-swarm PSO algorithm with an adaptive factor selection strategy. This novel approach is compared against conventional PSO, ANFIS, and classical P&O controllers. Simulation and experimental findings demonstrate that the FMSPSO algorithm outperforms existing methods, efficiently tracking the MPP with shorter convergence time and minimal oscillations. Experimental validation using a NI-myRIO-1900 card confirms that the proposed MPPT approach achieves an efficiency exceeding 99%, even amidst climatic variations in irradiation and temperature.[29]

In a prior study,[30] In a prior investigation,[25] a groundbreaking FL MPPT algorithm was developed to optimize the tracking of the MPP in PV arrays. Distinct from conventional FL-MPPT techniques that utilize changes in the P-V characteristic slope, this innovative method introduces a new parameter, “Ea,” obtained from I-V characteristics. This additional parameter significantly enhances tracking accuracy across various ECs and refines the precision of duty ratio calculations. By incorporating the “Ea” parameter, the algorithm can accurately identify the operating point within the voltage or current source regions and its proximity to the MPP region.

Another research study[31] highlights the crucial role of MPPT controllers in improving the efficiency of solar PV modules. The researchers compare different MPPT controller designs, such as an ANFIS-based controller, a fuzzy logic power controller, a PV module, an ANFIS reference model, and a DC–DC boost converter. Extensive simulations in MATLAB/Simulink demonstrate that the proposed ANFIS-based MPPT controller consistently extracts maximum power from the PV module under varying weather conditions. This contribution represents a significant advancement in MPPT methodologies for solar energy systems, emphasizing the importance of innovative controller designs in optimizing PV system performance.

In the domain of PV arrays, achieving maximum energy conversion efficiency hinges significantly on effectively tracking the MPP, particularly under partially shaded conditions. Under such scenarios, multiple peaks exhibited by the power voltage (P–V) characteristic curve of PV arrays which poses a challenge for traditional MPPT controllers to discern between local and global MPPs. Consequently, there has been a surge in research aimed at developing strategies to efficiently monitor the global MPP while mitigating the adverse effects of partial shading. Among these strategies, PSO has gained popularity due to its rapid tracking capabilities and adaptability to varying ECs. However, efforts to refine traditional PSO techniques have also been underway to address inherent limitations. In a recent study by Reference 32, the behavior of a PV system under diverse ECs, including intermittent atmospheric variations, was investigated. The study's primary objective was to enhance system performance by comparing two MPPT algorithms: PSO and P&O. Through rigorous testing, encompassing efficiency, stability, speed, and robustness assessments across various atmospheric conditions, simulation data revealed the superior performance of the PSO algorithm over the P&O approach. These findings underscore the PSO algorithm's efficacy in maximizing power generation across a spectrum of environmental scenarios. The study's insights offer valuable recommendations for optimizing solar system efficiency and underscore the importance of selecting appropriate MPPT algorithms for optimal energy harvesting.

In other research,[33] authors present an innovative hybrid method called fuzzy PSO combined with a PV-fed shunt active power filter, aimed at boosting power quality and generating clean energy. The MPPT function within the fuzzy PSO system optimizes energy capture from the PV system by accurately locating the MPP. The PV-fed shunt active power filter, guided by fuzzy logic and synchronous reference frame theory, connects between the boost converter's output and the grid. The study results show that this proposed controller significantly improves power quality under different load conditions, promoting the generation of eco-friendly electricity.

Diverging from conventional MPPT methods, intelligent MPPT algorithms demonstrate higher flexibility in responding to diverse ECs, ensuring precise alignment with the MPP under scenarios such as partial shading, temperature variations, and fluctuations in solar irradiance. Building upon the advancements in intelligent MPPT control, this study[34,35] introduces an innovative MPPT approach that harnesses ANN. Utilizing ANN technology, the proposed MPPT algorithm swiftly and accurately adjusts to dynamic weather conditions, encompassing fluctuations in temperature and solar radiation. The research encompasses a thorough design and modeling phase for the PV system architecture, seamlessly integrated with the ANN-MPPT controller. The primary objective of the study is to develop an ANN-based MPPT controller capable of delivering exceptional performance for solar applications.

3 | RESEARCH METHODOLOGY

In this section, we will explore the design, modeling, and functioning of a solar PV system paired with an MPPT controller. Solar PV systems generally fall into two categories: standalone and grid-connected systems.[36] Since the standalone system concentrates more on enhancing supply-side generation than demand or load side, it was selected for this work. A standard solar PV setup consists of four main components: the load, the MPPT controller, the power converter (either DC–DC or DC–AC), and the solar panel array. The research process for this study is outlined in Figure 1.

3.1 | System design

A MATLAB 2021a Simulink version is used to design a standalone PV system with MPPT controller, as illustrated in Figure 2. Figure 3 shows the system without an MPPT controller, which varies depending on the controller. This standalone PV system is used with all ten MPPT controllers (INC, INC-PSO, P&O, P&O-PSO, ANN, PSO, FLC, ANFIS, ANN-PSO, and FLC-PSO) to show how well they track the maximum power output. The standalone PV system uses following components to be used for design:

1. PV array
2. Boost converter
3. 02 capacitors
4. 01 inductor

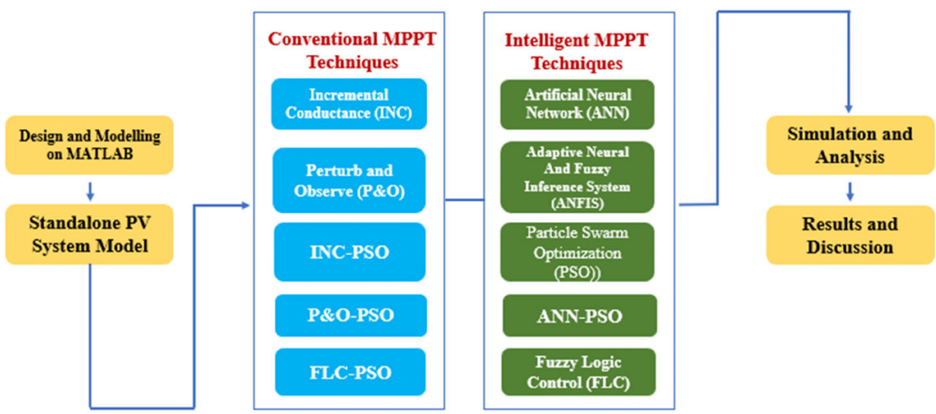

FIGURE 1 Shows the flow chart for methodology.

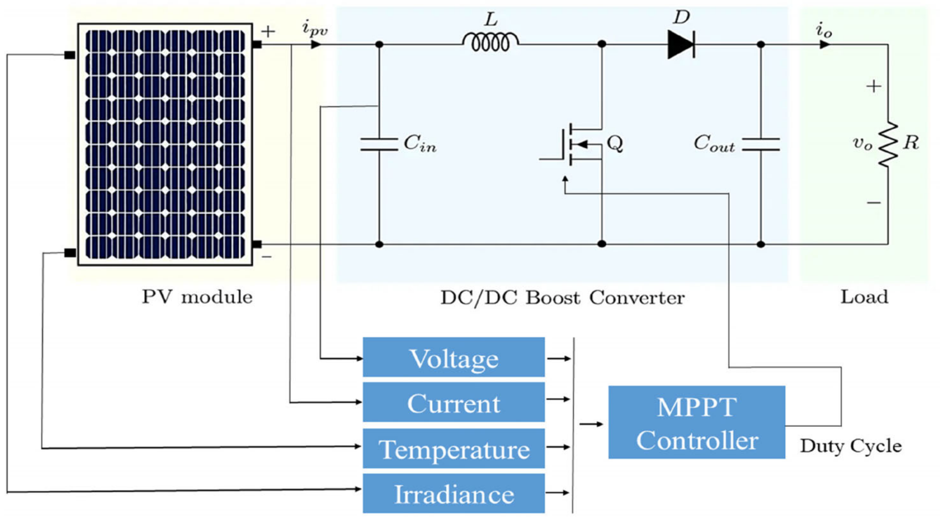

FIGURE 2 Represents the block diagram for solar photovoltaic (PV) system with maximum power point tracking (MPPT) controller.

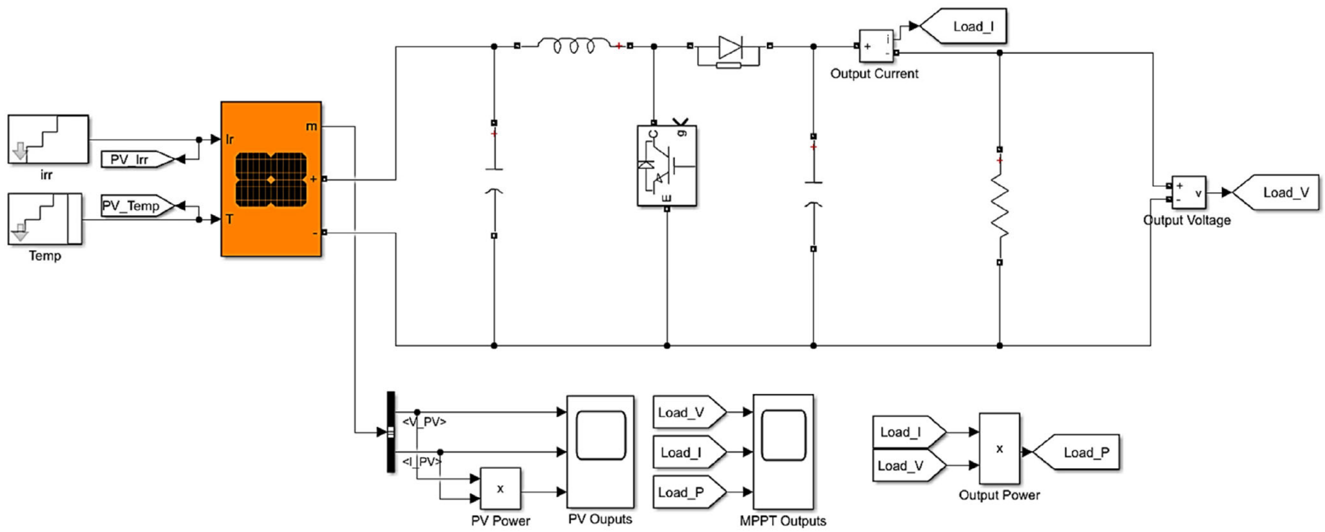

FIGURE 3 Shows the standalone system without maximum power point tracking (MPPT).

5. 01 resistor (used as load)
6. MPPT controller

The ramp up or down module is used to simultaneously adjust and vary the temperature and irradiance values to mimic real-world ECs for solar PV system. These varying irradiance and temperature values are then applied to PV panel as its inputs, which then generate a specific amount of voltage and current according to its rating based on the precise temperature and irradiance parameters.[37,38] The PV panel's output is routed to a DC–DC boost converter, which raises the voltage. The MPPT controller then creates a duty cycle based on measurements of the array's voltage and current. In order to determine the final output values to be supplied to the load or DC link, the MPPT controller provides the boost converter with a continuous duty cycle computation based on the input PV voltage and current value.[39]

3.1.1 | PV module

Modern PV technology have produced a variety of PV panel varieties, such as amorphous, multi-crystalline, and mono-crystalline silicon cells, each with a unique voltage, power rating, and number of cells.[40] Because of their higher efficiency, mono-crystalline silicon cells are well-known, which is why this research study chose to employ them. Table 1 shows the parameters of the 1Soltech 15TH-FRL-4H 250-M60-BLK solar module used in this project.

The PV panel generates a maximum power of 250 W with maximum voltage and current of 30.7 V and 8.11 A, respectively at standard conditions which include irradiance value of 1000 W/m^2 and a temperature of 25°C. The simultaneously varying values of irradiance and temperature are applied to the panel to analyze and capture the clear picture the power generated by the panel ideally and even in real world applications.

3.1.2 | Irradiance and temperature

Simultaneously varying irradiance and temperature values as shown in Figure 4, are applied to the PV system to mimic the dynamic response, behavior, and power generation by solar PV system under ECs. The varying values of irradiance and temperature are given in Table 2.

TABLE 1 Solar photovoltaic (PV) panel specifications.

S. no	Data	Value
1.	Power (maximum)	248.9 W
2.	Cells per module	60
3.	Voltage V_{oc} (open circuit)	38.7 V
4.	Current I_{sc} (short circuit)	8.85 A
5.	MPP voltage (V_{mp})	30.7 V
6.	MPP current (I_{mp})	8.11 A
7.	Temperature coefficient of V_{oc}	−0.35599
8.	Temperature coefficient of I_{sc}	0.07

Abbreviation: MPP, maximum power point.

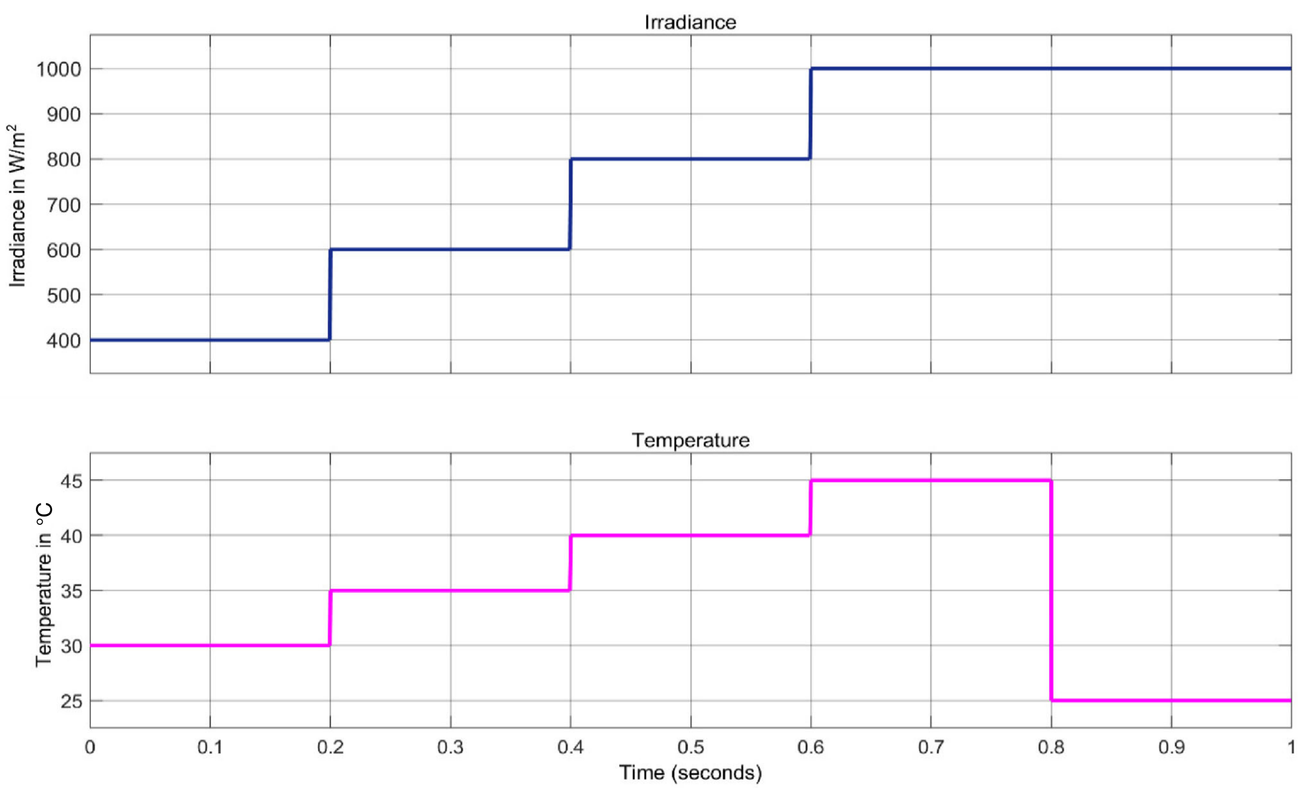

FIGURE 4 Shows the irradiance and temperature values.

TABLE 2 shows the varying irradiance and temperature.

Time (S)	Irradiance value (W/m^2)	Temperature (°C)
0.0–0.2	400	30
0.2–0.4	600	35
0.4–0.6	800	40
0.6–0.8	1000	45
0.8–1.0	1000	25

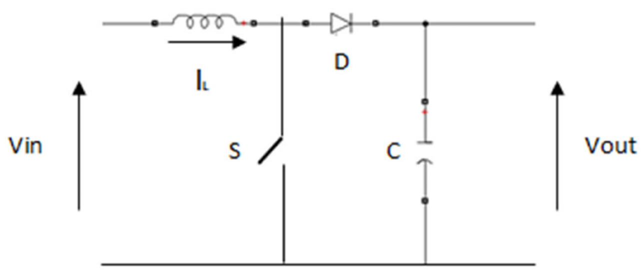

FIGURE 5 Shows the circuit of boost converter.

3.1.3 | DC–DC boost converter

A boost converter, a specialized DC–DC converter, is applied in situations requiring the output voltage to exceed the input voltage[41]; in this case, the output voltage is increased from 30.7 to 120 V. The boost converter reduces the output current by raising the output voltage. By increasing the output voltage, the boost converter reduces the output current, thereby minimizing thermal losses. Figure 5 shows the fundamental parts of a boost converter, including a diode, a switch, and one or more energy storage units. Typically, an insulated gate bipolar junction transistor (IGBT) serves as the switch, while an inductor is used for energy storage.[42]

The boost converter operates under two conditions: when the switch is closed and when it is open.[43] This makes it a very simple device to use. In the closed switch state, the branch wire's resistance is much lower than the load's, allowing current to pass from the source and charge the inductor. In the open switch state, the diode is forward biased, enabling all current, including the previously stored energy, to flow through the inductor and to the load. Adding a capacitor to filter out the output ripple from the switching can convert this into a steady DC output voltage.[44] Additionally, with an MPPT controller, the boost converter can increase the voltage to reach the MPP. The controller uses algorithms to instruct the boost converter to adjust the voltage to quickly reach the MPP.[45]

3.1.4 | Boost converter design

As mentioned earlier the boost converter design includes few electronic components which will have specific ratings. The values of boost converter components, for example, inductance, capacitance, duty cycle and the minimum load to be applied are calculated using Equations (1)–(4).[34] Using these equations in MATLAB Simulink, the values for all the components are determined as shown in Table 3. The Equation (1) was used to fine the values of inductor which is the fundamental energy storage unit in boost converter. For capacitor, minimum load to be connected and duty cycle values Equations (2)–(4) were used respectively.

$$L = \frac{Vin \times (Vout - Vin)}{dI \times fs \times Vout}, \tag{1}$$

$$C = \frac{Io \times D}{fs \times dV}, \tag{2}$$

TABLE 3 Ratings of components used.

S. no	Component	Rating
1	Resistor	57.6000
2	Inductor	1e-3
3	Capacitor	1.2920e-04

$$\mathrm{RL} = \frac{V\mathrm{out}}{Io}, \tag{3}$$

$$D = \frac{(1-(V\mathrm{in} \times n))}{V\mathrm{out}}, \tag{4}$$

This parameter quantifies the amount of energy that the inductor can store in the magnetic field; input voltage (V_{in}): This denotes the level of DC voltage that is provided to a boost converter to be boosted to the required output level; output voltage (V_{out}): this determines the desired voltage level that should be achieved at the end of the converter, which will hypothetically be greater than the input voltage; switching frequency (*fs*): this variable stands for the time period between the on and off durations of the converter switch. However, increased switching frequencies lead to advantages like using smaller components and the adverse effect of switching losses; ripple current of the inductor (dI): this means that the wave amplitude of the inductor current during the operation is the total maximum or peak current it goes up to. Ripple current is a factor that decreases efficiency but increases the flexibility of size for inductors; output current (Io): this sets the limiting of the amount of current taken out of the converter's output by the load; duty cycle (D): this indicates the percentage of the switching cycle during which the switch of the converter is on; minimum load resistance (RL): this indicates the minimum resistance value into which the converter will run, which also assists in establishing power needs.

3.1.5 | MPPT controllers

Ten distinct MPPT techniques/algorithms (INC, P&O, INC-PSO, P&O-PSO, ANN, FLC, ANFIS, PSO, ANN-PSO, and FLC-PSO) are designed in this work using MATLAB Simulink. Within Simulink, MPPT can be designed via coding or by creating a Simulink model using various blocks. In this investigation, the Simulink model for each MPPT controller is created independently on a shared standalone solar PV system.

INC-based MPPT design

The PV panel's terminal voltage is adjusted using the INC algorithm so that it is in line with the MPP voltage. The INC algorithm stabilizes, preventing additional shifts around the operating point, once it recognizes the MPP's accomplishment.[46] By comparing the INC ($\Delta I/\Delta V$ ratio) to the instantaneous conductance (I/V ratio), the MPP is completed. The way the $\mathrm{d}P/\mathrm{d}V$ relationship behaves makes it possible to identify the MPP's achievement. When the MPPT is positioned to the right of the MPP, the relationship turns negative; when it is positioned to the left of the MPP, it becomes positive. To trace the MPP, the INC method essentially examines the PV array's power characteristics' slope. When this slope reaches zero, the MPP is successfully established.[47]

MATLAB code is used to implement the INC algorithm based MPPT as shown in Figure 6, utilizing the function block that comes with MATLAB. The boost converter's component values are identical to those utilized with the standalone PV system. The voltage and current are supplied by the bus, which receives the PV panel's outputs, and the memory blocks are used to store the previous voltage and current values before supplying them to the INC function block. This is because the INC MPPT uses both current and previous values of voltage and current. The outputs are ultimately limited within the designated ranges by the saturation block.

P&O-based MPPT design

In MATLAB, the P&O MPPT is implemented through custom coding and using MATLAB's built-in function block. The algorithm is simple and easy as already discussed the power may be calculated and compared to the previous cycle power using only a voltage and current sensor, making it one of the easiest methods to implement.[48] Initially, voltage and current are used to determine power, which is then compared to a previous power value. If the change is zero and the same

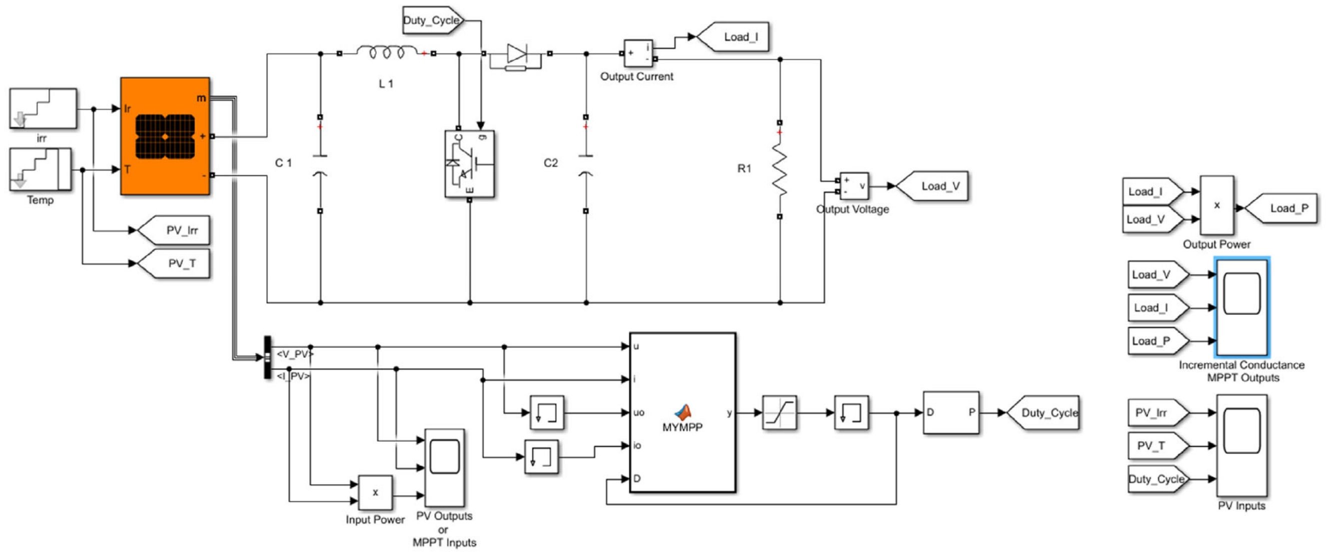

FIGURE 6 MATLAB Simulink model of incremental conductance maximum power point tracking (INC MPPT).

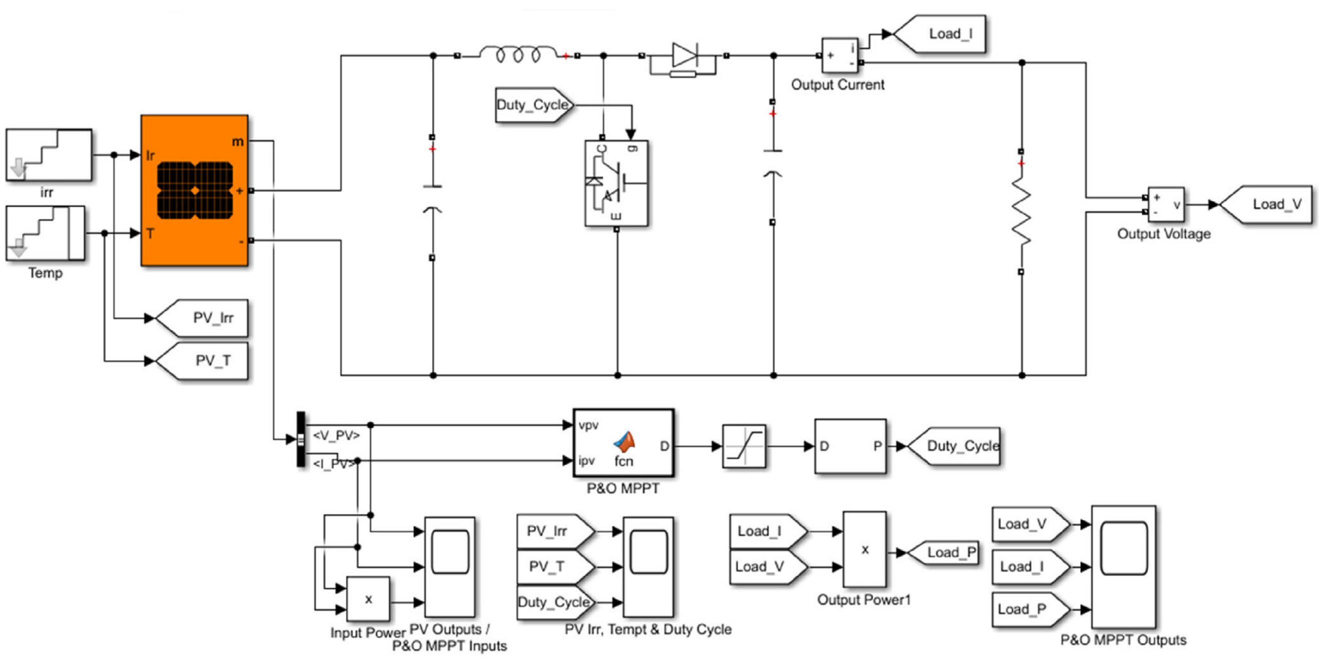

FIGURE 7 MATLAB Simulink model of Perturb and Observe maximum power point tracking (P&O MPPT).

voltage is reversed, the algorithm attempts to oscillate around the same MPPT. If there is a power variation, the program examines the change in voltage levels. The algorithm detects a positive power differential and adjusts the voltage accordingly, either up or down, as it did before.[49] In the case of a negative power differential, the software reverses the electricity direction. Consequently, the algorithm increases the voltage if the voltage decreases and decreases the voltage if the voltage increases. The algorithm controls the operating voltage by adjusting the duty cycle ratio. Any duty cycle variation inversely affects the DC–DC converter's input resistance and controls the operating voltage to meet the four previously mentioned conditions.[50,51]

The MATLAB SIMULINK model of P&O-based MPPT is shown in Figure 7. The various blocks are utilized to guarantee appropriate power extraction with adequate efficiency, and the ratings of the components used in the construction of the boost converter are the same as those listed in Table 3. The blocks are used to store the current, voltage, and power outputs prior to visualization, and the saturation block is used to ensure that the output is within acceptable bounds.

INC-PSO-based MPPT design

The hybrid INC-PSO MPPT technology combines the advantages of the PSO algorithm and the INC approach to improve the efficiency and accuracy of the MPPT process.[52] Both strategies complement one another in terms of benefits and drawbacks. Within the hybrid INC-PSO approach, the INC method functions as the primary MPPT algorithm, rapidly tracking the MPP in situations that change. The PSO algorithm improves the INC method with its fine-tuning capability. Optimizing the duty cycle received from INC helps to further improve tracking accuracy and efficiency. To maximize the duty cycle, the PSO approach can also lessen power oscillations and more closely converge to the true MPP.[53] The Simulink model of hybrid INC-PSO is given in Figure 8.

Hybrid INC-PSO MPPT advantages

1. Increased MPP tracking speed under various settings as a result of the INC method's effectiveness.
2. Enhanced accuracy and convergence to the real MPP thanks to the PSO algorithm's ability to be fine-tuned.
3. Improved resistance to irradiance or load fluctuations that occur suddenly.
4. Improved handling of local optima and non-linear PV panel behavior.
5. Adaptability to various environmental factors and system setups.

P&O-PSO-based MPPT design

P&O and PSO are two separate MPPT techniques that combine their respective potentials.[54] The model is created by summing the duty cycle outputs of both controllers using a sum block. The outputs are then supplied to a PWM generator, which creates a pulse that is then given to a boost converter switch, resulting in outputs at the DC link and load.[55] The hybrid MPPT design is depicted in the Figure 9.

ANN-based MPPT design

The design of ANN-based MPPT includes several steps which are explained below:

- Collection of data: Gathering data is the initial stage in developing an ANN (inputs, outputs). The input and output values are generated through MATLAB coding. Increasing the amount of data helps ANN function better.[56] Numerous temperatures, sun irradiances, and matching duty cycle proportions are measured. By changing the PV array's inputs

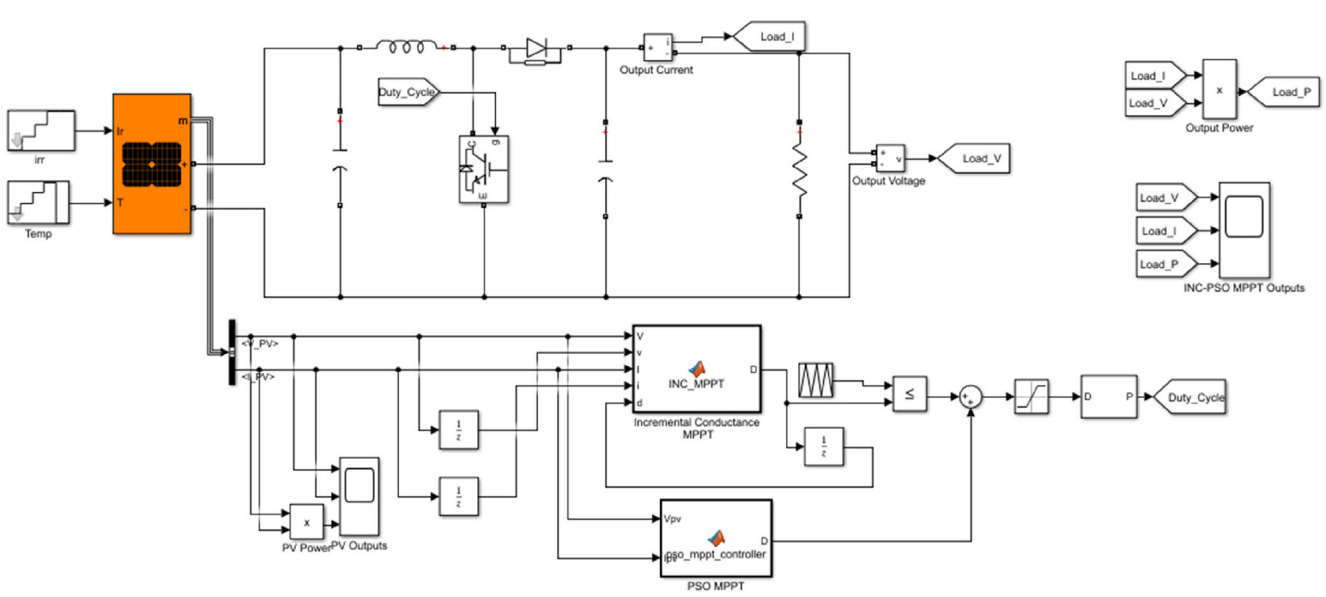

FIGURE 8 MATLAB Simulink model of incremental conductance and Particle Swam Optimization maximum power point tracking (INC-PSO MPPT).

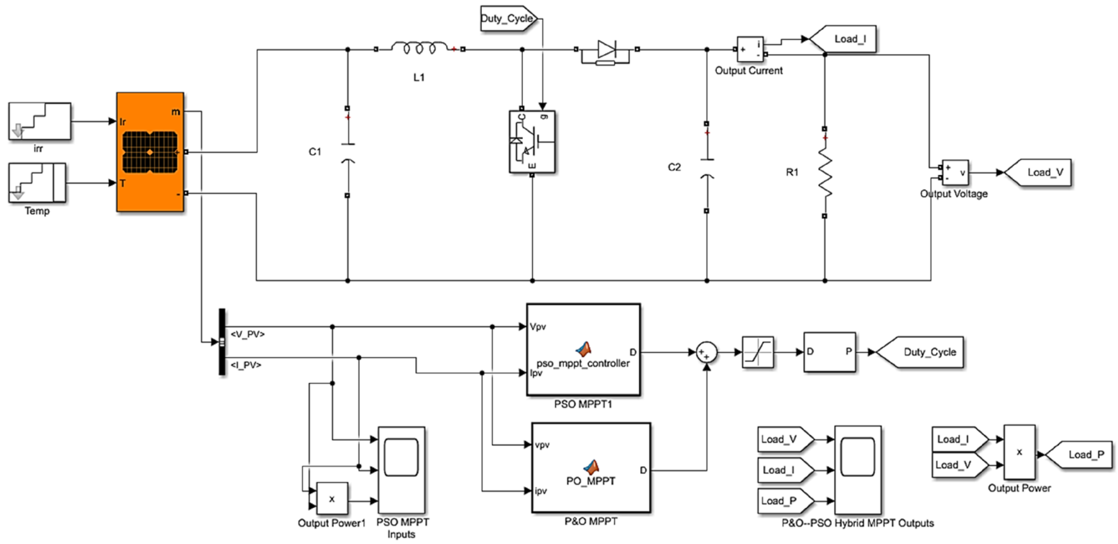

FIGURE 9 MATLAB Simulink model of Perturb and Observe and Particle Swam Optimization maximum power point tracking (P&O-PSO MPPT).

for irradiance and temperature and measuring duty ratios, samples are obtained. By using managed learning, marked data, or a set of already known data, a learning algorithm is chosen.[57]

- Network training: After the settings are completed, the ANN must be trained on generated data.[58] Several training algorithms, including Quasi-Newton Back-Propagation, Levenberg Marquardt Back-Propagation, and One-step Secant Back-Propagation, can be used to train ANNs. For this work, the Levenberg Marquardt back-propagation was employed. As seen in Figure 10, the data was separated into three sets: training, testing, and validation.

- Deploying the trained ANN-algorithm block: Once the ANN is trained on the data next step is to deploy it to the SIMULINK to implement in the simulation. The MATLAB library does not have any block to use ANN in the Simulink therefore the MATLAB ANN Toolbox provides this flexibility to easily deploy the trained ANN model by using the "To Simout" function in the end of training and we get the SIMULINK block of the trained ANN model.

The trained ANN model as shown in Figure 11 takes input values of temperature and irradiance[59] which in this work are kept according to the real ECs. The output voltage from PV panel and predicted voltage by ANN model are compared and the proportional integral (PI) controller is used which helps ANN to increase the strength and stability of the MPPT.

ANFIS-based MPPT design

Figure 12 displays the MATLAB Simulink model of the ANFIS-based MPPT algorithm. The solar PV system and component ratings are the same as those used in the MPPT algorithm mentioned previously. The temperature ranges from 25 to 45°C and the irradiance ranges from 400 to 1000 W/m^2. The MATLAB controller setup for the adaptive neural and fuzzy inference system has already been built, and it is trained using the temperature and irradiance generated for this research work. The PI controller's job is to obtain the output without distortion.[60]

PSO-based MPPT design

Figure 13 displays the MATLAB SIMULINK model of the PSO-based MPPT algorithm. The PSO-based MPPT is coded using a function block that comes with MATLAB.[61] The convergence counter, which measures the number of successive iterations where the difference between the previous and current best duty cycles is small, suggesting convergence, was retained at 10 and the maximum number of iterations was maintained at 1000. The other parameters are defined below:

Population size

- Number of particles: Number of particles in the PSO population kept: 20

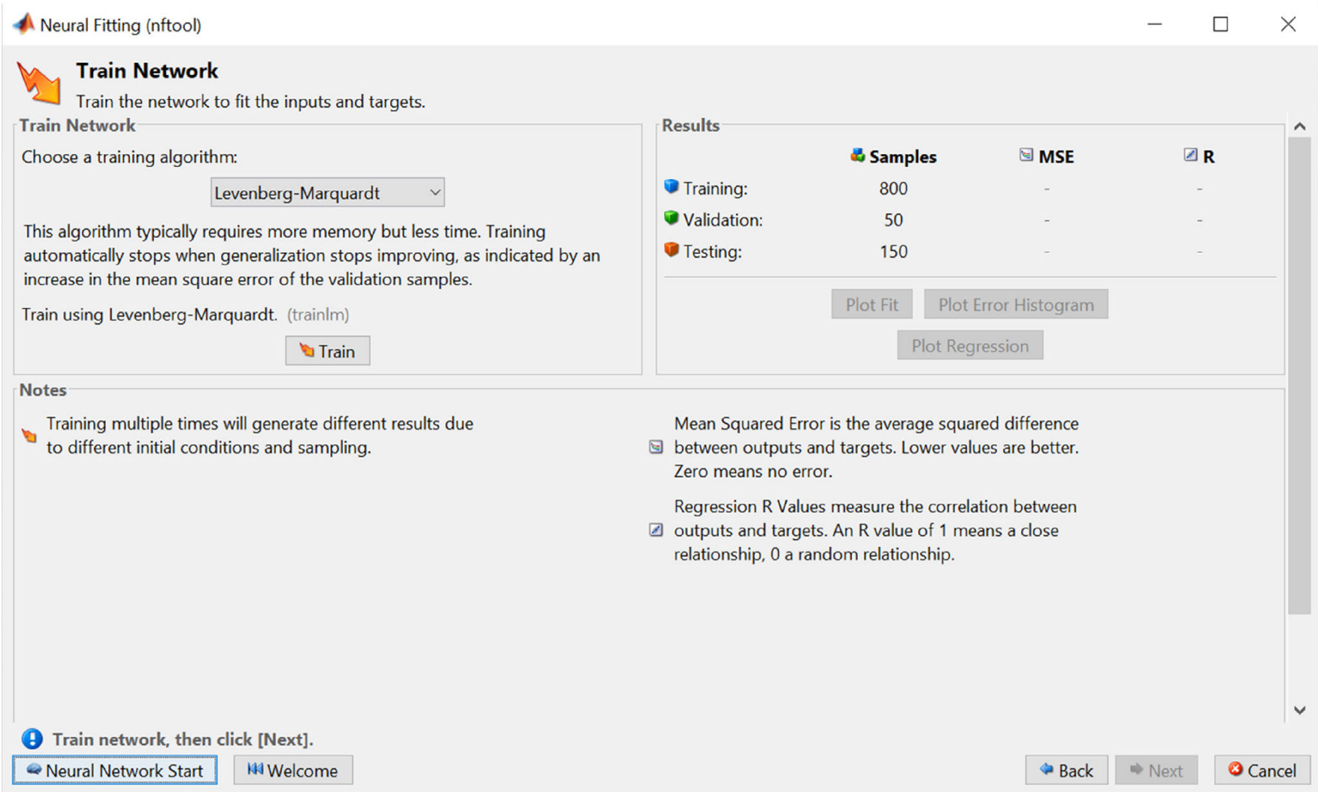

FIGURE 10 Training Artificial Neural Network (ANN) on temperature and irradiance data.

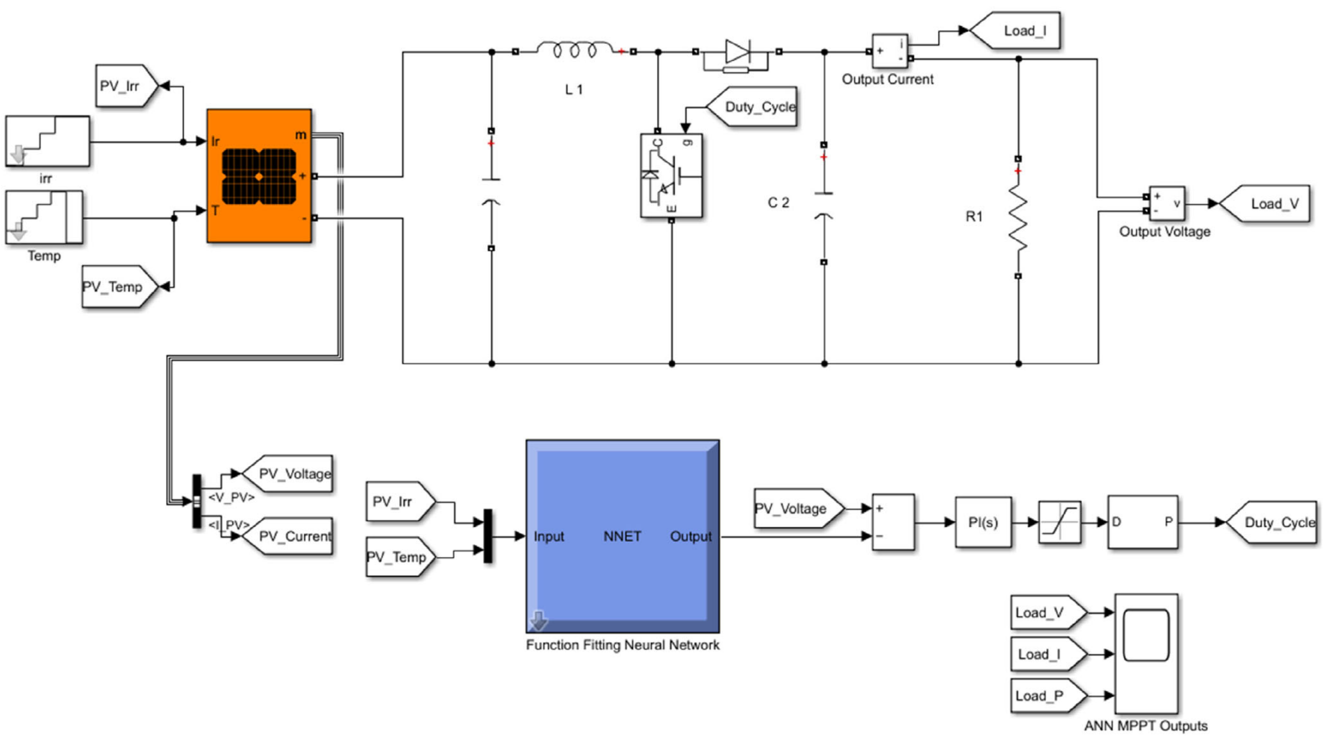

FIGURE 11 MATLAB Simulink model of Artificial Neural Network maximum power point tracking (ANN MPPT).

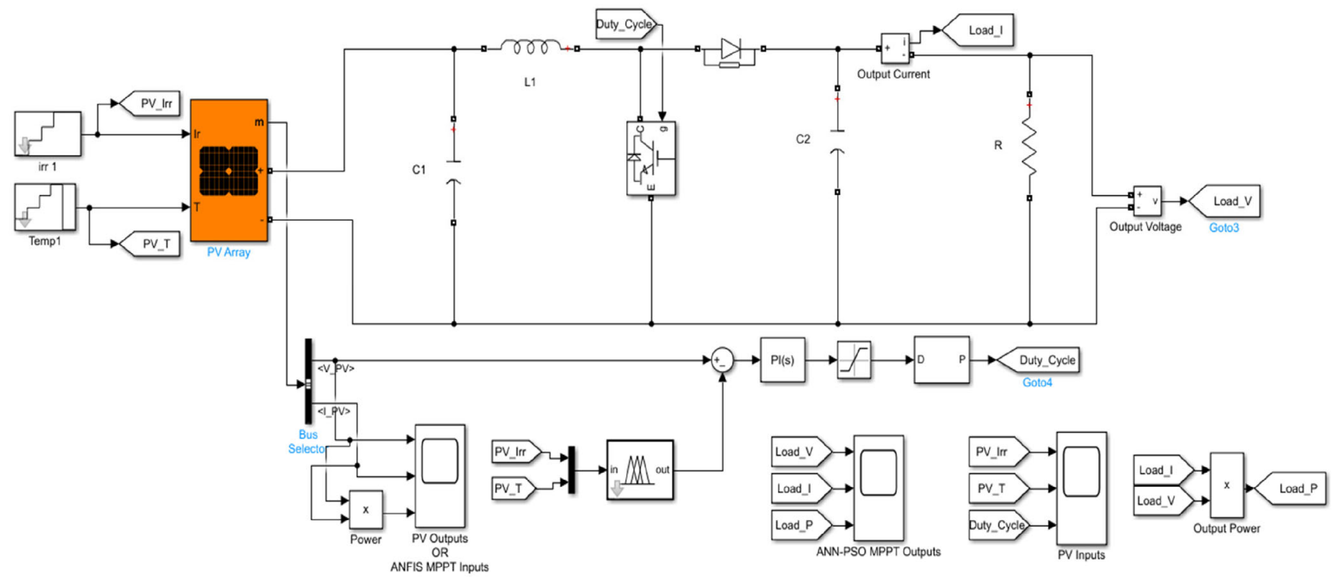

FIGURE 12 MATLAB Simulink model of Artificial Neural Fuzzy Interference System maximum power point tracking (ANFIS MPPT).

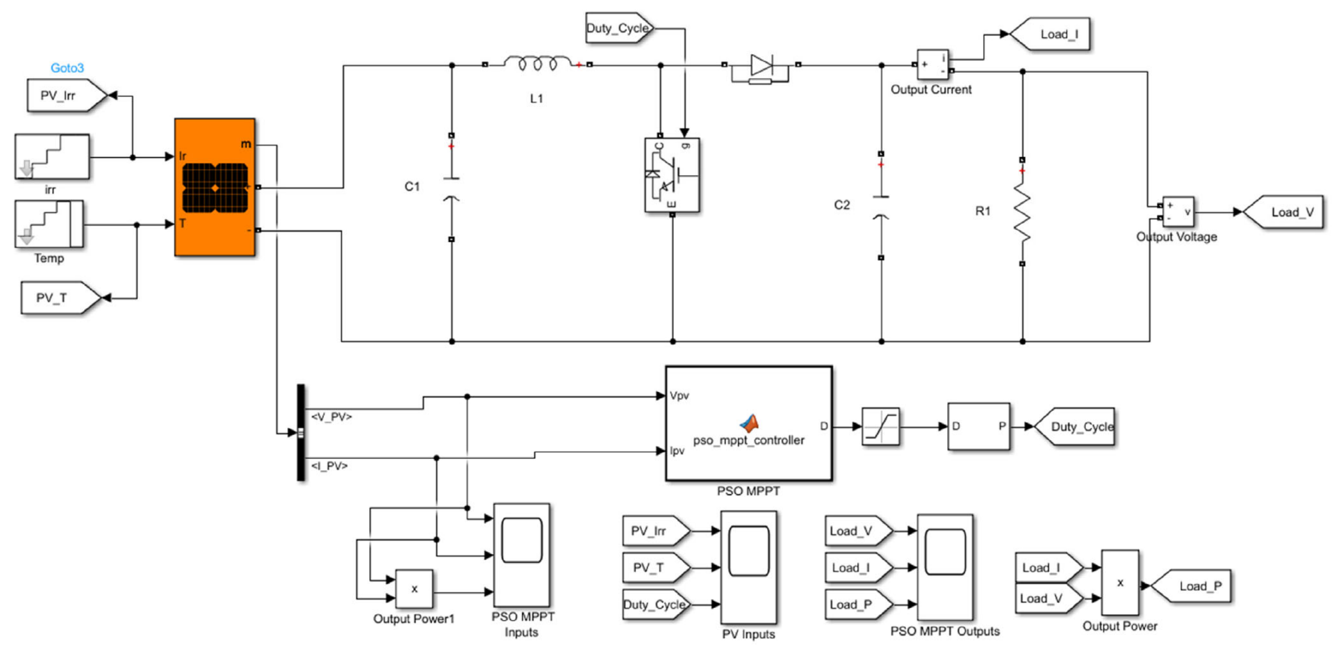

FIGURE 13 MATLAB Simulink model of maximum power point tracking Particle Swam Optimization (PSO MPPT).

PSO parameters

- w: Inertia weight used in the velocity update equation: 0.6
- c1: Cognitive coefficient for balancing personal experience: 1.4
- c2: Social coefficient for balancing global experience: 1.4

FLC-based MPPT design

Figure 14 shows the MATLAB Simulink model based on FLC MPPT algorithm. The FLC toolbox's FLC block is used to implement the FLC.[62] The temperature and irradiance are considered variables, and the memory blocks are employed

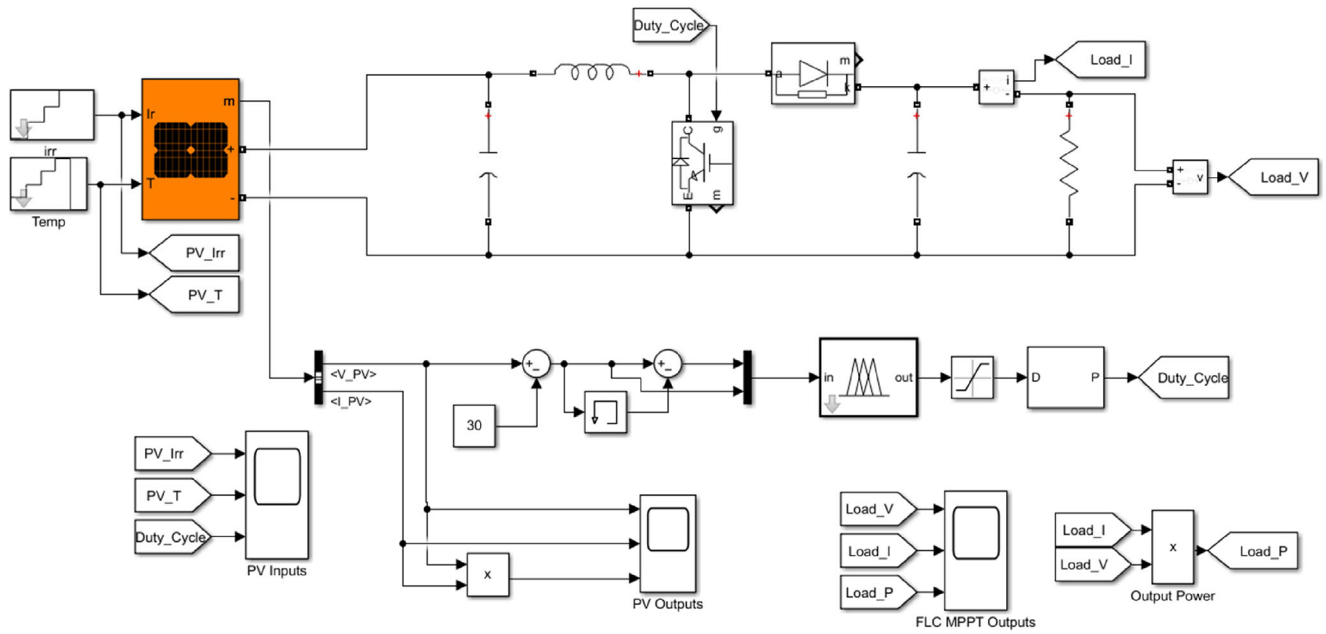

FIGURE 14 MATLAB Simulink model of Fuzzy Logic Control maximum power point tracking (FLC MPPT).

to store and give the prior voltage values. The solar PV system's irradiance block range is maintained between 400 and 1000 W/m^2, its temperature range is maintained between 25 and 45°C, and its component ratings are the same across all MPPT algorithms.

ANN-PSO-based MPPT design

Like the other hybrid techniques, the ANN-PSO hybrid approach is created by fusing the trained ANN-based MPPT with the PSO MPPT.[63] The method combines the unique power prediction capabilities of ANN, which give it intelligence, with the adaptive capability of PSO, which allows it to deal with changing ECs efficiently. In order to extract and maintain power at its highest power point, the controller employs a more versatile approach.[64] The outputs of the two separate controllers are combined in the model design as shown in Figure 15 and utilized to produce the duty cycle for the switch.

FUZZY-PSO-based MPPT design

Figure 16 shows the MATLAB Simulink model of Fuzzy-PSO-based MPPT design. PSO and FLC together create a hybrid MPPT that is faster and more reliable when they are combined.[65] Due to the PSO's use of particles in its optimization process, it is able to locate the global maximum point more quickly than other conventional MPPTs and explore a wider solution space with greater efficiency than the controller using FLC to control the power at the MPP.[66]

4 | COMPREHENSIVE RESULTS

This study evaluates the performance of various conventional and AI-based MPPT algorithms applied to a standalone solar PV system under varying irradiance and temperature conditions. The tested algorithms include INC, P&O, and several intelligent techniques such as, ANN, ANFIS, PSO, FLC, and ANN-PSO. Under the conditions of changing irradiance from 400 to 1000 W/m^2 and temperatures ranging from 25 to 45°C, the results reveal significant differences in the performance of these algorithms. Traditional methods like INC and P&O show adequate performance but are often outperformed by intelligent methods. For instance, at 1000 W/m^2 irradiance and 25°C, the INC algorithm achieved a power output of 235 W with an accuracy of 94%, while the P&O algorithm generated 244.1 W having 97.6% accuracy. In contrast, the intelligent algorithms demonstrated superior performance. The ANN method had an accuracy of 97.8 producing 244.4 W power, and the PSO method reached 99% accuracy and 247.6 W under the same conditions. The FLC-based MPPT controller extracted 247.9 W on an accuracy of 99.2, and the ANFIS system achieved highest accuracy and power of 99.8 and 249.5 W respectively, showcasing their capability to adapt and maintain high power outputs. Additionally, the

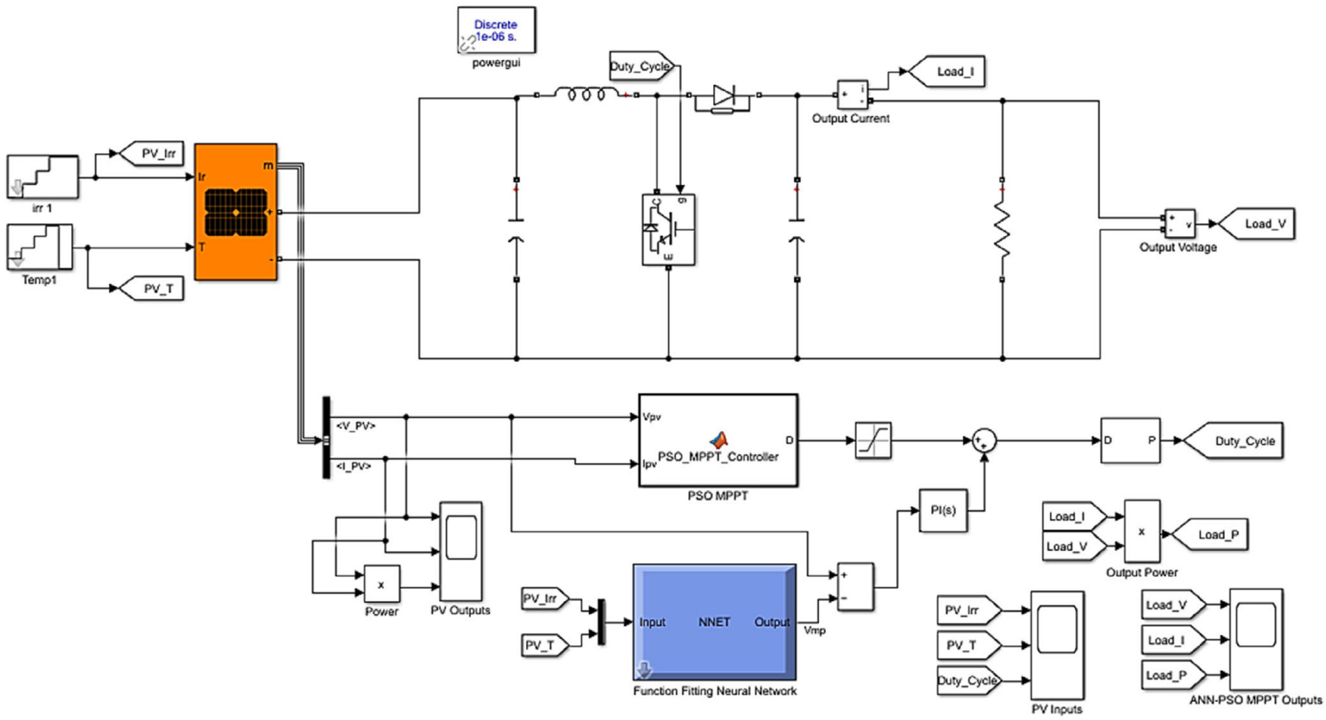

FIGURE 15 MATLAB Simulink model of Artificial Neural Network-Particle Swam Optimization maximum power point tracking (ANN-PSO MPPT).

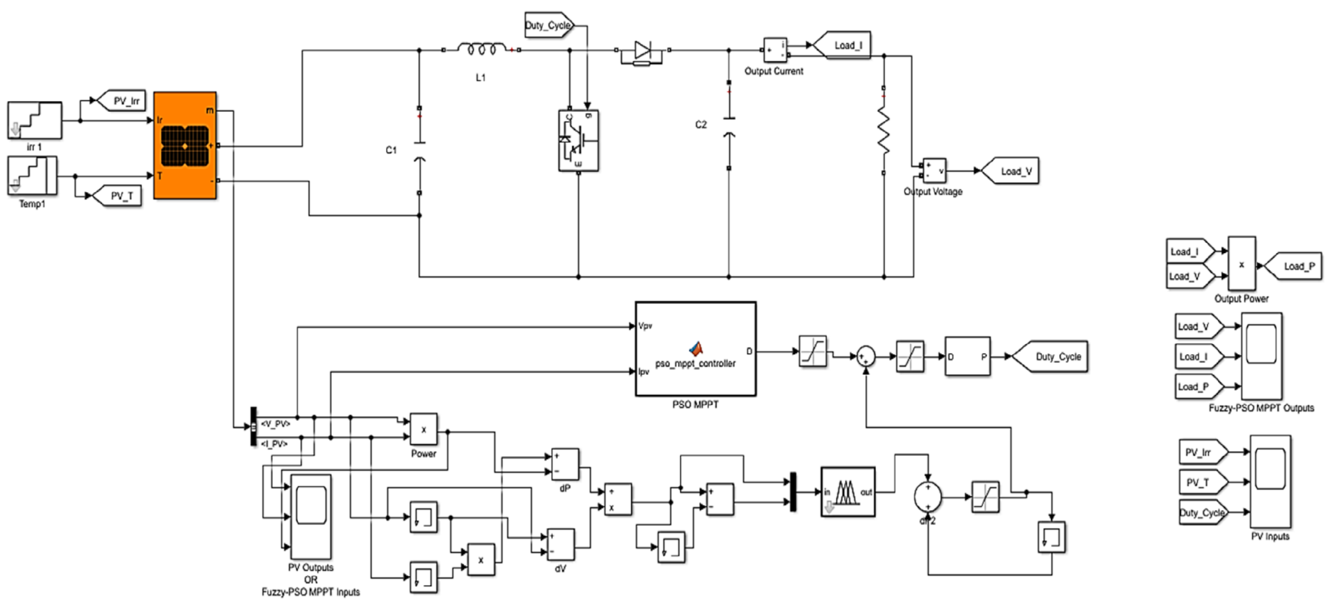

FIGURE 16 MATLAB Simulink model of Fuzzy-Particle Swam Optimization maximum power point tracking (Fuzzy-PSO MPPT).

performance of these algorithms under challenging conditions further highlighted their efficiency. For instance, under 600 W/m^2 irradiance and 35°C, the ANN algorithm produced 107.6 W, while the PSO algorithm achieved 101.3 W. The FLC system managed to extract 93.5 W, and the ANFIS method reached 100.6 W, indicating their robustness and adaptability. While the conventional MPPT controllers could achieve the low power. P&O produced 99.5 W and the INC-PSO produced 99.6 W, P&O-PSO Producing power of 102.7 and the FLC-PSO could achieve 97.2 W. The power extracted and the accuracy are shown in Figures 17 and 18 respectively.

Furthermore, the results show that the intelligent algorithms not only excelled in power output but also in tracking speed. The results of the settling time and tracking accuracies of the various MPPT algorithms reveal significant differences in performance, particularly highlighting the superior capabilities of intelligent MPPT controllers as shown in Figure 19. Conventional algorithms, such as INC and P&O, display moderate performance. The INC algorithm has a settling time of 0.043 seconds, indicating a reasonable response time, but it often struggles with tracking accuracy under rapidly changing conditions. The P&O algorithm shows a slightly better settling time of 0.039 s, improving its response

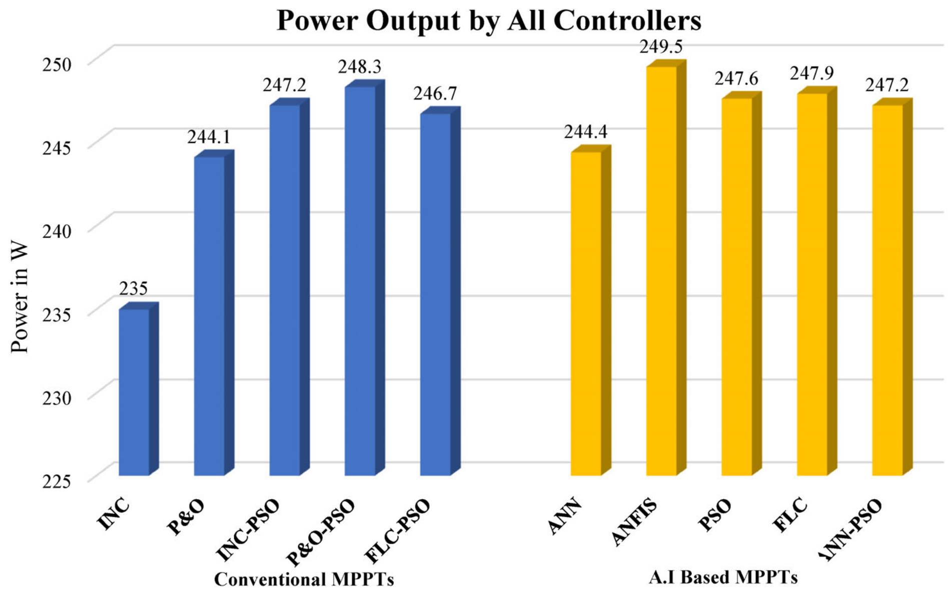

FIGURE 17 Shows the output power extracted by all the control algorithms.

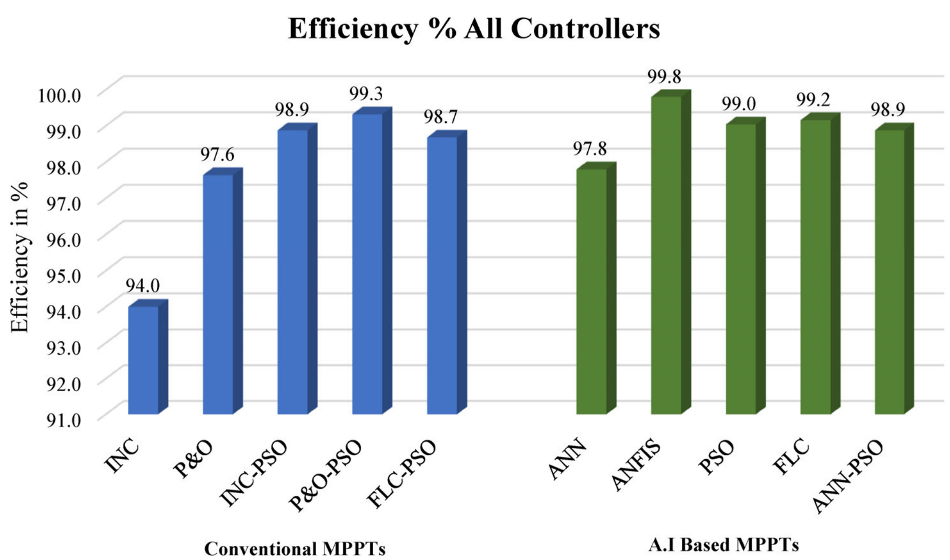

FIGURE 18 Shows the accuracies exhibited by all the control algorithms.

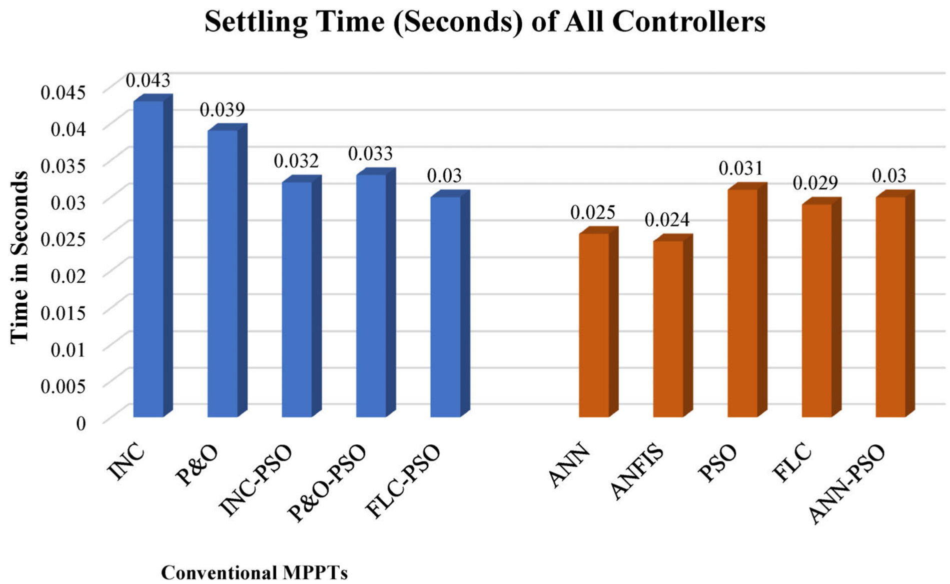

FIGURE 19 Shows the settling time in seconds taken by all the control algorithms.

time, yet it can suffer from oscillations around the MPP, impacting its overall accuracy. The INC-PSO achieves a settling time of 0.032 s, and the P&O-PSO closely follows with 0.033 s, as shown in Figure 19. On the other hand, intelligent MPPT algorithms exhibit notably higher tracking speeds due to their advanced predictive and adaptive capabilities. The ANN algorithm, accurately predicting and tracking the MPP by having a shorter settling time of 0.25 s. The FLC provides high tracking accuracy with a settling time of 0.29 s, using fuzzy logic to manage uncertainties and imprecise inputs effectively. The ANN-PSO, with a settling time of 0.30 s, merges ANN's predictive strengths with PSO's optimization, resulting in a highly accurate and moderately fast MPP tracking. The ANFIS outperforms with a lowest settling time of 0.24 s and achieves the highest tracking accuracy among all tested methods by combining ANN's learning abilities with fuzzy logic's reasoning. The standalone PSO algorithm, also delivers excellent tracking accuracy with a settling time of 0.31 s. The intelligent MPPT algorithms not only achieve superior tracking accuracies compared to conventional methods but also exhibit faster adaptation and stabilization times, ensuring more efficient power extraction from solar PV systems under varying ECs. This underscores the potential of intelligent MPPT controllers in enhancing the performance and efficiency of solar power generation, making them highly suitable for real-world applications where conditions are dynamic and require rapid, accurate power maximization.

4.1 | Irradiance and temperature

In selecting the parameters for our proposed method, careful consideration was given to replicating the real-world ECs or temperature and irradiance values encountered by solar PV systems across different regions and climates. By simulating dynamic changes in both irradiance and temperature, we aimed to create a universally applicable study that benefits various geographical locations. This approach ensures that our findings can be extrapolated globally, providing valuable insights into the performance of solar PV systems under diverse climatic scenarios. Our study's relevance extends beyond academic research, offering practical implications for real-world applications. One significant application is in the design and optimization of solar energy systems for residential, commercial, and industrial use. Understanding how different MPPT algorithms perform under varying ECs enables engineers and designers to make informed decisions to maximize the efficiency and reliability of solar power generation in different geographical regions.

Furthermore, our research findings can inform the development of advanced MPPT controllers and renewable energy management systems. By demonstrating the effectiveness of our proposed method in accurately tracking MPPs under changing irradiance and temperature conditions, we lay the groundwork for implementing more sophisticated control strategies in future solar PV installations. These advancements have the potential to enhance the overall performance and cost-effectiveness of solar energy systems, further promoting the adoption of RETs on a global scale.

Therefore, standalone PV system is subjected to simultaneously fluctuating temperature and irradiance values, as seen in Figure 4, in order to replicate the dynamic reaction, behavior, and power output of a solar PV system under actual climatic conditions. Table 4 lists the temperature and irradiance variations. For the first 0.2 s, the irradiation intensity stays constant at 400 W/m^2, but then it increases quickly to 1000 W/m^2. The power values change as the radiation level changes. When there is more irradiation, the PV panel generates more power as demonstrated in Table 4.

4.2 | Implementation of INC Algorithm on PV System

4.2.1 | Case 1

The PV system in this configuration is subjected to the INC algorithm. One kind of MPPT controller that tracks the MPP is an INC MPPT controller. The derivative of the power with respect to the voltage is known as the INC. The INC is zero at the MPP, and its outcomes are examined in the previously indicated temperature and irradiation ranges. At 57.6 ohms, the load is kept constant. The temperature is varied between 25 and 40°C while the irradiance is adjusted from 400 to 1000 W/m^2. The irradiance changes after an interval of every 0.2 s. During the first interval, the irradiance is 400 W/m^2 which gives an output power of 92.0 W at 30°C as the system starts, further it extracts 135.6 W under conditions of 600 W/m^2 irradiance and 35°C temperature, 175.4 W at 800 W/m^2 irradiance and temperature exceeding 40°C, and achieves a competitive power output of 215 W at irradiance levels of 1000 and 45°C. While maintaining a substantial power output of 235 W at the same irradiance level but at a lower temperature of 25°C. The simulation results are shown in Table 5 and Figure 20.

4.2.2 | Case 2

In the second scenario, standard testing circumstances (STCs) are subjected to the INC algorithm to ascertain how long it takes to track MPP and carry on extracting the maximum power. The INC algorithm's highest power extraction results are displayed in Figure 21. The INC MPPT takes 0.043 s to track the MPP and carry out the remaining power extraction, as can be observed.

TABLE 4 Shows the varying irradiance and temperature.

Time range (S)	Irradiance value (W/m^2)	Temperature (°C)
0.0–0.2	400	30
0.2–0.4	600	35
0.4–0.6	800	40
0.6–0.8	1000	45
0.8–1.0	1000	25

TABLE 5 Shows output power at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature (°C)	INC MPPT output power
0.0–0.2	400	30	92.0
0.2–0.4	600	35	135.6
0.4–0.6	800	40	175.4
0.6–0.8	1000	45	215
0.8–1.0	1000	25	235

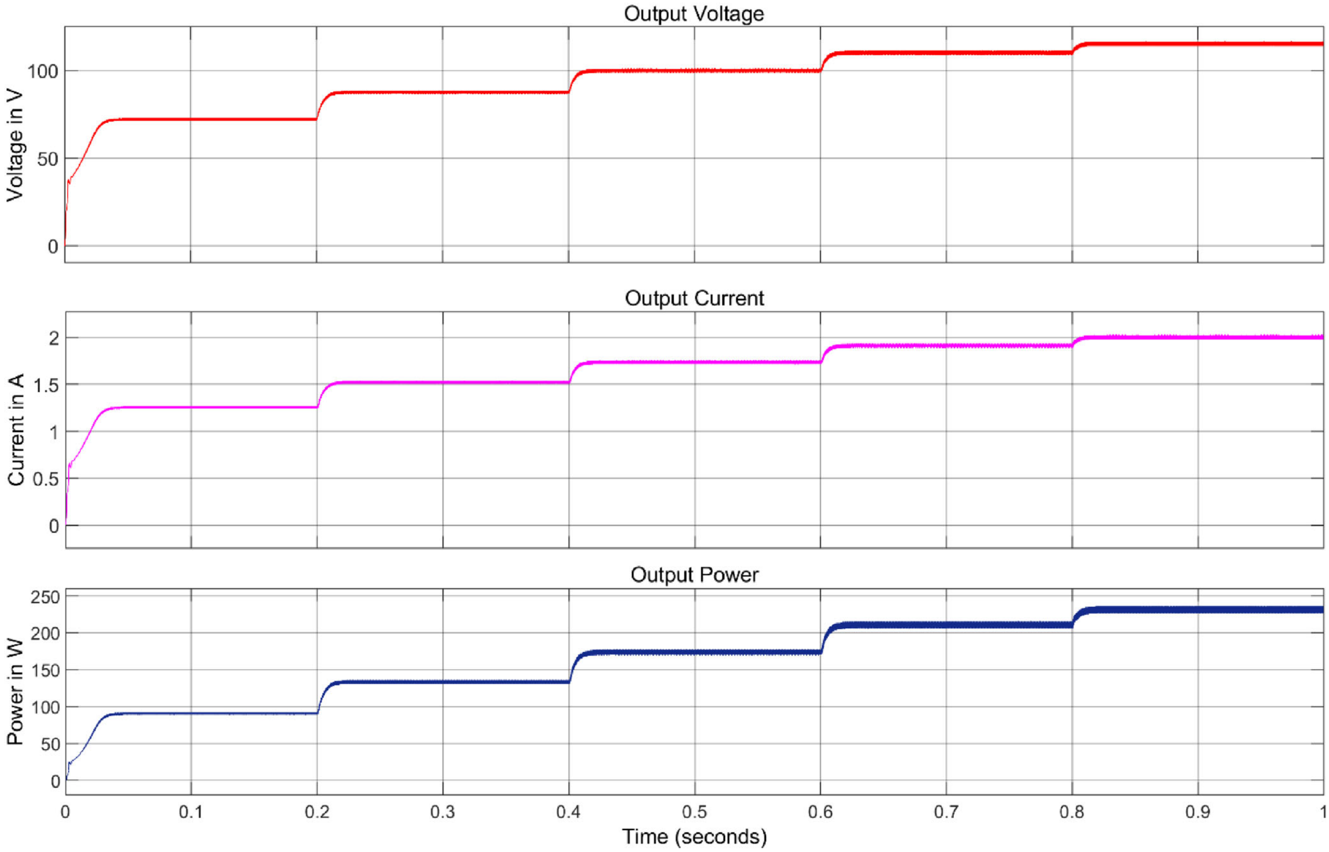

FIGURE 20 Maximum power point tracking (MPPT) output power after implementing incremental conductance (INC) method.

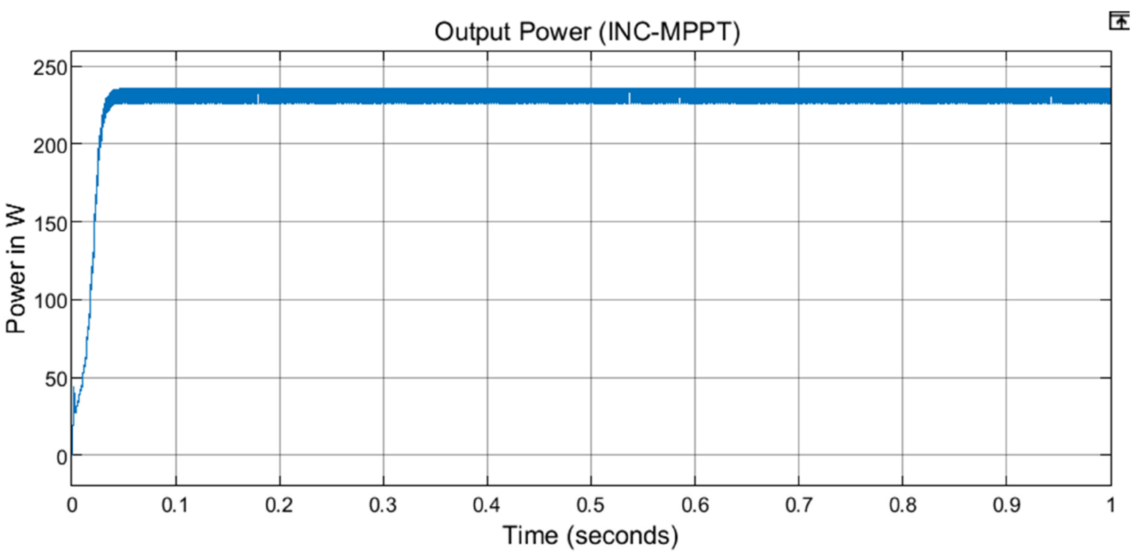

FIGURE 21 Incremental conductance maximum power point tracking (INC MPPT) outputs at standard testing conditions.

4.3 | Implementation of P&O algorithm on PV system

4.3.1 | Case 1

A P&O MPPT controller uses a straight forward algorithm to track the MPP of a PV system. The P&O algorithm monitors the change in output power that occurs when the operational voltage of the PV system is altered. As the output power increases, the algorithm also generates a voltage perturbation in the same direction. If the output power falls, the algorithm produces a voltage perturbation in the opposite direction. The P&O algorithm is run under the identical temperature and irradiance circumstances, and the outcomes are noted at each stage. P&O MPPT is more efficient in tracking the power at higher irradiance level. It extracts 44.7 W at 400 W/m^2 at 30°C, 99.5 W at 600 W/m^2 at 35°C and remains competitive with a power output of 173.6 W at irradiance levels of 800 W/m^2 and temperatures exceeding 40°C. Additionally, at a higher irradiance of 1000 W/m^2 and elevated temperature of 45°C, the P&O MPPT system excels, generating 222.5 W, and it further demonstrates its effectiveness by producing a significantly higher power output of 244.1 W at the same irradiance level but under lower temperature conditions of 25°C as shown in Figure 22 while on the lower irradiance, the P&O struggles to extract the higher power. Table 6 shows output of P&O at specified irradiance and temperature.

4.3.2 | Case 2

In the second case, typical STCs conditions are used to evaluate the P&O algorithm's performance. The purpose of this test was to determine how long it takes to locate and reliably extract the MPP. The findings show that the P&O MPPT algorithm identifies MPP in 0.039, as shown in Figure 23.

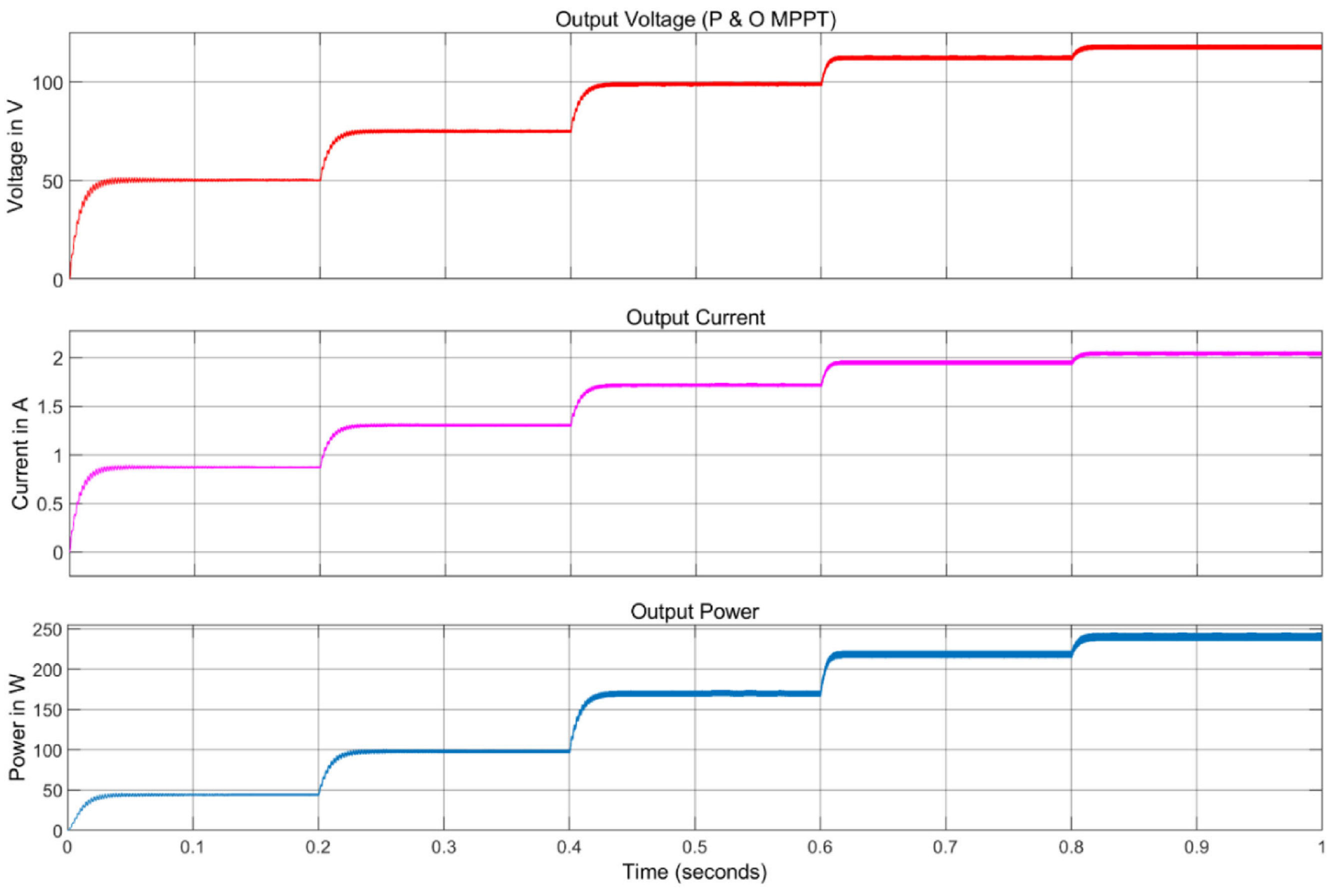

FIGURE 22 Perturb and Observe maximum power point tracking (P&O MPPT) outputs at standard testing conditions.

TABLE 6 Shows outputs of Perturb and Observe (P&O) at specified irradiance and temperature.

Time range (S)	Irradiance value (W/m^2)	Temperature	P&O MPPT output power
0.0–0.2	400	30	44.7
0.2–0.4	600	35	99.5
0.4–0.6	800	40	173.6
0.6–0.8	1000	45	222.5
0.8–01	1000	25	244.1

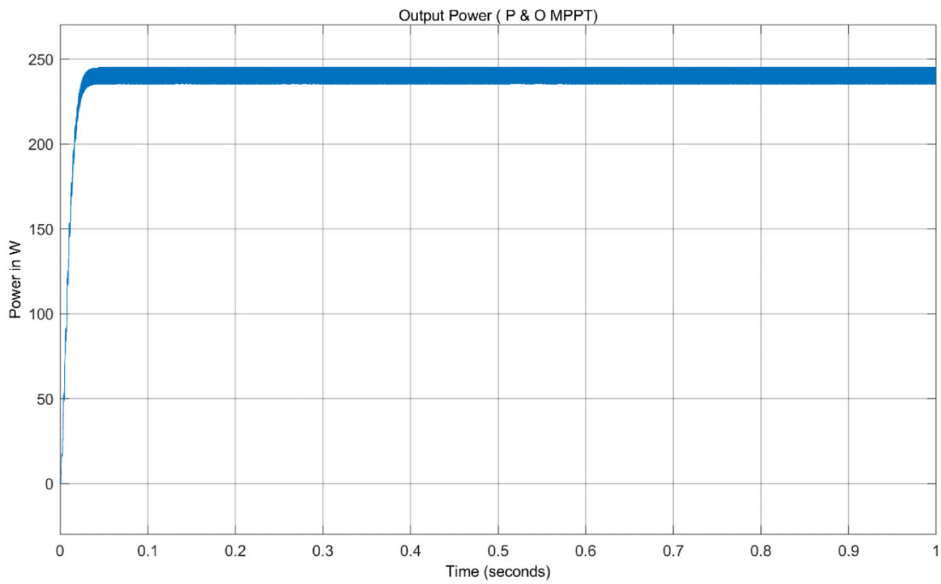

FIGURE 23 Maximum power point tracking (MPPT) output power after implementing Perturb and Observe (P&O) method.

4.4 | Implementation of INC-PSO MPPT on PV System

4.4.1 | Case 1

The INC-PSO MPPT combines the benefits of the INC method and the PSO algorithm. The combined capabilities enable this MPPT to exhibit outperformance over other MPPTs in tracking the highest power output under varying ECs. In Figure 24 the INC-PSO MPPT system demonstrates its adaptability and efficiency in harnessing solar energy across various ECs. It consistently delivers impressive power outputs, such as 44.5 W at 400 W/m^2 irradiance at 30°C, 99.6 W at 600 W/m^2 irradiance and 35°C, and a competitive 172.0 W output at irradiance levels of 800 W/m^2 and temperatures exceeding 40°C. While excelling in diverse settings, it's worth noting that under high irradiance conditions, the INC-PSO MPPT system outperforms, generating 225.5 W at 45°C and an impressive 247.2 W at 25°C, emphasizing its efficacy in specific temperature scenarios. These results underscore the INC-PSO MPPT system's reliability and adaptability for consistent power generation across varied climates, while recognizing the INC-PSO system's proficiency in maximizing output under specific temperature conditions, highlighting the importance of tailored MPPT system selection based on specific application requirements. Table 7 shows the INC-PSO outputs at specified irradiance and temperature.

4.4.2 | Case 2

In the second case, the MPPT method when applied standard testing conditions is able to efficiently locate the MPP within short period of time. In this case, the INC-PSO MPPT is evaluated under typical testing circumstances with 1000 W/m^2 irradiance and a temperature of 25°C. Figure 25 shows how the INC-PSO MPPT algorithm successfully locates the MPP in a relatively quick time of 0.032 s.

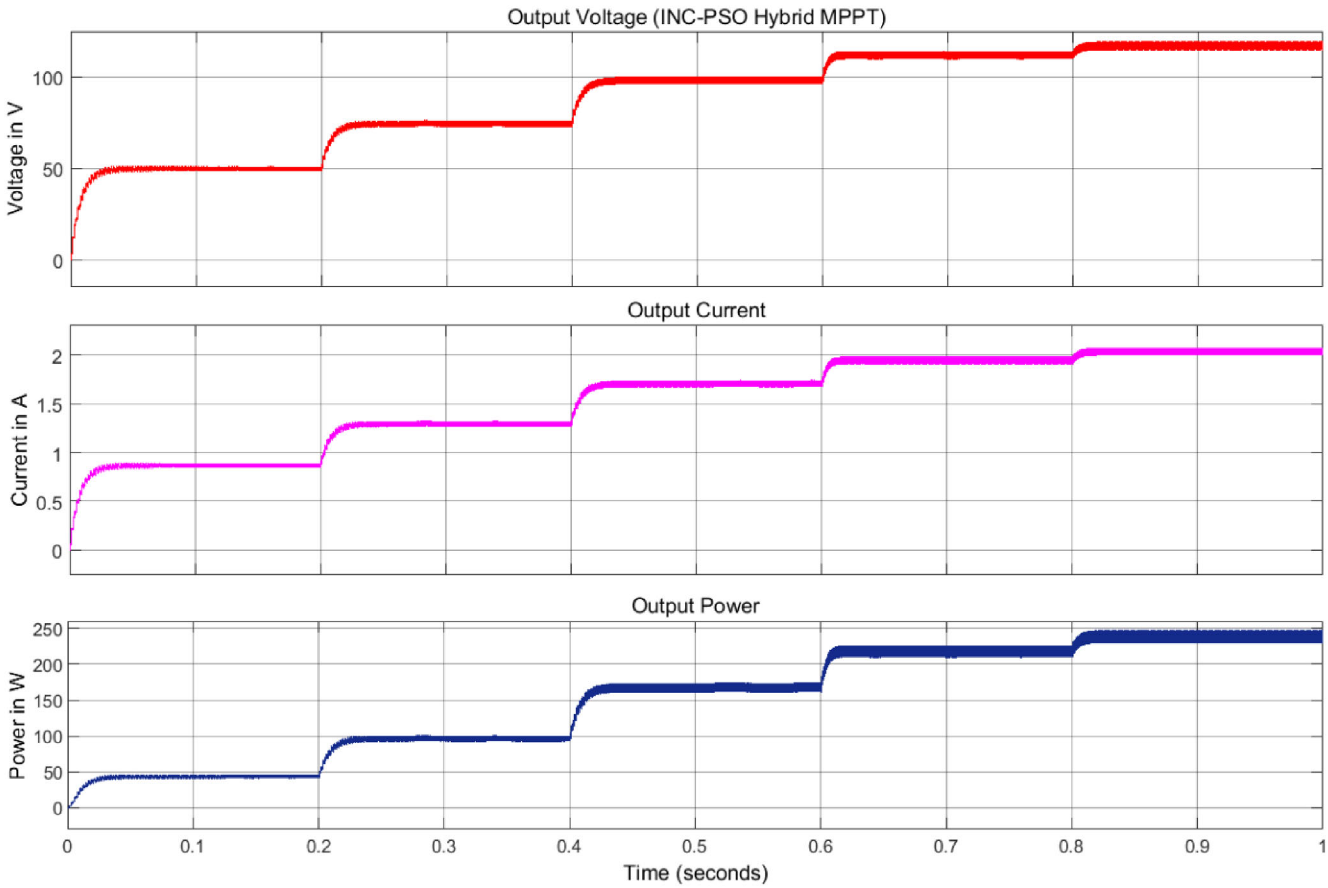

FIGURE 24 Maximum power point tracking (MPPT) output power after implementing incremental conductance and Particle Swam Optimization (INC-PSO) method.

TABLE 7 Shows incremental conductance and Particle Swam Optimization (INC-PSO) outputs at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	INC-PSO MPPT output power
0.0–0.2	400	30	44.5
0.2–0.4	600	35	99.6
0.4–0.6	800	40	172.0
0.6–0.8	1000	45	225.5
0.8–01	1000	25	247.2

4.5 | Implementation of P&O-PSO MPPT on solar PV system

4.5.1 | Case 1

P&O-PSO is a hybrid technique combines the two algorithms to improve performance of the system. The P&O algorithm monitors the change in output power that occurs when the operational voltage of the PV system is altered. The program then modifies the operating voltage to increase output power. For the system to function, a population-based optimization algorithm known as PSO imitates the social behavior of fish and birds. By optimizing the parameters of the P&O technique in the hybrid P&O-PSO algorithm, the PSO algorithm helps the P&O algorithm better adapt to the circumstances and postpone its convergence to the local optimal solution. Following the same ECs, the P&O-PSO algorithm is implemented as MPPT on solar PV systems to explore the combined performance of P&O-PSO controllers in PV applications to extract the maximum power. Figure 26 shows how well the P&O-PSO MPPT system adapts to changing ECs and is effective

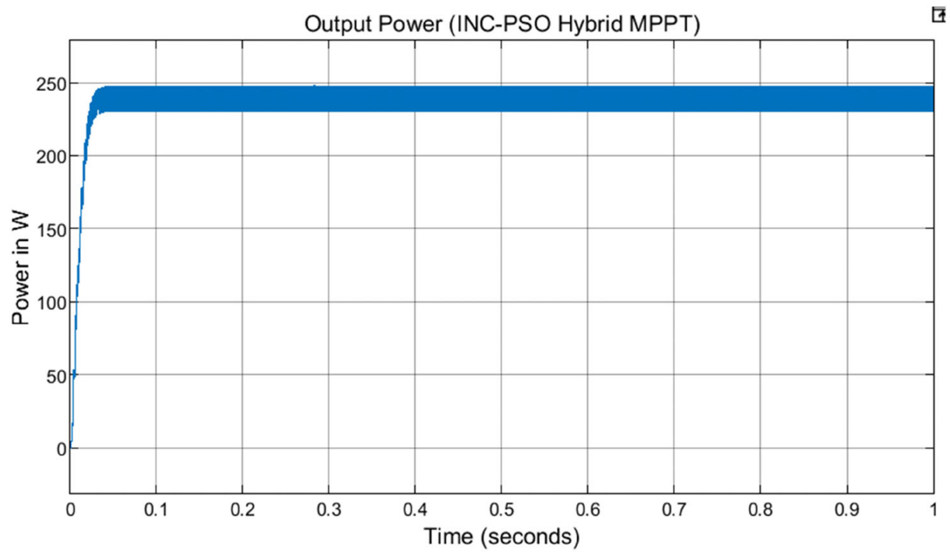

FIGURE 25 Maximum power point tracking (MPPT) output power implementing incremental conductance and Particle Swam Optimization (INC-PSO) at standard testing conditions.

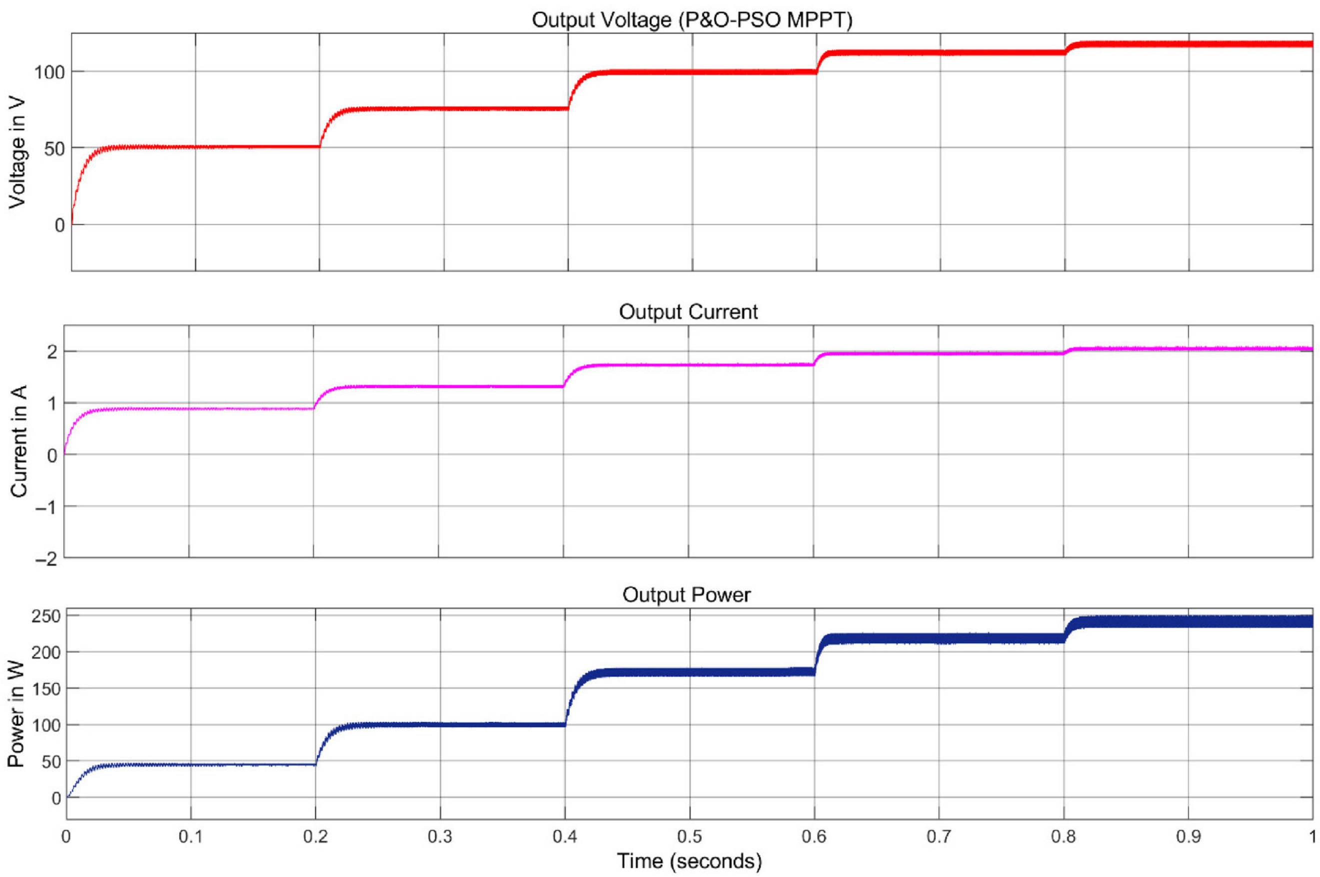

FIGURE 26 Maximum power point tracking (MPPT) output power after implementing incremental conductance and Particle Swam Optimization (INC-PSO) method.

at capturing solar energy. It consistently produces impressive power outputs, such as 46.9 W at 400 W/m^2 irradiance at 25°C temperature, 102.7 W at 600 W/m^2 irradiance at 30°C temperature, and a competitive 177.6 W output at irradiance levels of 800 W/m^2 at temperatures above 45°C. The P&O-PSO MPPT system outperforms in high irradiance conditions, generating 225.5 W at 40°C and an impressive 248.3 W at 25°C, highlighting its effectiveness in particular temperature scenarios while performing well in a variety of settings. Table 8 shows P&O-PSO outputs at specified irradiance and temperatures.

4.5.2 | Case 2

In the second case, the MPPT approach is able to efficiently identify the MPP faster than other standard MPPTs due to the combined control and capabilities of the Perturb and Observe and particle swarm optimization methodologies, respectively. In this instance, the P&O-PSO MPPT is evaluated at 25°C and 1000 W/m^2 of irradiation under typical testing settings. The P&O-PSO MPPT method finds the MPP with success in a mere 0.033 s, as Figure 27 illustrates.

4.6 | Implementation of ANN MPPT on Solar PV System

4.6.1 | Case 1

An ANN controller, also referred to as an ANN MPPT controller, monitors a PV system's MPP. The ANN is trained on PV array voltage, current, and power data. The ANN can be used to forecast the MPP voltage for any given input voltage and current once it has been trained. When the ANN algorithm is used as MPPT on solar PV systems, improved outcomes are

TABLE 8 Shows Perturb and Observe and Particle Swam Optimization (P&O-PSO) outputs at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	P&O-PSO MPPT output power
0.0–0.2	400	25	46.9
0.2–0.4	600	30	102.7
0.4–0.6	800	35	177.6
0.6–0.8	1000	40	225.4
0.8–01	1000	25	248.3

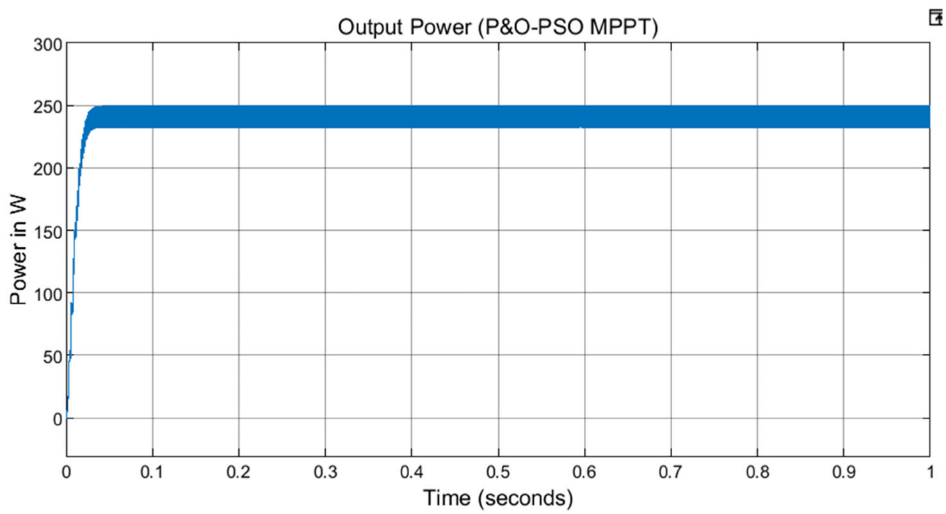

FIGURE 27 Perturb and Observe and Particle Swam Optimization maximum power point tracking (P&O-PSO MPPT) outputs at standard testing conditions.

obtained throughout the entire power extraction process. Temperature and radiation exposure are rising in tandem with the output. When the illumination is reduced, the ANN MPPT is more effective at tracking power. Figure 28 shows that the ANN MPPT extracts 48.1 W at 400 W/m^2 irradiance and 30°C temperature and it extracts 107.6 W at the 600 W/m^2 irradiance at 35°C temperature and competitive power value of 181.2 W at irradiance of 800 W/m^2 and higher temperature of 40°C. When the temperature and irradiance are 1000 W/m^2 at 45°C, respectively, the ANN extracts 217.0 W on the higher irradiance; when the temperature and irradiance are the same, however, it extracts 244.4 W. Table 9 shows ANN outputs at specified irradiance and temperatures.

4.6.2 | Case 2

The ANN algorithm, due to its efficient neural network architecture is faster to find the MPP when subjected to standard testing conditions (1000 W/m^2 irradiance and 25°C temperature) Figure 29 shows that the ANN MPPT algorithm finds MPP in a very short time of 0.024 s.

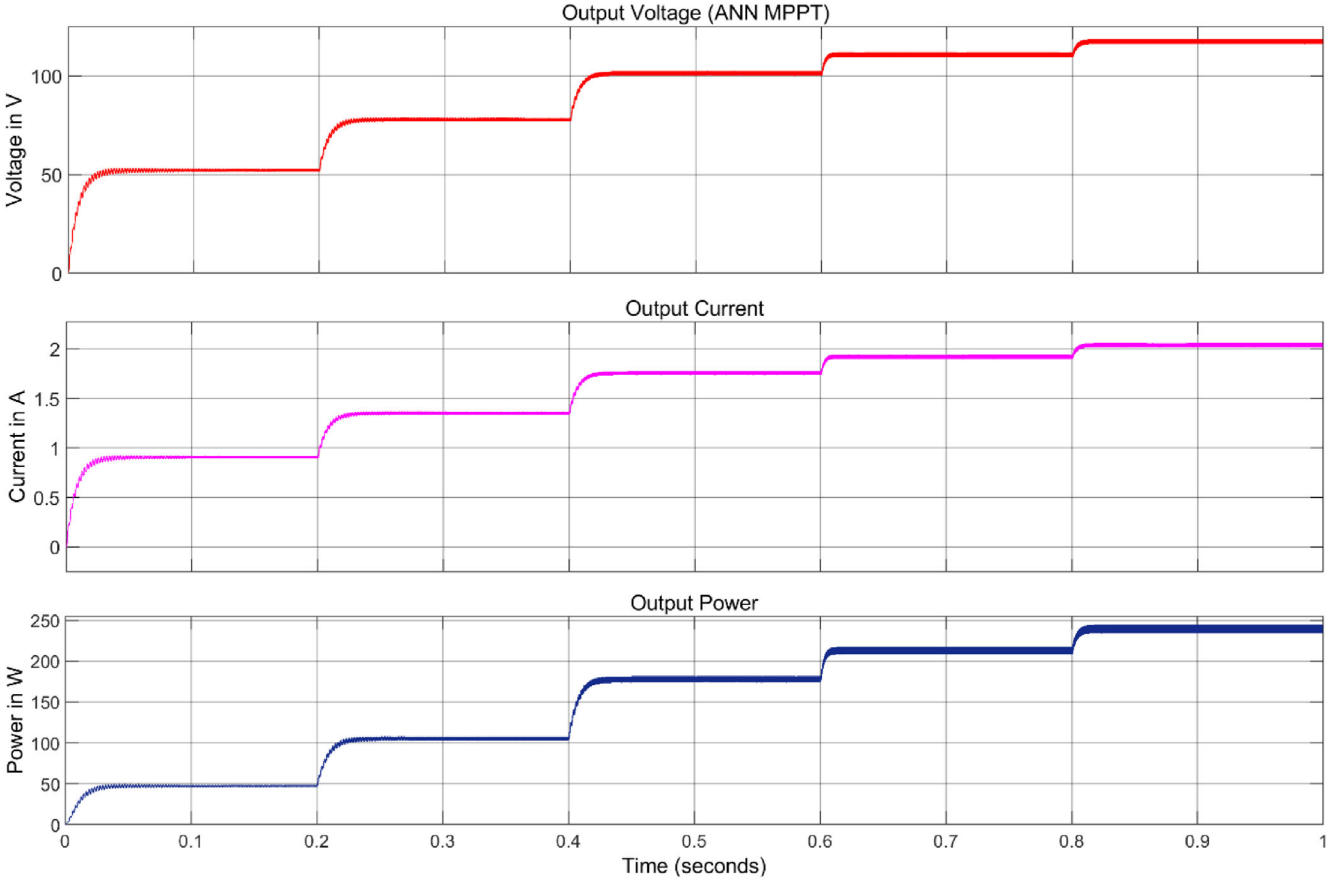

FIGURE 28 Maximum power point tracking (MPPT) output power after implementing Artificial Neural Network (ANN) method.

TABLE 9 Shows Artificial Neural Network (ANN) outputs at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	ANN MPPT output power
0.0–0.2	400	30	48.1
0.2–0.4	600	35	107.6
0.4–0.6	800	40	181.2
0.6–0.8	1000	45	217.0
0.8–01	1000	25	244.4

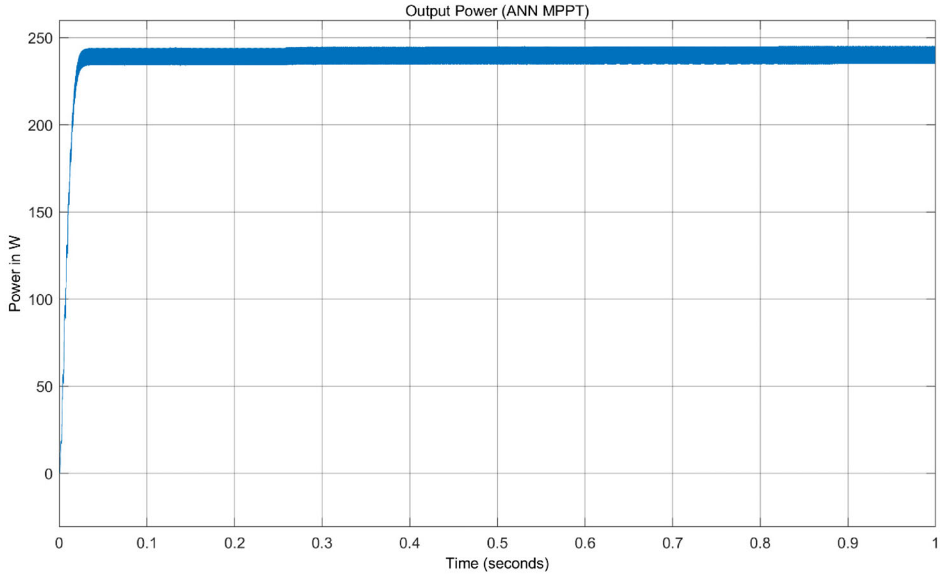

FIGURE 29 Artificial Neural Network maximum power point tracking (ANN MPPT) outputs at standard testing conditions.

4.7 | Implementation of ANFIS MPPT on solar PV system

4.7.1 | Case 1

The ANFIS MPPT, being a combination of fuzzy logic and ANN proves to be a highly efficient and robust MPPT for solar PV systems and it produces remarkable achievements in tracking MPP. As shown in Figure 30, the ANFIS MPPT system achieves power outputs of 45.2 W under conditions of 400 W/m^2 irradiance and 30°C temperature, 100.6 W at 600 W/m^2 irradiance at 35°C temperature, and remains competitive with a power output of 174.5 W at irradiance levels of 800 W/m^2 and temperatures exceeding 40°C. Additionally, at a higher irradiance of 1000 W/m^2 and elevated temperature of 45°C, the ANFIS MPPT system excels, generating 221.4 W, and it further demonstrates its effectiveness by producing a significantly higher power output of 249.5 W at the same irradiance level but under lower temperature conditions of 25°C. Table 10 shows outputs of ANFIS at specified irradiance and temperatures.

4.7.2 | Case 2

In the second case, the combined control and prediction capabilities of fuzzy logic and ANN respectively enable the ANFIS MPPT algorithm to efficiently locate the MPP faster than the other conventional MPPTs. The ANFIS MPPT in this case is tested under standard testing conditions, featuring 1000 W/m^2 irradiance and a temperature of 25°C. As depicted in Figure 31, the ANFIS MPPT algorithm adeptly identifies the MPP within a remarkably short duration of 0.024 s.

4.8 | Implementation of PSO MPPT on solar PV system

4.8.1 | Case 1

The PSO MPPT technique measures the MPP of a PV system by moving particles throughout the problem space in accordance with their present position and the positions of the best particles in their neighborhood. The implementation of the PSO MPPT system in solar PV setups yields remarkable results in maximizing power generation. As shown in Figure 32, the PSO MPPT system achieves power outputs of 45.0 W under conditions of 400 W/m^2 irradiance at 30°C temperature, 101.3 W at 600 W/m^2 irradiance and 35°C and remains competitive with a power output of 175.4 W at irradiance levels of 800 W/m^2 and temperatures exceeding 40°C. Additionally, at a higher irradiance of 1000 W/m^2 and elevated temperature of 45°C, the PSO MPPT system excels, generating 221.4 W, and it further demonstrates its effectiveness by producing

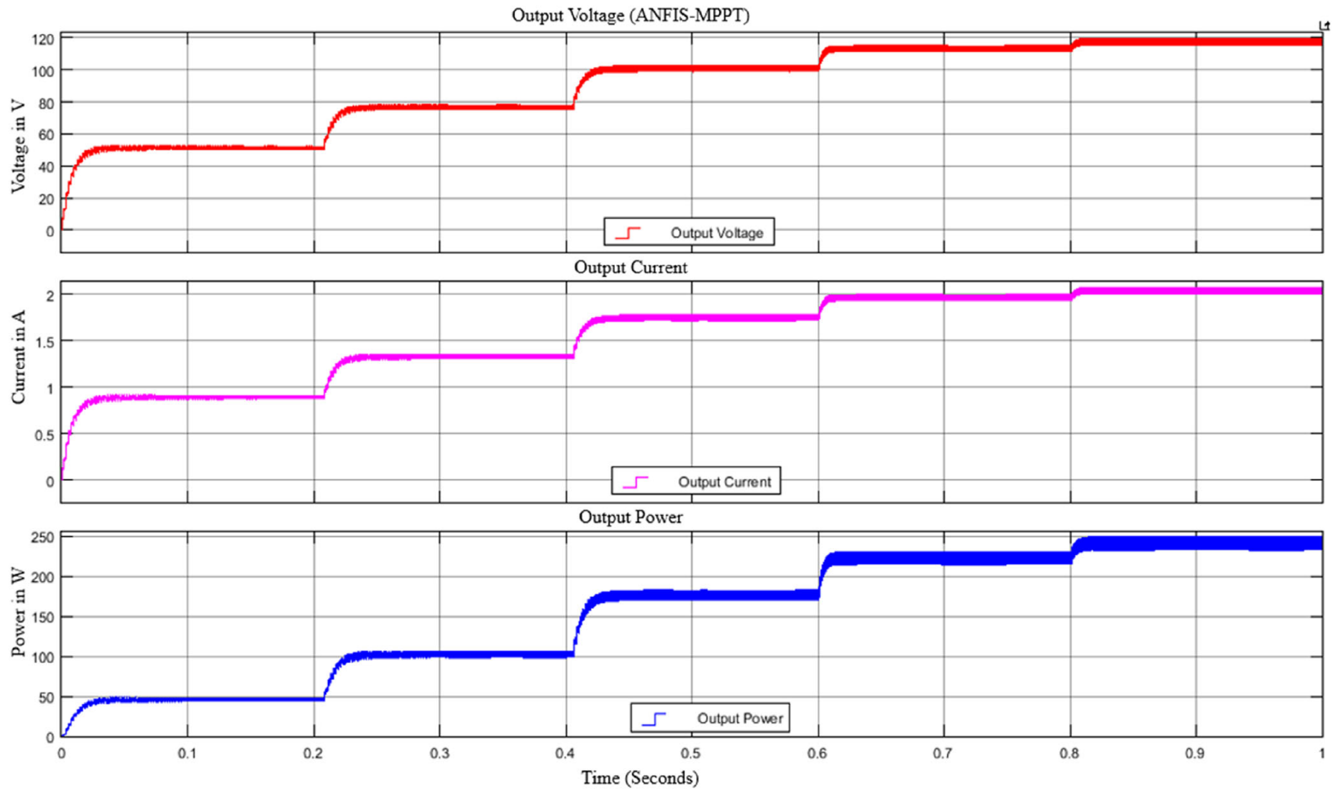

FIGURE 30 Maximum power point tracking (MPPT) output power after Implementing Artificial Neural Fuzzy Interference System (ANFIS) method.

TABLE 10 Shows outputs of Artificial Neural Fuzzy Interference System (ANFIS) at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	ANFIS MPPT output power
0.0–0.2	400	30	45.2
0.2–0.4	600	35	100.6
0.4–0.6	800	40	174.5
0.6–0.8	1000	45	230.9
0.8–01	1000	25	249.5

a significantly higher power output of 247.6 W at the same irradiance level but under lower temperature conditions of 25°C. Table 11 shows outputs of PSO at specified irradiance and temperatures.

4.8.2 | Case 2

In the second case, the PSO MPPT algorithm's outstanding optimization capabilities enable it to efficiently locate the MPP within acceptable timeframes, even under standard testing conditions, featuring 1000 W/m^2 irradiance and a temperature of 25°C. As illustrated in Figure 33, the PSO MPPT algorithm demonstrates its proficiency in identifying the MPP, achieving this task in just 0.31 seconds.

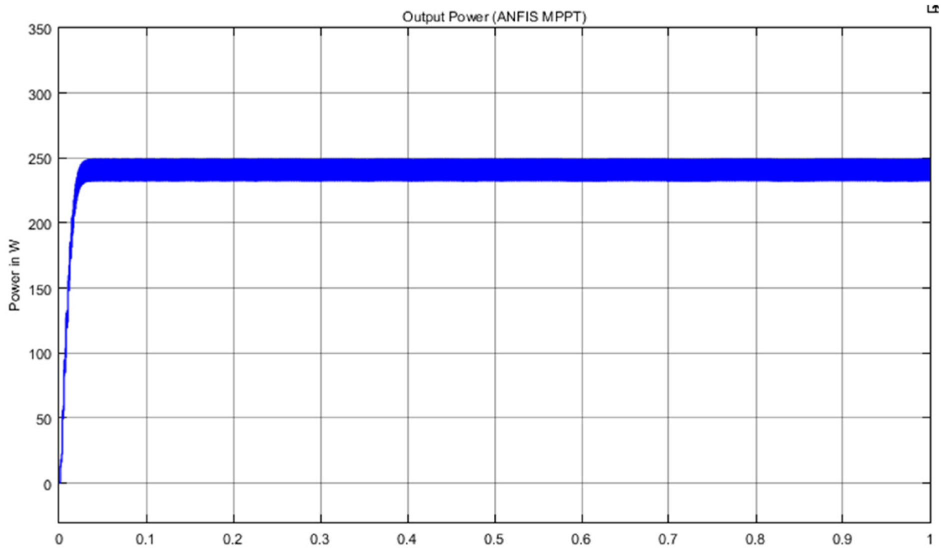

FIGURE 31 Artificial Neural Fuzzy Interference System maximum power point tracking (ANFIS MPPT) outputs at standard testing conditions.

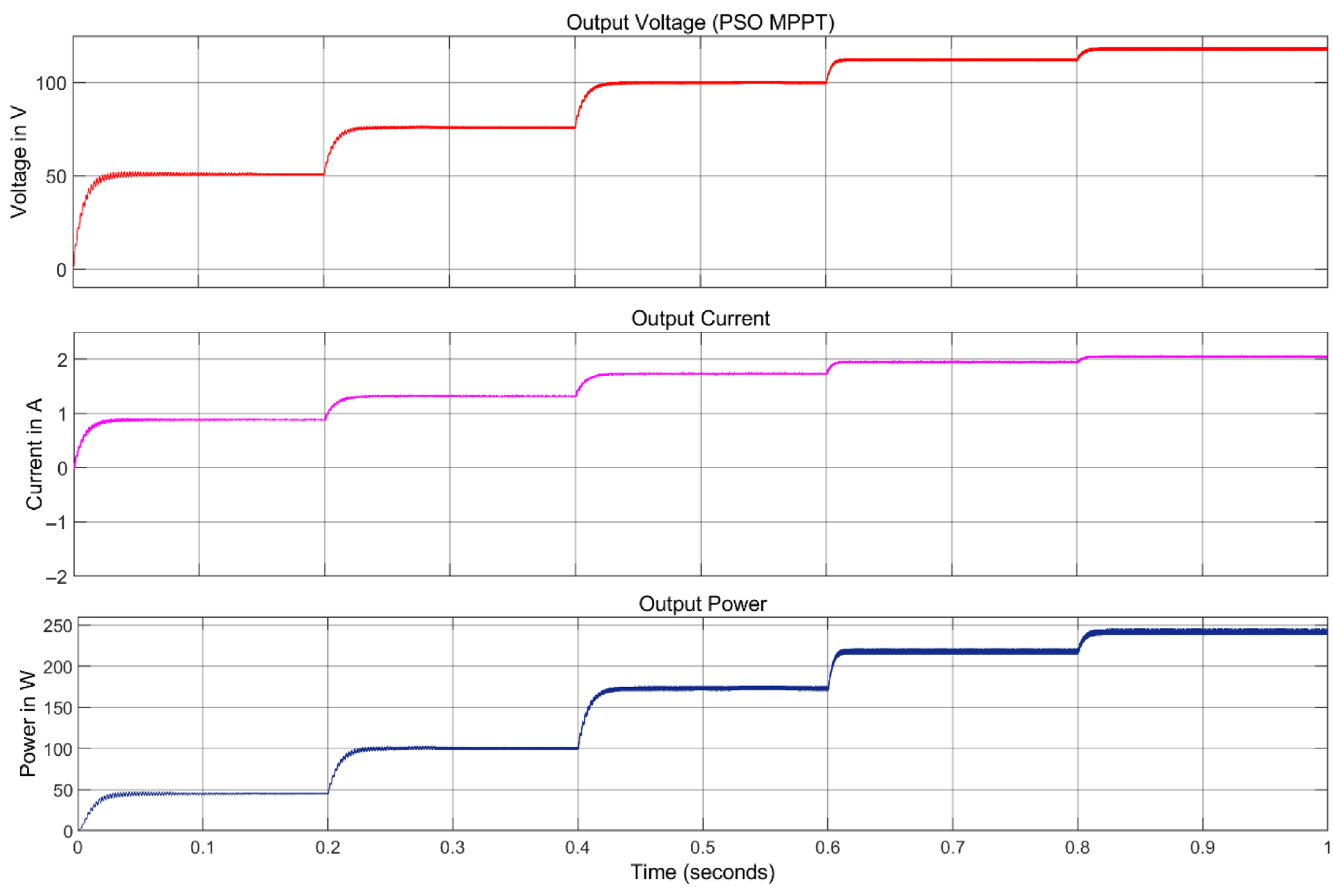

FIGURE 32 Maximum power point tracking (MPPT) output power after implementing Particle Swam Optimization (PSO) method.

TABLE 11 Shows outputs of Particle Swam Optimization (PSO) at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	PSO MPPT output power
0.0–0.2	400	30	45.0
0.2–0.4	600	35	101.3
0.4–0.6	800	40	175.4
0.6–0.8	1000	45	221.4
0.8–01	1000	25	247.6

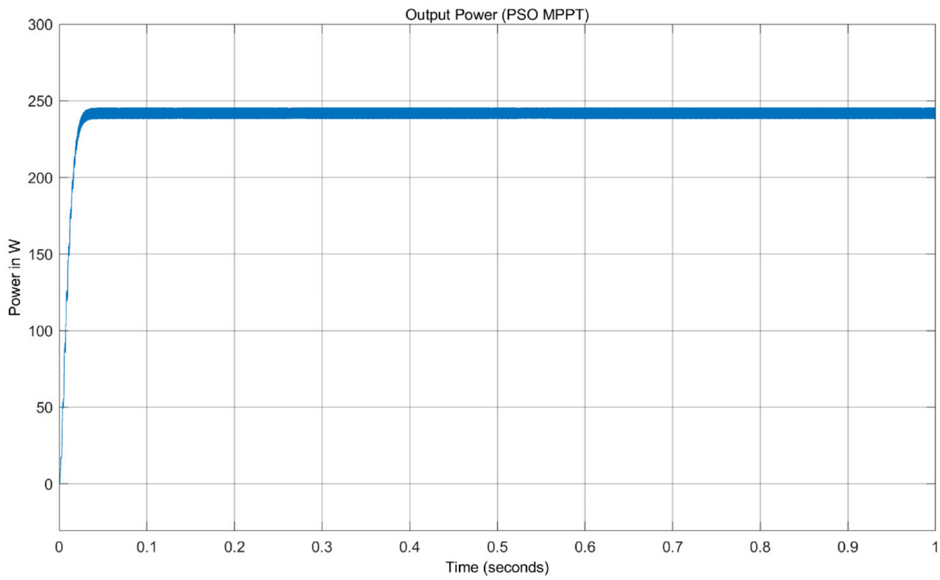

FIGURE 33 Particle Swam Optimization maximum power point tracking (PSO MPPT) outputs at standard testing conditions.

4.9 | Implementation of FLC On PV system

4.9.1 | Case 1

Following the same ECs, the FLC algorithm is implemented as MPPT on solar PV systems to explore the performance of FLC controllers in PV applications to extract maximum power. As depicted in Figure 34, the fuzzy logic-based MPPT system exhibits distinct power extraction performance. It extracts 48.1 W under conditions of 400 W/m^2 irradiance and 30°C temperature, 93.5 W at 600 W/m^2 irradiance and 35°C temperature and achieves a competitive power output of 162.9 W at irradiance levels of 800 W/m^2 and temperatures exceeding 40°C. Moreover, at a higher irradiance of 1000 W/m^2 at elevated temperature of 45°C, the fuzzy logic MPPT system excels, yielding a power output of 230.9 W, while maintaining a substantial power output of 247.9 W at the same irradiance level but at a lower temperature of 25°C. Table 12 shows results of FLC at specified irradiance and temperatures.

4.9.2 | Case 2

In Case 2, the FLC MPPT algorithm's proficiency in logic-based control enables it to swiftly track the MPP under standard testing conditions, characterized by 1000 W/m^2 irradiance and 25°C temperature. As depicted in Figure 35 the Fuzzy-Logic MPPT algorithm excels in MPP identification, accomplishing this task efficiently in a mere 0.29 s.

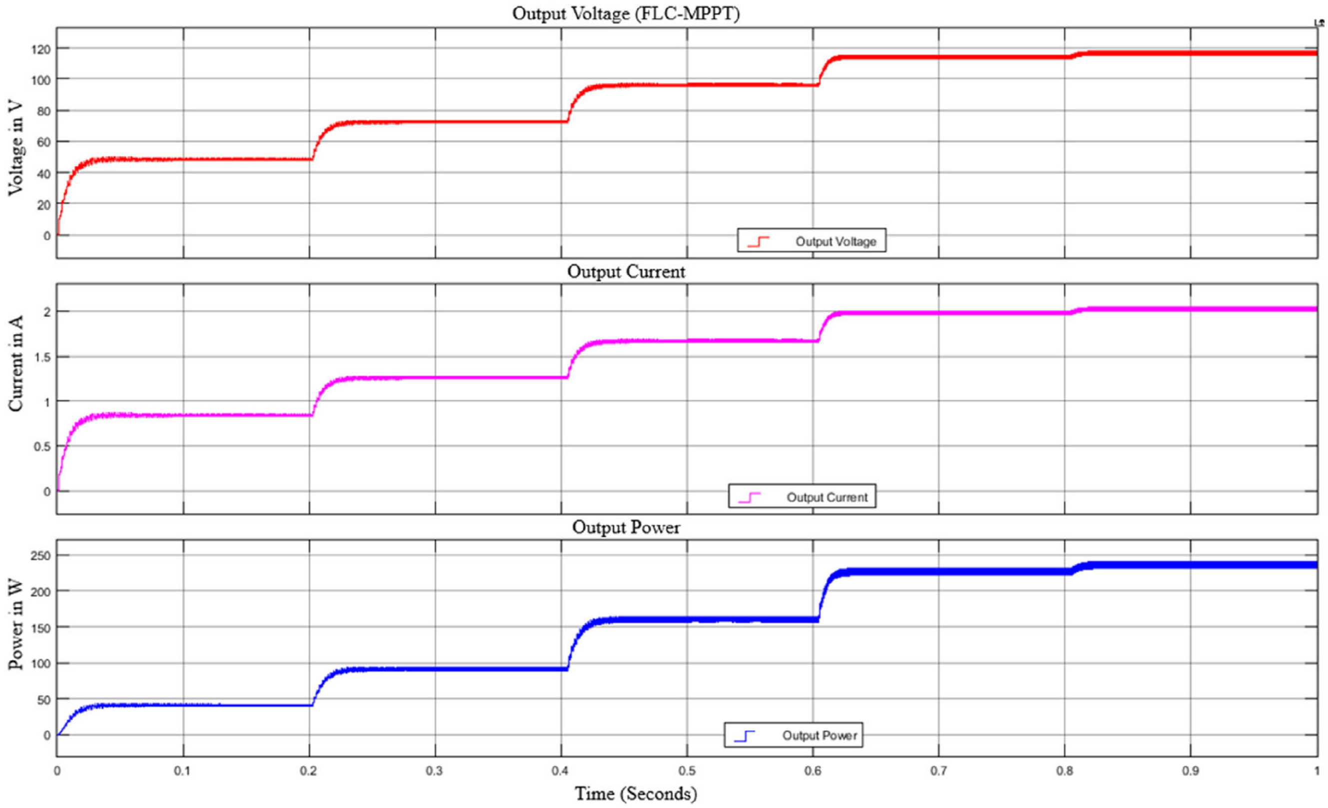

FIGURE 34 Maximum power point tracking (MPPT) output power after implementing Fuzzy-Logic method.

TABLE 12 shows results of Fuzzy Logic Control (FLC) at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	FLC MPPT output power
0.0–0.2	400	30	48.1
0.2–0.4	600	35	93.5
0.4–0.6	800	40	162.9
0.6–0.8	1000	45	230.9
0.8–01	1000	25	247.9

4.10 | Implementation of ANN-PSO MPPT on solar PV system

4.10.1 | Case 1

The ANN-PSO MPPT's adaptability and efficiency in harvesting solar energy under various environmental situations are shown in Figure 36. It extracts 50.8 W under conditions of 400 W/m^2 irradiance and 25°C, 104.5 W at 600 W/m^2 irradiance and 30°C temperature and achieves a competitive power output of 183.4 W at irradiance levels of 800 W/m^2 and temperatures reaching 40°C. While performing well in a variety of circumstances, it's important to keep in consideration that in high irradiance conditions, the ANN-PSO MPPT system outperforms, generating 221.1 W at 40°C and an impressive 247.2 W at 25°C, emphasizing its efficacy in specific temperature scenarios. These findings highlight the ANN-PSO MPPT system's dependability and adaptability for consistent power generation across a variety of weather conditions, while also recognizing the ANN-PSO system's skill in maximizing output under particular temperature conditions, emphasizing the significance of selecting an MPPT system that has been designed for a given application. Table 13 shows ANN-PSO outputs at specified irradiance and temperature.

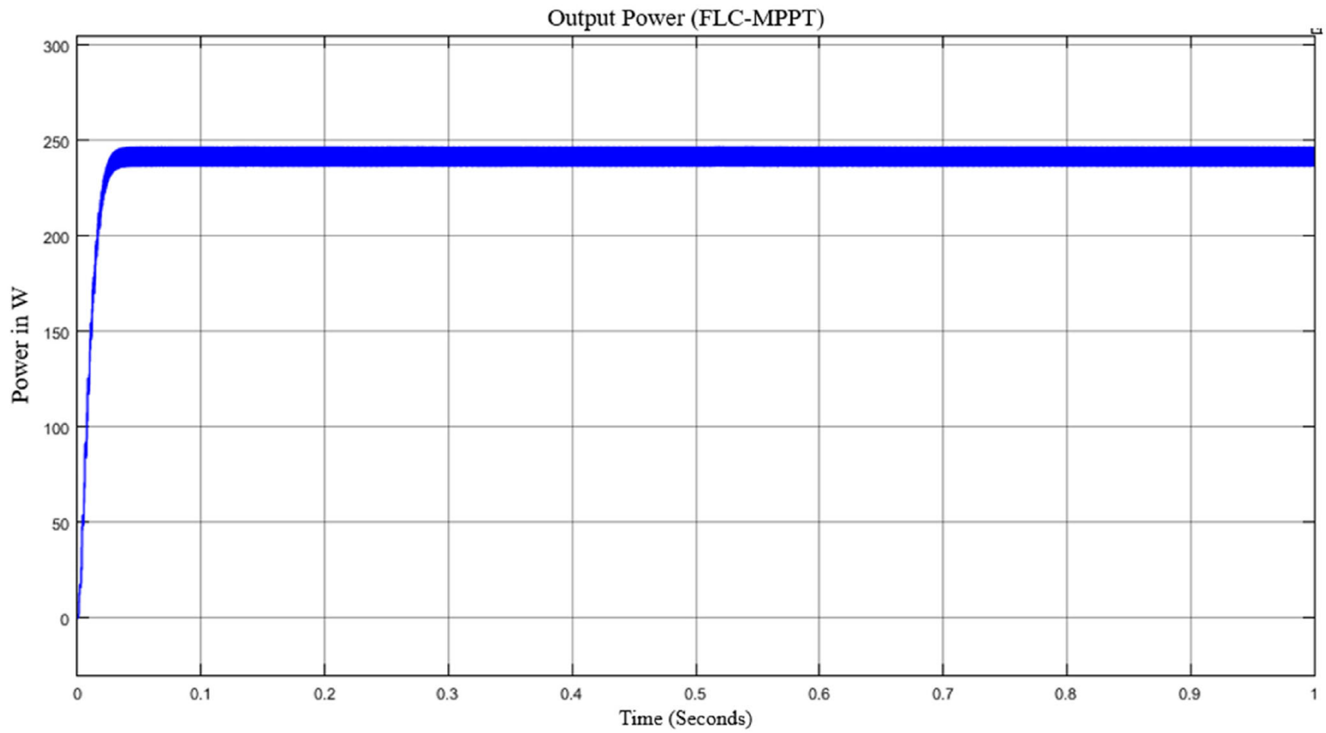

FIGURE 35 Fuzzy Logic Control maximum power point tracking (FLC MPPT) outputs at standard testing conditions.

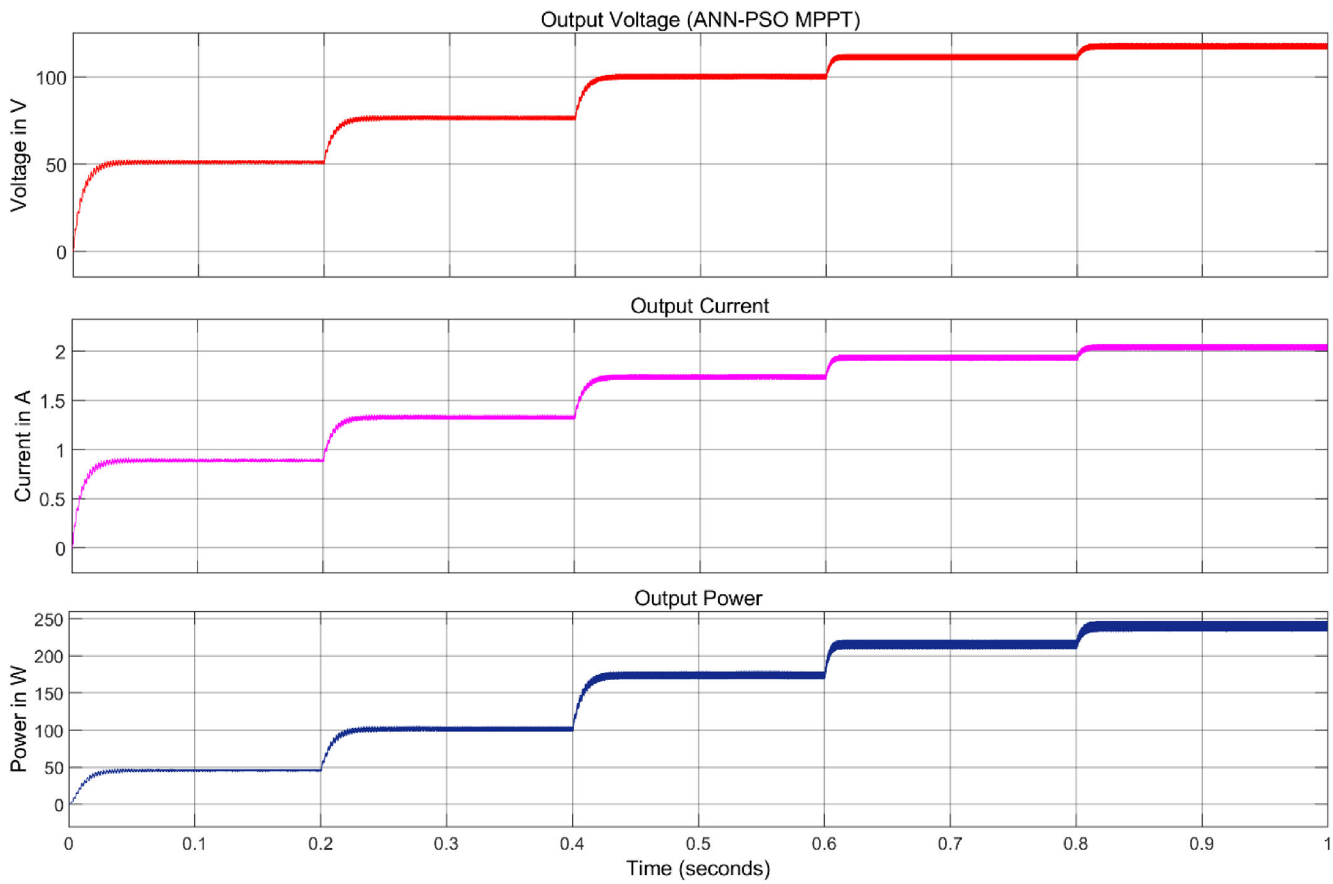

FIGURE 36 Maximum power point tracking (MPPT) output power after implementing Artificial Neural Network and Particle Swam Optimization (ANN-PSO) method.

TABLE 13 Shows Artificial Neural Network and Particle Swam Optimization (ANN-PSO) outputs at specified irradiance and temperature.

Time range (S)	Irradiance value (W/m^2)	Temperature	ANN-PSO MPPT output power
0.0–0.2	400	25	50.8
0.2–0.4	600	30	104.5
0.4–0.6	800	35	183.4
0.6–0.8	1000	40	221.1
0.8–01	1000	25	247.2

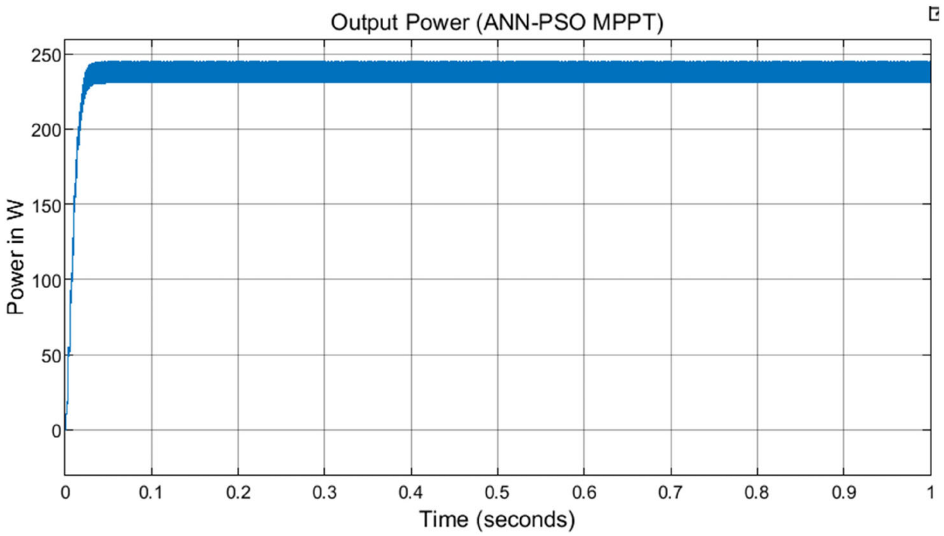

FIGURE 37 Artificial Neural Network and Particle Swam Optimization maximum power point tracking (ANN-PSO MPPT) outputs at standard testing conditions.

4.10.2 | Case 2

In Case 2, the ANN-PSO MPPT algorithm's proficiency in logic-based control enables it to swiftly track the MPP under standard testing conditions, characterized by 1000 W/m^2 irradiance and 25°C temperature. As depicted in Figure 37 the Fuzzy-Logic MPPT algorithm excels in MPP identification, accomplishing this task efficiently in a mere 0.30 s.

4.11 | Implementation of FLC-PSO MPPT on PV system

4.11.1 | Case 1

The advantages of both fuzzy logic and particle swarm optimization are combined in a hybrid strategy called FLC-PSO. FLC is a logical method for representing and analyzing uncertainty and inaccuracy, while PSO is a population-based technique for optimization that draws inspiration from the social behavior of fish and birds. FLC-PSO uses fuzzy logic to control the parameters of the PSO algorithm. Consequently, PSO can postpone the process of convergence to the local optimum solution and better adapt to the problem at hand. In order to investigate the combined performance of FLC-PSO controllers in PV applications, the FLC-PSO algorithm is applied as MPPT on solar PV systems under the same ECs. As depicted in Figure 38, the FLC-PSO-based MPPT system exhibits distinct power extraction performance. It extracts 44.5 W under 400 W/m^2 irradiance at 25°C temperature, 99.6 W under 600 W/m^2 irradiance and 30°C temperature and reaches a competitive power output of 172.0 W under circumstances of 800 W/m^2 irradiance and temperatures approaching 40°C. The FLC-PSO MPPT system excels in high irradiance conditions, generating 225.2 W at 40°C and an impressive 246.7 W at 25°C, emphasizing its effectiveness in particular temperature scenarios while performing well in a variety of situations. Table 14 shows the FLC-PSO outputs at specified irradiance and temperature.

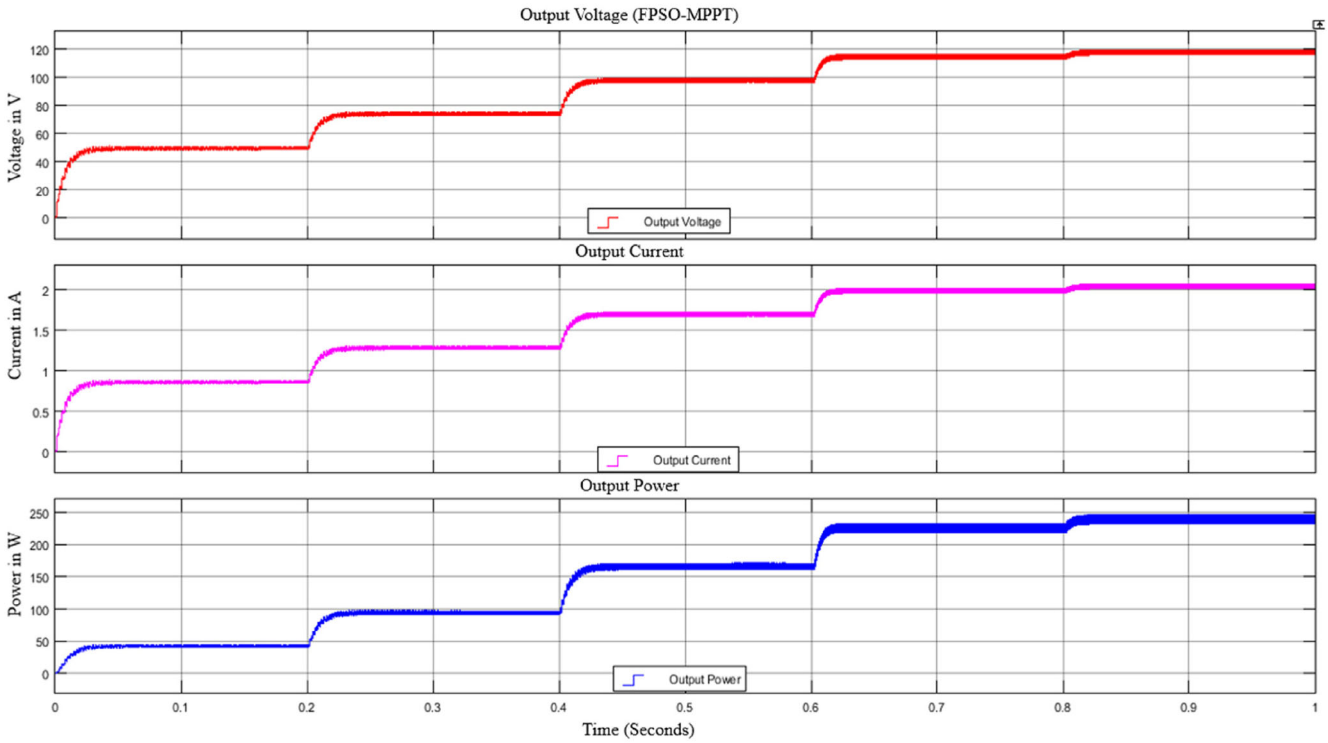

FIGURE 38 Maximum power point tracking (MPPT) output power after implementing Fuzzy Logic Control and Particle Swam Optimization (FLC-PSO) method.

TABLE 14 Shows Fuzzy Logic Control and Particle Swam Optimization (FLC-PSO) outputs at specified irradiance and temperatures.

Time range (S)	Irradiance value (W/m^2)	Temperature	FLC-PSO MPPT output power
0.0–0.2	400	25	44.5
0.2–0.4	600	30	99.6
0.4–0.6	800	35	172.0
0.6–0.8	1000	40	225.5
0.8–01	1000	25	246.7

4.11.2 | Case 2

In this instance, the FLC-PSO MPPT is evaluated under standard testing conditions with 1000 W/m^2 irradiance and a temperature of 25°C. Figure 39 illustrates how the FLC-PSO MPPT algorithm successfully locates the MPP in a relatively short amount of time of 0.030 s. In the second example, the MPPT method is able to efficiently locate the MPP faster than other conventional MPPTs due to the combined control and capabilities of fuzzy logic and particle swarm optimization approaches, respectively.

5 | COMPREHENSIVE DISCUSSION

Our study provides a comprehensive comparative analysis of these controllers, evaluating their performance under real ECs with fluctuating irradiance and temperature. The results offer critical insights and practical guidance for selecting the most effective MPPT controller optimized for specific ECs, ultimately enhancing the efficiency and reliability of solar power generation systems. However, the Global maximum partial (GMP) shading pattern is shown in Figure 40. The P–V curve consists of a uniform global peak in pattern 1, pattern 2 consists of multiple peaks with GMP in the rightmost, and a middle occurring GMP in pattern 3.

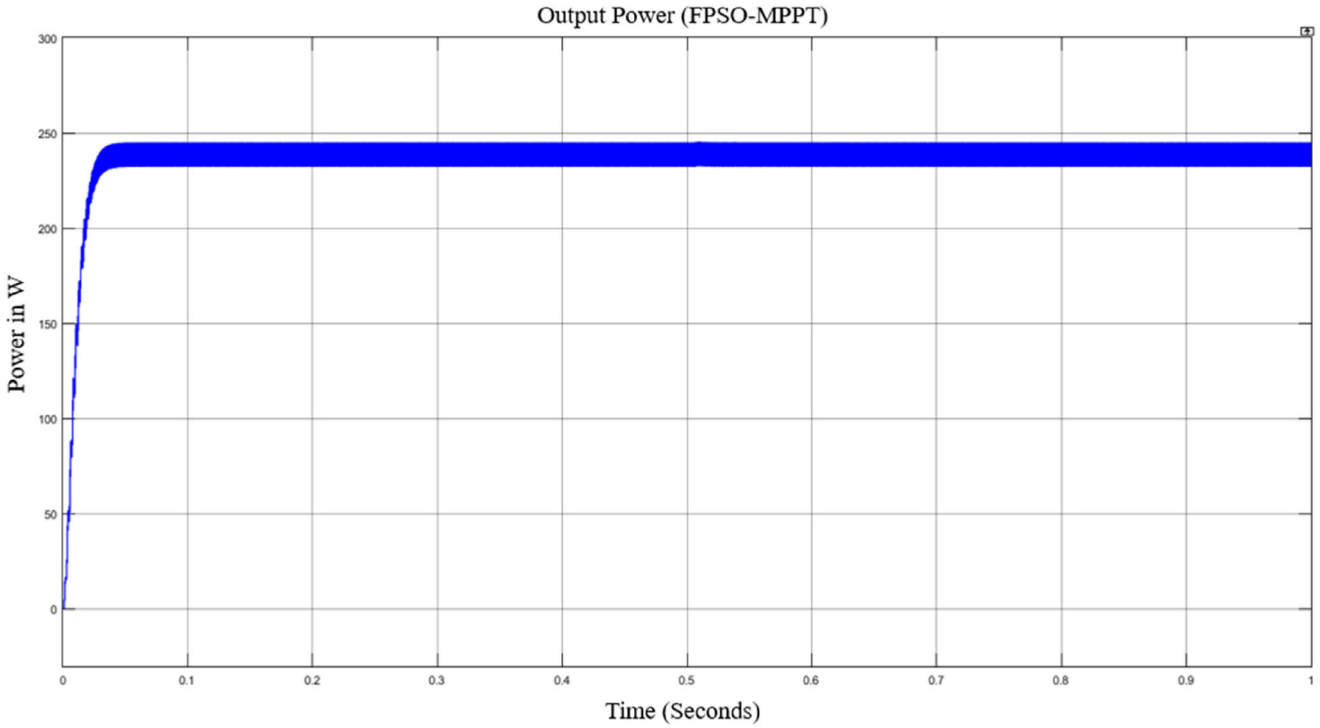

FIGURE 39 Fuzzy Logic Control and Particle Swam Optimization maximum power point tracking (FLC-PSO MPPT) outputs at standard testing conditions.

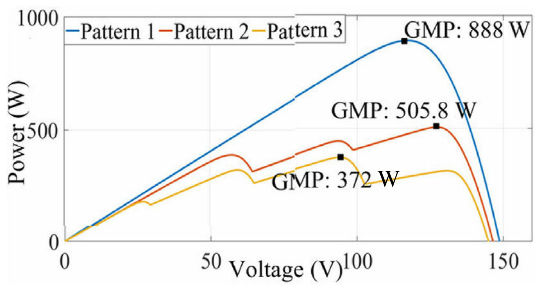

FIGURE 40 Global maximum partial shading.

The primary disadvantage of MPPT charge controllers lies in their higher cost and complexity compared to PWM charge controllers.[67] This is due to the need for additional components and circuitry to facilitate DC–DC conversion and power tracking. Additionally, MPPT controllers tend to produce increased heat and noise due to their frequent switching on and off at high frequencies, potentially impacting their longevity and dependability.[68] Moreover, MPPT charge controllers may not perform well in very hot or very cloudy conditions, where the voltage difference between the solar panels and the battery bank is too small or too large, resulting in low efficiency and high losses. If you decide to use an MPPT charge controller for your off-grid solar system, you need to consider some factors, such as the size, the features, and the quality of the device.[69] The size of the MPPT charge controller depends on the maximum power output of your solar panels and the maximum charging current of your battery bank. You can calculate the size by dividing the total wattage of your solar panels by the nominal voltage of your battery bank and multiplying by 1.25 to account for safety margin. The features of the MPPT charge controller include the display, the communication, the protection, and the programmability options, which can vary depending on the model and the brand. The quality of the MPPT charge controller depends on the design, the materials, the warranty, and the reputation of the manufacturer, which can affect the performance, the durability, and the safety of the device. Table 15 is presented to compare our results with the past/published research paper and the standard deviation of all MPPT techniques is given in Figure 41.

TABLE 15 Comparison of conventional and artificial intelligence based MPPT techniques with past literature.

Study year and reference	MPPT controller	Mathematical expression	Technical parameters[a]	Study purpose
2012[70]	FLC controller	Yes	Voltage	Utilizing a fuzzy logic approach, a two-tiered DC–DC boosting converter system was established to implement an MPPT controller. The primary stage functions to monitor and adjust to the MPP, whereas the secondary stage is responsible for supplying the requisite voltage to the DC bus for grid interconnection.
2023[71]	incremental conductance (INC) and perturb & observe (P&O)	Yes	Voltage and current	This article discusses a fresh adaptive control framework developed to elevate MPPT performance levels. Its primary focus is on simplifying system control complexities and efficiently addressing uncertainties and disruptions in both the environment and PV systems.
2021[47]	ANFIS controller	Yes	Voltage and current	This study introduces a framework for designing and simulating an MPPT controller using an adaptive neuro-fuzzy inference system (ANFIS). The design encompasses a photovoltaic (PV) module, an ANFIS reference model, a DC–DC boost converter, and a fuzzy logic (FL) power controller. The performance evaluation of the ANFIS-based MPPT controller is carried out via simulations conducted in MATLAB SIMULINK.
2014[72]	FLC controller	Yes	Voltage and current	This paper presents a novel MPPT controller employing fuzzy logic, and its effectiveness is verified through experimental testing on DC–DC and single-phase DC–AC converters.
2022[73]	P&O and FL	Yes	Voltage	This work introduces an innovative AI-driven adaptive P&O algorithm for real-time hybrid MPPT control in solar systems. The primary aim is to enhance the computational efficiency of controller design while addressing limitations associated with traditional MPPT and fuzzy logic (FL) controllers.
2020[74]	Distributed PSO	Yes	Voltage and current	The article discusses the utilization of a distributed MPPT method relying on PSO to maximize power extraction from solar PV installations. Based on both simulation and experimental findings, the authors assert that the suggested MPPT method demonstrates superior effectiveness compared to a neural network-derived MPPT approach.
2014[75]	FLC controller	Yes	Voltage and current	Employing genetic algorithms, the membership functions of a fuzzy logic-based MPPT controller were fine-tuned. This optimization process was then deployed on an FPGA chip and evaluated against various intelligent MPPT algorithms.

(Continues)

TABLE 15 (Continued)

Study year and reference	MPPT controller	Mathematical expression	Technical parameters[a]	Study purpose
2019[76]	PSO-ANFIS	YES	Voltage and temperature	Within this study, the incorporation of ANFIS into the PSO MPPT method is employed to optimize power transfer from the source to the load. Utilizing PSO, adjustments are made to the membership functions and consequent variables of ANFIS. Additionally, the ANFIS-PSO approach is contrasted with the firefly algorithm, revealing superior tracking speed, accuracy, and efficiency in the proposed algorithm.
2021[77]	P&O controller	Yes	Irradiance and temperature	This study introduced a smart approach to optimize maximum power point tracking via the P & O algorithm. The setup involves a photovoltaic (PV) module linked with a DC to DC boost converter. Testing the PV system under varying solar irradiation and temperature conditions revealed that the maximum power tracker effectively and accurately followed the maximum power output across all scenarios.
2012[78]	ANN controller	Yes	Irradiance and temperature	An MPPT controller based on artificial neural networks (ANNs) was suggested. The ANN underwent training using a dataset sourced from experimental measurements. Following this, genetic algorithms were utilized to ascertain the most suitable architecture for the ANN.
2020[79]	Cuckoo search with a proportional controller	Yes	Irradiance and temperature	This article provides an evaluation of the MPPT technique based on cuckoo search and compares it with neural network and fuzzy logic approaches. It discusses how the cuckoo search algorithm is utilized to adjust the parameters of the proportional controller. Additionally, it outlines the pros and cons of employing the cuckoo search-based MPPT technique.
2019[80]	Grey Wolf FLC	Yes	Voltage and current	The soft computing MPPT methods exhibit two limitations: significant steady-state oscillation around the MPP and inability to adapt to changes in the GMPP. This article presents a solution to these issues through the introduction of a grey wolf-FLC algorithm, which aims to track the global MPP.
2014[81]	ANN controller	Yes	Voltage and temperature	A budget-friendly MPPT algorithm and Irradiance sensor were suggested. The database creation utilized a mathematical model of the PV cell. The trained neural network furnishes both the MPP voltage and the irradiance value.
2018[82]	FLC and PSO	Yes	Voltage and current	Within this article, two hybrid MPPT strategies are analyzed and contrasted concerning their efficacy, tracking velocity, and convergence rate. The study evaluates how each hybrid MPPT approach performs under conditions of steady irradiation and rapid fluctuations.

(Continues)

TABLE 15 (Continued)

Study year and reference	MPPT controller	Mathematical expression	Technical parameters[a]	Study purpose
2019[83]	PSO, ant colony optimization, and differential	Yes	Voltage irradiance	Within this article, a comparative study is undertaken to assess the effectiveness of PSO, ant colony optimization, and differential evolution as MPPT strategies when juxtaposed with conventional methods. Moreover, the article delves into the merits and drawbacks associated with each MPPT methodology.
2015[84]	PSO based controller	Yes	Voltage and current	A customized MPPT algorithm utilizing a modified PSO technique was proposed. In contrast to the standard PSO approach, this adaptation employs parameters defined by linearly shifting functions based on the sampling time, aiming to expedite convergence.
2022[85]	INC, P&O, FLC, Adaptive FLC, and ANFIS	Yes	Voltage and current	The suggested MPPT method evidently enhances the ability to track the maximum power point (MPP) while concurrently diminishing stable-state fluctuations. Moreover, across five distinct parameter adjustments, the time required to detect MPP stands at 1.5 ms, a notably swifter pace compared to alternative cutting-edge methods. Additionally, the proposed approach boasts a tracking effectiveness of 99.75% and an overall system efficiency rating of 96%.
2023[68]	ANFIS and FLC	Yes	Irradiance and temperature	The findings of this study indicate that ANFIS outperformed both ANN and FLC, achieving an accuracy of 99.50%, while ANN and FLC attained accuracies of 97.04% and 98.50%, respectively. This establishes ANFIS as the most effective MPPT controller. Furthermore, this study also evaluates the strengths and weaknesses of all three MPPT algorithms.
2015[86]	PSO and P&O controller	Yes	Voltage and current	The proposed approach involves combining PSO and P&O methods for MPPT. Initially, PSO is utilized to pinpoint the MPP, and subsequently, the P&O technique is employed for MPP tracking.
Our Proposed study	INC, P&O, INC-PSO, P&O-PSO, Fuzzy-PSO, ANN, ANFIS, ANN-PSO, PSO, and FLC	No	Time response, duty cycle, current, voltage, power, temperature, irradiance and partial shedding	The findings from this research reveal that traditional methods such as INC, P&O, INC-PSO, P&O-PSO yielded accuracies of 94.3, 97.6, 98.4, and 99.6, respectively. In contrast, artificial intelligence (AI) approaches including Fuzzy-PSO, ANN, ANFIS, ANN-PSO, PSO, and FLC attained accuracies of 98.6, 98, 98.6, 98.8, 98.2, and 98, respectively. These results underscore the superior performance of intelligent techniques over conventional ones.

[a]Technical Parameters = PV array dependency, partial shading, and sensing variables (voltage/current/power/irradiance/temperature).

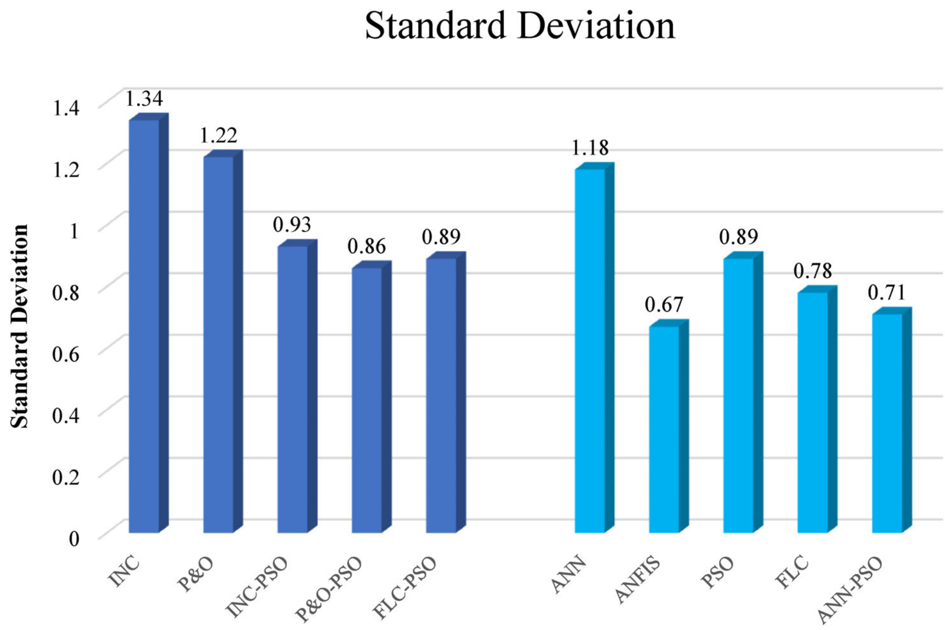

FIGURE 41 Standard deviation of all maximum power point tracking (MPPT) techniques at maximum power point (MPP).

To further quantify the performance of the MPPT controllers evaluated in this study, the standard deviation of power tracked after settling at the MPP is analyzed and compared. This metric provides analysis into the stability and consistency of each controller in maintaining optimal power output under fluctuating ECs. As shown in Figure 41, the standard deviation values for each MPPT controller illustrate the level of oscillations in power output during steady-state operation. Lower standard deviation values indicate more stable performance, with less variation around the MPP, whereas higher values suggest greater fluctuations.

- INC exhibits a relatively high standard deviation of 1.34, indicating moderate oscillations around the MPP. This suggests that while INC can effectively track the MPP, it struggles to maintain stability under varying conditions.
- P&O shows a standard deviation of 1.22, slightly lower than INC, yet still indicating significant oscillations. This aligns with the known characteristic of P&O where it tends to oscillate around the MPP, particularly in steady-state conditions.
- INC-PSO, with a standard deviation of 0.93, demonstrates improved stability compared to INC alone. The integration of PSO helps in reducing the oscillations, providing a more stable power output.
- P&O-PSO has an even lower standard deviation of 0.86, reflecting enhanced stability and reduced oscillations due to the optimization capabilities of PSO combined with the incremental adjustments of P&O.
- FLC-PSO exhibits a standard deviation of 0.89, indicating that the fuzzy logic controller combined with PSO results in a stable power output with minimal oscillations, showcasing the effectiveness of this hybrid approach.
- ANN shows a standard deviation of 1.18, which is lower than conventional method INC. This indicates that while ANN provides rapid convergence, its stability in steady-state can be improved.
- ANFIS demonstrates the lowest standard deviation of 0.67 among all controllers, indicating exceptional stability and minimal oscillations. This highlights ANFIS's superior performance in maintaining a steady power output.
- PSO has a standard deviation of 0.89, showing good stability and reduced oscillations, similar to other PSO-based hybrid methods.
- FLC exhibits a standard deviation of 0.78, indicating a stable performance with low oscillations, making it a reliable choice for MPPT.
- ANN-PSO, with a standard deviation of 0.71, combines the strengths of ANN and PSO to achieve high stability and minimal oscillations, making it reliable controller. These results underscore the enhanced stability and reliability of conventional and intelligent MPPT methods. The standard deviation values provide a quantitative measure of the oscillations in power tracking, highlighting the superior performance of intelligent MPPT methods like ANFIS.

To provide a comprehensive analysis, we examined the convergence characteristics of various MPPT algorithms.[87,88] These characteristics are shown below indicate the speed and reliability with which each algorithm can reach and maintain the MPP under varying ECs.

- The INC algorithm adjusts the operating point incrementally, resulting in a moderate convergence speed. The algorithm is highly reliable under steady-state conditions, effectively tracking the MPP once it is near. However, INC can struggle with rapidly changing conditions, such as varying irradiance levels. Additionally, INC can exhibit moderate oscillations around the MPP, especially under variable irradiance or partial shading conditions, which can affect the overall stability of the power output.
- The P&O algorithm also makes incremental adjustments to find the MPP, leading to a moderate convergence speed similar to INC. While P&O is effective under stable conditions, it can lose track of the MPP under dynamic conditions like rapidly changing sunlight, reducing its reliability. Moreover, P&O tends to show higher oscillations around the MPP compared to INC, particularly under steady-state conditions, which can lead to inefficiencies in the power extraction process.
- The hybrid INC-PSO algorithm leverages the strengths of both INC and PSO, leading to faster convergence to the MPP. The combination allows for incremental adjustments with the optimization capability of PSO, making it highly reliable under varying conditions. This hybrid method results in minimal oscillations, as the PSO component helps to refine the final MPP tracking, reducing fluctuations and improving overall stability.
- The P&O-PSO hybrid algorithm integrates P&O with PSO, resulting in rapid convergence to the MPP. The method is highly reliable under both steady and dynamic conditions due to the optimization capabilities of PSO. Compared to standalone P&O, this hybrid approach reduces oscillations significantly, with PSO stabilizing the final operating point and enhancing the overall performance.
- The ANN algorithm quickly predicts the MPP based on trained data, leading to very fast convergence. ANN is very reliable under various conditions, provided the network is well-trained on diverse datasets. The algorithm offers minimal oscillations, as ANN provides stable MPP tracking with very low fluctuations once the network is properly trained, ensuring efficient and stable power output.
- ANFIS combines the strengths of fuzzy logic and neural networks, allowing for quick and adaptive MPP tracking. This results in very fast convergence and very high reliability under changing conditions due to its adaptive nature. ANFIS exhibits minimal oscillations, as its adaptive capabilities result in very stable MPP tracking with negligible fluctuations, ensuring consistent power extraction.
- The PSO algorithm quickly converges to the MPP by optimizing a swarm of potential solutions. PSO demonstrates high reliability, being robust and effective under varying conditions. The algorithm tends to stabilize at the MPP with low oscillations, ensuring efficient and consistent power output with minimal fluctuations.
- FLC can quickly adapt to changes, resulting in moderate to fast convergence speed. FLC is highly reliable under a wide range of conditions due to its rule-based approach. The algorithm provides minimal oscillations, as FLC ensures stable MPP tracking with low fluctuations once the rules are well-defined, maintaining efficient power extraction.
- The hybrid ANN-PSO algorithm combines ANN's predictive capability with PSO's optimization, leading to very fast convergence. This hybrid method is extremely reliable under various conditions, offering very stable MPP tracking with negligible oscillations. ANN-PSO ensures consistent and efficient power extraction with minimal fluctuations.
- The hybrid FLC-PSO algorithm leverages FLC's adaptability and PSO's optimization for quick convergence. FLC-PSO is highly reliable under different conditions, benefiting from both methods' strengths. The hybrid method ensures minimal oscillations, providing stable MPP tracking with very low fluctuations, enhancing the overall efficiency and reliability of the power extraction process.

Based on the results obtained from our comprehensive evaluation of ten different MPPT controllers, we can now delve into a comparative analysis of their complexities. By examining both the design intricacies and the performance outcomes of each controller, we provide insights into their suitability for practical implementation in solar PV systems. This comparison not only considers the computational demands and implementation efforts but also assesses the overall design complexities inherent to each MPPT technique. The design complexities of conventional MPPT techniques vary significantly.

TABLE 16 Comparison of complexity of all the evaluated conventional and artificial intelligence based maximum power point tracking (MPPT) techniques.

MPPT technique	Design complexity	Key design elements
INC	Moderate	Voltage/current sensors, differentiation logic, decision algorithm
P&O	Low	Basic sensing, simple decision loop
INC-PSO	High	Complex control logic, iterative optimization, integration framework
FLC-PSO	High	Fuzzy logic system, PSO optimization, integration and tuning mechanisms
P&O-PSO	Moderate to high	P&O logic, PSO optimization loop, integration framework
ANN	High	Network architecture, training algorithm, data preprocessing
ANFIS	Very high	Neuro-fuzzy architecture, training/adaptation algorithms, rule base
FLC	Moderate	Fuzzy rule base, membership function design, inference engine
PSO	High	Optimization routine, parameter tuning, convergence criteria
ANN-PSO	Very high	ANN architecture, PSO optimization, hybrid integration framework

- INC involves moderate complexity, as it requires precise calculation and differentiation of voltage and current, but follows a straight forward logic structure. Its key design elements include voltage and current sensors, differentiation logic, and a decision-making algorithm. P&O has low design complexity, relying on a simple perturbation of the operating point and observation of the resulting power change, with basic sensing of voltage and current and a simple decision loop. Hybrid methods such as INC-PSO and P&O-PSO add significant complexity. INC-PSO combines the complexities of INC with the iterative nature of PSO, requiring sophisticated control logic and integration. P&O-PSO, while simpler than INC-PSO, still requires careful integration of P&O logic with PSO, involving medium to high complexity in design. Finally, FLC-PSO presents high complexity due to the need for defining fuzzy rules and membership functions along with the PSO algorithm, requiring an intricate integration and tuning mechanism.
- The AI-based MPPT techniques generally exhibit higher design complexities compared to conventional methods. ANN involves high complexity, necessitating the definition of network architecture, selection of training data, and ensuring robust training and validation processes. Key design elements include network architecture, training algorithms, and data preprocessing. ANFIS exhibits very high complexity, combining ANN with fuzzy inference systems, requiring intricate design and fine-tuning of both components to work seamlessly. FLC involves moderate complexity, focusing on defining fuzzy sets, membership functions, and rules, which is relatively straightforward compared to hybrid systems. PSO also has high complexity, involving iterative optimization processes and careful tuning of parameters for optimal performance. The hybrid ANN-PSO presents very high complexity, combining the design intricacies of both ANN and PSO, necessitating careful coordination and integration of ANN architecture with PSO optimization routines.

This comparative analysis of complexities provides a deeper understanding of the trade-offs between design intricacies and performance efficiencies inherent in each MPPT controller. Such insights are crucial for engineers and researchers[89-94] seeking to optimize solar PV systems with controllers that best align with specific operational requirements and ECs. Table 16 summarizes comparison of complexity of all the models.

6 | CONCLUSION AND FUTURE WORK

In the pursuit of renewable energy sources and addressing climate change concerns, solar energy emerges as a prominent global solution. The optimization of solar energy utilization demands selection of suitable and optimum MPPT techniques. This study presents a comprehensive analysis of both conventional and AI-based MPPT techniques for solar power generation. Ten distinct controllers, encompassing traditional methods such as INC, P&O, INC-PSO, P&O-PSO, and AI-driven approaches such as ANN, FLC, ANFIS, PSO, ANN-PSO, and FLC-PSO were rigorously evaluated. Our findings reveal that while conventional techniques exhibit effectiveness under certain conditions, they demonstrate limitations in adapting to variable environmental parameters. Conversely, AI-based intelligent techniques showcase superior adaptability, particularly in scenarios with fluctuating ECs. These controllers were simulated under fluctuating irradiation and temperature using MATLAB Simulink. The primary objectives of this study were to design and implement ten MPPT controllers suitable for real-world ECs, and secondly, to conduct a comparative analysis of their effectiveness in solar energy harvesting. Through detailed evaluation and analysis, we successfully achieved these objectives. Our research aimed to provide valuable insights for decision-makers, solar power consumers, and researchers by bridging the gap of comprehensive comparative analysis between conventional and AI-based MPPT algorithms. This work contributes to the advancement of solar energy technology, thus supporting the global transition towards sustainable energy solutions and facilitating climate change mitigation efforts. Based on the results, the following prospective suggestions are made:

- Grid integration for standalone systems: Consider integrating standalone PV systems with the main power grid, facilitated by bi-directional inverters capable of importing and exporting power. This connection would enable a comprehensive assessment of system behavior in conjunction with MPPT strategies under real-world conditions, shedding light on their practical performance.
- Optimization of MPPT techniques: Improve the efficiency of traditional MPPT algorithms, such as INC, P&O, ANNs, and FLC, by using cutting-edge optimization approaches. It is possible to investigate methods like Ant Colony Optimization (ACO) and Genetic Algorithms (GA) to improve the tracking resilience, efficiency, and speed of MPPT algorithms.
- Integration with energy storage (ES) systems: Look at how standalone PV systems can be integrated with energy storage devices, such as battery systems. With this combination, extra energy from high solar irradiance periods might be captured and stored for use during later low solar radiation periods. This kind of integration increases the system's resilience and dependability, increasing its ability to adjust to changes in the supply of solar energy.
- Exploration of machine learning (ML) ensembles: Delve into the realm of machine learning ensemble techniques, which harness the power of multiple ML algorithms to deliver more precise and resilient predictions. The potential of ML ensemble techniques lies in their ability to foster the development of highly efficient MPPT techniques, further advancing the field.

These recommendations offer a roadmap for prospective research endeavors, aimed at advancing the efficacy and versatility of MPPT strategies within solar PV systems. As the solar energy landscape evolves, these suggestions serve as guiding principles for harnessing the full potential of RETs.

AUTHOR CONTRIBUTIONS

Malhar Khan: Conceptualization; investigation; writing – review and editing; writing – original draft; methodology; software. **Muhammad Amir Raza:** Writing – original draft; writing – review and editing; supervision; project administration; conceptualization; methodology; software. **Muhammad Faheem:** Conceptualization; investigation; software; validation; formal analysis. **Shahjahan Alias Sarang:** Investigation; validation; formal analysis; resources; visualization; writing – original draft. **Madeeha Panhwar:** Writing – original draft; conceptualization; investigation; validation; visualization; formal analysis; data curation. **Touqeer Ahmed Jumani:** Data curation; resources; software; validation; visualization; investigation.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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