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A Comprehensive Analysis Of Mppt Techniques For Photovoltaic Systems Under Partial Shading Conditions

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Abstract

Maximizing power extraction from photovoltaic (PV) systems is crucial for improving efficiency, particularly under partial shading conditions (PSCs). The high cost and relatively low conversion efficiency of PV panels necessitate effective maximum power point tracking (MPPT) techniques to ensure operation at the maximum power point (MPP). This paper presents a comprehensive review of 11 MPPT methods reported in the literature, alongside recent advancements in hardware design methodologies. The MPPT techniques are classified into three categories—Classical, Intelligent, and Optimization-based—according to their underlying tracking algorithms. Under uniform irradiance, classical methods are generally preferred due to the presence of a single peak in the power–voltage (P–V) curve. However, under PSCs, the P–V curve exhibits multiple peaks, including one global MPP (GMPP) and several local MPPs (LMPPs). As a result, intelligent and optimization-based techniques have emerged to accurately identify the GMPP among all local peaks. Each MPPT technique is critically analyzed in terms of sensor requirements, hardware implementation complexity, performance under PSCs, cost, tracking speed, and tracking efficiency. This study consolidates recent advancements and highlights potential research directions to support further development in the field.

Key words: MPPT, Partial shading conditions, fuzzy logic, Incremental conductance MPPT, uniform radiation

1. Introduction

The eventual depletion of fossil fuel reserves, coupled with their adverse environmental impacts, underscores the urgent need for alternative energy sources. Renewable energy systems present several advantages over conventional energy sources, including minimal environmental degradation and the absence of fuel costs. These systems harness naturally occurring resources such as sunlight, wind, tides, and biomass. The advancement and deployment of renewable energy technologies have become critical to meeting the decentralized energy demands of various regions. Among these alternatives, solar photovoltaic (PV) technology has emerged as a promising option due to its ubiquitous availability, zero fuel costs, minimal environmental impact, and low maintenance requirements [1].

Recognizing these advantages, The development of renewable energy sources and the increase in the share of solar energy utilization are envisaged in the Concept for the Provision of Electric Power in the Republic of Uzbekistan for 2020–2030 [2]. The Government of Uzbekistan plans to increase the share of renewable energy in the country’s energy balance to 54% and commission 24,000 megawatts of "green" capacity by 2030.

In the same year, it is planned to generate 67.5 billion kWh of electricity in Uzbekistan, and by 2030, this figure is expected to reach 120 billion kWh. The construction of solar photovoltaic power stations in Uzbekistan is planned in the regions of Tashkent, Samarkand, Navoi, Jizzakh, Fergana, Surkhandarya, and Kashkadarya. Uzbekistan's energy sector is highly dependent on natural gas, which accounts for 82% of electricity production. By 2030, Uzbekistan plans to increase the share of solar energy in the country’s overall energy balance to 6%. By 2025, it is planned to increase the share of renewable energy in the total energy consumption to 19.7%, including an increase in the share of solar energy to 2.3% [2].

Currently, six “green” power plants with a total capacity of 2.4 GW have been commissioned in Uzbekistan, and work is underway on projects to construct 22 solar and wind power plants with a capacity of 9 GW in the coming years. Overall, by 2030, it is planned to increase the capacity of “green” energy sources to 27 GW. This will allow for annual savings of 25 billion cubic meters of natural gas and a reduction of harmful emissions into the atmosphere by 34 million tons [3].

However, despite the considerable advantages of solar energy, technical limitations hinder the complete extraction of solar power potential. Addressing these limitations is crucial for enhancing solar energy utilization and consequently reducing carbon emissions. Hybrid solar–wind standalone systems have also been developed to ensure continuous power supply for specific applications. Kong et al. [4] proposed a novel control strategy—hierarchical distributed model predictive control—for managing standalone wind–solar hybrid systems effectively.

The efficiency of PV modules is a critical factor influencing maximum power extraction. Crystalline silicon modules, one of the most widely used PV cell types, typically exhibit efficiencies ranging from 14% to 16%. Research has demonstrated that non-standard, high-quality designs can achieve efficiencies between 17% and 21%. Chen et al. [5] reported that cadmium telluride and copper gallium indium diselenide modules are projected to reach average efficiencies of 17.9% and 16.4%, respectively. Furthermore, commercial module efficiencies exceeding 21.8% are anticipated with the adoption of n-type silicon interdigitated back-contact technology.

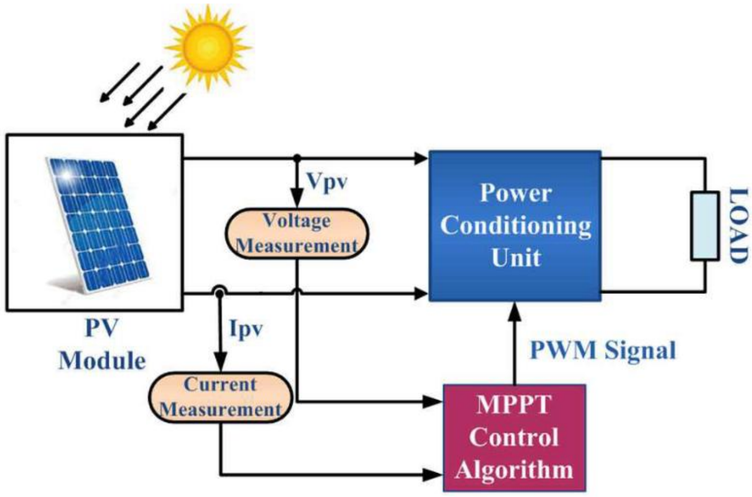

Fig. 1 MPPT Controller, Solar PV block diagram.

The amount of solar energy harnessed by photovoltaic (PV) arrays or modules is often limited due to the inherently dynamic nature of solar irradiance. To enhance power extraction, Koutroulis et al. [6] proposed real-time modification of two key control parameters: the duty cycle (D) and the switching frequency of the converter. Both parameters must be adjusted to optimize power transfer from the PV module. Given the typically low power output of PV panels, a DC–DC converter is employed to boost the voltage to a usable level. This converter utilizes the PV energy as its input and delivers regulated output power to an external load or energy storage system. In addition to voltage amplification, the converter transforms an uncontrolled DC source into a regulated one. Das et al. [7] introduced a novel high-gain converter designed for a three-phase PV standalone system, which effectively mitigates the effects of partial shading and parasitic capacitance on the PV source.

A schematic diagram of a PV system equipped with a maximum power point tracking (MPPT) controller is shown in Fig. 1. The system architecture comprises a solar PV array, a power converter, an MPPT control algorithm block, and a load. Under uniform irradiance conditions, a single maximum power point (MPP) typically appears on the power–voltage (P–V) curve of a solar array, representing the point at which the PV module delivers its maximum output power. However, under partial shading conditions (PSCs), the P–V curve exhibits multiple local MPPs (LMPPs). To mitigate hot-spot formation in PV modules under such conditions, bypass diodes are commonly employed. While these diodes reduce hot-spot risks, they also introduce multiple LMPPs, posing a challenge for MPPT controllers that must reliably track the global MPP (GMPP) amidst these local peaks.

Dhimish et al. [8] proposed a novel hot-spot mitigation technique involving MOSFET-connected panels, with hot-spot observation facilitated by a forward-looking infrared i5 thermal camera. The power losses resulting from diode-induced hot-spot effects are significant and warrant consideration. The presence of multiple LMPPs complicates GMPP identification, making it difficult for conventional MPPT techniques to operate effectively. Consequently, advanced MPPT algorithms have been developed to maximize energy extraction from PV systems [9].

To address these challenges, especially under PSCs, researchers have proposed a variety of strategies and techniques. Ghasemi et al. [10] introduced a two-step GMPP tracking algorithm that outperforms the particle swarm optimization (PSO) algorithm in PSC scenarios. Huang et al. [11] developed a methodology that predicts the MPP at an accelerated rate, leveraging a natural cubic spline-based prediction model incorporated within an iterative search process. Coelho et al. [12] proposed a temperature-based MPPT sensor with a sophisticated design, capitalizing on the relationship between module voltage and the PV panel's surface temperature.

Selecting an appropriate MPPT technique for a specific application remains a critical consideration in the PV system design process. Reference [13] has identified and distinguished several key parameters associated with maximum power point (MPP) tracking in the existing literature. However, the aforementioned review articles generally lack comprehensive discussions on the real-time implementation procedures of these MPPT techniques. Consequently, this paper aims to bridge that gap by presenting detailed hardware implementations of various MPPT methods, as demonstrated by different authors across multiple platforms, along with their corresponding tracking speeds and efficiencies. In addition, this review provides a systematic overview of the key parameters of each technique, their operational flowcharts, and concise explanations of their algorithmic implementation.

This study further endeavor to evaluate the performance of each MPPT technique based on its classification. Special emphasis is placed on comparative analysis of critical parameters, such as control strategies employed, microcontrollers utilized, and the sensors integrated into each application. The principal objective is to offer a comprehensive overview of contemporary technological advancements in MPPT techniques.

The remainder of the paper is organized as follows: Section 2 discusses the significance of tracking methods in PV systems. Section 3 presents a classification of MPPT approaches for PV systems. Section 4 reviews MPPT techniques based on classical methods and provides comparative analysis. Sections 5 and 6 describe various intelligent and optimization-based MPPT methods, respectively, along with comparative assessments of their parameters. Finally, Section 7 concludes the paper and outlines directions for future research.

2. Significance of Tracking Methods in Photovoltaic (PV) Systems

One of the most challenging and critical tasks for maximum power point tracking (MPPT) controllers is accurately locating the maximum power point (MPP) under partial shading conditions (PSCs). Partial shading arises within a photovoltaic (PV) array due to uneven illumination across the solar panels, typically caused by transient obstructions such as passing clouds, bird droppings, or shadows cast by surrounding structures. The size of the PV array is primarily determined by the power requirements of the specific application. Under uniform irradiance, identical solar insolation uniformly strikes all panels, leading to consistent output current generation across the entire array. In contrast, during PSCs, shading of even a single module reduces the current generation, resulting in substantial power losses.

The operating point of a PV system is strongly influenced by environmental parameters such as the angle of solar incidence, ambient temperature, and shading patterns, all of which fluctuate dynamically and cause continuous variation in the MPP [14]. When multiple solar cells are interconnected in series to form a module, non-uniform insolation on a single cell can induce thermal stresses that may rupture the lamination if left unaddressed. To mitigate such detrimental effects, bypass diodes are connected in anti-parallel with the cells. These diodes prevent significant voltage differentials in the reverse-current direction, thus safeguarding the cells. Typically, one anti-parallel diode suffices for every 15 to 20 cells in a series configuration. These bypass diodes facilitate current flow through the PV module even under shaded conditions and during instances of low voltage and power.

In the present study, a KYOCERA KC200GT high-efficiency multi-crystalline PV module is employed. The system configuration consists of four modules arranged in three rows, with bypass diodes integrated into each row and an additional blocking diode, as illustrated in Fig. 2. The bypass diodes (D_1) enable current diversion around shaded panels, thereby mitigating hot-spot effects—localized heating that can damage the panel. Simultaneously, the blocking diode (D_2) prevents reverse surges from penetrating the system.

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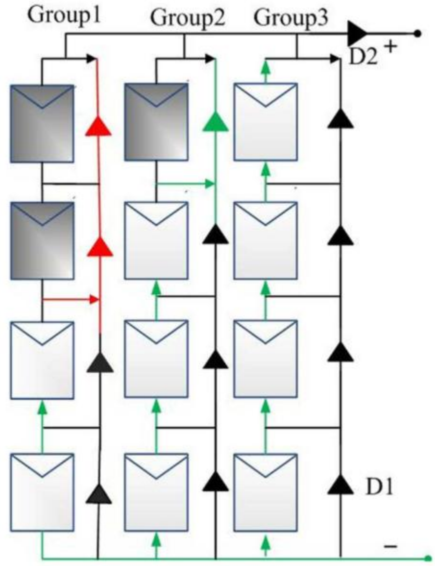
Simulation results reveal the emergence of multiple peaks, i.e., various local MPPs (LMPPs), due to shading effects. Among these, one peak corresponds to the global maximum power point (GMPP), while the remaining are LMPPs distributed across the array [15]. The corresponding I–V and P–V characteristics under shaded conditions are presented in Figs. 3 and 4, respectively. For a detailed numerical analysis of the MPP, Batzelis et al.[16] characterized MPP changes under both uniform and non-uniform irradiance conditions, explicitly accounting for key parameters such as insolation and temperature. At the MPP, the derivative of the output power (P) with respect to output voltage (V) equals zero. As shown in Fig. 5, both I_{mpp} and V_{mpp}, are identified, and the MPP is tracked along the load line through an appropriate MPPT technique. The condition for MPP under uniform irradiance is mathematically expressed as Equation (1).

$$\frac{dP}{dV}|_{mpp} = 0 \Leftrightarrow \frac{dI}{dV}|_{mpp} = -\frac{I_{mpp}}{V_{mpp}} \qquad (1)$$

It is well established that, for any given level of solar insolation and ambient temperature, there exists a unique operating point—designated as the maximum power point (MPP)—on both the current–voltage (I–V) and power–voltage (P–V) characteristics of a photovoltaic (PV) array. Since the MPP is inherently dependent on environmental parameters that are highly dynamic, the position of the MPP continuously shifts over time. Consequently, MPPT controllers are designed to ensure continuous tracking of the MPP regardless of fluctuations in irradiance, temperature, or other influencing factors, thereby constituting an indispensable component of modern PV systems.



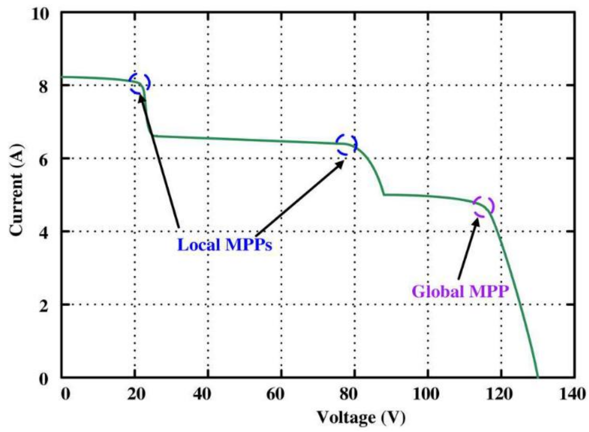
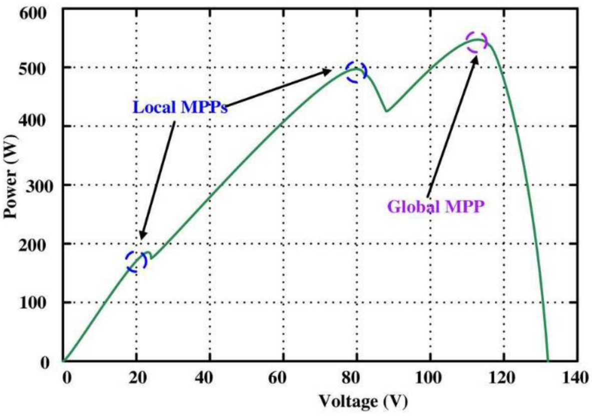


Fig. 2 4*3 solar PV configuration with shaded panels Fig. 3 Characteristic I–V curve of the PV configuration



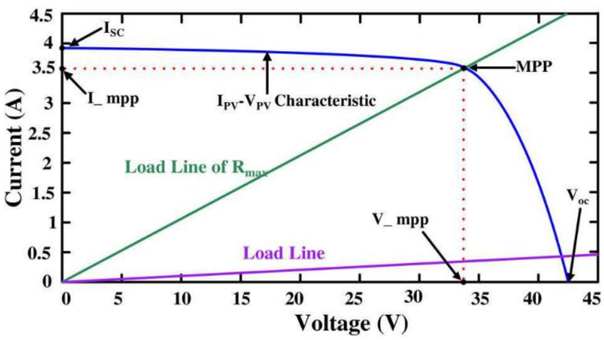


Fig. 4 Characteristic P–V curve of the PV configuration Fig. 5 I–V load curve depicting MPP

One of the most effective strategies for implementing an MPPT controller is through the integration of a power electronics (PE) interface between the PV source and the load. The inclusion of such a controller effectively adjusts the electrical impedance presented to the PV panel, thus enabling the panel to operate more consistently in proximity to its MPP. The controller achieves this by modifying the operating point of the load through variation of the duty cycle of a DC–DC converter, as illustrated in Fig. 5.

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3. MPPT Classification for PV Systems

Photovoltaic (PV) cells and modules generate varying amounts of power depending on environmental factors such as wind velocity, shading, and the angle of solar insolation. Consequently, the generation of maximum power is not assured under all electrical load conditions. To address this variability, MPPT techniques are employed to extract the maximum available power from PV configurations. These techniques are equipped with controllers that adjust operational parameters to ensure optimal power extraction.

The efficiency of any given MPPT technique is contingent upon its ability to track the maximum power point under rapidly changing environmental conditions. In particular, the performance of these techniques is significantly affected by partial shading conditions (PSCs), which present additional challenges. Based on their tracking characteristics in PSCs, MPPT techniques can be classified into several categories. A comprehensive discussion of these classified techniques is presented in this section, with categorization as illustrated in Fig. 6.

- **Classical MPPT**
- **Intelligent MPPT**
- **Optimization MPPT**

The classical MPPT techniques include methods such as incremental conductance (InC), fractional open-circuit voltage (FOCV), fractional short-circuit current (FSCC), hill climbing (HC), perturb and observe (P&O), variable step size P&O, constant voltage (CV), adaptive reference voltage (ARV), DC-link capacitor droop control based MPPT, ripple correlation control (RCC), look-up table method, linearization-based MPPT, and online-MPP search algorithm. These techniques are characterized by their simplicity in implementation, due to the relatively low complexity of their algorithms. They are most effective under uniform irradiance conditions, where the PV system generates a single global maximum power point (GMPP). However, these techniques exhibit rapid oscillations around the MPP, leading to power losses. Moreover, these classical methods fail to account for the impact of partial shading conditions (PSCs), resulting in an inability to reliably track the true MPP under such circumstances.

Intelligence-based MPPT techniques include fuzzy logic control (FLC), artificial neural networks (ANN), sliding mode control (SMC), Fibonacci series-based MPPT, and the Gauss–Newton approach-based MPPT. These techniques are designed to adapt to dynamic weather conditions, offering high accuracy in tracking the MPP. They exhibit excellent tracking efficiencies and fast tracking speeds. However, these methods typically involve increased complexity in their control circuits and require significant data processing, especially for system training. FLC is particularly notable for its ability to implement MPPT without prior knowledge of the system. ANN is a fast tracking technique but necessitates extensive data sets for training to enhance tracking accuracy. SMC, on the other hand, offers a higher tracking speed and is easier to implement. Both Fibonacci and Gauss–Newton methods are emerging as advanced solutions due to their ability to dynamically update the search range, making them increasingly efficient in real-time MPP tracking.

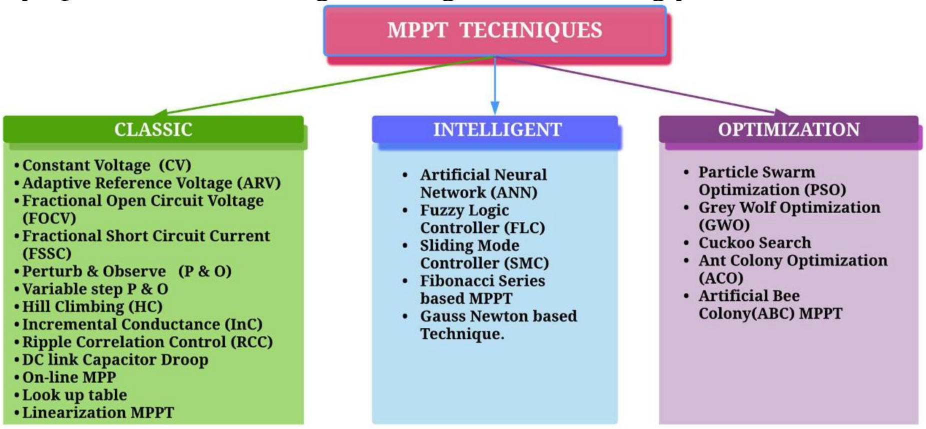

Fig. 6 Basic classification of tracking techniques

Optimization-based MPPT techniques include Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Cuckoo Search (CS)-based MPPT, Ant-Colony Optimization (ACO), and Artificial Bee Colony (ABC). These methods are particularly effective in dynamically changing environmental conditions and are capable of searching for the true maximum power point (MPP) under various scenarios.

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- PSO is a faster tracking algorithm that minimizes steady-state oscillations, offering a significant improvement in tracking performance. Its implementation is straightforward and can be easily executed on low-cost microcontrollers.
- GWO mimics the behavior of wolves searching for prey, which allows it to rapidly locate the optimum operating point. GWO is considered one of the most efficient evolutionary algorithms, with the advantage of not requiring prior knowledge of the system.
- CS-based MPPT is a bio-inspired algorithm based on the natural phenomenon of brood parasitism. It uses the Levy flight method to optimize the search for the MPP.
- ACO and ABC are other evolutionary-based optimization methods that have gained popularity. These methods also perform efficiently in real-time MPP tracking, while requiring fewer sensors (temperature and voltage) compared to classical methods.

These optimization techniques are highly adaptable and efficient, especially under non-uniform conditions like partial shading. Their reduced reliance on multiple sensors and their ability to perform complex searches in dynamic environments make them strong candidates for next-generation MPPT controllers.

4. Classical MPPT Techniques

4.1 Constant Voltage (CV)-Based MPPT Technique

The principal aim of the Constant Voltage (CV)-based Maximum Power Point Tracking (MPPT) technique is to maintain the photovoltaic (PV) system's operation in the vicinity of the Maximum Power Point (MPP) by regulating the PV voltage and comparing it to a fixed reference voltage (RV), which is set approximately equal to the voltage at the MPP. This technique is predominantly applied under uniform irradiation conditions and disregards the influence of both solar insolation and temperature variations.

The CV method estimates the MPP at a point that is slightly offset from the actual MPP, resulting in an operating point that does not precisely align with the true MPP. Consequently, consideration of varying geographical locations and environmental factors is required to optimize the reference voltage (RV) and minimize tracking errors.

A schematic block diagram of the CV-based MPPT technique is presented in Fig. 7. This method necessitates only a single sensor, used for measuring the PV module voltage, which is then used to determine the appropriate duty cycle for the DC–DC converter [17]. The technique is recognized for its simplicity, fast response, and ease of implementation; however, it exhibits limited accuracy. Periodic measurements of the open-circuit voltage are required to maintain effective operation. Additionally, the technique is most suitable in conditions with minimal temperature variations.

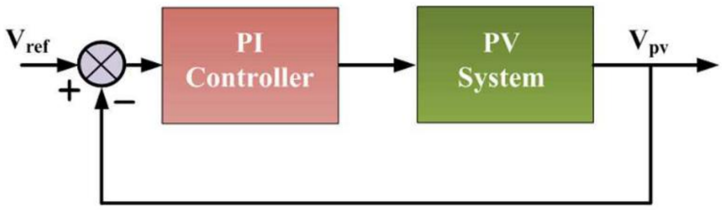

Fig. 7 Schematic block diagram of CV MPPT technique

4.2 Adaptive Reference Voltage (ARV)-Based MPPT Technique

The Adaptive Reference Voltage (ARV)-based Maximum Power Point Tracking (MPPT) technique represents an extension of the conventional Constant Voltage (CV) method, offering enhanced flexibility under dynamically changing climatic conditions. In this approach, the reference voltage (RV) for MPPT is adaptively adjusted based on real-time measurements of solar irradiance and temperature levels. A schematic block diagram of the ARV-based MPPT method is illustrated in Fig. 8.

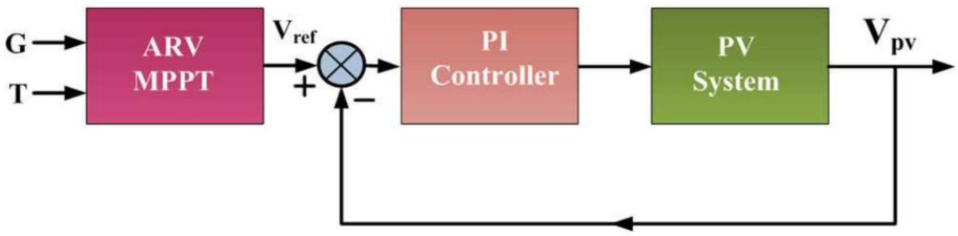

Fig. 8 Schematic block diagram of ARV MPPT technique.

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In this technique, the operating range of irradiance at a given temperature is divided into multiple segments, and the corresponding reference voltages are pre-determined and stored offline in a lookup truth table. The discrepancy between the reference voltage and the measured PV voltage is compensated using a proportional–integral (PI) controller, which generates an appropriate duty cycle for the associated DC–DC converter.

A key advantage of the ARV approach is that it does not require transient interruption of the PV module during operation. By incorporating real-time measurements of temperature (T) and irradiance (G) through the use of two additional sensors compared to the traditional CV method—and one additional sensor relative to the Perturb and Observe (P&O) technique—the ARV system incurs a marginally higher cost. Nevertheless, the resulting improvement in tracking efficiency compensates for this added expense.

Lasheen et al. [18] conducted a simulation-based comparison of the ARV method with the CV technique. Under constant irradiance conditions (approximately 1000 W/m²), both techniques achieved comparable efficiencies exceeding 99.7%. However, when the irradiance decreased to 400 W/m², the efficiency of the CV technique dropped to 98.3%, while the ARV method maintained a consistent efficiency across varying irradiance levels.

4.5 Hill Climbing (HC)-Based MPPT Technique

The Hill Climbing (HC) method is a mathematical optimization algorithm designed to iteratively search for the Maximum Power Point (MPP) of a photovoltaic (PV) system. The fundamental principle of this technique involves initiating the search with an appropriate initial guess, which is often an arbitrarily selected operating point. Subsequently, the algorithm incrementally adjusts the control variable in the direction that increases the output power. If the new operating point yields a higher power output, the process is repeated with the same incremental steps. This iterative search continues until no further improvement is observed in the output power, indicating convergence to a local or global optimum.

Within the category of hill-climbing-based methods, two prominent techniques are widely recognized: the Perturb and Observe (P&O) method and the Incremental Conductance (InC) method. Ahmed et al. [19] provided an in-depth analysis emphasizing the critical importance of selecting the initial perturbation step size, as it significantly affects the convergence speed toward the optimal operating point.

The key distinction between the P&O and HC methods lies in their choice of perturbation variable. While the InC method relies on the slope of the power–voltage (P–V) curve as its control parameter and the P&O technique utilizes voltage perturbations, the HC method employs the duty cycle (D) of the power converter as the perturbation variable. This characteristic renders the HC method a simple and effective MPPT technique that can be easily implemented on standard microcontroller platforms. Furthermore, the method does not necessitate sensors for irradiance and temperature measurements, nor does it require extensive prior knowledge of the PV system characteristics, thus making it a cost-effective and broadly applicable solution.

4.6 Perturb and Observe (P&O) MPPT Technique

The Perturb and Observe (P&O) method is one of the most extensively utilized and widely implemented Maximum Power Point Tracking (MPPT) techniques in both academic literature and practical applications. This technique operates based on a straightforward trial-and-error mechanism to search for and track the Maximum Power Point (MPP). The core algorithm involves comparing the PV output power at two successive operating points on the power–voltage (P–V) curve and subsequently adjusting the terminal voltage in a manner that steers the operating point toward the MPP.

A schematic block diagram representing the P&O method is illustrated in Fig. 9. The algorithm initiates by measuring the change in PV power (ΔP) and the corresponding change in voltage (ΔV). Based on the signs of these two quantities, the duty cycle (D) of the converter is perturbed either positively or negatively to move the operating point closer to the MPP. Specifically, if the derivative of power with respect to voltage (dP/dV) is positive, it indicates that the operating point lies on the left side of the MPP, whereas a negative dP/dV implies the point is on the right side of the MPP. The algorithm iteratively perturbs the voltage in small increments, continuing this process until the derivative approaches zero, signifying that the MPP has been reached. The algorithm's flow chart is presented in Fig. 10. At the peak of any P–V curve, the MPP condition is mathematically expressed as (2):

$$\frac{dP_{PV}}{dV_{PV}} = 0 = MPPP \qquad (2)$$

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To determine the relative position of the current operating point with respect to the MPP, the following relations are applied:

$$\frac{dP_{PV}}{dV_{PV}} > 0 \; Left\ side\ of\ MPP \qquad (3)$$

$$\frac{dP_{PV}}{dV_{PV}} < 0 \; Right\ side\ of\ MPP \qquad (4)$$

The P&O technique is appreciated for its simplicity for implementation, and minimal hardware requirements. However, one inherent limitation is its susceptibility to oscillations around the MPP, particularly under rapidly changing irradiance conditions. Despite this drawback, the method remains popular in practical applications due to its balance of efficiency, robustness, and low computational demand.

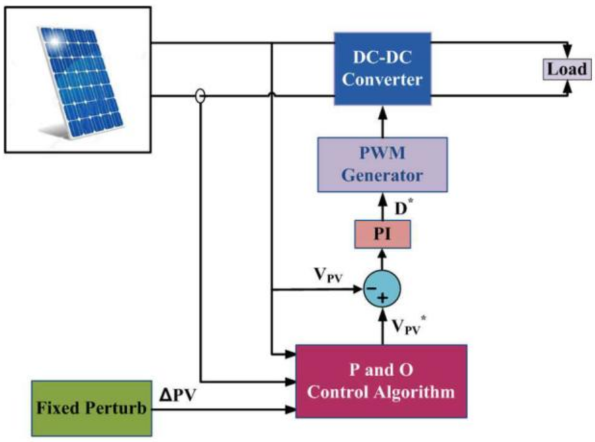

Fig. 9 Conventional P & O with fixed perturbation step

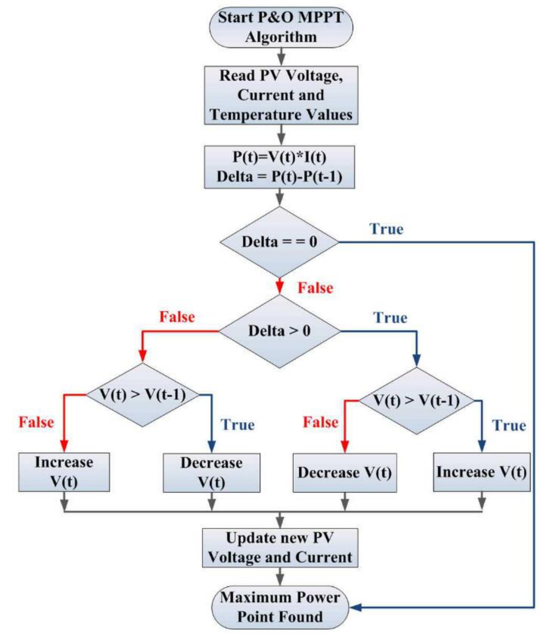

Fig. 10 Flowchart of P & O algorithm

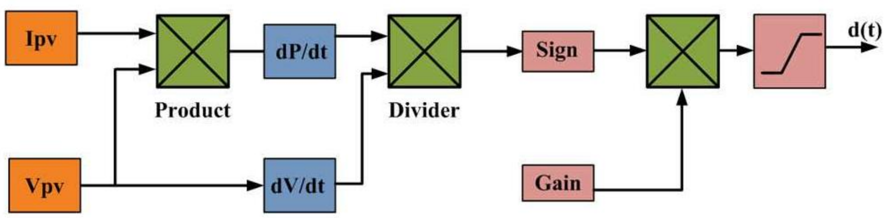

Fig. 11 Implementation of P & O method through MatLab/Simulink

The practical implementation of the Perturb and Observe (P&O) MPPT method can be effectively realized using Simulink blocks within the MATLAB environment, as illustrated in Fig. 11 [20]. Given the widespread adoption of this technique, it is well-suited for deployment in microcontroller-based platforms,

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requiring only two sensors for the simultaneous measurement of PV module voltage and current. According to the study conducted by Sera et al. [21], the system achieves a tracking time of approximately 2.5 seconds to reach the MPP, with a reported tracking efficiency of about 97.6%. The experimental setup employed a dSPACE 1103 controller board interfaced with Simulink, along with a Texas Instruments TMS320F335 microcontroller. The results demonstrated compliance with the EN 50530 standards for efficiency under both static and dynamic operating conditions.

4.8 DC-Link Capacitor Droop Control

The DC-Link Capacitor Droop Control MPPT technique is a highly reliable approach for mitigating the drooping behavior of capacitors in a PV system connected in parallel to the AC grid. In this technique, the duty ratio (D) of the converter is determined using the following equation:

$$D = 1 - \frac{V_{PV}}{V_{Link}} \quad (5)$$

where V_{PV} represents the voltage of the PV system and V_{Link} is the voltage across the DC-link. This method effectively maintains the Maximum Power Point (MPP) of the PV system through the coordinated operation of the converter, inverter, and control commands [22]. The V_{Link} is typically kept constant, which in turn increases the current flowing into the inverter, thereby boosting the power fed into the boost converter, and consequently, enhancing the overall power output from the PV system.

As the current increases, V_{Link} is maintained steady as long as the inverter's power demand does not exceed the maximum available power from the PV array. If the DC-link voltage is not appropriately sized for the maximum power, it may fail to maintain its steady-state, leading to a drooping effect. Prior to the droop occurring in the capacitor, the control system issues a signal to ensure that the peak current of the inverter remains at its maximum, thereby ensuring that the PV system operates at its MPP.

The AC system line current provides feedback to prevent the drooping of V_{Link}, and the duty ratio (D) is adjusted to maintain I_{peak} at its optimum value, thereby achieving MPPT. Notably, the DC-link capacitor droop control does not require direct calculation of the PV system's power. However, the effectiveness of this method may be reduced because its control parameter depends on the DC voltage control of the inverter.

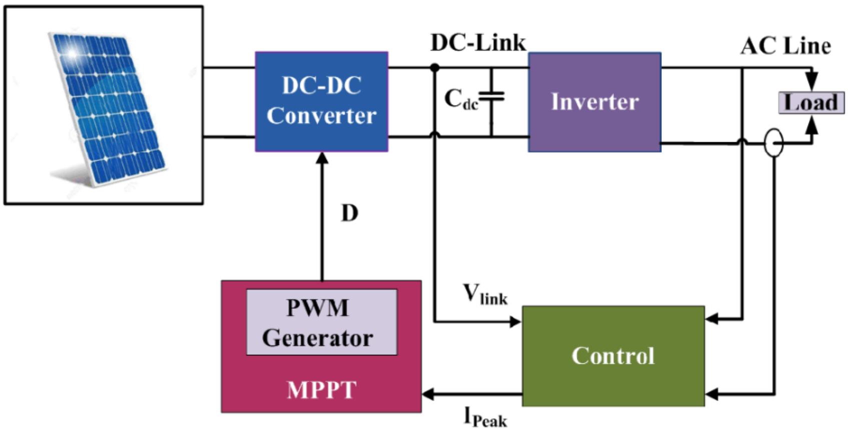

Fig. 12 Topology of a DC-link capacitor droop control

This control technique can be efficiently implemented using simple analog amplifiers and basic logic circuits. The schematic representation of this method is shown in Fig. 12, and the value of the DC-link capacitor C_{dc} is calculated based on the desired hold-up time. The calculation for C_{dc} as a function of the hold-up time is given by the equation:

$$C_{dc} = 2 * \left(\frac{Output\ Power\ Rated * (Hold-upTime)}{(V_{d.nominal}^2 - V_{d.min}^2) * \eta} \right) \quad (6)$$

The voltage across the DC-link capacitor (C_{dc}) is maintained constant despite fluctuations in the input side source. Kitano et al. [23] provide a comprehensive analysis of the variations in V_{Link}, particularly when the system is integrated with the grid. To address the negative sequence components generated by the grid, the circuit incorporates a low-pass filter (LPF), which helps mitigate their effects on the system. Additionally, adaptive droop control strategies for inverters operating in both isolated and grid-tied modes have been proposed by Vasquez et al. [24].

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4.12 Incremental Conductance (InC) MPPT

The Incremental Conductance (InC) strategy is based on the principle that the derivative of the output power PPP with respect to the panel voltage V is equal to zero at the Maximum Power Point (MPP). The execution strategy for InC is illustrated through a flowchart, as shown in Fig. 13. This method uses data to analyze the slope of the power–voltage (P–V) curve of the system and tracks the MPP based on that data. When the slope of the P–V curve, or the derivative of the PV array power (dP/dV) reaches zero, the tracking process is considered complete.

However, in rapidly changing atmospheric conditions, the tracking of the MPP becomes more challenging, and the rate of tracking decreases exponentially due to the continuous change in the P–V curve. Maintaining the operating point under these conditions is difficult. To mitigate this, many adaptive step-size techniques have been introduced to extract the MPP without causing oscillations.

The implementation of this method using Simulink blocks in Matlab is shown in Fig. 14. While this strategy follows a similar approach to the Perturb and Observe (P&O) method to reach the MPP, it uniquely incorporates the current–voltage (I–V) curve relationship. The technique uses current and voltage measurements from the PV cell to calculate the derivative of both the current (d*I*) and voltage (d*V*) [25]. The PV I–V curve is then employed to determine the trajectory of the operating point.

Due to its moderate complexity and improved performance compared to the P&O method, InC is considered one of the most widely used MPPT techniques in the literature, particularly for uniform conditions . Equations (7)–(16) outline the mathematical approach for calculating the position of the MPP on the P–V curve.

$$P = V * I \qquad (7)$$

$$\frac{dP}{dV} = \frac{d(VI)}{dV} \qquad (8)$$

The chain rule for the derivative of products yields

$$I\frac{dV}{dI} + V\frac{dI}{dV} = 0 \qquad (9)$$

$$\frac{dP}{dV}I + V\frac{dI}{dV} = 0 \qquad (10)$$

$$\frac{1}{V}\frac{dP}{dV} = \frac{I}{V} + \frac{dI}{dV} = 0 \quad (11)$$

At peak power point

$$\frac{dP}{dV} = 0, \qquad \frac{I}{V} + \frac{dI}{dV} = 0 \quad (12)$$

If the operating point is to the right of the curve then we have

$$\frac{dP}{dV} < 0, then\ if$$

$$\frac{I}{V} + \frac{dI}{dV} < 0, V\ is\ decreased, \qquad (13)$$

$$if\ \frac{I}{V} + \frac{dI}{dV} > 0, V\ is\ increased \qquad (14)$$

If the operating point is to the left of the curve then we have

$$\frac{dP}{dV} > 0, then\ if$$

$$\frac{I}{V} + \frac{dI}{dV} > 0, V\ is\ increased, \quad (15)$$

$$if\ \frac{I}{V} + \frac{dI}{dV} > 0, V\ is\ decreased. \qquad (16)$$

Like the Perturb and Observe (P&O) technique, it is challenging to make (dI/dV) exactly equal to (−I/V), resulting in less power loss compared to P&O. The Incremental Conductance (InC) method is faster and more resistant to oscillations than P&O. However, it cannot locate the Global Maximum Power Point (GMPP) in the presence of multiple local MPPs, as the P&O technique can. A basic microcontroller is sufficient for implementing this technique, similar to P&O, and both voltage and current sensors are utilized.

The enhanced InC method has demonstrated improvements in tracking speed and efficiency. Several contemporary studies have highlighted the broad implementation of these advanced InC methodologies. As detailed in reference [26], when implemented on a controller board, this strategy is able to reach the MPP in

2.3 seconds, with an efficiency of approximately 98.5%. However, larger increments tend to cause the system to oscillate around the MPP, leading to less efficient power output.

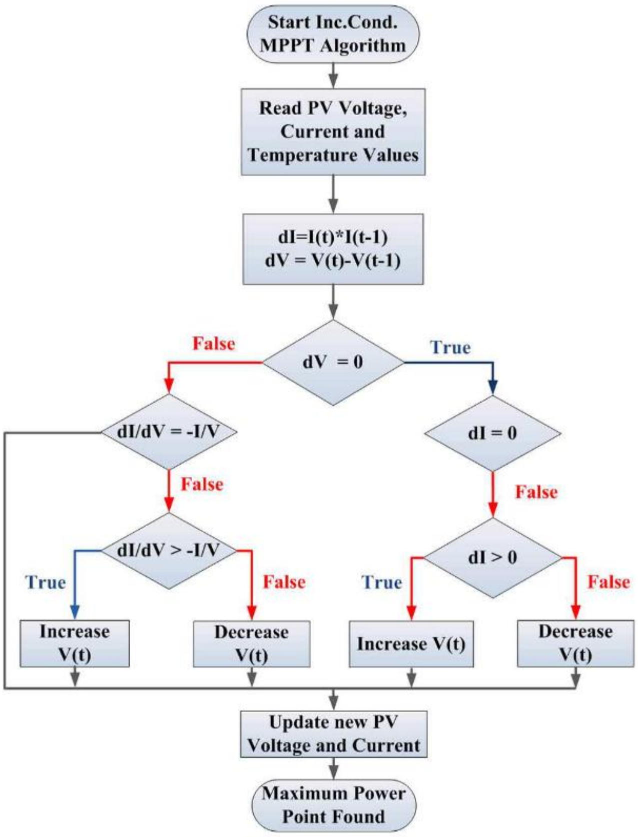

Fig. 13 Flowchart of the InC algorithm

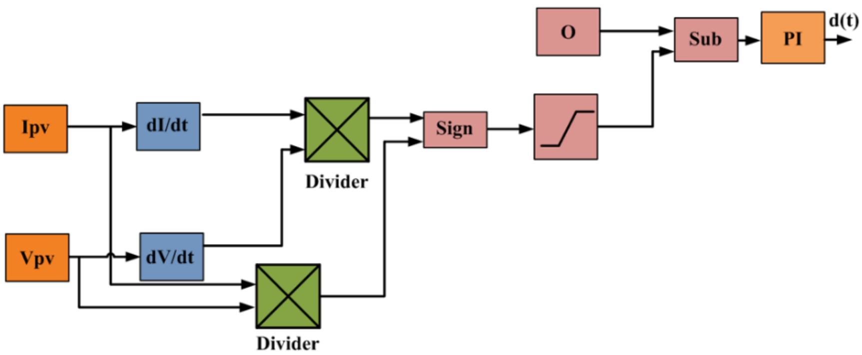

Fig. 14 Implementation of InC method using PI controller [26]

5. Intelligence MPPT techniques

5.1 Artificial Neural Network (ANN)

The Artificial Neural Network (ANN) is an intelligence-based, advanced Maximum Power Point Tracking (MPPT) technique, widely recognized for its ability to learn from data and adapt based on the biological nature of neurons. At its core, an ANN can be represented as a directed graph, where the nodes represent the neurons and the edges correspond to the synapses, which connect these neurons.

The model of a neuron in an ANN is defined by its activation function (AF), which dictates the output of the neuron based on the input data. The formulation of this activation function is illustrated in Fig. 15, with Z representing the argument of the activation function, as defined in equation (17).

$$Z = \sum_{m=1}^{M} X_m W_m + \alpha \qquad (17)$$

$X_1, X_2, \ldots, X_M$ represent the M incoming signals, and $W_1, W_2, \ldots, W_M$ are the corresponding synapse weights, while α\alphaα is the bias parameter. Generally, the activation function (AF) serves to convert a linear function into a non-linear one. The AF typically involves a hyperbolic tangent sigmoid or a log-sigmoid function.

Two primary types of ANN structures emerge based on the connectivity of neurons: the Feedforward Neural Network (FNN) and the Recurrent Neural Network (RNN). In the case of an ANN with a multi-layer feed-forward system, which typically consists of three layers-input, hidden, and output layers-the structure is depicted in Fig. 16.

The input to this technique can include parameters from the photovoltaic (PV) module, such as open-circuit voltage (V_{OC}) and short-circuit current (I_{SC}), as well as environmental data, including irradiance and temperature, or a combination of these two factors. The output of the ANN is typically the Maximum Power Point Voltage (V_{MPP}), reference voltage (V_{ref}), or the Global Maximum Power Point (GMPP). The essential task is performed within the hidden layer, where the network adjusts the weights and biases to estimate the optimal target value.

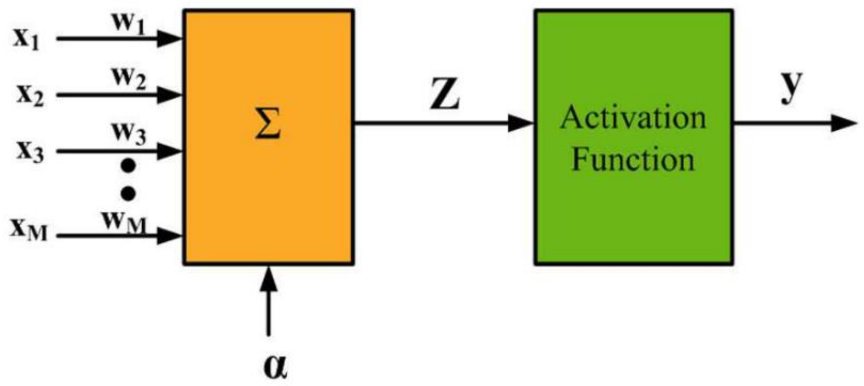

Fig. 15 Formulation of neural network-AF

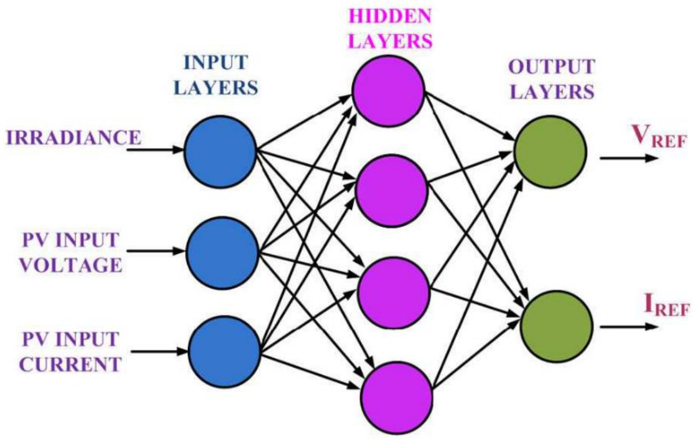

Fig. 16 Multi-layer FNN

The Artificial Neural Network (ANN) processes the available input sets to predict the Global Maximum Power Point (GMPP**)**. Based on the calculations performed within the network's hidden layers, the output of the ANN will yield the duty cycle signal. This duty cycle is used to drive the converter, enabling it to track the MPP in real-time. The duty cycle is adjusted according to the network's learned relationships, which depend on the specific calculations and weights used in the layers of the network. The ability of the Artificial Neural Network (ANN) technique to accurately identify the Global Maximum Power Point (GMPP) depends heavily on both the learning process and the structure of the network itself. The more data sets (i.e., V_{PV},I_{PV}) the network is exposed to, the closer the P-V curve will approach the GMPP. A notable advantage of ANN is its capacity for parallel processing, a feature not shared by many other techniques. The weights in the network are adjusted according to the functions used in the hidden layers, and all the weights can be re-initialized simultaneously, allowing for rapid responses and faster processing.

However, the accuracy of this technique is influenced by the quantity and quality of the data provided. ANN is typically applied under uniform conditions due to its dependence on PV characteristics such as the module, configurations, and shading. As a result, if the system configuration changes, the ANN requires retraining to adapt to the new conditions. Ongoing research is focused on improving the performance of ANN in Partially Shaded Conditions (PSC). For instance, Syafaruddin et al. [27] presented an ANN implementation tailored for PSCs, taking into account various shading conditions and configurations. Their work showed that

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ANN outperforms conventional techniques like P&O and InC under PSCs. The detailed implementation of ANN is shown in Fig. 17.

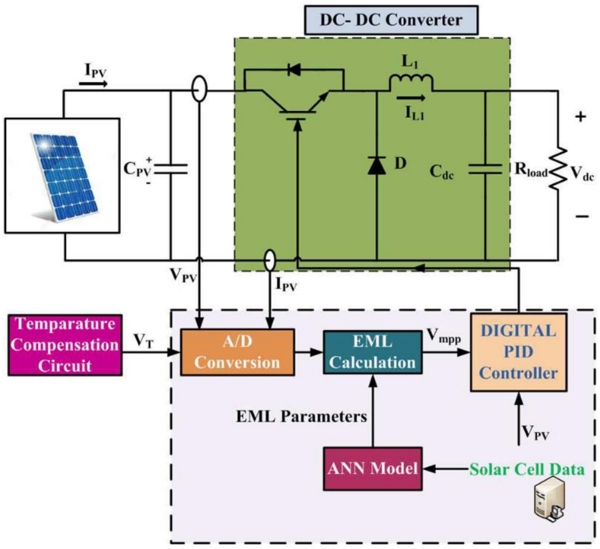

Fig. 17 Detailed implementation of ANN method

One of the advantages of the ANN technique is its simplicity in implementation, especially on small, cost-effective microcontrollers. The hardware implementation typically uses low-calculation-based controllers with efficient activation functions, ensuring high-speed calculations and a fast convergence rate. Zhang et al. [28] modeled a Hybrid Genetic Algorithm (GA)-ANN-based MPPT technique, which resulted in quicker tracking of the MPP.

5.2 Fuzzy Logic Controller (FLC)

Conventional tracking techniques often struggle with hardware implementation under Partially Shaded Conditions **(**PSC), where tracking efficiency can significantly degrade. To address this issue, the controller design must be modernized for optimal tracking performance. While traditional controller designs rely on mathematical modeling of the system, this becomes increasingly complex under PSCs, as the system may become too difficult to model accurately.

In contrast, Fuzzy Logic Controllers (FLCs) provide an intelligent solution that does not require precise mathematical modeling of the system. Fuzzy logic has become a preferred choice due to its robustness and adaptability, especially in environments with uncertain or variable inputs. FLCs can track the Maximum Power Point (MPP) even when the system's parameters are not precisely known, making them ideal for dealing with unpredictable conditions like PSCs.

FLCs offer two primary advantages over other methods:

1. No need for an exact mathematical model of the PV system.
2. The controller design process is guided by human expertise, allowing for greater flexibility and customization.

The fuzzy logic approach typically consists of three stages:

1. Fuzzification: In this step, the input PV parameters (such as voltage and current) are converted from crisp values into fuzzy sets, or linguistic variables. These linguistic variables represent different levels or ranges of input parameters.
2. Rule Base: The core of the FLC, where fuzzy rules are designed based on human knowledge and experience. These rules (if-then statements) define how the system should behave under varying conditions.
3. Defuzzification: This step reverses the fuzzification process, converting the fuzzy output into a crisp numerical value. Common methods for defuzzification include the centroid method, maximum membership function, and weighted average methods. The resulting numerical output is sent as an analogue signal to the converter.

The rule base is critical to the FLC's performance. By adjusting the rules, the controller can be fine-tuned to meet the specific needs of the application. In the case of PV systems, the FLC works by continuously adjusting the duty cycle of the converter. This is done by monitoring changes in the error (E) and change in

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error (ΔE), which are calculated based on the difference between the panel voltage and the reference voltage (V_{mpp}).

The error (E) is the difference between the instantaneous PV array voltage and the reference voltage (RV), which represents the maximum voltage for a given solar irradiance. As solar irradiance changes, both the reference voltage (RV) and the most significant voltage fluctuate, and the FLC adjusts the converter's duty cycle accordingly.

The implementation of the FLC for a solar PV system is shown in Fig. 18. Typically, the inputs to the FLC are the error (E) and the change in error (ΔE), which are defined by the following equations:

$$E(n) = \frac{V_{PV}(n)*I_{PV}(n)-V_{PV}(-1)*I_{PV}(n-1)}{V_{PV}(n)-V_{PV}(n-1)} \qquad (18)$$

$$\Delta E(n) = E(n) - E(n-1) \qquad (19)$$

When E and ΔE are determined and converted into linguistic variables (fuzzy sets), the output of the fuzzy controller is the adjustment in the converter's duty cycle (ΔD). In this context, the error difference between the reference voltage (V_{ref}) and the PV voltage (V_{PV}), denoted as e_v, serves as the input to the FLC, while the change in load angle (Δδ) is considered as the output of the FLC[29].

The block-level implementation of the FLC system is illustrated in Fig. 19, which demonstrates how the controller dynamically adjusts the duty cycle to continuously align the PV array voltage with the Maximum Power Point (MPP) under varying conditions.

FLC has been extensively proven to perform exceptionally well under dynamically changing atmospheric conditions, such as fluctuating irradiance and temperature. In this context, Syafaruddin et al. [27] introduced a neuro-fuzzy technique, a hybrid approach that combines the advantages of neural networks and fuzzy logic. This technique emphasizes the importance of distributed MPPT, wherein converters are installed at each PV array in a 4×3 solar PV configuration. This approach enhances MPP tracking speed and accuracy under Partially Shaded Conditions (PSCs), though it incurs higher costs due to the necessity of converters at each array segment.

The efficiency of FLC is highly dependent on two key factors:

1. Selection of optimal membership functions, which ensures the error value (E) converges to zero effectively.
2. Design of the fuzzy rule base table, which determines the robustness and responsiveness of the MPPT technique under variable conditions.

To further improve the tracking speed and system efficiency, Priyadarshi et al. [30] proposed the hybrid Artificial Neural Fuzzy Inference System (ANFIS) methodology. This approach utilizes dSPACE as the interfacing element between the controller code and hardware, enabling precise control and real-time implementation.

Additionally, Kottas et al. [31] introduced a novel MPPT technique based on Fuzzy Cognitive Networks (FCN), further demonstrating the growing potential of combining intelligent systems with fuzzy logic to enhance MPPT performance in complex PV environments.

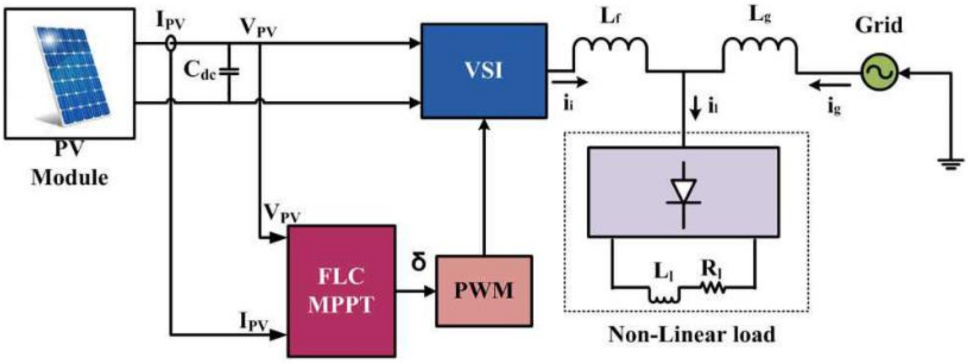

Fig. 18 Block diagram of FLC MPPT technique

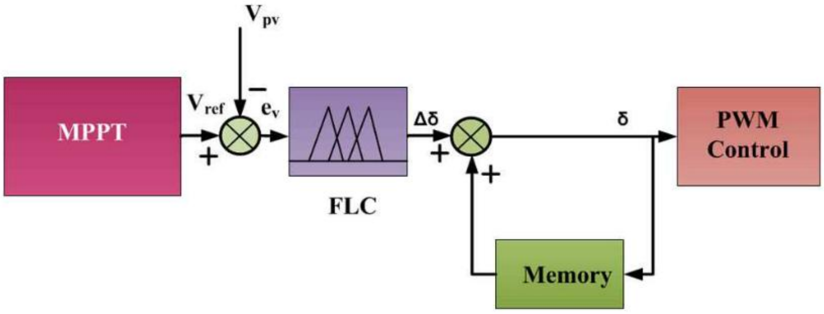

Fig. 19 Control block diagram of fuzzy logic controller

6. Optimization-based MPPT

This paper surveys optimization-based procedures demonstrated to be effective and feasible to implement and extremely common in literature for MPPT, including their limits and points of interest.

6.1 Particle Swarm Optimization (PSO)-Based MPPT Technique

Particle Swarm Optimization (PSO) represents one of the most effective swarm intelligence-based MPPT techniques, inspired by the social behavior of flocking birds. The foundational concept of this bio-inspired algorithm models each PV array or module as a particle, with the maximum power point (MPP) conceptualized as the target objective to be identified and tracked. In this framework, all PV modules function as subordinate units (slaves) governed by a master controller, facilitating coordinated communication to achieve convergence at the desired MPP.

The PSO algorithm consists of a swarm of individual agents (termed particles), where each particle symbolizes a potential candidate solution. These particles follow a simple yet efficient behavioral mechanism: they adjust their trajectories by emulating both the movement of neighboring particles and their own historical trajectories. Consequently, the position of each particle is dynamically influenced by two key components:

- The personal best position (P_{best}) — the best solution previously found by the individual particle.
- The global best position (G_{best}) — the best solution discovered by any particle within the entire swarm population.

The position update of a given particle, denoted as x_i, is executed based on these influences, mathematically formulated as in Equation (20). This iterative process enables the swarm to collectively and efficiently explore the solution space, converging toward the global optimum, i.e., the true MPP of the PV system.

$$x_i^{k+1} = x_i^k + \Psi_i^{k+1} \quad (20)$$

where the velocity part Ψ_i speaks to the progression size. The velocity is determined by the (21).

$$\Psi_i^{k+1} = W\Psi_i^k + c_1 r_1 \left[P_{best} - x_i^k\right] + c_2 r_2 \left[G_{best} - x_i^k\right] \quad (21)$$

where w is the inertia weight, c_1 and c_2 are the increasing speed coefficients, r_1, r_2, Uϵ(0, 1), P_{best}i is the individual best position of molecule i, and G_{best} is the best position of the particles in the whole population [32]. The objective function is characterized as given in (22).

$$P\left(d_i^k\right) > P\left(P_i^{k-1}\right) \quad (22)$$

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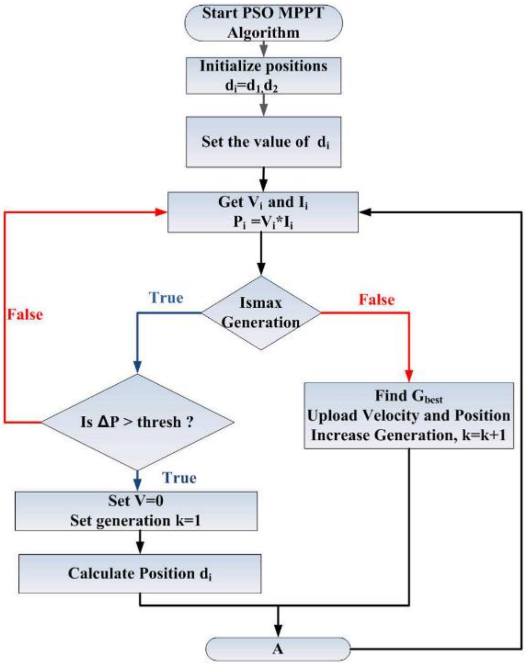

Fig. 20 Flowchart of PSO algorithm

The fundamental operational strategy of the PSO-based MPPT technique is illustrated through the flowchart depicted in Fig. 20. Owing to its inherent search-based mechanism, the PSO approach is capable of efficiently locating the global maximum power point (GMPP) with relative ease. Several studies have proposed enhancements to the standard PSO algorithm, notably through the Improved PSO (IPSO) methodology, which aims to minimize steady-state oscillations during the tracking process.

An essential feature of IPSO lies in its capability to initialize particles effectively in the vicinity of the MPP. This strategic initialization reduces both unnecessary and redundant searching within the solution space, ensuring that the swarm concentrates its search within a sufficiently narrow region. As a result, the algorithm is able to locate the true GMPP within a shorter timeframe. Robustness to control parameter variations is a key strength of this approach.

For instance, Abdulkadir et al. [33] introduced a hybridized technique that combines PSO with the Incremental Conductance (InC) method. Their proposed system demonstrated superior tracking capability compared to conventional methods. Empirical results indicated that the hybrid system required only 1 second to reach the MPP at the initial stage, whereas the conventional method took 2 seconds. Furthermore, under variable insolation conditions (at t = 4 s and t = 8 s), the hybrid system successfully re-tracked the GMPP within just 0.1 seconds on both occasions. This innovative PSO-InC integration thus significantly enhances the overall efficiency of the PV system.

6.3 Ant Colony Optimization (ACO)-Based MPPT

This section presents a novel Ant Colony Optimization (ACO)-based MPPT technique, specifically designed to track the Global Maximum Power Point (GMPP) under conditions of variable insolation. The ACO algorithm integrates three fundamental components: a greedy search algorithm**,** a positive feedback mechanism, and distributed computing principles. Collectively, these mechanisms endow ACO with a robust capability to explore the solution space effectively.

The greedy search algorithm expedites the discovery of a satisfactory solution, thereby enhancing the overall efficiency of the MPPT process. The positive feedback mechanism reinforces the search path towards the most promising solution, ensuring that the algorithm consistently identifies the optimal result. Simultaneously, distributed computing mitigates the risk of premature convergence by enabling the algorithm to periodically restart the search process. Re-initialization is triggered based on the detected climatic conditions, ensuring the system operates optimally in dynamically changing environments.

In the implementation of the ACO-based MPPT algorithm, several key parameters must be defined by the user. These include:

– Number of ants (M)

– Size of the solution archive (K)

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– Convergence speed constant (ξ)
– Locality factor of the search process (Q)

The number of ants (**M**) directly affects both the convergence speed and the accuracy of the optimization process. A larger number of ants improves the capability of the algorithm to locate the GMPP under diverse irradiance conditions. However, it also increases the time required for the entire swarm to converge to the MPP. Conversely, employing fewer ants can enhance the convergence speed, albeit at the risk of the swarm becoming trapped in local optima. The size of the solution archive (K) should not be smaller than the dimensionality of the problem to maintain search effectiveness.

The procedural flow for the implementation of this technique, including initial parameter settings, is illustrated in Fig. 21**.** Maskell et al. [34] conducted a comparative analysis between classical MPPT methods and the ACO-based approach. Their results demonstrated that the ACO algorithm consistently delivers superior performance in locating the GMPP under varying shading conditions, thereby enabling greater power extraction from PV arrays.

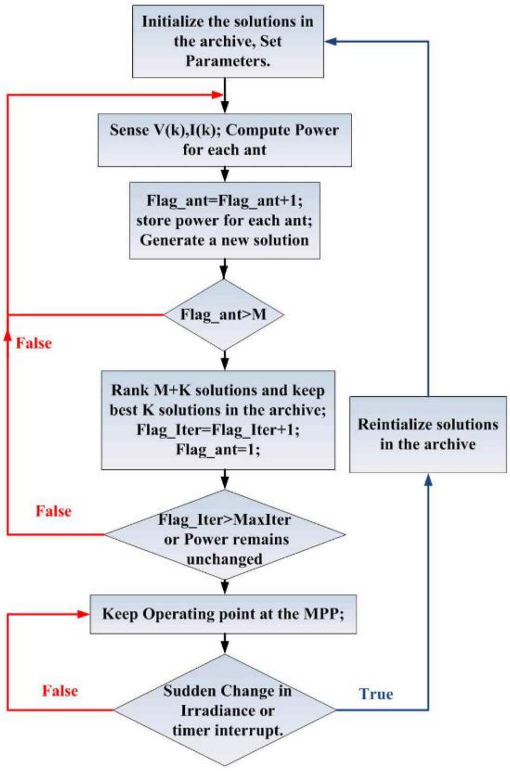

Fig. 21 Flowchart of ACO-based MPPT algorithm for PV systems

6.5 Artificial Bee Colony (ABC)-Based MPPT

The Artificial Bee Colony (ABC) algorithm represents one of the most effective techniques for identifying the Global Maximum Power Point (GMPP) in photovoltaic (PV) systems. This algorithm is inspired by the foraging behavior of honey bees**,** which systematically search for food sources by dividing tasks among distinct groups. Analogously, the process of tracking the optimal MPP is executed by distributing the search tasks among individual agents within the algorithm.

In the ABC algorithm, the bee colony is broadly classified into three functional groups: employed bees**,** onlooker bees**,** and scout bees**.** The search process initiates when employed bees gather food source information (analogous to potential MPP candidates). This information is subsequently shared with onlooker bees through a mathematically structured communication process. Simultaneously, scout bees search for alternative food sources, facilitating exploration of new regions within the solution space. The ultimate objective is to identify the most abundant food source, which corresponds to the maximum available power point in the PV context. A higher number of employed bees typically enhance the performance of the algorithm by intensifying the search in promising regions.

This food foraging paradigm is effectively adapted to PV systems to locate the GMPP efficiently by using a suitable objective function (AF)**.** By applying the ABC algorithm, the GMPP—representing the point of maximum available power—can be tracked rapidly and accurately.

Sundareswaran et al. [35] introduced the ABC-based MPPT technique and compared its performance against Particle Swarm Optimization (PSO) and Enhanced Perturb and Observe (EPO) methods. The results demonstrated that the ABC method achieved an efficiency of approximately 99.99%, with tracking times of 4.234 s, 9.375 s, and 1.425 **s** for ABC, PSO, and EPO methods, respectively. However, the efficiency of the ABC algorithm was observed to decline under rapidly changing shading patterns.

Recently, Padmanaban et al. [36] proposed a novel hybrid ANFIS-ABC technique, which has been identified as one of the most advanced approaches to date. The hardware implementation of this hybrid technique was conducted on a DSP platform within a grid-integrated system. Experimental results demonstrated an efficiency of 98.39%, with the grid voltage and current Total Harmonic Distortion (THD) maintained at 2.3% and 2.5%, respectively—well within acceptable operational limits [37].

7. Conclusion

This paper has presented a comprehensive review of a wide range of Maximum Power Point Tracking (MPPT) techniques designed to enhance the extraction of maximum power from photovoltaic (PV) systems, particularly under Partial Shading Conditions (PSCs). An extensive survey of the literature has been conducted, examining various MPPT methods while considering a range of critical parameters.

From the literature, it can be concluded that the deployment of MPPT controllers represents the most effective approach for tracking the Maximum Power Point (MPP) under PSCs, thereby stimulating substantial research activity in this domain. This review provides detailed explanations of the operational principles of each MPPT technique, complemented by process flow representations to facilitate understanding.

In this study, selected MPPT techniques have been categorized into three primary groups, based on the nature of the tracking algorithms employed to locate the MPP under PSCs. A thorough understanding of several key parameters is necessary to successfully implement a specific MPPT technique. Accordingly, design considerations such as algorithmic complexity, measured parameters, type of converters employed, grid integration capability, tracking speed, ability to track MPP under PSCs, control parameters, and sensor requirements have been systematically analyzed. The advantages and limitations of these techniques have also been discussed and summarized in tabular form.

Furthermore, while existing literature has largely overlooked the hardware implementation aspects of MPPT techniques, this review makes a deliberate effort to investigate and discuss both software and hardware platforms for these methods. In addition, the corresponding efficiencies and tracking speeds of the various approaches have been documented.

In summary, traditional (or classical) algorithms are most suitable for uniform irradiation conditions due to their low complexity and relatively slower tracking speeds. In contrast, intelligent techniques are increasingly gaining prominence, as they offer superior performance in diverse irradiance conditions through faster tracking, advanced sensing capabilities, and efficient data handling, while also reducing dependence on complex mathematical formulations. Moreover, optimization-based techniques exhibit strong compatibility with various PV systems, even in the absence of detailed panel parameter information. A significant advantage of these techniques lies in their adoption of bio-inspired algorithms, which can be applied universally across different PV configurations without prior characterization.

In conclusion, this study serves as a valuable reference for researchers and practitioners seeking to select the most appropriate MPPT technique tailored to their specific applications.

References

[1] Burke, M.J., Stephens, J.C.: ‘Political power and renewable energy futures: a critical review’, Energy Res. Soc. Sci., 2018, 35, pp. 78–93

[2]. https://minenergy.uz/uz/lists/view/77

[3]. https://www.gazeta.uz/oz/2023/12/28/green-energy/

[4] Kong, X., Liu, X., Lee, K. Y., et al.: ‘Hierarchical distributed model predictive control of standalone wind/Solar/Battery power system’, IEEE Trans. Syst. Manage. Cybern., Syst., 2019, 49, (8), pp. 1570–1581

[5] Chen, Y., Altermatt, P.P., Chen, D.: ‘From laboratory to production: learning models of efficiency and manufacturing cost of industrial crystalline silicon and thin-film photovoltaic technologies’, IEEE J. Photovolt., 2018, 8, (6), pp. 1531–1538

ISSN NO: 2770-4491
May 2025

[6] Koutroulis, E., Sason, N., Georgiadis, V.: 'Combined tracking of the maximum power and maximum efficiency operating points for real-time maximization of the energy production of PV systems', IEEE Trans. Power Electron., 2019, 34, (9), pp. 8634–8645
[7] Das, M., Agarwal, V.: 'Novel high-performance stand-alone solar PV system with high-gain high-efficiency DC-DC converter power stages', IEEE Trans. Ind. Appl., 2015, 51, (6), pp. 4718–4728
[8] Dhimish, M., Holmes, V., Mather, P., et al.: 'Novel hot spot mitigation technique to enhance photovoltaic solar panels output power performance', Sol. Energy Mater. Sol. Cells, 2018, 179, pp. 72–79
[9] Kamarzaman, N.A., Tan, C.W.: 'A comprehensive review of maximum power point tracking algorithms for photovoltaic systems', Renew. Sustain. Energy Rev., 2014, 37, pp. 585–598
[10] Ghasemi, M.A., Foroushani, H.M., Parniani, M.: 'Partial shading detection and smooth maximum power point tracking of PV arrays under PSC's', IEEE Trans. Power Electron., 2016, 31, (9), pp. 6281–6292
[11] Huang, C., Wang, L., Yeung, R.S.C., et al.: 'A prediction model-guided Jaya algorithm for the PV system maximum power point tracking', IEEE Trans. Sustain. Energy, 2018, 9, (1), pp. 45–55
[12] Coelho, R.F., Concer, F.M., Martins, D.C.: 'A MPPT approach based on temperature measurements applied in PV systems'. 2010 IEEE Int. Conf. on Sustainable Energy Technologies (ICSET), Kandy, 2010, pp. 1–6
[13] Bhatnagar, P., Nema, R.K.: 'Maximum power point tracking control techniques: state-of-the-art in photovoltaic applications', Renew. Sustain. Energy Rev., 2013, 23, pp. 224–241
[14] Verma, D., Nema, S., Shandilya, A.M., et al.: 'Maximum power point tracking (MPPT) techniques: recapitulation in solar photovoltaic systems', Renew. Sustain. Energy Rev., 2016, 54, pp. 1018–1034
[15] Pendem, S.R., Mikkili, S., Bonthagorla, P.K.: 'PV distributed-MPP tracking: total-cross-tied configuration of string-integrated-converters to extract the maximum power under various PSCs', IEEE Syst. J., 2020, 14, (1), pp. 1046–1057
[16] Batzelis, E.I., Kampitsis, G.E., Papathanassiou, S.A., et al.: 'Direct MPP calculation in terms of the single-diode PV model parameters', IEEE Trans. Energy Convers., 2015, 30, (1), pp. 226–236
[17] Esram, T., Chapman, P.L.: 'Comparison of photovoltaic array maximum power point tracking techniques', IEEE Trans. Energy Convers., 2007, 22, (2), pp. 439–449
[18] Lasheen, M., Abdel Rahman, A.K., Abdel-Salam, M., et al.: 'Adaptive reference voltage-based MPPT technique for PV applications', IET Renew. Power Gener., 2017, 11, (5), pp. 715–722
[19] Ahmed, A., Ran, L., Bumby, J.: 'Perturbation parameters design for hill climbing MPPT techniques'. IEEE Int. Symp. on Industrial Electronics, 2012, pp. 1819–1824
[20] de Brito, M.A.G., Galotto, L., Sampaio, L.P., et al.: 'Evaluation of the main MPPT techniques for photovoltaic applications', IEEE Trans. Ind. Electron., 2013, 60, (3), pp. 1156–1167
[21] Sera, D., Mathe, L., Kerekes, T., et al.: 'On the perturb-and-observe and incremental conductance MPPT methods for PV systems', IEEE J. Photovolt., 2013, 3, (3), pp. 1070–1078
[22] Subudhi, B., Pradhan, R., et al.: 'A Comparative Study on Maximum Power Point Tracking Techniques for Photovoltaic Power Systems', in IEEE Trans. Sustainable Energy, 2013, 4, (1), pp. 89–98
[23] Kitano, T., Matsui, M., Xu, D., et al.: 'Power sensor-less MPPT control scheme utilizing power balance at DC link-system design to ensure stability and response'. 27th Annual Conf. of the IEEE Industrial Electronics Society (Cat. No.37243) (IECON'01), 2001
[24] Vasquez, J.C., Guerrero, J.M., Luna, A., et al.: 'Adaptive droop control applied to voltage-source inverters operating in grid-connected and islanded modes', IEEE Trans. Ind. Electron., 2009, 56, (10), pp. 4088–4096
[25] Safari, A., Mekhilef, S.: 'Simulation and hardware implementation of incremental conductance MPPT with direct control method using cuk converter', IEEE Trans. Ind. Electron., 2011, 58, (4), pp. 1154–11611450 IET Renew. Power Gener., 2020, Vol. 14 Iss. 9, pp. 1433-1452
[26] Kandemir, E., Cetin, N.S., Borekci, S.: 'A comprehensive overview of maximum power extraction methods for PV systems', Renew. Sustain. Energy Rev., 2017, 78, (C), pp. 93–1123
[27] Syafaruddin, S., Karatepe, E., Hiyama, T.: 'Artificial neural network polar coordinated fuzzy controller based maximum power point tracking control under partially shaded conditions', IET Renew. Power Gener., 2009, 3, (2), pp. 239–253

[28] Zhang, L., Bai, Y., Al-Amoudi, A.: 'GA-RBF neural network based maximum power point tracking for grid-connected photovoltaic systems'. Int. Conf. on Power Electronics, Machines and Drives, (Con Pub. No. 487), Sante Fe, NM, USA, 4–7 June 2002, pp. 18–23

[29] Choi, B.-J., Kwak, S.-W., Kim, B.K., et al.: 'Design and stability analysis of single-input fuzzy logic controller', IEEE Trans. Syst., Man Cybern., B, 2000, 30, pp. 303–309

[30] Priyadarshi, N., Farooque, A., Sharma, A.K., et al.: 'An adaptive neuro-fuzzy inference system-based intelligent grid-connected photovoltaic power generation'. Advances in Computational Intelligence, 2019, pp. 3–14

[31] Kottas, T.L., Boutalis, Y.S., Karlis, A.D.: 'New maximum power point tracker for PV arrays using fuzzy controller in close cooperation with fuzzy cognitive networks', IEEE Trans. Energy Convers., 2016, 21, (3), pp. 793–803

[32] Miyatake, M., Toriumi, F., Endo, T., et al.: 'A novel maximum power point tracker controlling several converters connected to photovoltaic arrays with particle swarm optimization technique'. Proc. European Conf. Power Electronicas and Applications, Aalborg, 2007, pp. 1–10

[33] Abdulkadir, M., Yatim, A.H.M., et al.: 'Hybrid maximum power point tracking technique based on pso and incremental conductance'. IEEE Conf. on Energy Conversion (CENCON), Johor Bahru, 2014, pp. 271–276 IET Renew. Power Gener., 2020, Vol. 14 Iss. 9, pp. 1433-1452

[34] Jiang, L.L., Maskell, D.L., Patra, J.C.: 'A novel ant colony optimization- based maximum power point tracking for photovoltaic systems under partially shaded conditions', Energy Build., 2013, 58, pp. 227–236

[35] Sundareswaran, K., Sankar, P., Nayak, P.S.R., et al.: 'Enhanced energy output from a PV system under partial shaded conditions through artificial bee colony', IEEE Trans. Sustain. Energy, 2015, 6, (1), pp. 198–209

[36] Padmanaban, S., Priyadarshi, N., Sagar Bhaskar, M., et al.: 'A hybrid ANFIS- ABC based MPPT controller for PV system with anti-islanding grid protection: experimental realization', IEEE Access, 2019, 7, pp. 103377– 103389

[37] Bollipo, R. B., Mikkili, S., & Bonthagorla, P. K. (2020). Critical review on PV MPPT techniques: classical, intelligent and optimisation. *IET Renewable Power Generation*, *14*(9), 1433-1452.