Hindawi
International Transactions on Electrical Energy Systems
Volume 2024, Article ID 8363342, 24 pages
https://doi.org/10.1155/2024/8363342

Review Article

Overview of Solar Photovoltaic MPPT Methods: A State of the Art on Conventional and Artificial Intelligence Control Techniques

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Received 4 October 2022; Revised 11 January 2024; Accepted 21 March 2024; Published 17 April 2024

Academic Editor: Kamran Iqbal

Due to their inherent ability and environmentally friendly nature, renewable energy sources are the only real option for producing pollution-free energy in the modern era. Solar energy is one of the best possibilities in this family for supplying civilization with the power and energy it needs. Researchers can efficiently boost a PV panel's efficiency by using the maximum power point tracking (MPPT) approach to extract the most power from the panel and send it to the load. The authors of this study examined and surveyed the sequential advancement of solar PV cell research from one decade to the next, and they elaborated on the upcoming trends and behaviours. Many maximum power point tracking algorithms (MPPTs) that are employed in photovoltaic systems (PVSs) that function under both uniform and partial shade situations are structurally summarized in this work. Well-written descriptions of the features of photovoltaic modules are followed by a variety of effective control strategies, including both AI-based and traditional controllers. In addition, appropriate knowledge of the various controllers is essential when the PV system is exposed to partial shade, keeping in mind the different control systems' classifications in this situation. A thorough analysis of several soft computing-based techniques is also included, as well as many classical controller-based PV systems. First, well-developed traditional MPPT methods are used, followed by artificial intelligence-based MPPT approaches. Later, a thorough comparison of the various MPPT-controlling approaches is established. For PV systems operating under partial shade conditions (PSCs), the advantages and disadvantages of the various MPPT techniques are outlined, contrasted, and assessed. Future research directions for MPPT are also being investigated. A collection of several datasets pertaining to various control processes that were gleaned from various research articles has also been presented. Researchers working on PV-based MPPT and those working in the sectors of renewable energy production and environmentally sustainable development would be very interested in the findings of this review study.

1. Introduction

Since the turn of the century, renewable energy sources (REGS) have taken the lead as an energy source. Conventional energy sources cannot meet the energy demand of the civilization and the industrial revolution. More so, these sources create natural contamination, which is hazardous for us. In this scenario, nonconventional energy sources may be a perfect and prominent alternative for the sophistication of human development. So, using nonconventional energy is an important and correct decision in this current century. The three technologies that have been most widely used in recent decades are solar photovoltaic systems, wind turbines, and energy storage systems [1, 2]. The solar PV system takes the main limelight on itself due to its ease of availability in most parts of the world, large irradiance, and least running cost (i.e., maintenance and operating cost). The primary problems researchers face are irregular irradiance and variable atmospheric temperature, two of which are the main input parameters for solar PV modules during implementation. Solar PV module faces drastically lower efficiency under fluctuating weather conditions. To overcome this drawback, maximum power point tracking (MPPT) is an effective and hot technique for researchers to harvest the maximum power from PV panels [3, 4].

Various MPPT methods have been discussed and summarized in [5, 6]. Future research must include a thorough examination and summary of the various MPPT approaches. Irradiance and ambiguous temperature have an impact on the nonlinear behaviour of the output nature from a PV array. Scientists know about this nonlinear behaviour of PV systems from the I-V and P-V curves [7]. To uplift the efficiency of the PV system, detecting maximum PV power (MPPT) is essential and vital under both normal and partial shedding conditions [8, 9]. PV panel installation experiences various surrounding factors such as clouds, tall mansions, and birds, which can create nonuniform shades over the panel. In this circumstance, several peaks take place in P-V curves [10, 11]. These points are known as local maximum power points (LMPPs); furthermore, only one point among these meets the highest point known as the global maximum power point (GMPP) [12, 13].

Numerous research studies have already been carried out to monitor maximum power points (MPPs) in order to get the most power possible from PV panels under constant irradiation levels. Over the past few years, scientists have shared multiple review articles on this subject. Many of these articles elaborated on conventional MPPT techniques such as the Pb&O technique [14–20], incremental conductance method [20–22], constant voltage algorithm (CVA) [23–25], hill climbing algorithm (HCA) [26, 27], and traditional metaheuristic controllers such as the conventional fuzzy logic controller [28–33] and neural network [34]. An adaptive MPPT on PI controller-based parameters optimized through the harmony search (HS) algorithm was introduced in [35]. Easy implementation, simple structure, and rapid convergence made these methods attractive and unique. However, these methods cannot make a disparity between LMPP and GMPP. The superiority and drawbacks of these traditional techniques have been summarized in [36, 37]. To eliminate the disadvantages faced by conventional techniques, researchers are now focusing on artificial-intelligence-based methods along with optimization algorithms to enhance the efficiency of solar PV modules. Soft computing, artificial intelligence (AI), and bioinspired (BI) are some of the most important advanced MPPT technologies that can alleviate some of the issues raised by standard MPPT controllers [38].

The global maximum power point (GMPP) is routinely tracked using metaheuristic optimization techniques when dealing with partial shading issues [39]. Intensive use of an optimization-based method, such as particle swarm optimization (PSO) and artificial bee colony (ABC), has been implemented in the past to increase the efficiency of solar PV panels [40–43]. However, these algorithms do not give superior performance separately. Hybrid metaheuristic algorithms give fruit-bearing results for tracking maximum power in the solar P-V curve to overcome this discrepancy. A novel grasshopper-based FLC system optimization of the solar PV system for handling specific temperature changes as well as irradiance [44], the merger of differential evaluation (DE) and particle swarm algorithm (PSO) [45–47], grey wolf optimizer [48, 49], whale optimization-based MPPT controller [50], genetic algorithm [51], cuckoo search algorithm [52], salp swarm optimization (SSO) [53, 54], and grasshopper optimization (GHO) [55] were introduced for increasing the tracking speed and efficiency of the panel. A detailed survey of the MPPT performance comparing four metaheuristic algorithms has been introduced in [56]. The closest survey of searching MPPT by finding the utmost duty cycle was used in [57]. The tracking efficiency of five separate optimization methods, i.e., PSO, GA, differential evolution (DE), harmonic search (HS), and differential PSO (DPSO), was compared. Choosing the right control parameters for several of these algorithms is crucial to their performance. Making the best choice for the control parameters is a difficult process, especially under changing weather conditions. Some researchers like hybrid MPPT methods for enhanced efficiency, low settling time, and better convergence rate towards maximum power point [50, 58–62]. The hybrid GA-P&O-based MPPT technique was introduced in [63] for minimising the steady-state oscillations in the traditional P&O technique. A new model reference adaptive control (MRAC) is introduced in [64]. The proposed controller's average tracking efficiency is 99.77% and 99.69% under diverse temperature and radiation conditions. The combination of artificial intelligence-based MPPT methods and traditional methods is a hot cake for many researchers. Intelligence control-based methods have strong optimization ability and superior controlling capability. However, researchers are facing some drawbacks of the aforesaid methods that these intelligence-based MPPT methods are suffering from poor real-time performance, low practicality, and high computational complexity. Therefore, MPPT control for a PV system should fully utilise the existing range of control methods to give full play to their individual advantages, growing strengths, and avoiding weaknesses, especially under crucial situations such as PSCs. The authors firmly feel that some improvisation on the intelligence-based MPPT's limitations must be made, and this may be a potential route for future research in this area. Following the abovementioned discussion, it is required to summarise these techniques through one review article. While writing the article, the authors must emphasise that soft computing and artificial intelligence techniques must look into the partial shedding problem. In this paper, chief MPPT techniques are analyzed and segregated based on their enactment. Their good parts are elaborately discussed and differentiated among themselves, mostly in variable atmospheric conditions. The original contributions of the article are summarized as follows:

(1) To elaborate briefly on materialising MPPT techniques considered in a few articles. Many review articles published earlier were deficient in discussing the advantages and weaknesses of various MPPT algorithms. As most of the articles were trying to cover all traditional and updated approaches, it is natural that deep and adequate discussion was not present in them. The concern paper eliminates this drawback efficiently.

(2) To emphasise MPPT algorithms considering the partial shading problem as choosing an efficient technique demands new considerations to ensure that they are well organized and show the best results in typical environmental conditions. AI-based methods can fulfil the problems mentioned above. That is why, the present paper primarily deals with those algorithms.

(3) To establish interfacing between conventional and AI-based modified controllers on solar MPPT so that they easily meet the requirements of researchers.

(4) To overcome the low areas (i.e., wrong real-time performance, low practicality, and excessive computational complexity) and future direction of research in the MPPT field.

The rest of the paper is organized as follows. Section 2 discusses mathematical modelling and characteristics of the solar PV cell. Section 3 concentrates on various MPPT-controlling methods, including conventional and artificial intelligence methods. Section 4 compares various MPPT techniques and modern research, and possible future directions are outlined in Section 5, and last, the gist of the discussion is encapsulated in Section 6.

2. Photovoltaic Module Characteristics

2.1. Under Uniform Irradiance and Atmospheric Condition. The two main variables that directly affect the output power of solar PV panels are sun irradiation and air temperature. To achieve MPPT, new values of those two components will therefore be needed. It is also crucial that the solar cell manufacturer accurately specifies the open circuit voltage (V_{OCN}) and short circuit current (I_{SCN}) values on the datasheet. Notably, a PV module is made up of a number of cells connected in both series and parallel. Series connection is generally used for increasing the voltage level, and the current level is increased by parallel connection. An array of PV cells is framed by several PV panels [65, 66]. Seven parameters are generally helpful in analyzing the PV output characteristics such as open circuit voltage (V_{OCN}) and short circuit current (I_{SCN}) [67, 68]. All these parameters are introduced with their name in Table 1. It is worth mentioning that the solar cell manufacturer provides the datasheet containing the parameters mentioned above and under standard test conditions (STCs), their solar irradiance is maintained at 1000 W/m^2, and the atmospheric temperature is 25 C. In this paper, SOLKAR 36 W is chosen, and different electrical parameters are summarized in Table 1. Without the equivalent circuit model, it is impossible to define the actual characteristics of the PV module. So it is very much needed to design a solar PV cell equivalent circuit illustrated in [14]. The I-V curve is accustomed to knowing about the behaviour of solar PV characteristics.

To increase the output power, the slide of the solar cell is continuously connected either in series or parallel, confirming that all slides in the PV module increase the output power. According to the equivalent circuit of the PV module [7], we have

$$F\left(I_{\mathrm{PVC}}, V_{\mathrm{PV}}, T_{\mathrm{KL}}, G_R\right) = I_{\mathrm{PH\_}C} - I_{\mathrm{PVC}} - I_{\mathrm{DSC}}\left[\exp\left(\frac{q\left(V_{\mathrm{PV}} + I_{\mathrm{PVC}}\right)}{N_{\mathrm{SE}}\,\mathrm{AKT}_K}\right) - 1\right]\frac{V_{\mathrm{PVC}} + I_{\mathrm{PVC}} R_{\mathrm{SE}} N_{\mathrm{SE}}}{R_{\mathrm{PL}} N_{\mathrm{SE}}}, \tag{1}$$

where I_{PVC} is the output current and V_{PVC} is the output voltage of the solar PV panel, I_{PH_C} is the solar photoelectric current, I_{DSC} is the diode saturation current, A is the diode's ideality factor (value lies between 0 and 1), q is the charge of the electron ($q = 1.602 \times 10^{-19}$ C), and K is the Boltzmann constant ($K = 1.380649 \times 10^{-23}$ joule per Kelvin (K)). In the abovementioned equation, R_{PL} is the parallel resistance of the PV panel, which is generally a significant value and often approaches infinity because it has very little influence. R_{SE} is the series resistance of the panel.

A solar PV system typically consists of a variety of PV modules. A structure resembling a thread is created by connecting these in sequence. One peak, known as the maximum power point (MPPT), can be found in both the P-V and I-V curves under typical operating conditions (i.e., homogeneous ambient temperature and constant solar irradiation) [69]. Multiple peaks are seen in the P-V and I-V curves when those two components are not uniform under partial shedding situations, as opposed to the usual operating ambient conditions. The global maximum power point (GMPP) is one of these peaks that displays supremacy, and the other peaks are referred to as local maximum power points (LMPPs) [70–72].

2.2. Partial Shedding Condition (PSC). PV modules are connected in series or parallel mode to increase the system's overall output power and efficiency. A solar PV system incorporated under uniform and nonuniform irradiance is shown in Figure 1. It is crucial and impenetrable to track

Table 1: Parameter specification of SOLKAR 36 W PV module.

Parameter	Variable	Value
Open circuit voltage	V_{OCN}	21.24 (V)
Short circuit current	I_{SCN}	2.55 (A)
The voltage at maximum power	V_{MPPN}	16.56 (V)
Current at maximum power	I_{MPPN}	2.25 (A)
Power at maximum power	P_{MPPN}	37.08 (W)
No. of slide in series	N_{SE}	36
No. of slide in parallel	N_{PA}	1

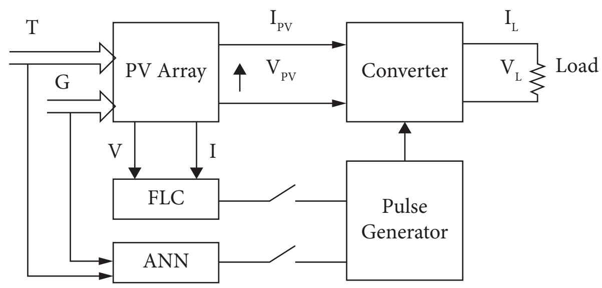

Figure 1: Block diagram of the PV system with the MPPT technique.

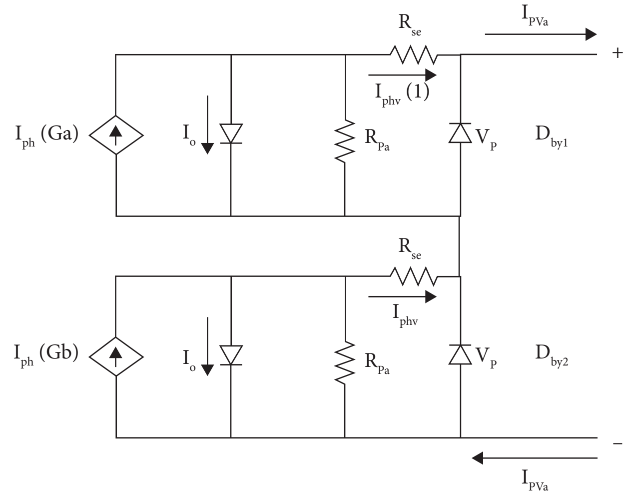

Figure 2: PV array with bypass diode.

maximum power points under shaded and nonuniform solar irradiance [73–78]. The entire PV panel, or perhaps a portion of it, is obscured by the enormous mansion, flying birds, long trees, or occasionally by clouds. In this nonlinear and nonuniform shadowed state, a hotspot emerges in the PV module, which significantly increases the PV string output. In order to mitigate such an issue, the bypass diode is linked with the module. In addition, this setup guarantees the least amount of systemic harm.

Uninterrupted operation in the cell of the PV system, which is under shaded, imprudent reverse biased voltage, can cause the creation of the abovementioned hotspot. As a result, an open circuit condition occurs in the whole PV system, which is another cause for inserting a bypass diode with a prearranged number of cells in series [79, 80]. To defend the PV system during reverse current conditions, the blocking diode may connect at the termination of each series string. Figure 2 shows the PV array along with the bypass and blocking diode. The property of the PV system, along with the bypass diode, is divergent from those without this diode. Under partial shading conditions, the same current does not flow as the bypass diode provides a substitute path for the current to flow. As a result, a number of peaks are created in the P-V curve. Thus, suitable MPPT techniques must be required to choose the global maximum point among these local peaks.

3. Controlling Methods of the Solar PV System

The performance of the many main MPPT algorithms is evaluated and categorised in this paper. Their benefits are described and contrasted with those of other techniques, with an emphasis on partial shade circumstances and nonuniform solar irradiation. Figure 3 classifies the ongoing techniques. They fall under the following three primary groups:

(a) Conventional MPPT methods
(b) MPPT methods based on artificial intelligence
(c) MPPT methods under nonuniform irradiance and temperature

3.1. Conventional MPPT Methods. Further conventional MPPT methods are subdivided into two types: based on parameter selection and straight controlling methods, which depend on sample data.

3.1.1. Methods Based on Parameter Selection. Controlling methods under this section are primarily the constant voltage algorithm, open circuit voltage tracking algorithm, short circuit tracking algorithm, and current scanning method.

The constant voltage algorithm (CVA) is the most straightforward and effortless method based on the hypothesis that a linear correlation is maintained between the open circuit voltage and the voltage of the PV module at a maximum power point [25, 81]. The major drawback of this method is that MPPT cannot be efficiently tracked in lower settling time when there is a substantial atmospheric change in the temperature.

The open circuit voltage tracking algorithm (OCVTA) originates from the open circuit, and in this method, the voltage of the PV module decreases in floating voltage steps and thus senses the varying voltage. The output nature of the maximum power point voltage V_M will change proportionally with open circuit voltage V_{OC} under nonlinear atmospheric conditions. A relation between V_{0C} and V_m can be calculated as

$$V_M = K_a.V_{OC}, \tag{2}$$

where K_a is a proportionality constant, always smaller than 1, because open circuit voltage depends logarithmically on the short circuit current [82, 83]. We can estimate the value of the proportionality constant by detaching the PV module

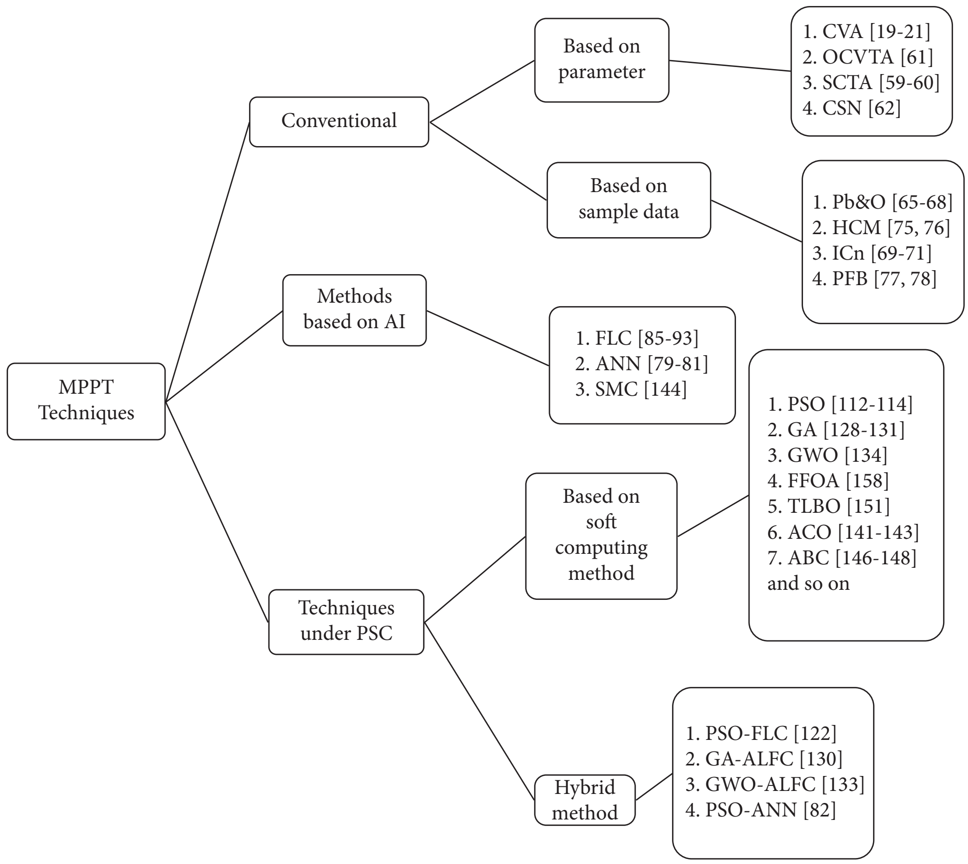

Figure 3: Classification of MPPT methods.

from the load. Some research articles used OCVTA in stubby light irradiance [84].

The short circuit tracking algorithm (SCTA) is another conventional approach where the working principle is almost analogous to the CVA algorithm. The short circuit current of the PV array (I_{SCC}) continuously changes with an uncertain atmosphere, mainly due to irradiance. The PV module's current in maximum power point condition (I_{MAX}) varies directly with short circuit current (I_{SCC}). The following equation can express this relationship:

$$I_{MAX} = K_{SCTA}.I_{SCC,} \tag{3}$$

where K_{SCTA} is a proportional constant whose value is always smaller than 1, which is very lightly affected by temperature [25, 81].

The current scanning method (CSN) is another parameter selection based on the conventional MPPT method. This method suffers from a slower tracking speed than conventional approaches [85].

3.1.2. Straight Controlling Approaches Depending on Sample Data. Implementing such methods is quite easy as these do not follow any model. Due to this, such kind of an approach is quite attractive to researchers. These are sampled data-based approaches which help to track maximum power points. Some methods under this category are perturb and observation (Pb&O) methods, incremental conductance (ICn), hill climbing method (HCM), and power feedback (PFB).

Pb&O is the most popular and extensively used method because this approach does not need any prior knowledge of the system. Voltage is an essential function, as the PV array's output power differs. This method measures little changes in operating voltage; consequently, changes in power (ΔP) are also estimated. If a change in power (ΔP) is positive, an escalation in voltage is also observed to reach MPPT. So change in power error can be quickly scented by a little voltage error. In this algorithm, MPPT can be achieved by constantly tracking the voltage change of the PV array, which is the primary source of output power fluctuation. Due to its uncomplicated structure and easy execution, Pb&O is well-suited for grid connections and standalone systems and can give higher efficiency [86, 87]. This method yields increased efficiency and is ideal for uniform and constant temperature conditions. The output of the system oscillates about MPPT under partial shade, which is undesirable because temperature and irradiance are continually changing. To resolve this Pb&O issue, a minor adjustment has already been made [19, 88–90].

The incremental conductance method (ICn) is another popular approach for finding MPPT, mostly dependent on the solar P-V curve slope [21, 22, 58], [91] maintaining $dp/dv = 0$ and $dI/dP = 0$ [92]. Under changing atmospheric conditions, this algorithm tracks MPPT efficiently. Due to its complex control process, accuracy is hampered sometimes. More so, voltage incremental step size varies directly with tracking error here. To overcome these drawbacks, modified approaches were adopted [93]. In another modified approach, the voltage from the PV array (V_{PV}) and current (I_{PV}) is taken into consideration [94]. So, uncertain atmospheric conditions can be noticed according to PV array voltage and current for reaching MPPT. Compared with traditional ICn, modified methods can efficiently track MPPT with lower settling time and negligible oscillation around MPPT [95].

The Pb&O algorithm is similar to the hill climbing technique (HCM). The MPPT point in the P-V curve may deviate with certain variations in irradiance and temperature. Therefore, this issue can make it difficult for the HC controller to track MPPT. Global MPPT tracking control could therefore go in the incorrect way. A modified adaptive technique was suggested in [96, 97] as a solution. Thus, adaptive HCM can more closely track MPPT than traditional HCM, and power loss is also reduced.

Power feedback (PFB) is another rare tracking method for MPPT. After accumulating output voltage and current from the solar PV array, this method computes output power in both hardware and software. This method is workable and suitable under fluctuating weather conditions but is not dependable. It modifies output voltage depending on the power difference between current and past cycles. The output voltage may differ from the same output power. The operating principle of these approaches is well elaborated in [12, 98].

3.2. MPPT Methods Based on Artificial Intelligence. The behaviour of the P-V curve is not uniform and will fluctuate continuously under changing irradiance and atmospheric temperature. This situation generates several peaks, so the traditional technique cannot track MPP. To overcome this drawback, nowadays, artificial intelligence-based MPPT methods are extensively applied in solar PV systems. Some methods that fall under this category are FLC and ANN.

Artificial neural network (ANN) is one of the popular and simple methods based on biological neural systems [99–102]. A neural network is constructed by interrelated basic units called neurons. Neurons pass information and signal. A neural network generally has three layers: an input layer, an intermediate layer, and an output layer, as shown in Figure 4. Each neuron is connected through synaptic weight with the next layer. Instructions are kept as a set of connection weights. An appropriate training process can achieve proper modification of connection weights. After getting proper training, weights carry essential information, but those are haphazard and meaningless before training. When ANN is implemented in a solar PV system, illumination, short circuit current, and open circuit voltage may be used as input and duty ratio, and the voltage is an output parameter. In modern research, ANN collaborates with other intelligent techniques to get better results. For a reduction in training time, particle swarm optimization (PSO) was incorporated with ANN [103]. A different strategy was presented in [104] to improve control settings and enhance

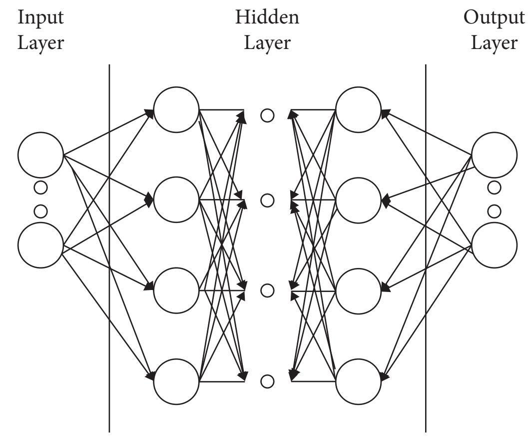

Figure 4: Schematic diagram of an artificial neural network.

output outcomes. In [105], a hybrid approach based on ANN and incremental conductance was presented. The primary objective is to track MPP in a variety of atmospheric situations. Field programmable gate array (FPGA)-based experimental verification was used to replicate the suggested approach and test its viability. When compared to perturbs and the observation approach for partial shade situations, the new method demonstrated its superiority. An artificial neural network (ANN) has the main advantage of not requiring a mathematical function in a physical system model. ANN performs well, but it has a problem with its lack of internal state memory. As a result, it takes a long time to analyze input and cannot process a sequence of data. Due to the long computational time, the ANN method is not suitable for tracking GMPP under changing atmospheric conditions.

Fuzzy logic is the most frequently used artificial intelligence-based technique whose operation is based on a predetermined set of rules [106–109]. FL is the most attractive controller to researchers due to its simplicity, and it does not need prior knowledge about the system [110]. Each decision is based on a degree; approximation values occur despite exact values in the fuzzy logic controller [111, 112]. A classical fuzzy logic-based controller is based on the following three steps: fuzzification, rule interfacing engine, and defuzzification. A simple block diagram of this controller is shown in Figure 5

Based on the controller outline, input variables are generally termed as error "e" and change in error "Δe." In a fuzzy logic-based MPPT controller, input variables can be expressed as

$$e(t) = \frac{\Delta P(t)}{\Delta V(t)} = \frac{P(t) - P(t-1)}{V(t) - V(t-1)}, \tag{4}$$

$$\Delta e(t) = e(t) - e(t-1), \tag{5}$$

where $P(t)$ and $V(t)$ are the PV module's power and voltage, respectively. The work function of the fuzzification block is to convert crisp input data into specific linguistic binary values, which is impossible without the help of the membership function. Although several types of membership

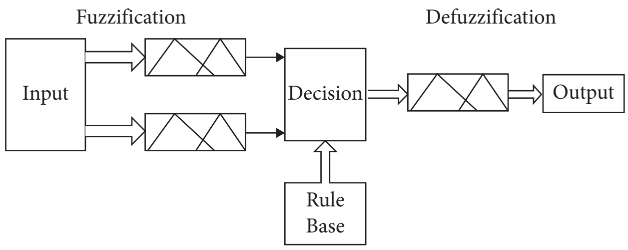

Figure 5: Block diagram of the conventional fuzzy logic controller.

functions such as trapezoidal, triangular, and Gaussian are already used in fuzzification, the triangular membership function is mainly used and popular. Abbreviations such as "NL," "NS," "ZO," "PS," and "PL" given in Table 1 are used as negative large, negative small, positive small, and positive large [113, 114]. As the complexity increases with more membership functions introduced in the fuzzification process, processing time increases comprehensively, but a higher accuracy can be claimed. The rule interface engine is used to control output variables according to the behaviour of the interface engine. Five rule-based interfaces have already been introduced in Table 2. The "If-then" rule concept has been introduced here, which needs knowledge about the system. Another interface method is the "Mamdani" approach which is based on the max-min approach. In the defuzzification process, membership functions are once again converted into a crisp output, that is, a numeric value from a linguistic value. Among the different defuzzification methods such as the center of the area (COA) and the mean of maxima (MOM), the COA approach is more prevalent in application [115].

3.2.1. *Ancient Research on FLC and Their Limitations.*

When the system is highly nonlinear, complex, and has unpredictable model alterations over time, the fuzzy logic controller (FLC) is a dependable technique. The main characteristic of FLC is the integration of specialised knowledge and experience into language rules for system control. Furthermore, FLC exhibits superior dynamic and steady-state performance since it can track the MPPT rapidly and is stable once it is reached. Nevertheless, the primary drawbacks of FLC are its complicated implementation and the possibility of drift due to variations in irradiance. The creation of rule tables, the definition of fuzzy sets, and the form of membership functions all call for greater intuition and experience from designers, which has an immediate impact on the accuracy and speed of tracking. In early works, the authors used [116] fuzzy logic controller in the MPPT system, but the main problem was that its efficiency was compromised under partial shading conditions. Another asymmetrical fuzzy logic controller was introduced by Liu et al. [117]. Their ultimate results give less transient time with 42.8% improvement and higher accuracy with 0.06% than symmetrical FLC. Concerning the abovementioned method, it is worthwhile to say that the FLC controller also suffers from disadvantages such as excessive dependency upon membership function and sound knowledge required on the PV system.

Table 2: Rule base used in FLC controller.

ΔV	ΔP				
	NL	NS	ZO	PS	PL
NL	PL	PS	NL	NS	NS
NS	PS	PS	NL	NS	NS
ZO	NS	NS	NS	PL	PL
PS	NS	PL	PS	NL	PL
PL	NL	NL	PL	PS	PL

Taking into account the drawbacks listed above, several scientists combine optimization techniques with standard fuzzy logic controllers. The fuzzy logic controller is combined by the authors of [118, 119] with the BAT algorithm and the grasshopper algorithm, respectively. To increase system independence, the FLC controller is integrated with various optimization techniques in [117, 120–123], [109]. Another updated fuzzy logic controller [124] uses a single input to cut operation time and complexity.

3.3. *MPPT Methods under Nonuniform Irradiance and Temperature.*

Under partial shading conditions, when the solar irradiance and temperature are not uniform, FLC or artificial neural network alone may not be efficient due to the long settling time and lack of accuracy. Under these circumstances, different soft computing techniques, as mentioned above, have been introduced. These hybrid methods not only improve overall system accuracy but also reduce complexity and give higher efficiency in minimum tracking time. In this section, several optimization methods such as particle swarm optimization (PSO) [125], genetic algorithm (GA) [126],grey wolf optimization (GWO) [127], ant colony optimization (ACO) [128], artificial bee colony optimization (ABC) [129], cuckoo search algorithm (CSA) [130], and teaching learning-based optimization (TLBO) [131], and their implementation on MPPT are discussed.

3.3.1. *Particle Swarm Optimization.*

Particle swarm optimization (PSO) is a robust metaheuristic search-based optimization algorithm introduced by Kennedy and Ebrahat in 1995. Community behaviour of flocking birds and schooling fish is the key to developing this algorithm. Different communal agents are used to interchange their knowledge in this process. Every agent is called a particle, and these particles try to move to their best position found by themselves. Following this procedure, each particle is addressed towards an optimal solution or close to the optimal solution at the end [132, 133].Compared with other optimization algorithms, better class solutions within a shorter period of time can be claimed from PSO [134]. We can obtain the prospective solution by the particle used in this algorithm. With predetermined velocity, each particle flies, which can be managed considering their flying experience. The main steps of this algorithm are described as follows.

(1) Allocation. The population size of the algorithm is initialized in this first step by haphazardly selecting particles that are taking part in the optimization. According to the

quantity of variables, D is creating a solution in dimensional space. From this space solution, particles are selected. When information is missing, particles randomly initialise the first step of the algorithm, and subsequent phases perform the optimization process.

(2) Gesture. The present location (X_l) of every particle acquires a velocity of (V_l), which is essential for finding a superior position compared with the present. The best position (P_{be}) and global best position (G_{be}) of an l-th particle are already introduced, which is achieved from the real solution.

The succeeding position of the particle solution of the conventional algorithm is given in the following equations:

$$\begin{aligned} V_1^{k+1} &= u * V_1^k + m_1 * c_1 * \left(P_{\text{be}} - X_1^k\right) \\ &\quad + m_2 * c_2 * \left(G_{\text{be}} - X_1^k\right), \end{aligned} \tag{6}$$

$$X_1^{k+1} = X_1^k + V_1^k, \tag{7}$$

where i denotes the optimization vector variable, k is the iteration number, V_1^k and X_1^k are the velocity and position of the ith variable for the k th iteration, u is the inertia weight factor, c_1 is an individual coefficient particle, c_2 is a social coefficient particle, and m_1 and m_2 are random variables and the value of these variables lies between 0 and 1.

c_1, c_2, and u values are highly sensitive, as a slight change in this parameter can harshly affect the convergence speed and accuracy of the system. The effect of inertia weight is also not negligible as it has a relation directly with the convergence speed. A slower convergence may be observed if the value of inertia weight is significant.

(3) Judgement. In the modified location, the fitness of the particles is examined and reserved for subsequent iterations. Most OK location $(P_{-}(f))$ is the superior position denoted by the ith particle up to the updated iteration, which is updated if equation (6) is satisfied. The present condition of G_{be} and P_f is expressed as follows:

$$P_f = X_1^k \text{ if } \quad F(x) \geq \mathrm{F}\left(P_f\right), \tag{8}$$

$$G_{\text{be}} = P_f \text{ if } \quad F\left(P_f\right) \geq F\left(G_{\text{be}}\right). \tag{9}$$

Here, PSO is applied to MPPT.

The main aim of PSO is to discover the best particle that carries an optimal global solution in a solar PV system, which is the PV array's global maximum power point (GMPP). Here, output voltage or current may act as a particle and output power is treated as an objective function. The location matrix of particle c can be written as

$$x_l^k = \left[x_1^k, x_2^k, x_3^k, \ldots\ldots\ldots, x_n^k\right], \tag{10}$$

where x_l^k is the position of its h particle in the k th iteration, and the output power oscillates due to a partial shading problem. So, the algorithm must be started if the criteria of equation (11) are fulfilled.

$$\left|\frac{\{F(x_{l+1}) - \mathrm{F}(\mathrm{x}_l)\}}{F(x_l)}\right| > \Delta P. \tag{11}$$

Until convergence occurs, the particle operation continues. The flowchart is shown in Figure 6.

Prior and Modern research work on PSO-based MPPT:

The primary goal of introducing this technique in MPPT is to provide researchers with the small particles discovered via PSO in order to achieve a globally optimal solution. Under nonuniform situations, particularly when there is a partial shading, the controller system becomes stable, inherent, and independent. Numerous research investigations have created PSO-based MPPT [135, 136]. PSO has been incorporated to increase the overall PV module's efficiency and track global maximum power points in the lowest settling time [137]. On the other hand, the performance of PSO is greatly affected by the environment's change and the group's initiation. In modern days, conventional PSO has been improved and modified, incorporating PV systems by many scientists. To improve tracking performance, three different strategies have been developed in PSO [138, 139]. Artificial neural networks are also connected with PSO to increase the tracking speed [103]. Another modified version of PSO in which both global and local mode has been used to find global maximum power point is discussed in [140].

By collaborating the direct duty cycle method with the conventional PSO algorithm, steady-state oscillation has been minimized [141]. In [142], converging speed is improved by a two-step procedure. In the first case, PSO finds the nearest local MPPT; in the later case, global MPPT is reached. Table 3 briefly describes the PSO-based MPPT.

3.3.2. Genetic Algorithm. Genetic algorithm (GA) is yet another potent metaheuristic method for finding a better solution based on biological behaviour. Holland, in 1975, first discovered this algorithm through survival for suitability [143]. By the constant population of genes, chromosomes can be made up and carry either natural or binary formations. The population of chromosomes develops gently over generations in this optimization procedure. The population of chromosomes grows and is modified by generations influenced by GA operators in this computing algorithmic process. Parents have been chosen in every generation, and that helps produce children in succeeding generations. For a better population with time, the objective function is a primary essential factor. The detailed process is represented in Figure 7. The succeeding steps of this algorithm are described as follows.

(1) Start. Objective function setup is a primary vital tool for categorizing candidates' solutions' robustness all over the algorithm process. The objective function is chosen and formed depending on the necessity and complication of the

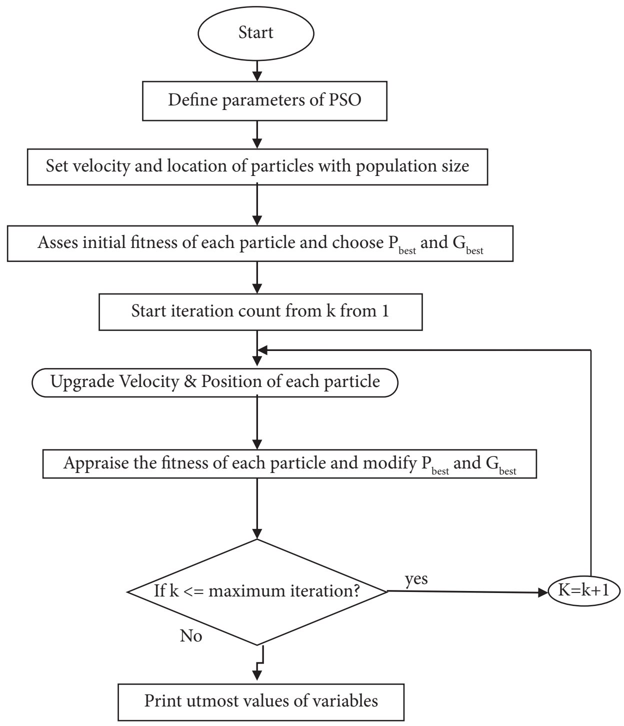

Figure 6: Flowchart of particle swarm optimization.

Table 3: Summarization of PSO-based MPPT.

Algorithm	Reference	Comments
PSO	[135, 136]	Conventional PSO has been incorporated into different solar PV modules
	[137]	To increase efficiency and tracking speed, PSO has been implemented
	[138, 139]	To improve accuracy and to track speed, modified PSO was introduced to the PV system
	[103]	ANN connected with PSO to increase the accuracy and efficiency of the PV system
	[140]	Modified PSO algorithm was introduced in the PV module to find the global MPPT
	[141]	The direct duty cycle method incorporates PSO to reduce oscillation
	[142]	Converging speed of the PV module increased by modified PSO

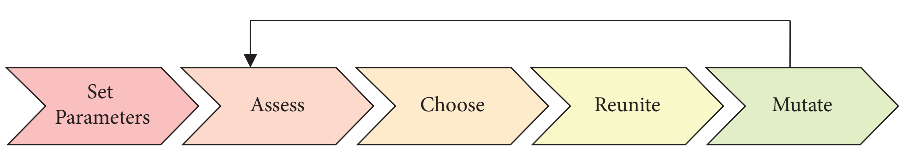

Figure 7: Successive steps of the GA algorithm.

target system. By random picking, the first set of chromosomal populations was selected. The population dimension is a critical factor for the convergence speed of the algorithm. Like all other optimization problems, a vast population size is needed for reducing the converging speed.

(2) Choice of Selection. By selecting the objective function, the fitness values of chromosomes in the beginning population are assessed. Chromosomes are incorporated into the ongoing population, depending on the fitness assessment results. Usually, chromosomes containing more excellent value will have a better chance of being promoted to promotion in the next generation.

(3) Crossover. Two predetermined chromosomes are merged in this step. The conventional crossover process only occurs if genes are in a binary arrangement. As with standard crossover, there are no restrictions on where the crossover points may occur. The only requirement is that the corresponding crossover points on the two parents should "match up semantically." That is, if one parent is being cut on a rule boundary, then the other parent must be cut on a rule boundary. Arbitrary integer number, containing less number of genes in a chromosome, attuned to break parent chromosomes and produce offspring as represented in equation (12) [144, 145]. Considering α is the crossover rate, offspring will be crossed over as discussed. If the genes are

coded with continuous numbers, then the children can be obtained from the following equation:

$$\begin{aligned}\text{Offspring}_a &= \alpha \times \text{parent}_a + (1-\alpha) \times \text{parent}_b,\\ \text{Offspring}_a &= (1-\alpha) \times \text{parent}_a + \alpha \times \text{parent}_b.\end{aligned} \quad (12)$$

(4) Mutation. To get a new solution from the GA, mutation is actually used. Traditional crossover operation does not deliver this solution. The mutation operator haphazardly operates chromosomes with a predetermined rate called mutation rate (β). Mutation obtained the statement for continuous coded chromosomes which are given in equation (13) (146). If the genes are coded in binary format, the mutation process will invert the bit value from random positions. If the genes are coded with continuous numbers, the mutation is performed by using the following equation:

$$\text{Offspring} = \pm \beta. \text{Offspring} + \text{offspring}. \quad (13)$$

This process carries over until a flagship condition occurs. Depending on the complication and demand, flagship conditions may be set. The flowchart is given in Figure 8.

(5) GA-Optimized MPPT. Due to its inherent capability and supremacy, the GA approach has been widely used in nonconventional energy fields. Despite its advantages such as good convergence speed and less oscillation around maximum power point, GA suffers from some disadvantages. This algorithm is not helpful for very long and complex problems. At first, the parent population is shown as

$$X^l = \left[\text{parent}^a.\text{parent}^b \ldots\ldots\ldots.\text{parent}^n\right], \quad (14)$$

where n is the size of the population, and the objective function is defined as the output power of the PV system. The objective function is used to find fitness value in every solution. Due to sudden changes in solar irradiance, atmospheric temperature, and load variation, GA must be reformed in the MPPT application.

(6) Previous and Recent Works. There are not many well-explained works from the ancient age where GA was only utilised in MPPT. The GA technique was used to determine the PV system's overall maximum power point [147]. GA algorithm [148], which was suggested and validated by two different shading patterns, was used to create the MPPT controller. Under various partial shade scenarios, the performance of the conventional perturb and observation approach and the GA-based MPPT controller was examined. These days, GA approaches work in conjunction with other controllers to create systems that have good efficiency and convergence rates when applied to PV modules. The GA method in [121] is used to fine-tune the fuzzy logic controller's parameters. Under nonuniform conditions, this correct hybrid technique outperforms fuzzy logic controllers solely. In [149], GA is used to tune parameters of artificial neural network (ANN) where the PV module has an excellent tracking speed and convergence approach. Table 4 shows a summarized table of genetic algorithm-based solar MPPT systems.

3.3.3. Grey Wolf Optimization. Another population-based soft computing optimization technique was introduced by Mirjali et al. in 2015, which is based on the cooperative behaviour of grey wolves [150]. This algorithm follows the grey wolf's structural guidance and coursing behaviour. Usually, grey wolves consist of small packs and like to live in packs comprising 5–10 wolves. These wolves solely follow a rule of hierarchy which is described in Figure 9.

Wolves are divided into alpha, beta, delta, and omega groups based on the potentiality of hunting. Alpha wolves are the primary king of these packs and can be male or female. Alpha wolves take all critical decisions. All other wolves rigorously follow the orders of alpha wolves. Only alpha wolves can mate in packs. The primary importance in the grey wolf pack is regulation, and organizational hierarchy is maintained compared to their strength. Beta wolves are second in command in the pack. These wolves aid the dominant wolf in making decisions. Beta wolves lead the pack when the alpha wolves are unable to do so due to illness or other circumstances. In that circumstance, beta wolves guide other subordinate wolves while respecting alpha wolves. In the hierarchy pack, delta is at level three, and omega is at level zero. Omega is a ground-level wolf, hence it will follow any orders given by other wolves in the pack. Another remarkable study of these wolves' hunting behaviour follows the following four basic steps.

(1) Communal Hierarchy. Maintaining the hierarchy rule, alpha wolves are given supreme solutions in the pack, followed by the beta-category wolves, and delta-category wolves are treated as the third-best solution providers. The last group, omega, lies in the last position in the hierarchy and always follows the instructions of other wolves.

(2) Enclosing Prey. A primary essential step in this hunting process is the enclosing behaviour of prey for GWO. It can be expressed in the following equations:

$$\vec{L} = |\vec{M}.\vec{X}_{\mathrm{p}}(n)\text{-}\vec{X}(n)|, \quad (15)$$

$$\vec{X}(n+1) = \vec{X}_{\mathrm{p}}(n)\text{-}\vec{N}.\vec{L}, \quad (16)$$

where n is the number of current iterations, X_p and X are the positions of prey and grey wolf separately, and L, M, and N are coefficient vectors further elaborated in the equations as

$$\vec{N} = 2.\vec{a}\,\vec{v}_1\text{-}\vec{a}, \quad (17)$$

$$\vec{M} = 2.\vec{v}_2, \quad (18)$$

where elements of a are proportionately decreased from 2 to 0 across iterations and $v_{1,}$ and v_2 are arbitrary vectors in [0, 1].

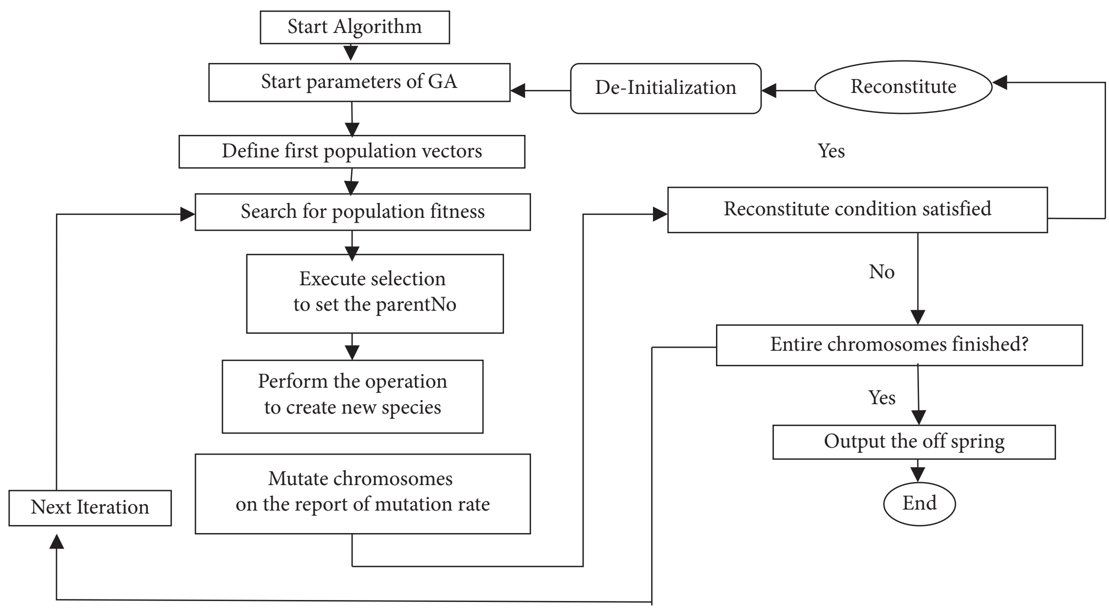

Figure 8: Flowchart of the genetic algorithm.

Table 4: Overview of GA-MPPT.

Algorithm	Reference	Comments
GA	[147]	Simple GA algorithm is used to find the global maximum power point from the PV system
	[148]	GA-optimized MPPT system has been introduced in the partial shading problem
	[121]	GA is used to tune the parameters of the fuzzy logic controller under partial shading conditions
	[149]	GA incorporates neural networks for increasing tracking speed and convergence

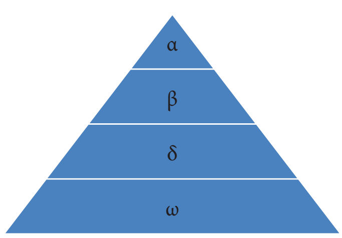

Figure 9: Hierarchy topology of GWO optimization.

(3) Hunting. The hunting process is mainly decided by an alpha wolf, followed by beta and delta wolves. All representative agents renovate their position depending on the best candidate's solution (α, β, δ).

(4) Attacking Prey. When prey stops their movement, the hunting process ends.

The flowchart of the GWO algorithm is well described in Figure 10.

(5) GWO-Based MPPT. The grey wolf optimization technique has already been employed in a number of research studies to fine-tune the MPPT controller for faster tracking speed and stable operation with little oscillation. This method of optimization is employed in [151] to fine-tune the adaptive fuzzy logic controller's parameters. In this work, four new shading patterns have been introduced. The fuzzy logic controller uses the GWO approach to produce the best possible duty cycle for the converter. The GWO approach incorporates MPPT in another study. Engaging grey wolves is used to describe the duty cycle of the converter [152].

3.3.4. Ant Colony Optimization (ACO). Another heuristic algorithm for finding the global best solution was introduced by Dorigo and Gambardella in 1997 based on the scrounging characteristics of real-life ants who are fond of food [128, 153]. ACO is widely used in nonconventional energy sectors [154, 155]. The only part of this algorithm is that it easily copes with uncertain changes, runs vigorously, and gives a high convergence rate bearing new conditions [156, 157]. The flowchart of this algorithm is shown in Figure 11. In [158], the SEPIC converter connects with the solar PV module, and a second-order ACO is used to tune the PI controller. The analysis confirmed that the ACO-tuned PV module results are better than the GA algorithm. ACO was utilised to determine the solar PV module's global maximum power point [159]. The new method outperformed other known heuristic methods in tests conducted under four different partial shade circumstances. Compared with PSO, ACO shows its supremacy due to its high convergence speed independent of the initial conditions. The adaptive fuzzy logic controller parameters were

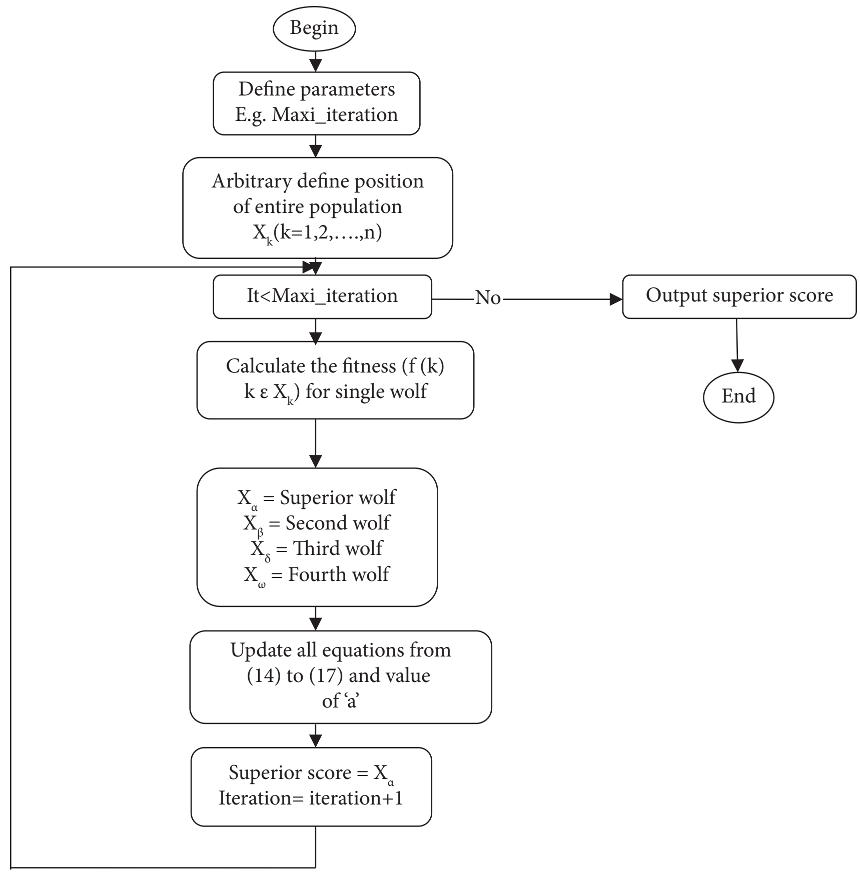

Figure 10: Flowchart of the GWO algorithm.

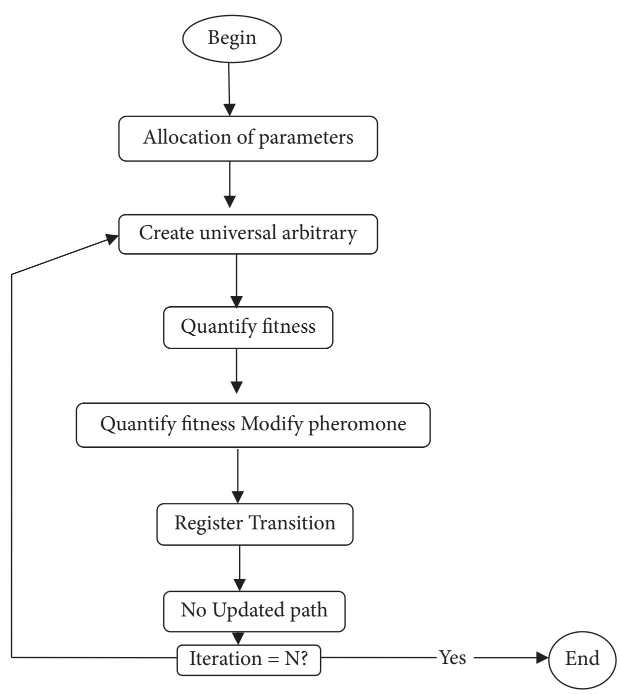

Figure 11: Conventional ant colony algorithm flowchart.

tuned by ACO in [160] to minimize steady-state error. The adequate dynamic performance shows its supremacy even under uncertain atmospheric conditions. Some of the ACO-based MPPT works are summarized in Table 5.

3.3.5. Cuckoo Search Algorithm. The cuckoo search algorithm (CSA), which is based on the reproductive traits of various cuckoo bird genera, is another bioinspired optimization tool [161, 162]. It is a trait of some cuckoo bird species to constantly lay their eggs in another bird's nest. The principal basis of this method is the parasitic reproduction process. Levy's flight procedure is utilised here to search for the step size of the nest. Step sizes are not fixed and are usually large compared to the conventional PSO method in this algorithm. Gradually, its convergence rate is higher when the particles come nearer to MPPT. As mentioned earlier, the step size is variable, successively gets minimal, and comes to zero. CSA is most similar to HC and PB&O from per operational point of view. The CSA-MPPT controller was introduced in [162] and tested under different partial shading conditions. The proposed simulation model showed efficient results compared to PSO and the standard PB&O methods.

3.3.6. Artificial Bee Colony Algorithm (ABC). ABC is a comparatively new approach based on a swarm intelligence algorithm. It was first introduced by Karaboga [129, 163] in 2005. This algorithm is mainly a bioinspired-based method with attractive features, such as a few controlled parameters and independent convergence criteria (i.e., not depending on initial conditions). Artificial bees are mainly divided into three classes: employed bees, onlooker bees, and scout bees. Employed bees are mainly responsible for the collection of food or making most of the foods, whereas onlooker bees stay in hives to determine food sources. Scout bees are generally used for searching for new food sources. All these three types of bees coordinate with each other and work accordingly to find optimal solutions in minimum settling time. In the PV-based MPPT system, the duty cycle is treated as food position and maximum output power as the food source of the ABC algorithm. The flowchart of the ABC algorithm is shown in Figure 12. This is divided into four steps. In the PV-based MPPT system, when researchers introduce ABC, the duty cycle of the DC to DC converter computer is represented as follows:

$$d_c = d_{\mathrm{low}} + \mathrm{rand}[0,1]\left(d_{\mathrm{high}} - d_{\mathrm{low}}\right), \tag{19}$$

$$\mathrm{new}d_c = d_c + \delta_e\left(d_c - d_k\right), \tag{20}$$

where d_c is the current duty cycle, d_{low} is the lower value of the duty cycle, d_{high} is the higher value of the duty cycle, δ_e is a constant whose value lies between −1 and 1, and d_k is the former duty cycle.

(1) ABC-Based MPPT. ABC technique merges with Pb&O to enhance the algorithm's stability [164]. Another hybrid method implements a neural network-based fuzzy controller and the ABC algorithm to optimize the membership function [165]. In [166], scientists put in the ABC algorithm into the solar MPPT system which operates under non-uniform atmospheric conditions and compared its MPPT tracking ability with the PSO-based system. Results show that the ABC-based MPPT system not only gives higher tracking efficiency but also lower oscillation around MPPT.

3.3.7. Firefly Optimization Algorithm. FFOA is quite similar to PSO, which Xin she Yang developed in 2007 to solve different optimization-based problems [108, 168, 169]. Based on the behaviour of the bugs illuminated, this algorithm is developed, and the mathematical model of this algorithm is well described in [170, 171] FFOA requires a minimum parameter tuned compared to PSO and with negligible oscillation. It comes to an optimal solution compared with PSO. Shining light plays the main role in the population-based nature of these bugs, which helps mating partners come closer to bugs. This illumination is a key factor which helps to determine the updated position of bugs [172]. The flowchart of FFOA is well described in Figure 13. If we consider one example where firefly b has higher brightness than firefly a, a new position of a can be defined by the equation as

$$x_a^{t+1} = x_a^t + \beta(d)\left(x_a - \mathrm{x_b}\right)\left(\mathrm{random} - \frac{1}{2}\right), \tag{21}$$

where the parameter of attractiveness can be described in the equation as

$$\beta(d) = \beta_o e^{-\delta(\mathrm{Xpq})n}, \quad n \geq 1; \tag{22}$$

where x_a and x_b are the two positions of fireflies, d is the distance between the two flies, β is an attractive level parameter, and α is the random movement factor whose value lies between 0 and 1. The performance of FFOA incorporated the MPPT method in [173], and it shows supremacy compared with the standard PSO in terms of better tracking speed and accuracy as well as in low oscillation points of concern. A flowchart is given in Figure 13.

3.3.8. Teaching-Learning-Based Optimization (TLBO). Another modern soft computing technique introduced by Rao et al. in 2011 does not need any parameter for its execution. This algorithm was created by the authors with inspiration from the teaching and learning process in the academic world. For this reason, they called it an optimization strategy based on teaching and learning. Nominal parameters such as population size and number of iterations are the only requirements for this algorithm [167]. TLBO is a population-based iterative method comprising two stages: the "learner phase" and the "teaching phase." In the first phase, learners gather knowledge from their teachers; in the last phase, by interacting with each other, learners gain more knowledge. Learners enhance their knowledge in both steps.

(1) Teacher Phase. Teachers are the prominent vital people in this phase. They share their knowledge with each learner

Table 5: Overview of the ACO-based MPPT.

Algorithm	Reference	Comments
ACO	[158]	Second-order ACO algorithm is used to tune the PI controller, which gives better efficiency compared with the GA algorithm
	[159]	ACO is used to find the global maximum power point and the developed method gives a higher convergence rate than PSO
	[160]	Parameters of the adaptive fuzzy controller were tuned by ACO to increase dynamic response and minimize steady-state error

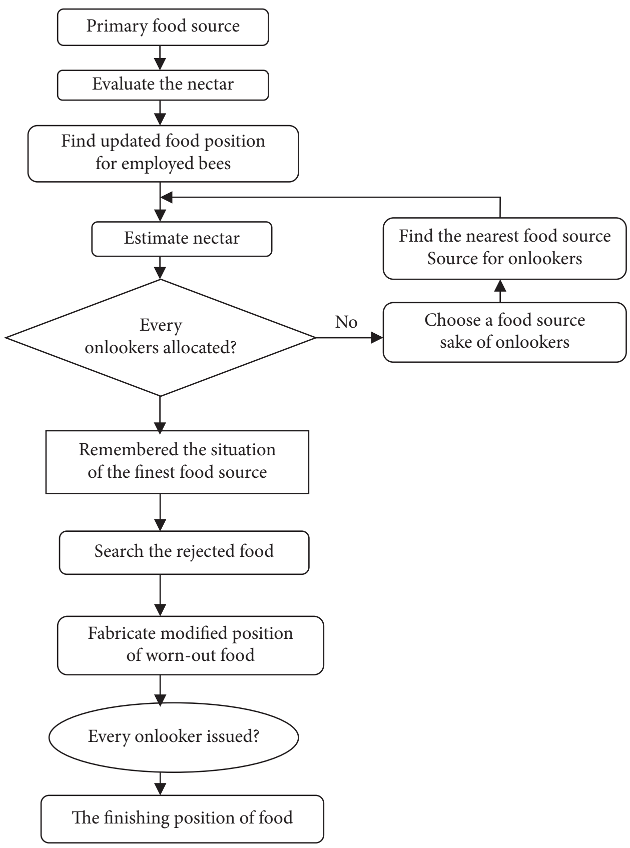

Figure 12: Traditional artificial bee colony algorithm flowchart.

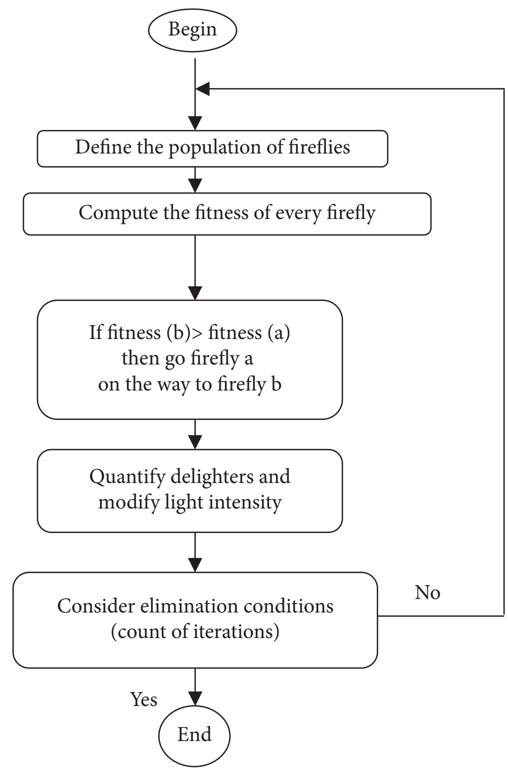

Figure 13: Flowchart of the firefly algorithm.

separately. M_k is the mean, and T_k is the teacher at iteration, k. T_k attempts to uplift M_k towards its level. The solution is updated vigorously, depending on the current and the new mean variance.

A new mean expression is

$$\text{Difference\_Mean}_i = k\left(M_{\text{modified}} - \text{T}_\text{r}\text{M}_{\text{modified}}\right), \quad (23)$$

where T_r is the teaching factor, whereas k is the random number whose value is between 0 and 1, and T_r value is generally either 1 or 2, which can be mathematically represented as

$$T_r = \text{round}\left[1 + \text{random}(0,1)\{2-1\}\right]. \quad (24)$$

Depending upon Difference_Mean$_{i,}$ the current solution is modified as

$$X_{\text{modified},k} = X_{\text{previous},k} + \text{Difference\_Mean}_i. \quad (25)$$

(2) Learner Phase. Despite gathering knowledge from teachers, learners also acquire knowledge by speaking with each other, so their results are also boosted. By random and arbitrary iteration, learners perform their work to enhance knowledge. Mathematical expressions are developed by randomly selecting learned X_p and X_q (where $X_p \neq X_q$). If the accomplished objective function of X_p is less than the accomplished objective function of X_q, then according to (26) and (27), we have

$$X_{\text{modified},k} = X_{\text{previous},k} + k\left(X_p - X_q\right), \quad (26)$$

else

$$X_{\text{modified},k} = X_{\text{previous},k} + k\left(X_q - \text{X}_\text{p}\right). \quad (27)$$

Whenever an updated solution is healthier, it will be considered.

4. Interpretative Comparison

Research articles show the struggling evaluation and differentiation of the best MPPT methods and algorithms. However, researchers always choose the utmost MPPT techniques based on the situation and low complexity. So, the essence of any project and restrictions are crucial aspects of knowledge gathering. More so, haphazard and unpredictable environmental conditions are also essential aspects of measuring the performances of various MPPT-based PV systems. Among all methods, artificial intelligence-based techniques give higher tracking speeds, better convergence with the lowest settling time, and negligible oscillation around MPPT, especially under certain atmospheric changing conditions. The principal point of concern is system independence, efficiency, and high reliability. Considering these factors, the PV-based system is analyzed under both ordinary and partial shading problems elaborated in Table 6. The summary table makes it obvious that ANN and FLC algorithms are unable to track the global maximum point when temperature and irradiance are unpredictable due to fluctuating atmospheric conditions. Though the ANN method is independent of system conditions, its reliability depends mainly on training. That is why, when the array's characteristics change as a result of ageing, its efficiency is likewise impacted. Due to its system independence, simplicity, and moderate convergence rate, FLC-based MPPT technology stands out among most traditional approaches. Three difficult stages raise the computational cost of it. Fuzzy logic controllers' quick tracking, capacity to make decisions, and high efficiency made them the most effective method among all traditional approaches. Thus, this controller is one of the most dependable methods in constant atmospheric conditions and few PSC conditions. Most PSO-dependent methods may be updated versions but are efficient under various PSC conditions. The primary dark side of the PSO algorithm is its complexity, slow tracking speed, and dependency upon initial conditions. Keeping in mind these discrepancies, many researchers have developed modified PSO, and those algorithms can fulfil the demand for a high convergence rate, low oscillation around MPPT, and high efficiency around MPPT.

A comparison of concern for PSC conditions for some MPPT algorithms is also shown in Table 7 [5]. Here, in the concern table, three shading patterns have been taken into consideration and the performance of various MPPT controllers has been compared. Output power, energy production per day, and efficiency are the three parameters considered for choosing supremacy. GA can follow the global MPPT under a variety of atmospheric situations since it has the inherent ability to deal with collective objective functions. System independence, increased efficiency, low tuning requirements, lack of oscillation are the other benefits of GA.

GWO and FFOA are almost similar in characteristics as these algorithms are not system dependent, have high converging speed, and have a superdynamic response with a better efficiency than PSO.

CSA is a bioinspired technique similar to conventional approaches, such as Pb&O and HC. However, it attracts researchers due to its sound characteristics such as high tracking ability under partial shading conditions, best efficiency, and system independence. However, drawbacks are also noticed in this algorithm, such as high complexity algorithm and moderate oscillation around MPPT, which cannot be ignored. Comparing the various techniques, it is worthwhile to write that based on parameters selection, various soft computing-based techniques have their own advantages and certain limitations.

The comparative results of tracking the MPPT using different shedding under PSC are shown in Table 8 [57]. The comparison of several performance indicators in this context, including real output power, measured power, tracking time, and efficiency analysis, directly aids power system engineers and researchers in the relevant field in determining the specific scope of work.

5. Hybrid Methods

Recently, many researchers have implemented hybrid methods to track global maximum power point (GMPP). These techniques overcome the issues faced with conventional AI-based algorithms such as PSO, GA, GWO, and ABC. Major oscillation around GMPP, long settling time, and high overshoot are common problems with conventional techniques which are overcome by various hybrid methods nowadays by researchers.

If the membership functions (MFs) are not chosen correctly, the standard fuzzy logic controller (FLC) may generate some issues. Using swarm approaches, FLC's output parameters and input scaling factors are optimized to enhance the algorithm's performance. Several methods are available for tuning the MFs of fuzzy logic controllers. In [151], Laxman et al. used the GWO method to tune the MFs of FLC. They took four different partial shedding conditions and compared their tracking efficiency with conventional FLC and PO and proved that their implemented hybrid methods were efficient compared to other traditional MPPT techniques even in uncertain weather conditions as well.

In the conventional design of FLC, expert knowledge is required; on the other hand, without such information, design is typically slow and nonoptimized. In [121], Messai et al. introduced a one hybrid approach where MFs of fuzzy logic controllers were tuned by the genetic algorithm (GA). They suggested an FLC-based MPPT design that is more effective for usage in standalone PV systems.

While they are less stable and more fluctuating around the maximum power point (MPPT), conventional MPPT approaches such as perturb and observe (P&O), incremental conductance, and artificial neural network (ANN) are still adequate for tracking the PV systems' maximum power. To overcome the aforementioned drawbacks of the ANN method, Hamdi et al. proposed an innovative method where

Table 6: Comparison of symmetrical soft computing-based MPPT techniques.

Parameter	Pb&O [19, 88–90]	FLC [106–114]	ANN [99–101]	PSO [132–134]	GA [121, 147–149]	GWO [152]/FFOA [173]	TLBO [167]	CSA [162]
System dependency	High	Low	Low	High	Low	Low	No	No
Ability to track under normal conditions	Fast	Fast	Poor	High	High	High	High	High
Ability to track under nonuniform conditions	Slow	Slow	High	High	Average	High	High	High
Efficiency	Poor	Poor	Poor	High	High	High	High	High
Convergence speed	Low	Moderate	Average	Fast	Fast	Medium	High	High
Algorithm difficulty	Simple	Moderate	Simple	Simple	High	Medium	Medium	High
Oscillation around MPPT	Highest	No	No	No	No	No	No	Moderate
Lowest settling time	No	No	No	Average	Moderate	Moderate	High	Moderate

Table 7: Comparison between different MPPT algorithms.

Sl no.	MPPT methods	Output power obtained (W)	Energy produced per day (kWh)	Efficiency (%)
PSC1	Pb&O [19, 88, 89]	74.58	745.8	97.55
	INC [20–22] and [21, 22, 58]	75.08	750.8	98.21
	ABC [129, 163]	76.12	761.2	99.57
	ABC-PO [164]	76.4	764	99.93
PSC2	P&O [19, 88, 89]	36.12	362	84.42
	INC [20–22] and [21, 22, 58]	41.2	412	96.08
	ABC [129, 163]	42.3	423	98.64
	ABC-PO [164]	42.78	427.8	99.77
PSC3	Pb&O [19, 88, 89]	27.04	270.4	90.76
	INC [20–22] & [21, 22, 58]	28.56	285.6	95.87
	ABC [129, 163]	29.12	291.2	97.57
	ABC-PO [164]	29.67	296.7	99.59

Table 8: Comparative study of various MPPT methods under unequal illuminated conditions.

MPPT methods	Real output power obtained (W)	Measured power (W)	Tracking time (s)	Efficiency (%)
Differential particle PSO [103, 138–142]	739	739	0.19	100
PSO [135–137]	739	711	0.24	96.2
GA [143–146]	739	720	0.28	97.4
Harmony search algorithm [35]	739	709	0.24	96.0
Differential evolution [45]	739	645	0.35	87.2

particle swarm optimization (PSO) has been used to optimize the parameters of ANN. This hybrid approach proved its efficiency in real-time comparison through the myRIO-1900 board.

From the abovementioned discussion, it can be worthwhile to say that in modern times, hybrid methods are very efficient for tracking GMPP in solar PV systems. That is why, researchers are now spending a lot of time researching these methods.

6. Modern Research and Future Challenges

Some controlling algorithms yet to be categorized are already applied to PV systems. Segmentation and random search methods are already applied in [174, 175]. These two techniques can naturally track GMPP in challenging circumstances. The Fibonacci linear search algorithm (FLSA) was introduced by Ramaprabha et al. and their particular algorithm has excellent response speed during climate-changing conditions [176]. More so, by this method, power oscillation at a steady state is minimized. Some hybrid methods are also introduced in [81, 156, 177]. These combined methods are well aware of tracking global MPPT under variable atmospheric conditions. To reduce the fuzzy rules without compromising efficiency, Danandeh and Mousavi developed another hybrid technique where the Incremental conductance method and FLC are merged [178]. This system exhibits some fuzzy properties such as high speed and accuracy but just a little amount of nature like incremental conductance techniques with straightforward and affordable implementation. An efficient energy management strategy is introduced by D. Chatterjee et al. in [179].

Nowadays, some modified and newly developed AI-based algorithms have been introduced by scientists such as gravitational search algorithm (GSA), biogeography-based optimization (BBO), krill-herd optimization (KHO), water cycle algorithm (WCA), and harmony search algorithm (HSA). These algorithms are yet to be applied to MPPT-based solar PV systems, and it is worthwhile to say that new approaches may play some optimistic role under partial shading conditions. It is tough to select a particular optimization algorithm because all have advantages and drawbacks. However, depending on controlling parameters, system complexity, steady-state oscillation, and high tracking speed, we can still choose a particular one, which is not an easy task. To minimize cost and complexity during hardware setup, sensorless MPPT may be used.

It is a great challenge to implement the new innovative hybrid concept in real-time experiments. This is a hot cake for the researchers and they are successfully implementing it in most of the cases. Implementing cost and complexity are two major factors during real-time experiments. Researchers are very aware of the cost optimization side and reduction in complexity during real-time implementation. Various agencies, companies, and governments of almost every nation are sanctioning huge funds nowadays for these works because it is well known that sustainable energy resources are the only way to generate power for the next decade.

7. Conclusion

The rapid outgrowth of the civilization along with expanding industrialization forces us to build up our affection towards renewable resources. With modernity, the need for energy has been sharply rising during the past few decades. Excessive use of conventional resources creates huge environmental contamination which can be fatal for the civilization. It is emphasized that the PV system based on MPPT techniques has been a viable topic for the last few decades for researchers, but rapid and more improvement is still needed for accuracy, efficiency enhancement, and less oscillation around the MPPT point of view. This review article briefly describes most of the traditional methods and modern MPPT algorithms based on artificial intelligence strategies. The manuscript expeditiously briefs various techniques that are distinct on their own route but draw attention to their advantages and drawbacks. It is well established from the discussion above that the MPPT method of solar PV systems has been a widespread and energetic topic for researchers over the last few decades. Traditional MPPT methods suffer from drawbacks such as high oscillation around MPPT and inefficiency under partial shading conditions. Both atmospheric conditions (i.e., uniform and variable irradiance and temperature) are considered, and different MPPT approaches, which are convenient under both conditions, are elaborated. Moreover, different concepts, flowcharts, advantages, and drawbacks of each AI-based algorithm are also presented. Each technique's ultimate evaluation is scrutinized based on factors such as convergence rate, efficiency, capability of tracking under uncertain irradiance and temperature, cost, system independence, and oscillation around MPPT. This extensive essay highlights the following potential directions for research in addition to reviewing many contemporary MPPT algorithms.

Since AI-based algorithms have better optimising capabilities and offer better tracking performance, the combination of these algorithms and conventional methodologies still has to be adjusted. However, these methods have some drawbacks, such as little practicality and high complexity in some aspects. Proper modelling of PV systems under variable atmospheric conditions still needs some attention from researchers. Finally, adequate methodization of the MPPT-interpreted indicator still requires improvement. Existing methods for evaluating MPPT performance are based on whether or not the applied algorithm efficiently tracks the MPPT. However, a more informative index is required in this regard. In a nutshell, the authors accomplished that there is a vast range of possibilities for improving hybrid MPPT approaches by employing miscellaneous other intelligent techniques. This review article is expected to meet future research direction for the scientists and engineers interested in working on PV-based MPPT systems.

Data Availability

The data used to support the findings of the study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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