IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 4 February 2023, accepted 16 March 2023, date of publication 28 March 2023, date of current version 3 April 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3262502

SURVEY

Comprehensive Review of Conventional and Emerging Maximum Power Point Tracking Algorithms for Uniformly and Partially Shaded Solar Photovoltaic Systems

MADHAV KUMAR[1], KAIBALYA PRASAD PANDA[2], (Member, IEEE), JULIO CESAR ROSAS-CARO[3], (Senior Member, IEEE), ANTONIO VALDERRABANO-GONZALEZ[3], (Senior Member, IEEE), AND GAYADHAR PANDA[1], (Senior Member, IEEE)

[1]Department of Electrical Engineering, National Institute of Technology Meghalaya, Shillong 793003, India
[2]Department of Electrical Engineering, Pandit Deendayal Energy University, Gandhinagar, Gujarat 3820007, India
[3]Facultad de Ingeniera, Universidad Panamericana, Zapopan, Jalisco 45010, Mexico

Corresponding author: Antonio Valderrabano-Gonzalez (avalder@up.edu.mx)

This work was supported by Universidad Panamericana through the Project ''Estudio de topologías de convertidores de cd-cd'' under Grant UP-CI-2022-GDL-06-ING.

ABSTRACT Renewable energy utilization is the only suitable solution to diminish the increasing level of greenhouse gas emissions, fuel costs, and energy crisis in the next generation. Out of many renewable sources, solar energy sources that are clean, green, and emissions-free have gained wide utilization despite their intermittency nature. Several solar photovoltaic (PV) panels are connected in parallel to achieve the energy demand. In such a system, each panel operates differently due to uneven temperature and irradiation, resulting in a uniform and partial shading conditions. Thus, a unique and efficient mechanism is required to extract maximum power from uniformly and partially shaded PV systems. Many researchers across the world have developed various maximum power point tracking (MPPT) techniques to increase the efficiency and lifetime of PV systems. This study provides a unique, in-depth, and organized review of MPPT methods under four categories: classical, intelligent, optimization, and hybrid techniques. All possible selection benchmarks are considered to do a comprehensive review, which is not deliberated in the existing review literature. Based on the selection benchmarks, the advantages and disadvantages of each MPPT technique under different categories are summarized in tabulated form. To address the research gaps for further investigation in this field, a concise discussion is included at the end. This review article may find an accessible reference for engineers to understand the most useful MPPT method and to undertake extensive research in PV systems.

INDEX TERMS Maximum power point tracking (MPPT) techniques, renewable energy source, solar photovoltaics (PV), partial shading condition (PSC), global maximum power point (GMPP).

I. INTRODUCTION

The conventional generating stations are producing stress on the existing fossil fuel reserves; hence renewable energy sources utilization has attracted significant interest owing to their abundant availability and clean nature. From the installed capacity of various renewable energy sources shown in Figure 1, it is noticeable that solar photovoltaic (PV) is the most prominent source, and the research is increasing day by day towards establishing the solar as a main source of energy to the grid. The Indian government has set an objective to install 500 GW of renewable power by the end

The associate editor coordinating the review of this manuscript and approving it for publication was Sudhakar Babu Thanikanti.

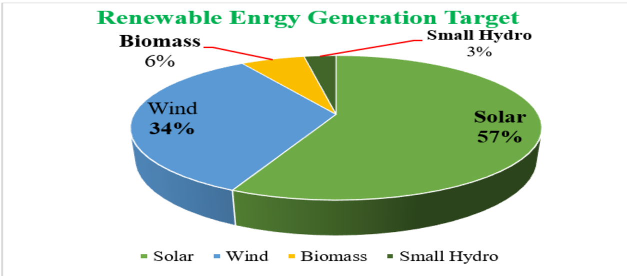

FIGURE 1. In 2022 renewable energy generation target by Indian Government.

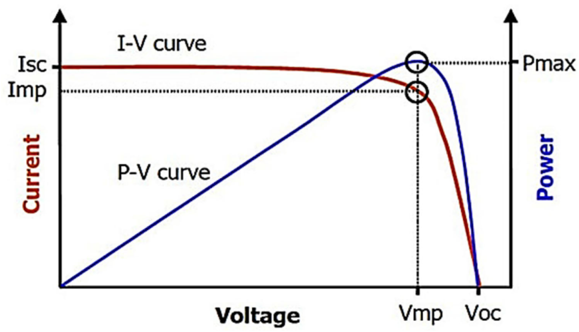

FIGURE 2. P-V and I-V characteristics of PV.

of 2030 [1], [2]. However, the energy generated from renewable sources is subject to different environmental conditions and is not always available. Therefore, the intermittent nature of solar power is a challenging issue.

Also, energy received from solar PV systems is futile; during a high load condition, solar alone may not be able to fulfill the load demand. But renewable energy is the future of electricity generation as renewable energy is the only way to meet the power shortage due to the ever-decreasing sources of fossil fuels and indiscriminate use by people [3].

Solar energy is an excellent renewable energy source. Its presence during the day is a disadvantage, but integrating energy storage systems can address this issue. Another drawback is its low efficiency and not delivering maximum power in variable environmental conditions or partial shading conditions [4]. The maximum power point tracking (MPPT) algorithm is necessary to overcome this. Figure 2 shows a nonlinear PV panel characteristic with maximum power point [5].

Literature manifests many traditional MPPT algorithms to extract maximum power from solar photovoltaic systems and to increase the overall system efficiency [6]. The conventional algorithm gives good performance at standard temperature and irradiance value and can reach maximum power. But in practice, the state of the environment keeps changing, i.e., the temperature and irradiation keep changing [7], [8]. In the case of rapidly changing irradiation conditions, conventional MPPT techniques fail to track the MPP efficiently in less time. Due to this, the performance and efficiency of solar PV systems are greatly reduced [9], [10]. Furthermore, partial

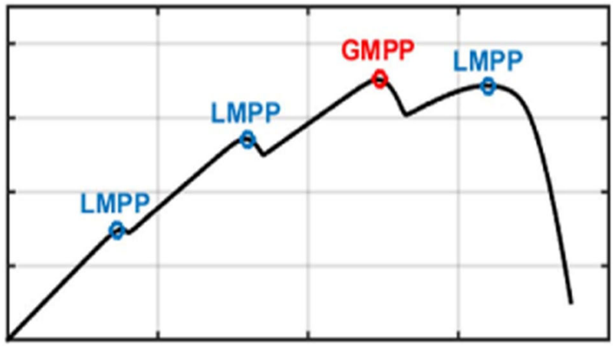

FIGURE 3. Power vs Voltage Curve of PV in Partial Shading Condition.

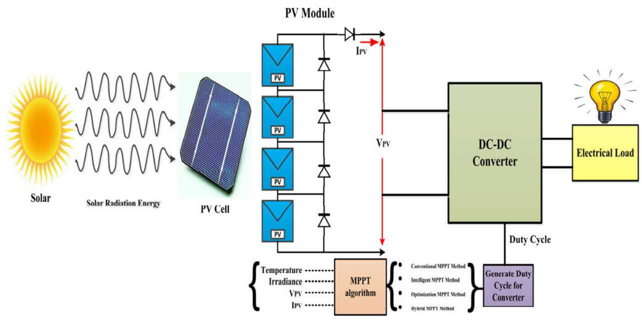

FIGURE 4. The basic structure of MPPT algorithm with boost converter.

shading due to different solar irradiation incidents on different panels creates multiple peak points on a PV characteristic. Under partial shading conditions, more than one maximum point (local MPP) and one global maxima point (global MPP) exist, as shown in Figure 3. The traditional algorithm does not differentiate between a local and global MPP [11], [12]. Due to this, the conventional algorithm starts tracking from the local MPP as the global MPP and the overall performance and efficiency of the system thus degrades.

To address the issues discussed above, researchers across the globe have developed different advanced MPPT methods that have been successful in solving the problem to an extent. However, there is still a research scope for tracking the MPP faster with high accuracy.

In general, the traditional maximum power point tracking algorithm is divided into two categories: online method and offline method, depending on the parameters and values of the requirements. The offline method is essentially a model-based approach. Normally, the control signals are generated based on the physical values of the PV system panel. On the other hand, in online approaches, the control signals are generally obtained from the instantaneous values of the PV output voltage (or) current. Different traditional MPPT techniques reported in literature has distinct benefits and drawbacks and thus selecting one from among the many available strategies might be challenging. Existing review literature compares various MPPT algorithms; however, they can sometimes be difficult to understand [4],

[5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]. There are several parameters and approaches-based methods discussed in the literature, i.e., voltage- and current-based MPPT approaches [21], perturb and observation (P&O) methods [22], [23], incremental conductance (INC) methods [24], [25], [26], temperature and irradiance-based method [27], intelligence techniques base MPPT method [28], [29], fuzzy logic control methods [30], [31], artificial neural network base method [32], [33], [34], optimization techniques base method, etc. [35], [36], [37]. The P&O and INC procedures are well-known traditional techniques with some benefits and drawbacks. Due to oscillations around the MPP, a significant amount of power is lost while using the P&O approach [38]. Additionally, the P&O algorithm responds slowly to rapidly changing environmental conditions, and its dependent on the steps of varying sizes (Δd) [23]. The drawbacks of the P&O and INC methods may be overcome by some other conventional algorithms. Although it seems straightforward, the voltage and current-based MPP tracking algorithm suggested in [21] has low accuracy and efficiency. The Gradient Descent Method, among others, overcomes the shortcomings of the Standard Method by using the Variable Step Size Technique [39], [40], [41]. The ripple correlation control (RCC) and sliding mode control technique is addressed in [42], [43], and [44] and has a few advantages over P&O systems. Although difficult to implement in hardware, but it is more accurate than traditional approaches.Somee conventional or intelligence method required fewer sensors than some traditional approaches. This type of approach is both easy to use and cost-effective [45], [46], [47], [48], [49]. In addition to this, there is some another approach based on Bisection search, Fibonaccian series, steepest decent based MPPT etc., which was described in [16], [17], [18], and [19]. This approach is typically utilized when a PV array exhibits two or more local MPPs under different climatic circumstances, making the employment of other techniques challenging. Also, there some optimization techniques such as Genetic algorithm, partial swarm optimization, Cuckoo search, ant colony optimization, Jaya algorithm is also used for MPPT algorithm are discussed in [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], and [20]. Optimization techniques have also lots of challenges like parameters initializing, parameters tuning, number of iterations, search space, etc. A dual tracking system that consists of an electrical MPPT and a mechanical tracker, both of which are controlled by different controller, is also described by some researchers [50], [51]. But now a day most of the researchers focus towards the hybrid MPPT algorithm by using conventional algorithm along with intelligence or optimization techniques [52], [53], [54], [55], [56]. Several hybrid MPPT algorithms have been in recent trend to overcome the problem with conventional or intelligence techniques. All the algorithms have some advantages and disadvantages in different applications of the PV system. Therefore, a detailed review is carried out in this work that works as a suitable reference material for the engineers. Section II presents all possible selection benchmarks such as sensor type, efficiency, tracking speed, complexity, convergence speed, and implementation cost considered to make a comprehensive review, which is not deliberated in existing review literatures. Based on the selection benchmarks, the advantage, and disadvantages of each MPPT techniques under four different categories such as, classical, intelligent, optimization and hybrid techniques are summarized in Section III to VI. Section VII delineates an overall summary of different techniques and concluding remarks are given in Section VIII.

II. MPPT TECHNIQUES

The maximum power point tracking (MPPT) algorithm is implemented for extracting the maximum possible power from the Photovoltaic system and providing it to the load. Environmental factors, such as solar irradiance and temperature, also have an impact on the solar photovoltaic system. PV's maximum power point shifts as a result of changes in the surrounding environment. This means that the ideal operating voltage and current for the PV module will vary depending on the specific conditions [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20].

A. CHALLENGES OF MPPT ALGORITHMS

The MPPT algorithm's efficiency is hampered by several issues. Due of these issues, it is becoming increasingly difficult to determine whether the MPPT algorithm is the best option available. If the algorithm designers fail to account for these changes, a given working condition may fail. One can deduce that the most typical obstacles are the nonlinearity of PV features, variations in ambient conditions, and system functioning conditions [52], [53], [54], [55], [56], [57], [58], [59], [161], [162].

- Nonlinearity of the PV Characteristic
- Ambient Condition Variation
- System Working Condition

B. SELECTION CRITERIA OF MPPT ALGORITHMS

It is necessary to analyze several parameters before choosing an MPP algorithm for real-time implementation. Here we discuss a few crucial variables [63].

Location: - When choosing the MPP algorithm, location is one of the crucial and important term. Were your solar MPPT algorithms successfully implemented, considering how completely dependent solar power is on the environment? What are the weather conditions in the area? In that location, how much partial shading is feasible? Particulate matter? Before installing solar photovoltaic systems, you should consider the following issues, among others.

- ➢ **PV array dependency: -** Some traditional and sophisticated MPP algorithm depends on PV arrays. So, it is difficult to detect the MPP without knowing the details

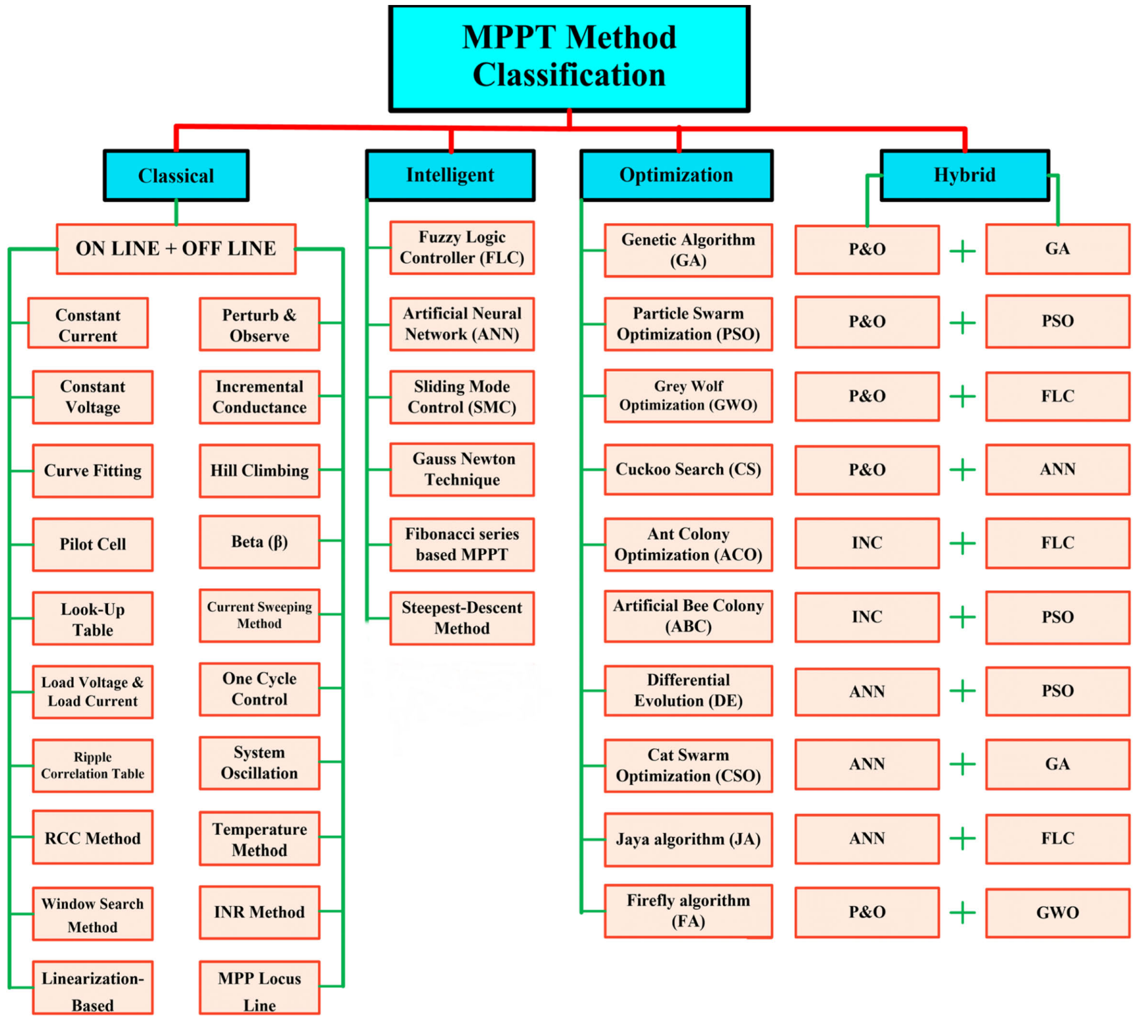

FIGURE 5. Classification of different types of MPPT method.

of the PV array and its configuration. PV modelling and a profound understanding of PV panels are necessary for this.

- **True MPPT: -** The partial shading situation changes the traditional properties of PV. In that case, P-V curves generate the multiple peaks, so it is curious for the MPP algorithm to track the global MPP.
- **Analog or digital: -** MPPT can be applied using both analogue and digital control. Analogue or digital circuits have been used by many researchers to implement the MPPT algorithm in real time. It's possible that analogue methods are less accurate but less expensive, whereas digital methods are expensive and accurate. Consequently, when choosing the best MPPT schemes, this parameter is essential.
- **Sense parameters: -** Voltage, current, temperature, and irradiance are the four main variables used to design the MPPT algorithms for solar photovoltaic systems. In general, adding more sensors makes systems more complex and expensive. Thus, tracking the MPP points typically involves two sensors.
- **Design complexity: -** Systems' overall accuracy depends on the MPP algorithm designs. Common MPPT algorithms are typically less complex in nature, but they are also less effective under partial shading conditions. Additionally, it increases the oscillation and ripple around the MPP point. Thus, in general, algorithms become more complex as a means of increasing their effectiveness and overcoming the limitations of traditional MPP algorithms.
- **Tracking accuracy: -** The efficiency of your algorithms is reflected in their accuracy. Most conventional algorithms have fixed step sizes, so once they reach the MPP, they oscillate around it. MPP algorithms based on a variable step size were used to solve these problems.
- **Tracking speed: -** Time required to reach the MPP points illustrates how well your algorithms tracking speed. When the environment is rapidly changing,

these are the most crucial factors. If algorithms are taking longer to reach the MPP and the environment is changing in between, MPPT algorithms will not arrive at the MPP. Many traditional algorithms lack the ability to follow the MPPT in quickly changing environmental conditions. To solve these issues in that situation, hybrid MPPT algorithms are a better option.

- ➢ **Efficiency: -** Efficiency is a direct indicator of the precision and accuracy of your algorithms. Most of the algorithm efficiency is high under normal circumstances or fixed surrounding condition. However, the environment is constantly changing. so, it is important to understanding the algorithm efficiency in real time.
- ➢ **Efficient in PCS: -** Most algorithms are effective under normal temperature and irradiance conditions, but under partial shading, they are unable to reach the MPP. No clear distinction can be made between local and global MPP. Design hybrid and intelligent MPPT algorithms to address these issues. But most of the time, this kind of algorithm is complex.
- ➢ **Economy: -** Cost is a significant consideration when electing the MPP algorithm. Therefore, cost analysis is necessary prior to selecting the MPP algorithms.

C. CLASSIFICATION OF MPPT TECHNIQUES

In the past several years, numerous MPPT algorithms and designs have been put up in the scientific community for consideration. You cannot use the same technique to every problem. No single evaluation study can categories procedures because each one can be used in a variety of contexts. As a result, there is no single MPPT algorithm classification. Tracking, sensor implementation, and contemporary MPPT algorithms are all considered in this work. There are various subcategories depending on different aspects under each of these classes, such as the operating concept or implementation [5], [6], [7], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [52], [53], [54], [55], [56], [57], [58], [59].

- Conventional MPPT Method
- Intelligent Techniques Based MPPT Method
- Optimization Techniques Based MPPT Method
- Hybrid MPPT Method

III. CONVENTIONAL MPPT TECHNIQUES

From its inception in 1954 onward, research into improving the efficiency and effectiveness of photovoltaic (PV) systems has focused on identifying and maintaining the maximum Power Point. Mechanical single- and dual-access trackers, as well as electrical trackers, are the two main categories of MPP trackers. With the help of a mechanical "sun tracker," the PV model can be steered towards the direction of the sun. However, this type has low efficiency, is difficult to execute, and is expensive. Because of this, all efforts on the part of scientists have focused on electrical tracking. Electrical MPPT methods can be classified into three families: offline, online, and intelligence. Traditional MPPT methods can be roughly categorized as either online or offline approaches. It is Bsicly simplest and easy MPPT algorithm. The fundamental steps are followed by the maximal conventional MPPT algorithm to arrive at the MPP point. They calculate the power and compare it to the previous power at each stage. Depending on the value of the power change, he decided the algorithm's direction or movement. Numerous conventional MPPT algorithms have already been released. Each algorithm has various benefits and drawbacks, however in the case of partial shading, the conventional technique is ineffective or not capable to extract the most power possible in that situation. This section contains information on numerous conventional MPPT algorithm types, flowcharts, extra features, advantages, and disadvantages of each method under various conditions. also provided a brief explanation regarding real time implementation [6], [8], [10], [12].

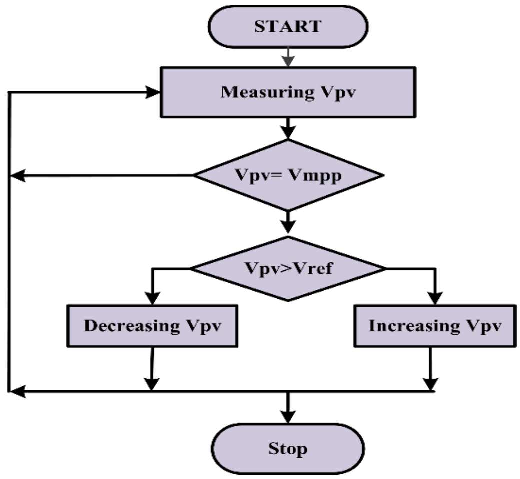

FIGURE 6. Flow chart of constant voltage method.

A. CONSTANT VOLTAGE METHOD

The CV technique is one of the simplest methods for controlling a PV system's maximum power point voltage (MPPT) using a reference voltage (V_{ref}) or a value determined under particular conditions. Consequently, the reference voltage may be calculated without the requirement for extra input and the PV module's output voltage can be used as the reference voltage. Temperature and solar radiation affect the MPP of a PV module. As a result, the CV technique cannot reliably track the MPP since it employs a fixed reference voltage for certain radiation and temperature circumstances. Figure 6. displays the flowchart for the CV approach. In order to track the maximum power point, it is necessary to compare the current PV module voltage to the reference voltage [60].

B. CONSTANT CURRENT METHOD

The CC (Constant Current) strategy is dependent on the CV technique's analogous miracle in order to function correctly. The photovoltaic array operates at a constant voltage when using the CV technique, but the array operates at a steady

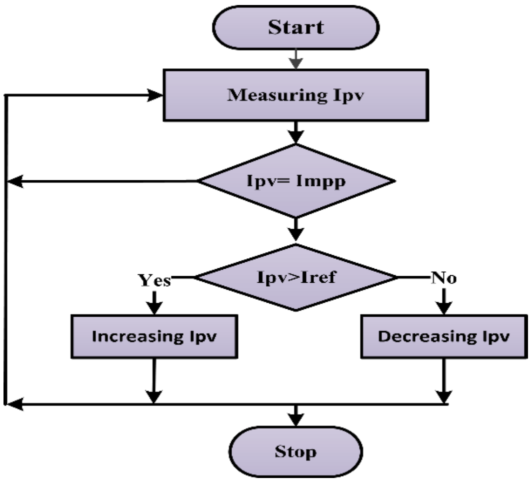

FIGURE 7. Flow chart of constant current method.

current when utilizing this strategy. The MPP encompasses about 78 and 92 percent of the SCC and ISC respectively. As a result, the SCC parameter is identified as the one that was detected using this method [60], [61].

C. BETA METHOD

Jain and Agarwal proposed the beta method theory [62], in which the coefficient beta (β) is produced from equation (1) to find an intermediary value between voltage and current in order to determine the MPP. It is generally agreed that the beta approach is one of the more rapid tracking methods. The variable coefficient, often known as beta, is utilized in this method to carry out MPP. Beta is determined through the utilization of a reference and a closed loop control, in addition to the measurement of the PV panel's voltage and current.

$$\beta = \text{In}\,(\text{Io} \times \text{C}) = \text{In}\left(\frac{\text{Ipv}}{\text{Vpv}}\right) - \text{C} \times V_{PV} \tag{1}$$

The method is utilized in conjunction with any normal MPPT method, such as P&O, INC, HC, etc., for improved efficiency and faster MPP tracking. You begin by looking into MPPT techniques in the algorithm. As a result of both uniform and non- uniform solar radiation, The PV array/VPV module's and IPV values are measured in a Retrospective. In order to determine whether or not is in a steady state, the following equation is used: When reaches a steady state, the MPPT method that has been in use for decades is used. It is also possible to utilize equation (2) to regulate the duty cycle if is not in steady-state or is not in its usual range. The assessment method is then repeated for calculating.

$$\text{Error} = \beta_{\min} - \beta_{\max} \tag{2}$$

When used in conjunction with other standard MPPT approaches, the beta method is regarded as a good and trustworthy optimization alternative for tracking the MPP. The most significant limitation of this method is that its execution and coordination, in terms of determining the beta value, require a great deal of attention to detail. Additionally, the technique is made more difficult by the fact that its traceability with V_{PV} and I_{PV} in order to follow the MPP [63].

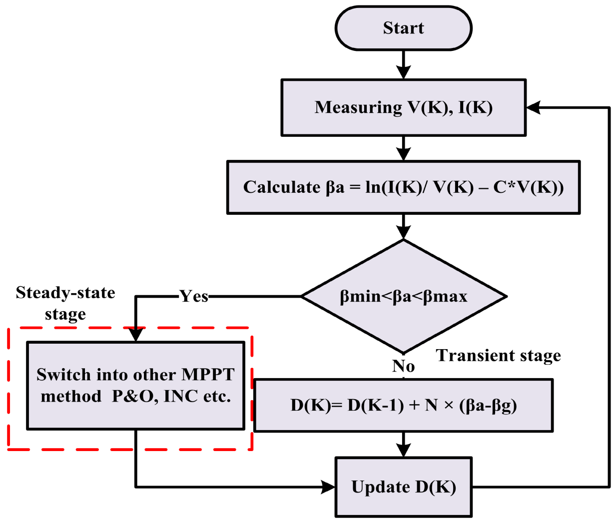

FIGURE 8. Flow chart of beta algorithm.

D. CURVE FITTING METHOD

The curve-fitting approach is an offline method that requires knowledge of PV module features, including production information, data, and equations that describe the output characteristics. Equation (3) describes the characteristics of a PV module. Coefficients a, b, c, and d are derived from sampling m values of the PV voltage (VPV), PV current (IPV), and PV output power P PV. After calculating these coefficients, equation can be used to determine the voltage at which power is at its peak [64].

$$\text{P}_{\text{PV}} = \text{aV}_{\text{PV}}^3 + \text{bV}_{\text{PV}}^2 + \text{cV}_{\text{PV}} + \text{d} \tag{3}$$

At maximum power point,

$$\text{dP}_{\text{PV}} / \text{dV}_{\text{PV}} = 0$$

This approach has the benefit of being straightforward. The disadvantage is that precise prior knowledge of physical properties is needed. Large memory is needed since there are more computations to be made and the speed is slower [65].

E. PILOT CELL METHOD

Pilot cell technology has emerged to address the issue of energy wastage that might occur when using a constant voltage measurement approach. So that we don't have to take measurements from the supply panel, we utilize an approximation between a solar panel's open circuit voltage and the voltage at its highest power point to perform this measurement [66].

$$\text{V}_{\text{mpp}} = \text{K}_0 \times \text{V}_{\text{oc\_cell}} \tag{4}$$

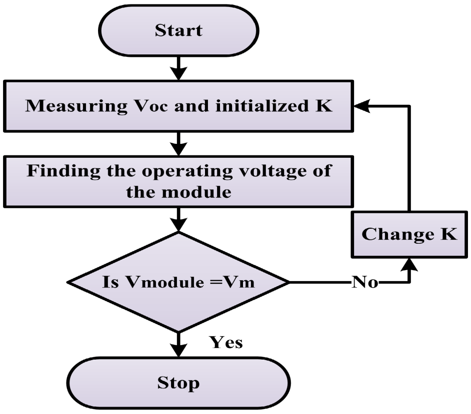

FIGURE 9. Flow chart for the open-circuit voltage approach.

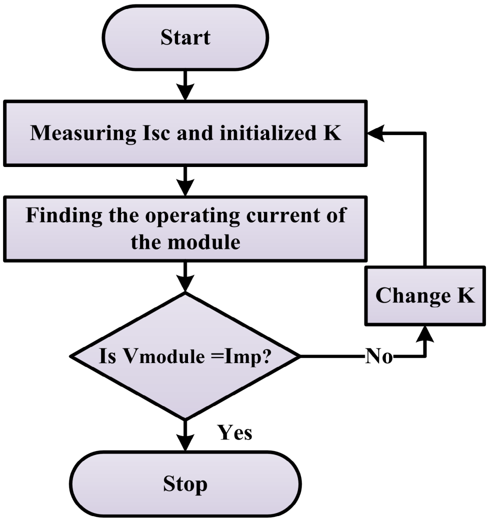

FIGURE 10. Short-circuit current technique flow chart.

F. LOOK-UP TABLE METHOD

In order to identify the MPP using this method, previous information on the PV panel material, technical information, and panel features under a variety of natural settings is necessary and preserved. At each cycle, the controller will impose a new voltage V_{MPP} based on the correlation between the deliberate temperature and insolation estimations and the data that is recorded in the look-up table. The look-up table is compiled using either the manufacturer's specs or the results of exploratory testing performed on the PV system in a variety of different environmental settings. The storing of look-up tables might take up a significant amount of memory when using this approach, which is a drawback [67], [68].

G. FRACTIONAL OPEN-CIRCUIT VOLTAGE TECHNIQUE

The maximum power from any PV system is obtained at point P (V_{MP}, I_{MP}) is called MPP point. The power of any photovoltaic system depends on its environmental conditions at that time. Maximum power will always come at a fixed voltage and current value for a fixed environmental condition

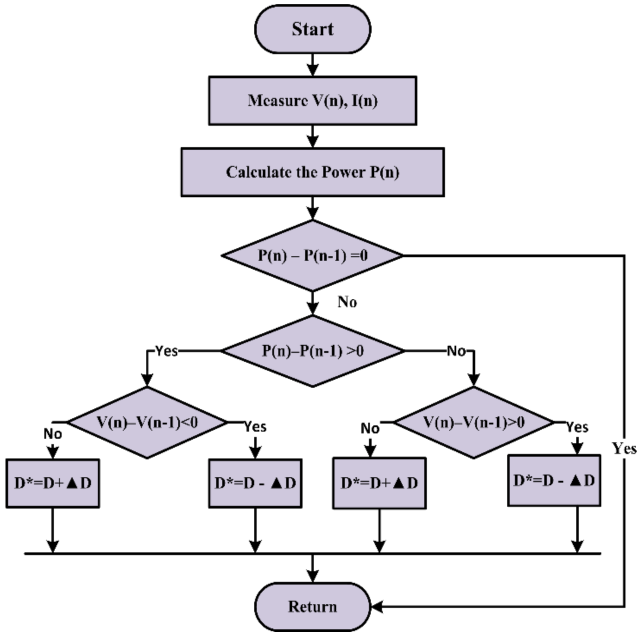

FIGURE 11. Flowchart of P&O based MPPT algorithm.

[69]. The open-circuit voltage techniques are dependent on open-circuit voltage and multiplying factor K. The flow chart of open-circuit voltage techniques is shown in Figure 9 [70].

$$V_{mpp} \approx K_{oc} * V_{oc} \tag{5}$$

H. FRACTIONAL SHORT-CIRCUIT CURRENT TECHNIQUE

Any photovoltaic system that generates maximum power at a given voltage and current value, this point is called the maximum power point for that photovoltaic system for that environment. short-circuit current techniques depend on short circuit current and multiplying factor K. the flow chart of short-circuit current techniques is shown in Figure 10 [71].

There,

$$I_{mpp} \approx K_{sc} * I_{sc} \tag{6}$$

The short-circuit current technique is built using equation (6). The value of K_{sc} typically ranges from 0.64 to 0.85. can be approximated by looking at the PV system under a variety of solar radiation and temperature conditions [71].

I. PERTURBATION AND OBSERVATION (P&O) TECHNIQUE

For the purpose of tracking the maximum power point, a perturb and observe (P&O) based MPPT algorithm is utilized. Due to its simple implementation, high reliability, and good tracking efficiency on standard conditions. 2. This technique involves comparing recent power output samples to those taken at various points in the past. i.e., $P_{Present} - P_{Previous} = \Delta P$. If ($\Delta P>0$). if the operation is in progress and a perturbation occurs, it will continue; if not, it will reverse course. The P&O MPPT algorithm constantly adjusts the size of the perturbation at predetermined intervals. The output from the previous system state is used as a basis [72]. As can be seen in

Figure 11, a typical flowchart for the P&O MPPT algorithm is presented.

In order to determine the variation in PV voltage and PV power (P_{PV}), the P&O algorithm continuously monitors the PV module's voltage (V_{PV}), current (I_{PV}). Calculated values are used by the algorithm to incrementally increase or decrease the converter's duty cycle (d) value by the given perturb value (d=0.01).

In the subsequent perturbation, the duty cycle is increased, ($d = d+\Delta d$) if, $\Delta P_{PV}> 0$ and $\Delta V_{PV}> 0$ or $\Delta P_{PV}< 0$ and $\Delta V_{PV}< 0$, because of a shift in the duty cycle of the previous perturbations.

In the subsequent disturbance, the duty cycle is reduced, ($d = d-\Delta d$) if, $\Delta P> 0$ and $\Delta V_{PV}< 0$ or $\Delta P_{PV}< 0$ and $\Delta V_{PV}> 0$, because of the shift in duty cycle during the previous perturbations.

As stated before, the algorithm will keep repeating this process until the MPPT is reached.

i.e.,

$$\Delta P_{PV}= 0 \text{ and } \Delta V_{PV}= 0$$

This is because the algorithm will fail to satisfy the preceding condition if the duty cycle value is allowed to fluctuate at each perturbation step. That's why the P&O algorithm gyrate around the MPP. The P-V curve's slope is used in this technique. Assuming the system is operating at the MPP, the algorithm works under the assumption that the slope of the power and voltage curve is close to zero [73], [74].

J. INCREMENTAL CONDUCTANCE TECHNIQUE

The incremental conductance algorithm is based on the slop of the power voltage curves. At MPP, the solution of equation (7) is zero, if the solution is positive then MPP point is on the left side, and the solution is negative the MPP point is on the right. The flow chart of incremental conductance methods is given in Figure 12.

$$\frac{\mathrm{dP}}{\mathrm{dV}} = \frac{\mathrm{d(IV)}}{\mathrm{dV}} = \mathrm{I} + \mathrm{V}\frac{\mathrm{dI}}{\mathrm{dV}} = \mathrm{I} + \mathrm{V}\frac{\Delta \mathrm{I}}{\Delta V} \tag{7}$$

The incremental conductance technique works by monitoring and comparing the PV module's incremental and instantaneous conductance to calculate the PV module's terminal voltage. The maximum power point is reached when the incremental conductance matches the instantaneous conductance. The power curve has a positive slope, and output power rises as the PV module's terminal voltage rises within working limits. The output power declines when the terminal voltage of the PV modules climbs beyond MPP, and the power curve's slope is negative [74].

When point is on MPP point then,

$$\frac{\Delta \mathrm{I}}{\Delta \mathrm{V}} = -\frac{\mathrm{I}}{\mathrm{V}}$$

When the point is on the left side of the MPP point then,

$$\frac{\Delta \mathrm{I}}{\Delta V} > -\frac{\mathrm{I}}{\mathrm{V}}$$

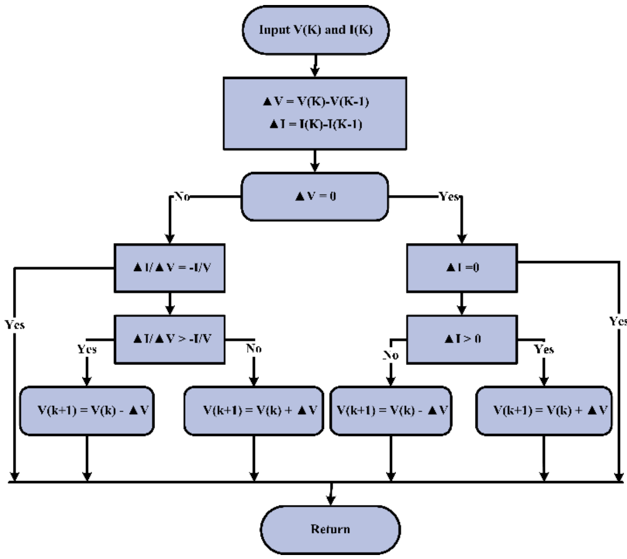

FIGURE 12. Flow chart of incremental conductance method.

When the point MPP is to the right of the point, then

$$\frac{\Delta \mathrm{I}}{\Delta V} < -\frac{\mathrm{I}}{\mathrm{V}}$$

The MPP may be determined by making a comparison between the instantaneous conductance and the incremental conductance. It operates at the same level of efficiency as P&O and still manages to produce a satisfactory harvest despite the unpredictable weather. The same problem with the amount of the perturbation happens here as it did with the P&O, and an attempt has been made to overcome it by making the step size flexible. On the other hand, it requires control circuits that are both intricate and costly [75].

K. HILL CLIMBING METHOD

There is only one difference between the Hill climbing (HC) and P&O methods, and that is the parameter of the perturbation. In order to track the MPP, P&O sense and disrupt the voltage or current, while the HC perturbs the duty cycle. The trade-off in performance between steady-state and dynamic response error is a difficulty that both techniques face. This is a bigger issue for the HC approach, which controls instead of voltage. The hill climbing technique is widely used in real-world PV systems because it is easy to implement, takes into account characteristics drift due to ageing, shading, and other operational anomalies, and does not necessitate research or modelling of the source characteristics. Flow chart of hill climbing method is shown in Figure 13. A PV array voltage V_k and current I_k measurement is the first step in this process. The generated power Pk can be calculated and compared to the value calculated in the previous iteration, thereby allowing for a more accurate model. The duty cycle of the PWM output is adjusted in accordance with the comparison's outcome, which can either complement or leave unchanged the "slop" indication. While the set step size is an varies with initial design, it does not guarantee that voltage

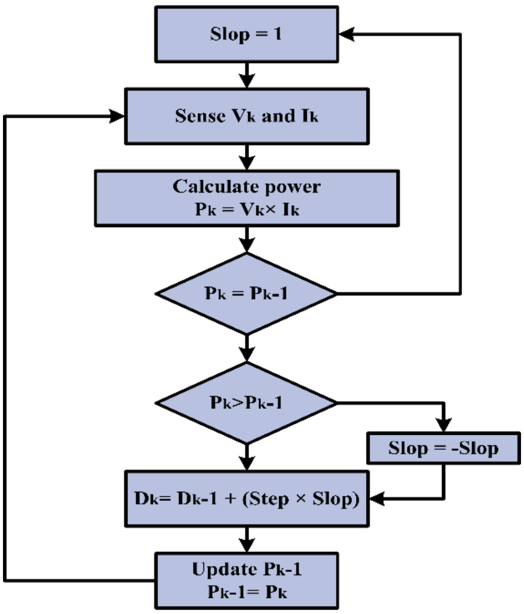

FIGURE 13. Flow chart of Hill climbing method.

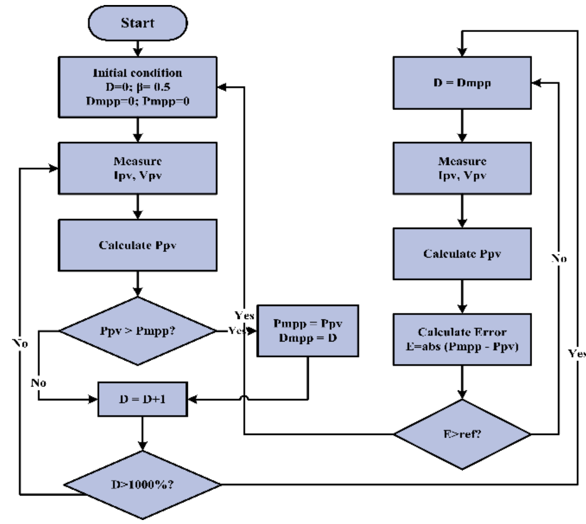

FIGURE 14. Flow chart of curve sweeping based MPPT method.

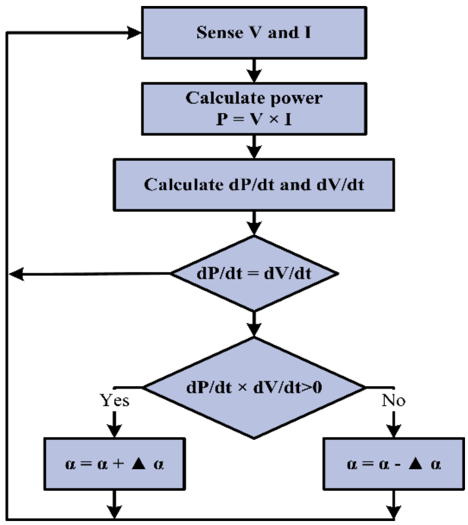

FIGURE 15. Flow chart of RCC based MPPT method.

will remain constant throughout the procedure. Because the classic HC technique has a constant duty cycle, it is unable to accurately track the MPP when the weather shifts [76].

L. CURRENT SWEEPING METHOD

The I-V characteristic curve is created by employing a sweep waveform for the PV array current in the current sweep method. This approach is named after its namesake, the current sweep. Therefore, in order to periodically update the I-V curve, the sweep is repeated at predetermined time intervals, and the VMPP voltage can be calculated based on this information. Contains all the information necessary to understand the process of determining the I-V curve and selecting the function that will be used for the sweep waveform. The genuine MPP can be attained in this manner. On the other hand, the sweep lasts for a certain amount of time, during which the operating point is not the MPP. This results in a reduction in the amount of power that is available. Since MPP is continuously changing in response to irradiation, it is not possible to completely track MPP values while considering irradiation slopes. Under the stipulation that the sweep is completed in a millisecond, it is possible to locate the global MPP. In addition to this, the convergence speed is sluggish, the implementation complexity is large, and it is necessary to measure both voltage and current. According to what is stated in [77], the MPPT approach is only worthwhile to implement if the gain in power that it contributes to an all-PV system is less than the amount of additional power that it consumes. This MPPT technique is not the ideal choice to monitor the MPP in a continuous manner as a result of the limitations and complexities that were discussed previously. Nevertheless, it is useful in that it can be utilized in conjunction with other approaches.

M. CURVE SWEEPING METHOD

The PV module's current and voltage must be sensed in order to sweep the entire I-V and P-V characteristics using the curve sweeping approach. Once the irradiance and temperature conditions are known, the algorithm can calculate the maximum power PMPP and the corresponding duty ratio DMPP for the system to operate at maximum efficiency. In this way, the duty cycle DMPP of the DC-DC converter's active switch can be set to the optimal value for maximizing power extraction. Figure 14. shows that the PV module's output power is continuously monitored and compared to the PMPP. The method is restarted from the beginning if the error E is larger than a designer-specified threshold value. Like P&O and INC, the curve sweeping technique makes use of two sensors to collect data on the input voltage and input current. However, when partial shading is present, the existence of numerous local maxima and a single global maximum MPP in the P-V curve can cause some MPPT algorithms to inaccurately determine the MPP. Since the entire curve is swept a priori to compute PMPP, the new approach avoids this behavior associated with P&O and INC if a large enough number of points are gathered to plot the curves [78].

N. RIPPLE CORRELATION CONTROL (RCC) METHOD

Ripple Correlation Control, often known as RCC [79], is a method that performs MPPT by utilizing ripple in PV voltage and current. In order to bring the power gradient down to zero and attain the maximum power point, RCC correlates the time derivative of the time-varying power produced by the PV array with the time derivative of the time-varying current or voltage produced by the PV array. RCC can be implemented with the use of analogue circuits that are straightforward and low-cost. Experiments were carried out to demonstrate that the RCC can precisely and rapidly track the MPP notwithstanding the presence of variable amounts of irradiance. The switching frequency of the power converter and the gain of the RCC circuit both play a role in determining how long it takes for the system to converge on the MPP. RCC has the additional benefit of not requiring any prior information about the properties of the PV array; as a result, adapting it to various PV systems is a simple process. This is also one of the advantages of RCC method.

O. ONE CYCLE CONTROL (OCC) METHOD

In this MPPT approach, a single stage inverter is utilized, which performs both the function of converting DC to AC as well as the function of MPPT. Adjustments are made to the inverter's output current, which is also the current flowing through the grid, based on the PV array's output voltage. In this procedure, the calculation of power is not required [80]. An integrator with reset, a comparator, a flip-flop, a clock, and an adder make up the one-cycle controller. An adder in front of the one-cycle controller implements the MPPT. This method is more straightforward, has fewer steps, and has lower overall costs. In order to avoid delayed response and to reject transients induced by external disturbances in switching converters, OCC was created as an alternative.

P. SYSTEM OSCILLATION METHOD

This is a new approach to getting the most electricity out of a solar panel under a variety of different weather situations. Connecting a pulse-width modulated DC/DC converter (PWM) to a solar panel's load or battery bus is how this technology works. When the converter's input current is constant, it functions in the discontinuous capacitor voltage mode. It is possible to modulate the duty cycle of the primary switch by introducing a small-signal sinusoidal disturbance into its duty cycle and measuring its maximum variation in input voltage and stress. The nominal duty cycle of the converter's primary switch is set to a certain value such that the converter's input resistance matches the solar panel's corresponding output resistance at the MPP. This method guarantees maximum power transfer in all conditions without the use of microprocessors [81].

Q. STATE SPACE CONTROL METHOD

The difficulty of nonlinear time-varying systems is simplified in this way using the state space approach, which first tracks MPP and then reduces the problem to the more conventional one of dynamic system stability. Along with a time-varying dynamic feedback controller, a state space model that makes use of a time-averaged switch model is used in the execution of this approach [82]. This technique ensures that there is global asymptotic stability, discovers MPP even when there are variations in the weather, and is less affected by changes in both the parameters and the load.

R. LOAD VOLTAGE AND LOAD CURRENT MAXIMIZATION

A PV array's output can be maximized using MPPT techniques. Because of this, optimizing a PV array for maximum load output necessitates likewise optimizing the PCU output at the PCU load. Assuming the PCU is loss-free, increasing the output power also increases the PV array's power. Most loads are either voltage source, current source, or resistive. In order to achieve optimum power, the load current I_{out} for a voltage-source type load should be maximized. The load voltage V_{out} should be maximised for a current-source type load [83].

S. LINEARIZATION-BASED MPPT TECHNIQUE

This MPPT method is very easy, quick, and economical. All the traditional MPPT methods rely on the non-linear I-V characteristics of PV arrays' tracking MPP. In order to determine MPP on the curve at the point where the solutions of two algebraic equations cross, the current linearization approach first linearizes the current equation and the power equation. The intersection of the maximum power line and the PV array characteristic curve yields the maximum power point [84].

T. TRANSIENT BASED MPPT TECHNIQUE

When PV voltage or current is managed by an inverter to track MPP, this kind of approach is employed in single stage systems. Due to the absence of an energy buffer stage DC/DC, this method differs from other traditional methods. It is not based on continuous perturbation, but rather on the MPP detection during transitory processes that are introduced in response to an irradiance shift. Only current needs to be measured in this manner since power and current both fluctuate whenever the irradiance varies, but voltage does not change very much.

U. MPP LOCUS LINE TECHNIQUES

Standard MPP-Locus methodology is first proposed by (Vladimir V.R. Scarpa, et al). It is suggested that the convergence time can be shortened by establishing a linear relationship between the module voltage and current values at the

TABLE 1. **(a). Comparison chart in between different conventional MPPT algorithms. (b). Comparison chart in between different convectional MPPT algorithms.**

(a)

	Constant Current	Constant Voltage	Beta	Curve Fitting	Pilot Cell	Look-Up Table	FOCV method	FSCC Method	P&O Technique	Temperature Method
Classification	Off- Line	Off-Line	Off Line	Off Line	Off-line	Off-Line	Indirect	Indirect	On-Line	On-Line
PV Array Dependent	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	No
True MPPT	No	No	Yes	Yes	No	Yes	No	No	Yes	Yes
Analog or digital	Digital	Digital	Digital	Digital	Digital	Digital	Both	Both	Both	Digital
Periodic Tuning	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	No	Yes
Sense Parameters	Current	Voltage	V, I	V, I	Voltage	V, I	Voltage	Current	V, I	V, T
Tracking accuracy	Low	Low	Medium	Low	Medium	Low	Medium	Medium	Medium	High
Tracking Speed	Slow	Slow	Medium	Slow	Slow	Slow	high	high	Medium	Medium
Efficiency	Low	Low	Medium	Medium	Medium	Low	Low	Low	Medium	Medium
Efficient in PCS	No	No	Medium	No	Low	No	No	No	No	No
Convergence Speed	Medium	Medium	Fast	Medium	Medium	Fast	Medium	Medium	Varies	Medium
Implementation complexity	Low	Low	High	Low	Medium	Medium	Low	Medium	Low	High
Economy	Cheap	Cheap	Expensive	Cheap	Cheap	Cheap	Cheap	Cheap	Moderate	Expensive
Application	Off Grid	Off-Grid	Grid	Off-Grid	Off-Grid	Off-Grid	Off-Grid	Off-Grid	Both	Off-Grid

(b)

	INC	Hill Climbing Method	Current Sweeping Method	Curve Sweeping Method	RCC	One Cycle Control Method	System Oscillation Method	State Space Control Method	Load Voltage and Load Current Maximization	Linearization-Based MPPT Technique
Classification	On-Line	On-Line	On-line	On-line	Indirect	Indirect	Indirect	Indirect	Indirect	Indirect
PV array dependent	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes
True MPPT	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No
Analog or digital	Digital	Both	Digital	Digital	Analog	Both	Analog	Both	Analog	Digital
Periodic tuning	No	No	Yes	Yes	No	Yes	No	Yes	No	Yes
Convergence speed	Varies	Varies	Slow	Medium	Fast	Fast	N/A	Fast	Fast	V, I
Implementation complexity	Medium	Low	high	High	Low	Medium	Low	High	Low	Very High
Sense parameters	V, I	V, I	V, I	V, I	V, I	Current	Voltage	V, I	V, I	Fast
Tracking accuracy	High	Medium	Medium	High	High	High	High	High	High	High
Tracking speed	Fast	Medium	Medium	Medium	Fast	Fast	Medium	Medium	Slow	Medium
Efficiency	Medium	Medium	Medium	High	High	Medium	Medium	High	Medium	Fast
Efficient in PCS	Yes	No	No	Yes	Yes	No	No	Yes	No	Medium
Economy	Moderate	Moderate	Medium	Moderate	Expensive	Medium	Expensive	Expensive	Medium	Low
Application	Both	Both	Off-grid	Off-grid	Grid	Off-Grid	Off-Grid	Off-Grid	Off-Grid	Off-Grid

MPP. Menes the maximum power points of all the I-V curves lie near to a straight line, based on the PV array's properties. Then operating the power conditioning units (PCU) on this locus line would be the only way to track MPP for any given condition [86]. The MPP locus line's equation is as follows:

$$V - R_{eq} \times I - V_{th} = 0 \tag{8}$$

The slope of the MPP locus line is ${}^{1}/_{R_{eq}}$ and the intercept on the voltage axis is V_{th}.

V. INCREMENTAL RESISTANCE (INR) METHOD

The INR is a particularly noteworthy algorithm that was developed in order to track the MPP of the PV power plant. The fundamental concept that underpins the INR-based tracker is that, at the MPP, the derivative of the PV power with respect to current is equal to zero. There is a full explanation of the mathematical model in [87] describing how to extract the PV power using this method.

W. TEMPERATURE METHOD

By taking the solar module's temperature and comparing it to a standard, this technique can approximate the MPP voltage V_{MPP}. Since variations in irradiation levels have such a small impact on the MPP voltage, those influences can be safely disregarded; instead, the voltage is assumed to vary linearly as temperature changes. The algorithm determines the following equation (9):

$$V_{MPP}(T) = V_{MPP\_ref} + K_{K/T}(T - T_{ref}) \tag{9}$$

To calculate V_{MPP} at a given temperature T, where $K_{K/T}$ is the voltage change per unit of temperature change [88]. At the standard temperature of T_{ref}, the MPP voltage is specified by the parameter V_{MPPref}.

X. CONSTANT DUTY CYCLE METHOD

Solar modules can be controlled by simply selecting an appropriate constant duty cycle that drives their voltage near to the MPP. No measurements or feedback are needed because the duty ratio does not change; consequently, there is no need for it. Alternatively, a constant reference voltage can be selected. It is necessary to measure the solar panel's voltage here in order to achieve the preselected target voltage. Assuming temperature and irradiance conditions are constant, both strategies presume that these variables are irrelevant. Despite their simplicity, these methods do not follow the MPP; rather, they just get the panel's output close enough to the MPP to maximize the amount of power available. At low irradiance levels, these techniques may be superior than all others [89].

Y. WINDOW SEARCH METHOD

The window search technique also makes use of the information that is known about the system in order to restrict the scope of the area that is being searched. This is accomplished by beforehand setting the voltage range or duty cycle that will be implemented by the algorithm. It is possible to implement it as a pre-searching approach within a conventional or even a stochastic strategy, which will speed up the algorithms' ability to converge on a solution [90].

Z. FULL SCANNING METHOD

Koutroulis and Blaabjerg [91] presented the idea for the Full Scanning (FS) technique in the year 2012. This is an easy approach that searches for the GMPP by going through the entire voltage range in a random order. This approach takes advantage of the simplicity of the technology, but it does include a few powers loss sites in the scanning area (e.g., short-circuit point and open-circuit point). In addition to that, the performance of the tracking is extremely reliant on the scanning step. The device can track the precise GMPP with a smaller scanning step; nevertheless, the scanning method takes significantly more time. When using a larger scanning step, the scanning speed increases, but there is a greater chance that the system will miss the GMPP.

IV. INTELLIGENT TECHNIQUES BASED MPPT METHOD

Recent years have seen a rise in the adoption of MPPT controllers based on intelligence approaches for PV systems. This is because it can resolve many of the problems associated with traditional MPPT approaches. Even more importantly, these strategies do not require sophisticated mathematics or precise parameters to manage the system. Fast tracking speed, low computation time, and reduced volatility around optimal MPP point make MPPT one of PV system's most powerful controllers. There are, however, two significant drawbacks: the absence of correct training data and the difficulty of fine-tuning the algorithm. That is why a variety of intelligent MPPTs have been developed, each with its own unique algorithm [16], [17], [18], [19], [20].

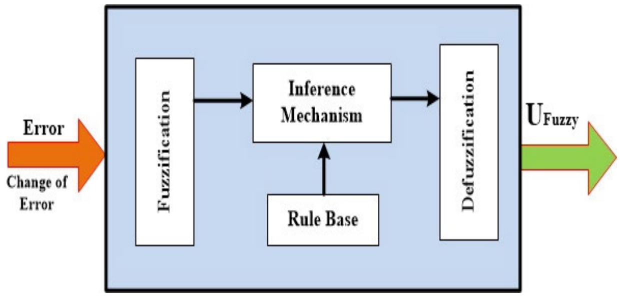

FIGURE 16. Block diagram of fuzzy logic control methodology.

A. FUZZY LOGIC CONTROLLER (FLC) BASED MPPT

Fuzzy logic control has gained popularity in the last decade due to its ability to accommodate nonlinearity, handle imprecise inputs, and function without an exact mathematical model. Fuzzy logic control has benefited greatly from the widespread use of microcontrollers. The three phases that make up fuzzy logic are fuzzification, the inference system, and defuzzification. The term "fuzzification" refers to the process of converting "crisp" numerical inputs into "fuzzy" linguistic variables based on the degree of membership in particular sets. Fuzzy control rules are typically based on an IF-THEN rule structure. The fuzzy logic based MPPT is depicted in a straightforward block diagram in Figure 16 [92].

A rule base, a de-fuzzifier, an inference engine, and a fuzzy logic generator are all components of the block system. Each individual piece of the block diagram serves a specific function. A function known as a membership function is one that transforms a set of clear values into another set of less clear values. The complete data is kept in the fuzzy set, which is represented by the membership function. The fuzzy membership function can be broken down into four distinct categories.

- Function of Trapezoidal Membership
- Function of Triangular Membership
- The function of Gaussian Membership
- The function of Generalized Bell Membership

The error (E) and the change in the error (ΔE) are commonly used as inputs to fuzzy controllers. Errors can be selected by the designer, but the most common one is $\Delta P/\Delta V$ because it is zero at the MPP [93]. The following is the definition of E and ΔE:

$$E = \frac{P(K) - P(K-1)}{V(K) - V(K-1)} \tag{10}$$

$$\Delta E = E(K) - E(K-1) \tag{11}$$

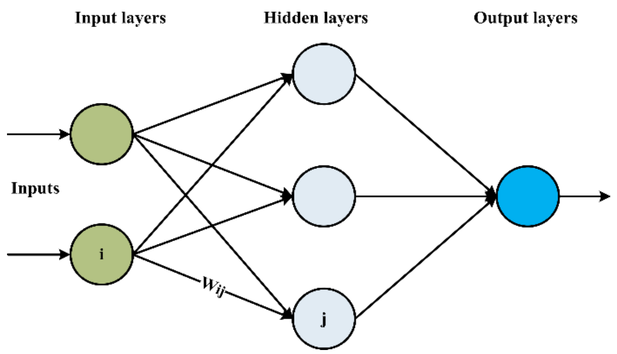

FIGURE 17. ANN overall structure.

Typically, the output of the fuzzy logic converter is a change in the power converter's duty ratio, ΔD. The fuzzy rule algorithm, also referred to as the rule base lookup table, associates the fuzzy output with the fuzzy inputs based on the power converter in use as well as the user's knowledge. These algorithm benefits include handling nonlinearity, dealing with imprecise inputs, not requiring a correct mathematical model, and having quick convergence. They also have little oscillations around the MPP [118].

B. ARTIFICIAL NEURAL NETWORK (ANN) BASED MPPT

An ANN methodology is a distributed processing method capable of storing application system experimental knowledge. An application system model does not necessitate much expertise, but it does require reliable data in order to accurately forecast output functions. A non-linear mapping between input and output nodes is created using this approach. Feedforward and feedback networks make up the majority of the ANN's topology. In terms of implementation, the first type is the most frequent because it requires less memory than the second type. It has also proven to be extremely effective when used in conjunction with non-linear systems, like as a photovoltaic array. The input layer, hidden layer, and output layer are the three layers that make up the simplest feedforward Artificial Neural Network (ANN), as depicted in Figure 17. The most common type of ANN is the multilayer feedforward ANN, which is able to accurately compute the weighting of the hidden layer. More hidden layers are added to create NNs that are more complex. The number of layers, the quantity of nodes within each layer, the function employed within each layer, and all these parameters change and are user-dependent. The input variables can be either a mixture of atmospheric data such as temperature and irradiance or PV array parameters like VOC and ISC. Typically, the duty cycle is the output [93], [94].

Training and functionality of the neural network are both factors that affect the NN's performance. There are weighted linkages between nodes. Weight between nodes i and j is shown in Figure 17, by the label W_{ij}. The weights are modified throughout training. The neural network's inputs and outputs are recorded over a long period of time so that the MPP can be followed correctly. The most significant drawback of this MPPT technique is that the data required for the training process must be specially gathered for each PV array and location [119]. This is because the properties of each PV array differ depending on the model, and the location depends on the weather conditions at that location. Because of the way in which these features change over time, the neural network needs to be trained on a consistent basis.

C. SLIDING MODE CONTROL (SMC) BASED MPPT

When compared with other varieties of nonlinear controllers, sliding-mode controllers (SMC) are considerably easier to put into action. Because the sliding-mode control makes it possible to operate as either a voltage-source or a current-source, it ensures stability across the whole photovoltaic curve, from the open circuit to the short circuit. The control can be implemented with little effort and only requires hardware that is not expensive. Transversality, reachability, and comparable control are the three requirements that need to be met by the SMC before it can be considered stable and have a sufficient performance. The transversality test determines whether the system can be controlled, the reachability test determines whether the closed-loop system can reach the surface, and the equivalent control determines whether there is local stability. In order to guarantee that the controller will have the power to influence the dynamics of the system, the transversality condition outlined in Equation (12) needs to be satisfied [94].

$$\frac{d}{du}\left(\frac{d\Psi}{dt}\right) \neq 0 \tag{12}$$

The system's ability to remain encased in the surface is examined using the corresponding control condition. If the analogue equivalent value U_{eq} of the discontinuous control signal u is confined within the operational limitations, the system will not be saturated and it will be possible to operate it at or near the surface. For example, the reachability conditions examine the system's ability to get to a desired state of $= 0$ If a system can meet the control conditions, it also meets the reachability requirements. This approach relies on calculating the difference between PV power and PV voltage, which is done using the (13).

$$s = \frac{dP_{PV}}{dV_{PV}} = I_{PV} + V_{PV} \times \left(\frac{dI_{PV}}{dV_{PV}}\right) \tag{13}$$

where S will learn the precise operating voltage value based on the MPP's region.

D. NEWTON–RAPHSON METHOD BASED MPPT

The Gauss–Newton technique is an example of a root-finding algorithm. This method, which can also be referred to as the Newton–Raphson method. The fact that this Gauss-Newton strategy is conceptually efficient in comparison to other methods described in the existing literature is the most crucial and significant component of this methodology. It will find the MPP with the assistance of the focused differentiation,

TABLE 2. Comparison chart of intelligence techniques based MPPT algorithms.

	Fuzzy Logic based MPPT	Artificial Neural Network based MPPT	Sliding Mode Control (SMC) based MPPT	Newton–Raphson based MPPT	Fibonacci Series based MPPT	Steepest-Descent based MPPT
Classification	Intelligence	Intelligence	Intelligence	Intelligence	Intelligence	Intelligence
PV array dependent	Yes	Yes	No	No	No	No
Ability to track True MPPT	Poor	Poor	Medium	Medium	Medium	Medium
Analog or digital	Digital	Digital	Digital	Digital	Digital	Digital
Periodic Tuning	Yes	Yes	No	No	Yes	Yes
Sense Parameters	V, I // T, Irradiance	V, I // T, Irradiance	V, I	V, I	V, I	V, I
Tracking accuracy	High	High	Medium	Medium	High	Medium
Tracking Speed	Fast	Medium	Very Fast	Fast	Very Fast	Fast
Efficiency	High	High	High	High	High	High
Efficient in PCS	Low	Low	Medium	No	Low	Medium
Convergence Speed	Medium	High	High	Medium	Medium	Medium
Implementation Complexity	Less	medium	High	High	Less	Medium
Economy	Medium	Expensive	Expensive	Medium	Medium	Less
Application	Off-grid	Both	Both	Both	Off-grid	Both

which is a more recent development of its kind. Out of all these mathematical computational MPPT strategies, the Gauss-Newton method is the one with the quickest execution time. The Newton–Raphson approach calculates an estimate of the path that the programmer should take and the distance it should go in order to get to a better place by using a first and second derivative of the change that occurs with the parameter value. The computation of the operational point can be shown by the symbol (*) when it is utilized for the purpose of tracking MPPs. This algorithm must be able to numerically do single differentiations in addition to double differentiations, as seen in the following:

$$\mathrm{V_k} = \mathrm{V_k} + \frac{\left(\frac{\mathrm{dP}}{\mathrm{dV}}\right)|_{\mathrm{V=Vk}}}{\mathrm{K} \in} \tag{14}$$

$$\mathrm{V_{k+1}} = \mathrm{V_k} - \frac{\left(\frac{\mathrm{dP}}{\mathrm{dV}}\right)|_{\mathrm{V=Vk}}}{\left(\frac{\mathrm{d^2P}}{\mathrm{dV^2}}\right)|_{\mathrm{V=Vk}}} \tag{15}$$

The Gauss-Newton method is the quickest way to solve a problem when compared to the traditional algorithm [95].

E. FIBONACCI SERIES BASED MPPT

This MPPT approach, which is based on the Fibonacci series, is an intelligent iterative search technique that greatly shortens the searching time by narrowing the operational range. With this approach, the range is progressively constrained before looking through the range to find the best functioning point. The two approximate points V_1, V_2 in the range of V_{min} and V_{max} determine the direction that it must shift. This method continuously alters its working range by utilizing the prior iteration, much like a divide and conquer strategy. Modelling the Fibonacci series is done by numerically, is given in equation (16) and (17).

$$R_{n+2} = R_{n+1} + R_n \; (n= 1, 2, 3, 4, \ldots\ldots.) \tag{16}$$

$R_1 = R_2 = 1$, the sequence is calculated as,

$$R_2= 2, R_4= 3, R_5= 5, R_6= 8, R_7= 13, \ldots\ldots \tag{17}$$

The Fibonacci series primarily functions to limit the operating point and its length. The fundamental Fibonacci method's workflow is depicted in Figure 18, which shows how the operational length is set using those Fibonacci numbers. The range is consistently reduced by this clever algorithm, ensuring that the ideal location is always contained inside it [116].

F. STEEPEST-DESCENT TECHNIQUE BASED MPPT

When the gradient of the function can be determined, the method of steepest descent is a useful tool for locating the nearest local MPP that may be used. The methodology for MPPT can be proven using the method of steepest descent by using the equation (18), where k_ε is the step-size corrector and dP/dV is the derivation. This equation can be found below. The value of k_ε determines how steep each step is relative to the previous one in the direction of the gradient [96].

$$\mathrm{V_{k+1}} = \mathrm{V_k} + \frac{\frac{\mathrm{dP}}{\mathrm{dV}}|_{\mathrm{V=V_k}}}{\mathrm{k}_\varepsilon} \tag{18}$$

V. OPTIMIZATION TECHNIQUES BASED MPPT METHOD

Evolutionary algorithms (EA) and swarm intelligence (SI)-based algorithms are key subgroups of population-based

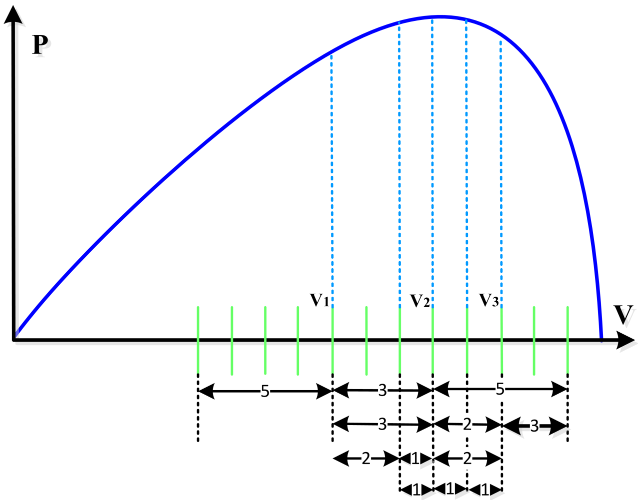

FIGURE 18. Fibonacci series method.

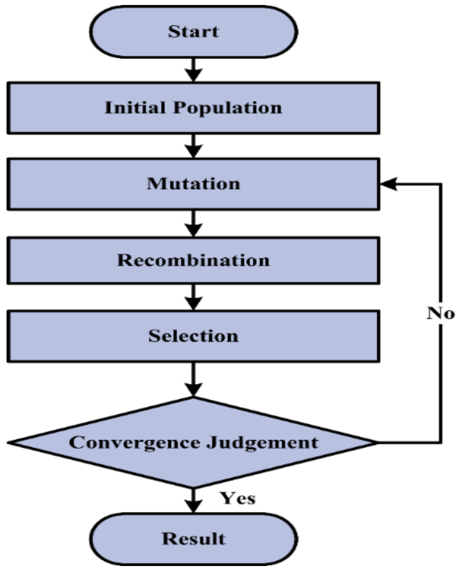

FIGURE 19. Flow chart of differential evolution based MPPT.

heuristic algorithms. Many other evolutionary algorithms have been developed throughout the years, including Genetic Algorithm, the ES, the DE, and others. Algorithms that use swarm intelligence, such as the PSO algorithm, the Ant Colony Optimization (ACO), the Firefly (FF) algorithm, and so on, have been widely used. In addition to algorithms based on evolutionary and swarm intelligence, additional algorithms are based on the principles of many natural phenomena. GSA, Biogeography-Based Optimization (BBO), Flower Pollination Algorithm (FPA), Jaya algorithm (JA), etc. are few examples. Scientific field called optimization works with finding the best possible solution to a given problem out of all possible options. This optimality of solutions is based on one or more criteria and conditions that are specific to the situation at hand and the users who will be implementing them. Hence, in many cases, the user, or the problem itself imposes limits to limit the number of possible solutions. A feasible solution is one that can meet all the constraints imposed on it. This is how the term "feasible solution" came to be. As a result, the global optimization problem revolves around identifying the best solution among all the alternatives. It is possible that this will not always be possible. Local optimization refers to situations when poor solutions are acceptable based on their relative value to the optimal option. Researchers have employed a variety of optimization-based MPPT strategies to maximize the amount of power that can be extracted from a PV in a critical state. Various MPPT algorithms based on optimization approaches will be discussed in this section [18], [19].

A. DIFFERENTIAL EVOLUTION (DE) BASED MPPT

Storn and Price in 1996 presented differential evolution as an evolutionary approach for global optimization [97]. Non-differentiable, noncontinuous, nonlinear, noisy, flat, multidimensional, or including multiple local minima, restrictions, or stochasticity can be solved using DE. This method is simple to construct since it only takes a few parameters. In DE, the ultimate answer can only be generated after many iterations with a large population of particles. In each cycle, the distinctions between the particles are used to introduce new mutations. As a starting point Two-dimensional target vectors are used in DE, with G as specified in and X_i as the population for each generation (19). In each repetition N_p, the total number of particles, remains constant.

$$X_{i,G} \quad i = 1, 2, 3 \ldots\ldots\ldots N_p \tag{19}$$

Target vectors from the first generation must be carefully picked and must cover the whole search space. Three target vectors are chosen at random when the findings of the first generation are known. By combining the weighted difference between the first two target vectors and the mutation factor F, the third target vector is used to construct a changed particle, or so-called donor vector V_i. The formula is as follows (20). This process may be characterized as the benefit of rivalry amongst people in real life. A community's advancement depends on each member of the group learning from the differences among themselves and producing a better individual. Think about the following:

$$\mathrm{V_{i,G}} = \mathrm{x_{r1,G}} + \mathrm{F}^{*}\left(\mathrm{x_{r2,G}} - \mathrm{x_{r3,G}}\right) \tag{20}$$

where F can take any value between 0 to 1. Donor vectors, which are made up of Np particles, are produced as a result of the mutation. After then, a procedure known as crossover is used to combine the donor vectors and the target vectors, which results in the generation of the trial vectors known as $\mathrm{u_i}$. The condition that is utilized in the crossover is demonstrated in (21). In this condition, in order to find the crossover rate (CR), we need a random number rand that is in the ranges of [0,1]. Consider the following:

$$\mathrm{u_i} = \begin{cases} \mathrm{V_i}; & \text{if rand} \geq \mathrm{CR} \\ \mathrm{x_i} & \text{else.} \end{cases} \tag{21}$$

Following the crossover, a choice is taken between the goal vectors x_i and the trial vectors u_i. The target vectors for the following generation, $\mathrm{x_{i+1}}$, are chosen from the best solutions from the selection [152]. The method is demonstrated as follows (22):

$$\mathrm{x_{i+1}} = \begin{cases} \mathrm{u_i} & \text{if } \mathrm{F(u_i) \geq f(x_i)} \\ \mathrm{x_i} & \text{else.} \end{cases} \quad (22)$$

Once the termination condition is fulfilled, the procedure is then repeated from the point of the mutation. Figure 19, depicts the flowchart for DE.

B. CUCKOO SEARCH (CS) BASED MPPT

Yang and Deb first presented the CS algorithm in 2009, drawing inspiration from cuckoo species' mating behaviors [98]. When CS is used, there are three idealized rules. In each cycle, each cuckoo first lays a single egg before picking a nest at random to place it in. Second, the best nest and greatest solution will be passed on to the following generation. Third, there are a fixed number of host nests, and a host bird finds the alien egg with a probability pa [0, 1]. The power is specified as the starting fitness value and the produced samples are applied to the PV modules first. After that, the Lévy flight is conducted, and fresh samples are produced using the following equation (23):

$$\mathrm{x_i^{t+1}} = \mathrm{x_i^t} + \alpha \oplus \mathrm{levy}\,(\lambda) \quad (23)$$

There is $x_i = [x_1, x_2, \ldots\ldots, x_D]$, D is the issue dimension, t is the number of iterations, $\alpha > 0$ is the step size, and t is the number of iterations. An entry-wise multiplication is indicated by a product $\oplus$, and Levy (λ) gives a random walk whose step length is taken from a Levy distribution [128].

$$\mathrm{levy}\,(\lambda) \approx \mathrm{t}^{-\lambda} \quad (24)$$

where $1 < \lambda \leq 3$, An infinite variance with an infinite mean may be seen in the Levy equation illustrated in (24).

Figure 20, shows the CS MPPT flowchart. The algorithm's implementation is well-described. First, all constants and variables are initialized, including voltage, current, power, samples, etc. Calculating power from voltage and current. The new voltage V_i^t and power J_i^t arrays record the values. Before each cycle, samples are checked for convergence. If samples converge to MPP, their values and powers combine. If the samples do not converge, their power values are measured and stored in J_i^t. The array's most powerful sample is the best. All samples must use this best value. Lévy flight determines step sizes. New samples are found. Then, the PV panel measures the fresh samples' Powers. If a sample has a lower power, it is rejected and a new one is created. Iterate until all samples converge on MPP [134].

C. GENETIC ALGORITHM (GA) BASED MPPT

The genetic algorithm (GA), also referred to as the evolutionary algorithm (EA), is based on the Darwinian theory of evolution, which states, in a nutshell, that the strongest individuals survive while the weakest individuals perish, leaving each time a stronger living organism that is better able to survive and reproduce. This is comparable to the optimization of an objective function in the framework of the GA, as in the prior stochastic algorithm. The function to be tracked is represented by the power curve, and the "genes" are the positions (duty cycle values) associated with each value (chromosome). The strongest genes (those that are closer to maxima or minima) are therefore meant to live and procreate, whereas the weakest genes just disappear, according to the algorithm. Every time two genes cross, a new set of potential answers emerges, ideally improving upon the previous ones through mutation. This point is used iteratively by the algorithm until the genes converge into a single gene code that cannot be improved further or reach a solution zone that is close enough to the maxima (optima reached) [99]. The flow chart of generation algorithm is shown in Figure 21.

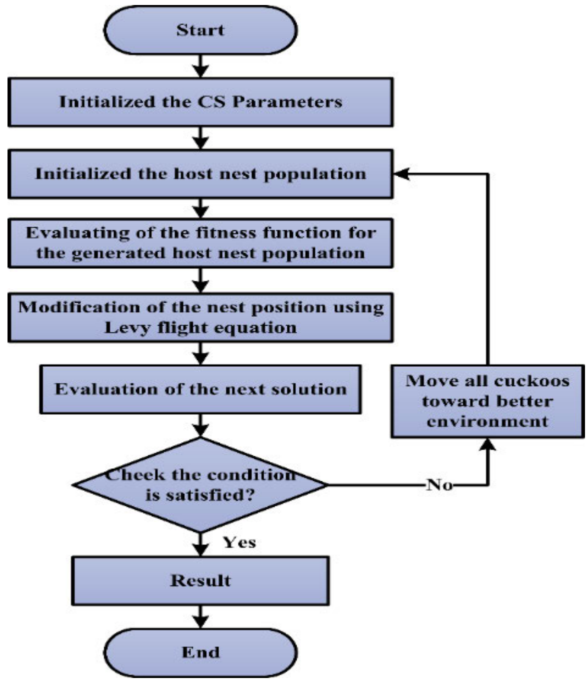

FIGURE 20. Flow chart of cuckoo search based MPPT.

D. PARTICLE SWARM OPTIMIZATION (PSO) BASED MPPT

One method of population-based search is the particle swarm optimization (PSO) algorithm, that is modelled after the social behavior of birds while they are gathered in a flock. Quickly finding the best answer to an issue is the goal of this method. The original goal of the particle swarm concept was to provide a visual representation of the graceful and unexpected motions of a flock of birds. An investigation into how birds fly in synchronization and fast shift direction while regrouping in the best possible configuration was the purpose of this investigation [100]. This primary aim served as the inspiration for the development of a straightforward

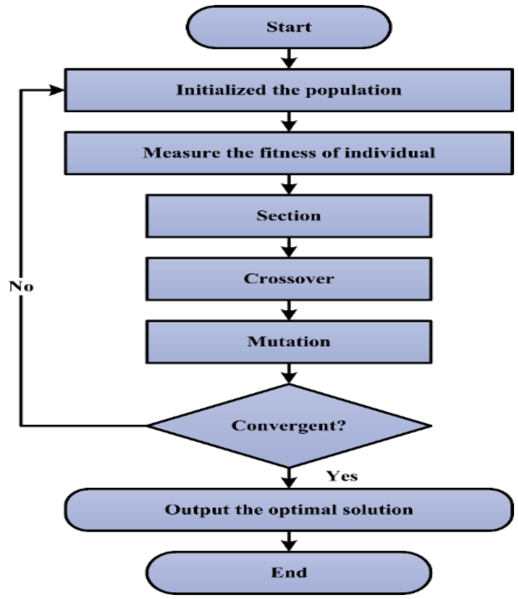

FIGURE 21. Flow chart of genetic algorithm based MPPT.

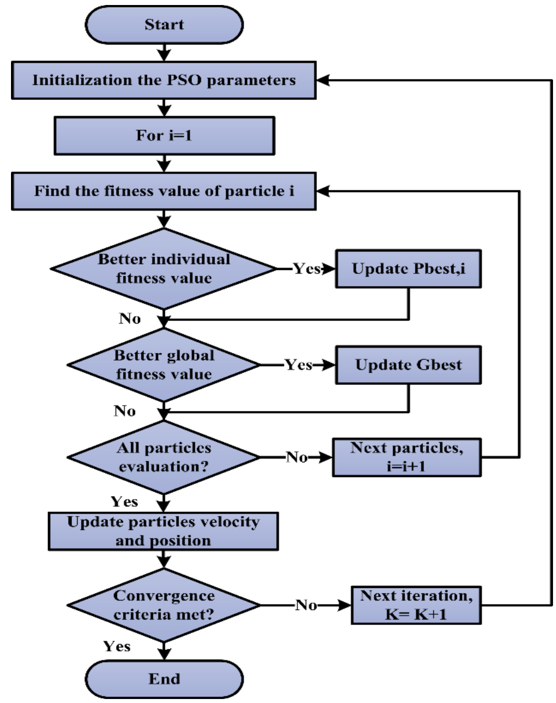

FIGURE 22. Flow chart of PSO techniques based MPPT algorithm.

and effective optimization technique, which was later implemented. Particle swarm optimization (PSO) "flies" individuals through hyperdimensional search space. These individuals are referred to as particles. The social-psychological inclination of individuals to strive to achieve the same level of success as those around them is the driving force behind the adjustments that are made to the positions of the particles within the search space. individuals. Because of this, the experiences or knowledge of a particle's neighbors will influence the changes that the particle goes through while it is part of the swarm. As a result, the behaviors of a particle's search are affected by the behaviors of other particles that are a member of the swarm (PSO) is therefore a kind of symbiotic cooperative algorithm [129]. Flow chart of Particle swarm optimization based MPPT algorithm is shown in Figure 22.

E. GREY WOLF OPTIMIZATION (GWO) BASED MPPT

The GWO algorithm is based on the research conducted by Mirjalili et al., who hypothesized that grey wolves in nature have a leadership hierarchy and a hunting mechanism. It is generally accepted that grey wolves occupy the highest possible position on the food chain, and these animals prefer to live in packs. For the purpose of mimicking the leadership hierarchy, four different varieties of grey wolves are used. These wolves are designated as alpha (α), beta (β), delta (δ), and omega (ω). In the process of developing GWO, a mathematical model of the wolf pack's social structure was necessary. The alpha (α) grey wolves were determined to be the optimal answer for this task. Because of this, the answers that came in second and third place are denoted by the Greek letter's beta (β) and delta (δ), respectively. The omega (ω) solution is going to be assumed for the remaining potential solutions. three primary processes that make up the GWO algorithm, which are known as hunting, chasing, and tracking for prey, surrounding prey, and striking prey. These steps are applied to build GWO for the purpose of performing optimization. When hunting, grey wolves will sometimes encircle their prey, and this behavior can be modelled using the equations that are provided below (25,26).

$$\vec{D} = \left|\vec{C}.\vec{X_p}\,(\mathrm{t}) - \vec{X_p}\,(\mathrm{t})\right| \tag{25}$$

$$\vec{X}\,(\mathrm{t}+1) = \vec{X_p}\,(\mathrm{t}) - \vec{A}.\vec{D} \tag{26}$$

$\vec{D}, \vec{A}$ and $\vec{C}$ are coefficient vectors, X_p represents the position vector of the prey, and $\vec{X}$ is the position vector of the grey wolf. Unlike other wolves, grey wolves can locate their prey and quickly encircle them. Alpha (also known as the leader) normally leads the search, with beta (commonly known as the follower) and delta (also known as the hunter) occasionally joining in. In the end, the pack's wounded wolves are looked after by delta(δ) and omega(ω). Alpha is a candidate solution because it has more information about where the prey is located. As soon as their prey has stopped moving, the grey wolves attack [101], [125].

The controller detects the PV voltage V_{PV} and the PV current I_{PV} through sensors and calculates the output power of the PV system in accordance with duty ratio. Figure 23. depicts the suggested MPPT algorithm based on GWO. Multiple peaks (LP) and a single global peak (GP) form the P-V curve during partial shade (PSC). Because of this, the MPP's correlation coefficients are almost zero when wolves detect it. GWO and direct duty cycle control have been combined in the suggested method to reduce the steady state oscillations that are present in standard MPPT techniques, which in turn

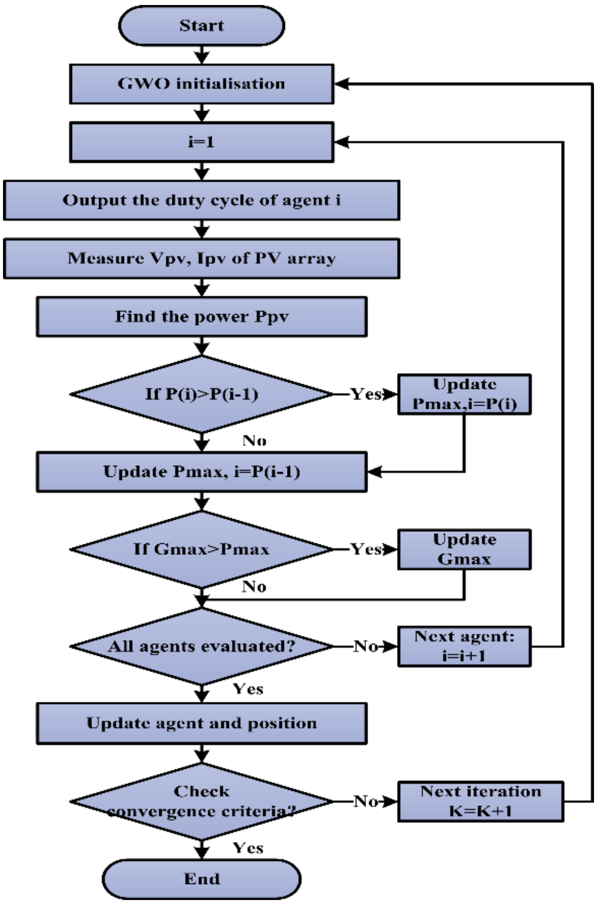

FIGURE 23. Flow chart of GWO techniques based MPPT algorithm.

reduces the power loss due to oscillation, resulting in higher system efficiency. Grey wolves are used to implement the GWO-based MPPT. The following modification can be made to equation (26), we get,

$$D_i\ (k+1) = D_i\ (k) + A.D \tag{27}$$

Thus, the objective function of the GWO algorithm is formulated as (28):

$$Pd_i^k > Pd_i^{k-1} \tag{28}$$

For the tracking problem, the operating power of the PV array is given above as P=V*I, where P stands for power, d for duty cycle, (i) for the number of current grey wolves, and (k) for the number of iterations [126].

F. ANT COLONY OPTIMIZATION (ACO) BASED MPPT

Another algorithm that is inspired by natural processes is this evolutionary algorithm. The phenomenon of emergence can also be used to describe the interaction of an ant colony with its surrounding environment, as was done earlier. It does this by sharing information with other members of the colony in order to determine the most efficient route to take when searching for a food source and bringing it back to the anthill.

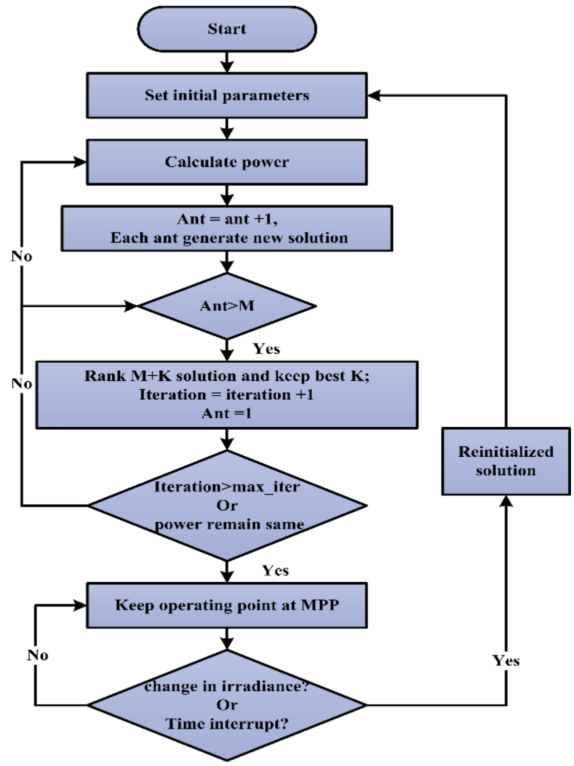

FIGURE 24. Flow chart of ACO techniques based MPPT algorithm.

This concept, which consists mostly of staggery, evaporation, and mistakes, is used in the ACO-based code that is used by the algorithm. In the first place, the family group particle integrant (ant/duty cycle value) communicates with its surroundings by secreting pheromones, which are odors, that contain global information. These pheromones will eventually dissipate as time passes. After that, ants investigate a starting position. If there are none present, they will wander aimlessly about the area. On the other hand, ants tend to follow pheromone-filled tracks in proportion to the amount of pheromone concentration they discover in that section of the trail. If the ants discover food, they will continue to wander aimlessly while leaving a pheromone trail, which will result in the creation of a new path for subsequent ants to follow. The ant trails that more than one ant follows have their strength enhanced (convergence in the optima). In conclusion, due to the nature of the information exchange that it engages in, this sort of algorithm is reliable and possesses a high degree of adaptability. The instability of the solution trail causes the ants to quit following the old pheromone trail because it begins to vanish and eventually ceases to exist. This causes the ants to stop following the path. As a result, it has the potential to be a useful tool in adjusting the phenomenon scenario. This method is proposed by Krzysztof Socha and Marco Dorigo [102] as an optimization algorithm, and a comparison is made between it and the algorithms used by metaheuristics.

Figure 24 provides a flow chart representation of the ACO-based MPPT algorithm. In this, the number of iterations of

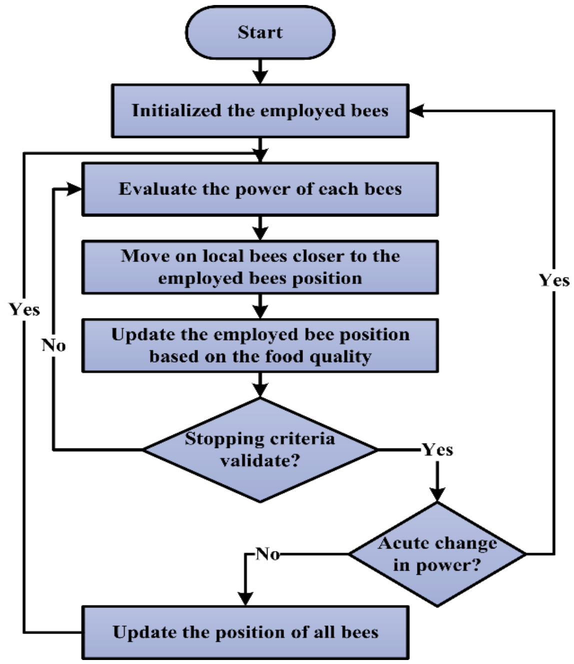

FIGURE 25. Flow chart of ABC techniques based MPPT algorithm.

this sampling technique is proportional to the number of optimization parameters. This process continues until M more solutions have been generated and added to the original set of K. The best K solutions from these (M+K) solutions are restored after being ranked. If more iterations are needed, the procedure is repeated from the beginning [124].

G. ARTIFICIAL BEE COLONY (ABC) BASED MPPT

One of the fastest methods for determining the ideal value of GMPP is the ABC algorithm. It results from honey bees' process of looking for nourishment. The honey bees divide themselves into groups and go on a food hunt in their colonies. Like how the best MPP is sought after, each tracking procedure is assigned a certain task. Honey bees can be generically divided into three types: workers, observers, and scouts. The process is initiated by the food data that the engaged honey bees have obtained. A methodical mathematical strategy is used to convey this information to the spectator honey bees. The scouts look for alternative meals at the same time. The goal is to learn more about the most plentiful food source. The performance of the algorithm is improved if there are more employed bees in the group. When looking for food, PV systems use this process to find the best location by employing the appropriate AF. By using this method, the GMPP point with the most power is tracked more quickly. In order to make use of this kind of MPP [103]. In Figure 25 we explain the steps involves in ABC based MPPT techniques [121].

H. FIREFLY ALGORITHM (FA) BASED MPPT

In order to address the optimization issue, DR. Xin She Yang created the firefly Algorithm (FA) in 2007 [104]. The movement of lightning bugs, also referred to as fireflies, served as the inspiration for this optimization process. In the tropical and temperate zones, the summer sky is a breath-taking sight when lit up by fireflies. Such flashes serve the dual purposes of luring in possible mates and potential prey. Furthermore, flashing might act as a safeguarding warning system. As part of the signal system that unites both sexes, the rhythmic flash, the rate of flashing, and the duration all play a role. Three presumptions are made in order to describe Firefly Algorithm simply;

- ➢ It does not matter what gender a firefly is, it will always be drawn to another firefly since all fireflies are unisex.
- ➢ Two fireflies will attract to each other based on their brightness differences, with the dimmer firefly gravitating toward the brighter of the two. Every firefly in a colony will flit around aimlessly if there is not a brighter one to follow.

Objective function landscape affects firefly brightness. In a maximizing problem, brightness equals the objective function. I and j are fireflies at x_i and x_j. Let us call the space separating these two lightning bugs r_{ij}. we would have to write (29),

$$r_{ij} = \left| x_i - x_j \right| \tag{29}$$

Attractiveness, denoted by, is a function of firefly separation and is given by (30),

$$\beta\,(r) = \beta_0 e^{-\gamma^2}, \quad n \geq 1 \tag{30}$$

The absorption coefficient, γ, ranges from 0 to 10 for $n = 2$, and governs the decrease in light intensity in the equation. In this case, the symbol for initial attractiveness is set to 1, which means that the location of the brightest firefly in the area has a significant impact on the locations of the other fireflies. If the brightness of firefly (i) is less than that of j, the new position of firefly (i) is given by the following equation (31):

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma^2} \beta_0 e^{-\gamma^2}{}_{ij} \left(x_j^t - x_i^t \right) + \alpha_1\,(\text{rand} - 0.5) \tag{31}$$

Here, rand is a random number that is equally distributed between 0 and 1 for each movement of the firefly, and random movement factor is a constant throughout the programmed and lies in the range [1, 0]. Smaller amounts of tend to make local searches easier, while larger amounts tend to explore the answer via a wider search field [123]. Overall flow chart of firefly based MPPT algorithm is shown in Figure 26.

I. GRAVITATIONAL SEARCH ALGORITHM (GSA) BASED MPPT

Scientists and engineers need it for optimization issues with a high dimension of search space. Traditional algorithms are inefficient for this task. As a result, an alternative strategy is required to address this issue. A workable answer can be found in algorithms inspired by nature. These algorithms have been shown to be effective in solving difficult equations. One such technique, the Gravitational Search Algorithm (GSA), was recently proposed. It's an optimization

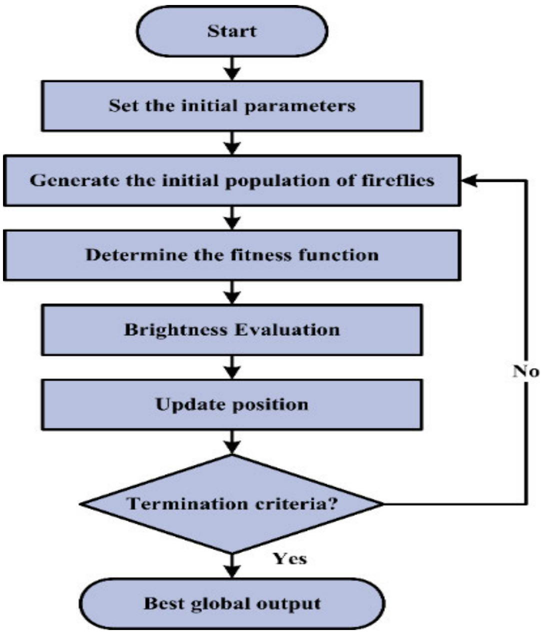

FIGURE 26. Flow chart of firefly techniques based MPPT algorithm.

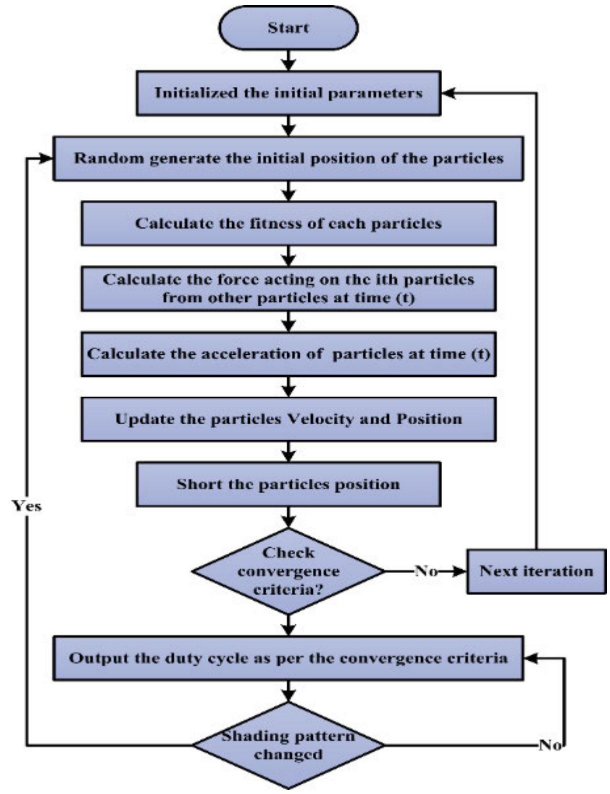

FIGURE 27. Flow chart of gravitational search techniques based MPPT.

algorithm that uses metaheuristics. Inspired by Newton's law of gravity, which states that ''in a universe among the many particles accessible, every particle attracts every other particle with the force that is directly related to the product of their masses and inversely proportional to the square of the distance between them,'' this method considers the gravitational attraction between particles. Each particle will have its own unique mass and location in an environment with a variety of particles. Now, as we have seen, each particle attracts every other particle with its own unique set of forces thanks to Newton's law. The more massive particle will be drawn to the lighter one. At some optimal point, all the multitudes will have been gathered in. The attraction is based on the peculiarities of the particles' masses. There will be three types of mass associated with each particle: inertial, active, and passive. The ability of an object to resist a change in its motion is measured by its inertial mass (M1), which increases as the mass of the object does. Greater inertial mass means slower motion for the particle. The magnitude of a gravitational field is proportional to the object's active gravitational mass (Ma). Likewise, the strength of the gravitational field exerted by a mass with a smaller ''active gravitational mass'' would be smaller. How much of a gravitational field a mass may be subjected to is quantified by its passive gravitational mass (MP). An object with a smaller passive gravitational mass will feel less force than one with a bigger value. We have now completed our examination of the meaning of GSA and can move on to its operation. As we have seen, the force between particles in a normal GSA is determined by gravitational attraction, so we know there must be force involved (32).

$$F_g = G_V \frac{m_1 m_2}{r^2} \tag{32}$$

where F_g represents the gravitational force, G_V the gravitational constant, m_1 and m_2 the masses of the particles r and the Euclidean distance between the particles [105].

The Figure 27 depicts the flowchart of the Gravitational Search Algorithm. To begin, we establish the boundaries of the search space and then randomly initialized the parameters. Each value's fitness is calculated, and then the G_V(t), best (t), and worst (t) values are determined (t). Then, determine the sum of the forces acting in each direction and their corresponding velocities and accelerations. After the particle's location has been updated. This process iterates until the stopping criterion is met by the function [146].

J. FLOWER POLLINATION ALGORITHM (FPA) BASED MPPT

FPA was first presented by Xie Yang in 2012 and was motivated by the process of flower pollination that occurs naturally [106]. Pollen movement from one species to another is referred to as the phenomena of pollination. Cross-pollination or self-pollination are the two processes that lead to the term ''pollination.'' The mechanism aids in the emergence of new species in the flowers. The two main types of pollination are biotic and abiotic, both of which rely on pollen. Abiotic pollination uses wind or water, whereas biological pollination uses pollinators. Cross-pollination and self-pollination are the two types of pollination that can occur based on physical proximity. While self-pollination uses the pollen of the same flower or a different blossom on the same plant, cross pollination uses the pollen of a separate plant to fertilize the plant. Pollinators, such as honeybees, visit flowers of the same species because they are aware that nectar is present in those blooms. The pollen transmission to the same species of flower and consequently its reproduction is maximized by such floral constancy. The following guidelines and presumptions were used to build the flower pollination algorithm (FPA), which is based on the characteristics of the flower pollination process mentioned above [107]:

- ➢ Since biological and cross-pollination occur across great distances, they are regarded as forms of global pollination. Levy flights are used to make an approximation of pollinator movement.
- ➢ Self-pollination and abiotic pollination are regarded as local pollination.
- ➢ Flower constancy is used as a proxy for the likelihood of reproduction and is inversely correlated with flower-to-flower compatibility.
- ➢ Local and global pollination are determined by a switch probability p [0,1].
- ➢ In order to keep the algorithm simple, it is assumed that each plant has a single flower, and that each blossom contains a single pollen gamete, which is the same as the response.

K. JAYA ALGORITHM (JA) BASED MPPT

The Jaya Algorithm is an alternative to gradient-based optimization methods. It can be used to either maximize or minimize a function's value. It is a population-based method that can deal with constrained and unconstrained optimization issues by constantly adapting a pool of potential alternatives. The Jaya method, which is used to extract MPP from PV systems, is based on a brand-new swarm-based approach. Jaya does not need parameters that are unique to an algorithm. As a result, Jaya is simple to implement even without sufficient parameter adjustment for the method [108].

The flow chart of Jaya algorithm based maximum power point tracking is shown in Figure 28. Jaya discovers the optimal solution by firstly initializing m candidate solutions and next iterative updating them using given equation (33),

$$V'_{i,j} = V_{i,j} + r_{i,1}\left(V_{i,best} - \left|V_{i,j}\right|\right) - r_{i,2}\left(V_{i,worst} - \left|V_{i,j}\right|\right)$$
$$V_{i+1,j} = \begin{cases} V'_{i,j}, & iff(V'_{i,j}) > f(V_{i,j}) \\ V_{i,j}, & iff(V'_{i,j}) \leq f(V_{i,j}) \end{cases} \tag{33}$$

where $V_{i,j}$ is the j_{th} candidate solution at iteration (i), $V_{i,best}$ is the best candidate at iteration i, and $V_{i,worst}$ is the worst candidate solution at iteration (i). $V'_{i,j}$ is the update of $V_{i,j}$ and $r_{i,1}$ and $r_{i,2}$ are stochastic numbers generated from the uniform distribution U ξ [0,1] [152].

L. CAT SWARM OPTIMIZATION (CSO) BASED MPPT

The Cat Swarm Optimization (CSO) algorithm considers the ways in which cats live and hunt for food. Individual cats' locations show which group they belong to, their velocity, and their fitness value in this algorithm. In addition, the cat's

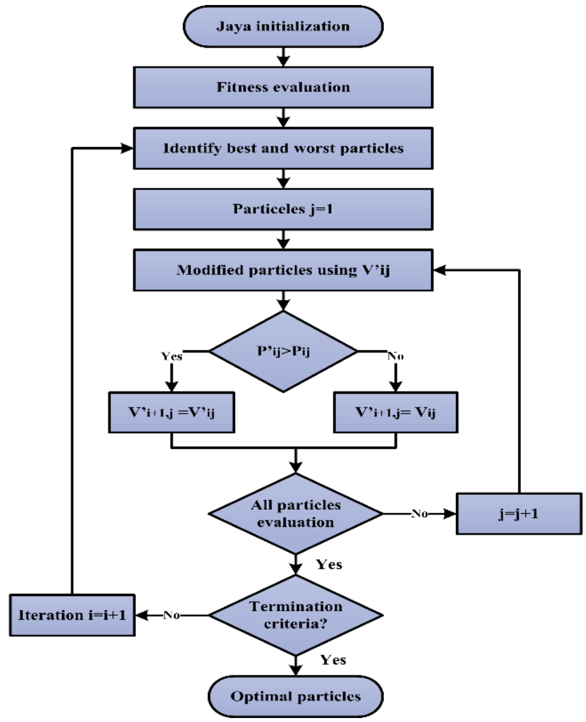

FIGURE 28. Flow chart of jaya algorithm based MPPT techniques.

mode is designated by a mark. The search mode (SM) in CSO has cats constantly attentive and moving extremely slowly, whereas the tracing mode (TM) has cats pursuing the target once it is detected. Each mode has its own advantages and disadvantages. At each recurrence, a random classification is performed along the middle sets using all the employed cats in the population. SM oversees carrying one of them, and TM oversees carrying the other. The proportion of each group to the other is determined by the ratio of the mixture (MR). Figure 29 displays the CSO algorithm's flowchart in entirety [109].

VI. HYBRID MPPT TECHNIQUES

The conventional method cannot extract the maximum power from the PV in conditions when the weather is fast changing or the irradiance value is changeable in nature. Also, Most MPPT algorithms, such as P&O, In-Cond, fuzzy logic etc. control, are unable to identify the global maximum when the PV array is partially or completely shaded. Based on the algorithm's starting point, it is common to find a local MPP Some algorithms to deal with this problem have been proposed in the last few years. We employ the hybrid MPPT algorithm in order to extract the maximum amount of power from this situation. The Hybrid MPPT algorithm is basically by using any other new algorithm with a conventional algorithm, or by using a new/conventional algorithm with an optimization or intelligence technique like ANN, Fuzzy, GA, PSO, GWO, etc. algorithm. The hybrid algorithm is basically designed in two ways, you can use any two or more algorithms together in such a way that the new hybrid

TABLE 3. (a). Comparison chart of optimization techniques based MPPT algorithms. (b) Comparison chart of optimization techniques based MPPT algorithms.

(a)

	Differential evolution (DE) based MPPT	Cuckoo Search (CS) based MPPT	Genetic algorithm (GA) based MPPT	Particle Swarm Optimization (PSO) based MPPT	Grey Wolf Optimization (GWO) based MPPT	Ant Colony Optimization (ACO) based MPPT
PV array dependent	No	No	No	No	No	No
Ability to track True MPPT	Medium-High	High	Low-Medium	Medium-High	V. High	High
Analog or digital	Digital	Digital	Digital	Digital	Digital	Digital
Parameter tuning	No	No	No	No	No	No
Convergence speed	Medium	Fast	Medium	Medium	Medium	Medium-High
Implementation complexity	Medium	Simple-Medium	High	Medium	Medium	Medium-High
Sense parameters	V, I	V, I	V, I	V, I	V, I	V, I
Tracking accuracy	Medium	High	High	Medium	high	Medium
Tracking speed	Medium	V. High	Medium	High	Medium	High
Efficiency	Medium-High	V. High	High	V. High	V. High	V. High
Efficient in PCS	Medium	High	Medium	Medium	V. High	High
Economy	Expensive	Expensive	Expensive	Medium	Medium	Medium
Application	Off-Grid	Both	Off-grid	Both	Both	Off-grid

(b)

	Artificial Bee Colony (ABC) based MPPT	Firefly algorithm (FA)	Gravitational Search Algorithm (GSA) based MPPT	Flower pollination algorithm (FPA) based MPPT	Jaya algorithm (JA) based MPPT	Cat Swarm Optimization (CSO) based MPPT
PV array dependent	No	No	No	No	No	No
Ability to track True MPPT	High	Medium-High	Medium-High	Medium-High	High	High
Analog or digital	Digital	Digital	Digital	Digital	Digital	Digital
Parameter tuning	No	No	Yes	No	No	No
Convergence speed	Medium	Fast	Medium	Medium	Fast	Fast
Implementation complexity	Medium-High	Simple	Medium-Hight	Simple	Medium	Simple-Medium
Sense parameters	V, I	V, I	V, I	V, I	V, I	V, I
Tracking accuracy	Medium	High	Medium	High	High	High
Tracking speed	High	Fast	Fast	V. fast	V. Fast	V. High
Efficiency	V. High	High	High	V. High	V. High	V. High
Efficient in PCS	High	Medium	Medium	High	V. High	High
Economy	Expensive	Expensive	Expensive	Expensive	Expensive	Expensive
Application	Both	Both	Off-grid	Both	Both	Both

algorithm is made more efficient than the conventional algorithm. and second, by creating a new algorithm or by using some optimization technique on the convolutional algorithm in such a way that on a certain guideline some parameter changes in such a way that the new parameter makes the convolutional algorithm more efficient. This type of algorithm is named as hybrid MPPT algorithm [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20]. Most researchers are now working on hybrid algorithms to overcome the shortcomings of traditional, intelligence- or optimization-based MPPT algorithms. Many hybrids' algorithms are already available in different papers. In this section, we discuss some efficient and currently developed hybrid algorithms and compare its.

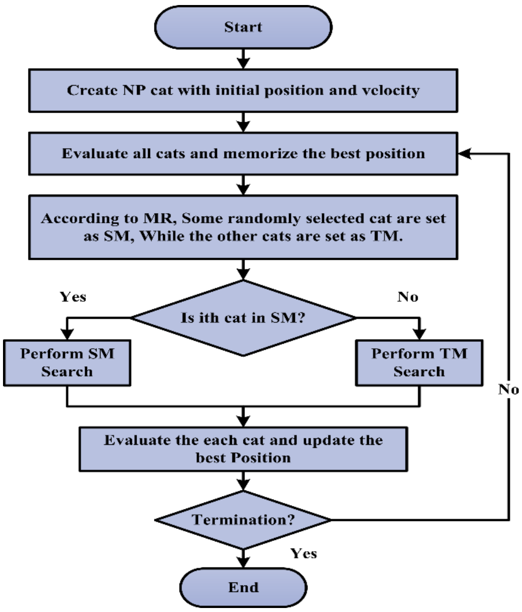

FIGURE 29. Flow chart of cat swarm optimization based MPPT.

A. FUZZY-P&O BASED HYBRID MPPT TECHNIQUES

When using conventional P&O methods, there is often a trade-off between limiting oscillation of PV array output power around MPP and achieving convergence of rising time towards MPP due to the set step size perturbation on which these methods typically operate. With a larger step size, the PV array's output power can dynamically respond more quickly to sudden changes in solar irradiance, but at the cost of power loss due to excessive steady-state oscillation around MPP.A slower dynamic reaction to a sudden change in solar irradiance is a trade-off for smaller step size, which ensures less oscillation of PV array output power near MPP. Furthermore, in partial shade conditions, solar power generates several peaks, making it difficult for the typical P&O algorithm to distinguish between global and local peaks and preventing it from reaching the MPP point for long periods of time. Many researchers have found that a Fuzzy-P&O based hybrid MPPT algorithm is the best way to get around these roadblocks [118], [163].

The Fuzzy-P&O based hybrid MPPT algorithm is shown in Figure 30. There is a wide variety of possible combinations of fuzzy logic and the P&O algorithm, and vice versa. Individually, P&O, or fuzzy logic algorithms have some drawbacks or challenges, so it depends on the researcher at what points he will be focused and what parameters he wants to improve. Many authors have turned to hybrid fuzzy-P&O based MPPT algorithms to get around the limitations of the individual algorithms they've previously used [52], [156].

B. ANN-P&O BASED HYBRID MPPT TECHNIQUES

A neural network (ANN) is a distributed system that takes its cues from biological processes and uses neurons, which are very basic processors. The training process activates neurons with a predisposition for encoding and retrieving experiential knowledge. Activities including classification, regression, and pattern recognition are carried out by ANNs. Combining an ANN technique with the traditional P&O method, the ANN-P&O approach efficiently tracks the MPP with the quick tracking convergence typical of the ANN approach. P&O MPPT controller performance is first analyzed for a PV panel coupled to a power electronics converter. In tests conducted with a wide range of irradiance levels and cell temperatures, it was found that the P&O MPPT controller oscillates more noticeably in response to rapid shifts in the solar radiation levels. The ANN-P&O approach combines an ANN technique with traditional P&O method to efficiently track the MPP with fast tracking convergence, a hallmark of the ANN approach, and thus overcome these types of problems [119].

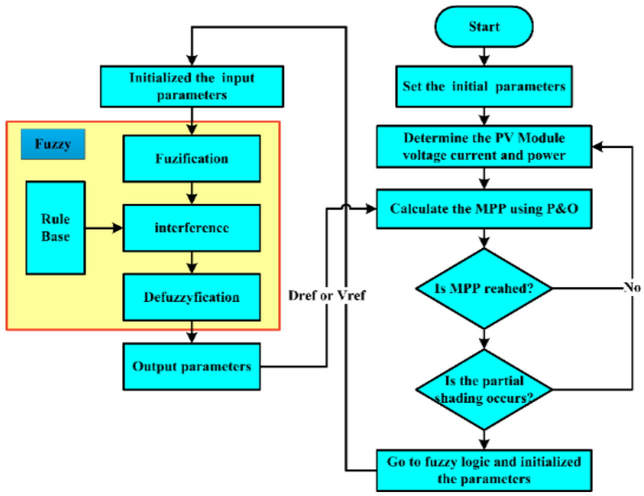

FIGURE 30. Flow chart of Fuzzy-P&O based MPPT algorithm.

$$D_{ref} = {}^{V_{out}}/_{V_{ref}} \tag{34}$$

where P&O uses D_{ref} to monitor the GMPP's progress. There is a delay of (0.0001 sec to.001 sec) before the MPPT is updated to ensure system stability at the new MPP [157].

The ANN determines the initial maximum power, and then uses a P&O algorithm to regulate optimal power, adapting to subtle changes in its surroundings. Duty cycle (D_{ref}), power output (P_{old}), and power change due to sudden irradiance shift (P_{sudden}) are all initialised after the training phase. P_{sudden} is a cut-off point indicating when shading begins. A new MPP's predicted region is determined by an ANN whenever the difference between two successive power values exceeds P_{sudden} [159], [160].

C. GA-P&O BASED HYBRID MPPT TECHNIQUES

The MPPT technique of "perturb and observe" is often employed because of the relative ease with which it may be put into practice. However, total system efficiency is reduced and power losses are increased due to some inability to track the GMPP under continuously changing solar irradiation and partial shading conditions. Many academics have explored using a genetic algorithm (GA) in conjunction with P&O MPPT to address these drawbacks. The genetic algorithm's

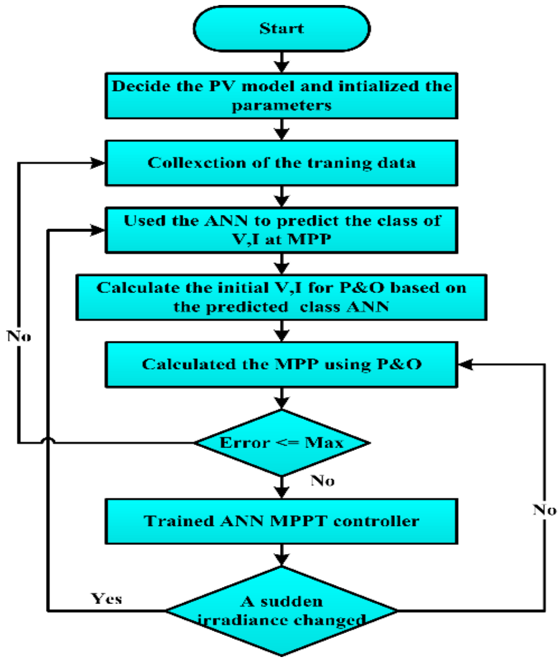

FIGURE 31. Flow chart of ANN-P&O based MPPT algorithm.

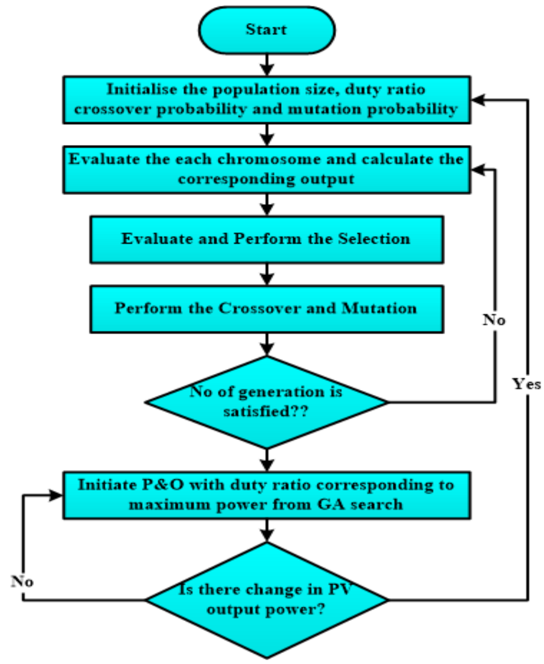

FIGURE 32. Flow chart of GA-P&O based MPPT algorithm.

first three chromosomes and the duty ratio are then used to calculate the PV system's theoretical maximum output power; this value is then used as a starting point for the hybrid Perturb and Observe method [158]. In order to get too global MPP in a realistic, accurate, and quick manner. As the search progresses, the P&O step sizes are varied to get the shortest possible step length. When adjusting the P&O algorithm's next move such that it follows the GMPP, the step size length is updated using the following equation (35).

$$d_k = d_{k-1} + \Delta d_k \tag{35}$$

where $\Delta d_k = \alpha * \Delta d_{k-1}$, α is the step size. The flowchart depicted in Figure 32 provides an explanation of the actions that take place in the hybrid algorithm in the order that they occur.

D. PSO-P&O BASED HYBRID MPPT TECHNIQUES

The swarm behavior of animals like birds, such as flocking and fish schooling, served as inspiration for PSO, a simple and effective meta-heuristic (Kennedy and Eberhart, 1995). Several sections of the power production industry have benefited greatly from PSO's implementation. Initially, particle swarm optimization is used, and subsequently the perturb and observe technique is implemented. Inspired by observations of animal social behavior, such as bird flocking, fish schooling, and swarm theory, PSO is a stochastic, evolutionary computer technique. It sustains what it calls a "particle population." In this method, the search space is traversed by a stream of particles, each of which represents a potential solution. Particles communicate their current locations and the knowledge they have gathered by flying with other particles in the area. As a result, each individual particle eventually reaches the optimal state for the entire cosmos. The optimization of multimodal functions (i.e., functions having numerous optima) is an attractive application of PSO, and PV systems operating under PSC are no exception. Each particle in the PSO-P&O approach represents a potential solution to the problem, and the swarm of particles is used to find the best one. For determining a particle's position and velocity, one uses (36):

$$\mathrm{V}_{\mathrm{i}}^{\mathrm{k+1}} = \mathrm{w}_{\mathrm{i}}\mathrm{V}_{\mathrm{i}}^{\mathrm{k}} + \mathrm{r}_1\mathrm{c}_1\left(\mathrm{P}_{\mathrm{best}_{\mathrm{i}}} - \mathrm{d}_{\mathrm{i}}^{\mathrm{k}}\right) + \mathrm{r}_2\mathrm{c}_2\left(\mathrm{g}_{\mathrm{best}} - \mathrm{d}_{\mathrm{i}}^{\mathrm{k}}\right) \tag{36}$$

$$\mathrm{d}_{\mathrm{i}}^{\mathrm{k+1}} = \mathrm{d}_{\mathrm{i}}^{\mathrm{k}} + \mathrm{V}_{\mathrm{i}}^{\mathrm{K+1}} \tag{37}$$

where k is the iteration number, w is the mass of the particles, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are independent random variables and r_1, $r_2 \varepsilon$ (0,1), P_{best_i} is the optimal location for particle i and g_{best} is the optimal location for the entire swarm [141], [145].

In Figure 33, we have a flowchart depicting the hybrid P&O-PSO MPPT algorithm for low-power oscillation. In this technique, the operative point is kept at the GMPP using the standard Perturb and Observes method until the system detects the appearance of partial shading. Once GMPP tracking is complete, data storage can begin (i.e., voltage, current and power). To detect partial shading, it then evaluates the original current and voltage levels in comparison to the new ones. After detecting partial darkening, the procedure will determine if the peak on the far right is the GMPP. If the power difference limit holds true, the current GMPP is used; otherwise, the "Main Process" begins tracking the GMPP once more and re-calls the "global peak tracking" subroutine. With this method, the optimal voltage range can be determined. The Particle Swarm Optimization technique then conducts a search of this region before continuing to the next. The necessity of following the other summits is examined.

TABLE 4. Comparison chart of hybrid method based MPPT algorithms.

	Fuzzy-P&O Based Hybrid MPPT Techniques	ANN-P&O Based Hybrid MPPT Techniques	GA-P&O Based Hybrid MPPT Techniques	PSO-P&O Based Hybrid MPPT Techniques	GWO-P&O Based Hybrid MPPT Techniques
PV Array Dependent	Yes	Yes	No	No	No
Ability to track True MPPT	Medium to High	Medium to High	High	High	V. High
analog or Digital	Digital	Digital	Digital	Digital	Digital
Periodic Tuning	Yes	Yes	No	Yes	Yes
Convergence speed	Medium	Medium	High	High	High
Implementation complexity	Medium	High	High	Medium to high	Medium to high
Sense Parameters	V, I	V, I	V, I	V, I	V, I
Tracking Accuracy	Medium	High	High	High	V. High
Tracking Speed	High	V. High	V. High	V. High	high
Efficiency	High	V. High	V. High	V. High	V. High
Efficient in PCS	Medium	High	High	High	V. High
Economy	Medium	Expensive	Expensive	Medium	Medium
Application	Off-grid	Off-grid	Both	Both	Both

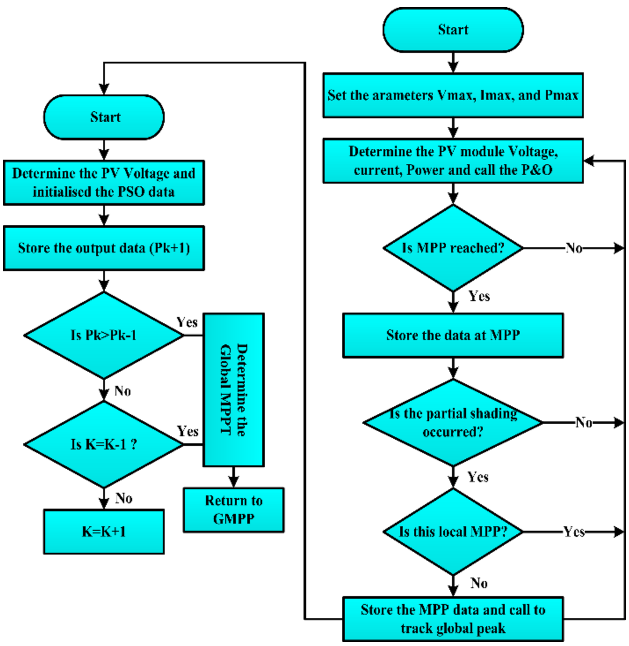

FIGURE 33. Flow chart of PSO-P&O based MPPT algorithm.

If the power difference constraints are met, the global MPP value is verified by checking that all the MPP values in storage agree. The procedure will be continued until all the local peaks have been considered to determine the global peak, or until the condition fails. The Perturb and Observe technique keeps the setpoint at the global MPP even after the ''global peak tracking subroutine'' has returned [150].

E. GWO-P&O BASED HYBRID MPPT TECHNIQUES

The GWO-PO hybrid MPPT approach is an intelligent computational algorithm that eliminates the misunderstanding that can arise while converting from homogeneous to non-homogeneous and vice versa. This technique is the result

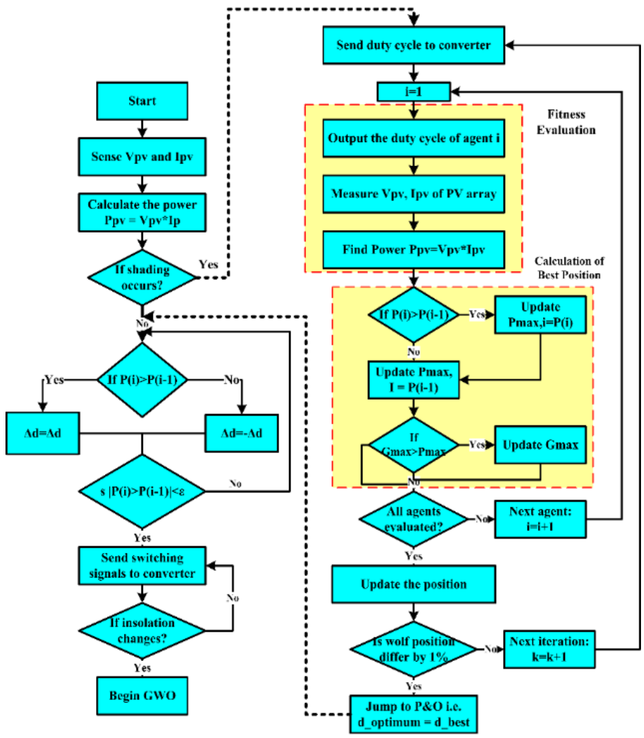

FIGURE 34. Flow chart of GWO-P&O based MPPT algorithm.

of the combination of the GWO and P&O based MPPT techniques. i.e., when there is uniform insolation, the P&O MPPT follows the MPP, but when there is non-uniform insolation, the hybrid MPPT follows the GP. In this case, the hybrid MPPT starts by initializing the GWO, then it moves on to the activity of following the GP. When the grey wolves get closer to one another, that is when the P&O MPPT gets underway at the location of the best wolf in the GWO process [126], [151].

The flow chart of the GWO-P&O-based MPPT algorithm is shown in Figure 34. First, we started with conventional

TABLE 5. Analysis of different MPPT algorithms implemented by different authors.

Reference	MPPT Method	Converter Type/ Control Variable	Efficiency (%)	Inputs	Experimental Setup Included	Remarks
Kok Soon Tey, et al. [110], 2014	Modified-INC	SEPIC converter / Duty Cycle	High	V, I	Yes	To track the MPP for PV modules under a rapidly varying solar irradiation level, a modified incremental conductance technique was employed. because it does not exhibit steady-state oscillation, power losses are minimized.
Bader N. Alajmi, et al, 2011 [111]	Modified Hill-Climbing	Boost converter / Duty Cycle	High	V, I	Yes	This study describes a Fuzzy-Logic-Control Hill-Climbing Method for MPPT. This controller improves hill-climbing search by fuzzifying the ground rules and eliminating their downsides. Fuzzy logic hill climbing is more efficient in steady-state and changing weather.
M. A. Ghasemi et al. [112], 2020	M-FOCV	Boost converter / Duty Cycle	High	V, I	No	Two-stage MPPT tracking for partially shaded solar systems is described. First-power-voltage samples are collected using fractional open-circuit voltage. MPPT controllers reduce sampling error to estimate module voltage. In simulations and testing, the tracker performs better than alternative strategies.
H. Fathabadi, et al. [113], 2016	Unified algorithm	Boost converter / Duty cycle	Medium	V, I	Yes	There is no requirement for sensors in the design of MPPT.
Chin-Sien Moo et al. [115], 2014	ripple current orientation based	Boost converter / Duty Cycle	High	V, I	Yes	In a novel maximum power point tracking method, the phase deviation of the rippling current and voltage from a PV panel is detected. The suggested tracking method has a faster convergence time than standard MPPT methods because it does not calculate or measure PV power.
M. Q. Yu, et al. [114]. 2018	Gauss Newton MPPT.	Boost converter / Duty Cycle	Medium	V, I	No	This Gauss-newton approach models the parameters that are altered for the PV system, and an enhanced method, dubbed PGN (Proposed Gauss-Newton), is designed and simulated in MATLAB.
J.H. Zhang, et al. [116] 2019	Fibonacci based MPPT	-------	99.71	T, V, I	No	This method's effectiveness is confirmed in both uniform illumination environments (UIE) and non-uniform illumination environments (NIE), and an updated Fibonacci method is used to narrow the search window.
A. Kihal, et al. [117] 2018	SMC	Boost converter / Duty Cycle	99.45	V, I	Yes	To achieve dynamic fast-tracking under PSCs, a new Voltage Oriented Maximum Power Point Tracking (VO - MPPT) for the standalone system is presented. Full tracking to the optimal location is achieved with the help of the AIDSM (Adaptive Integral Derivative Sliding Mode) controller in this method.
X. Li, et al. [118] 2019	FLC	Boost converter / Duty Cycle	98.6	V, I	Yes	A new three-input, one-output, parameter-based FLC is proposed, and its hardware implementation is complete; this approach will reduce the total number of membership functions.
L.M. Elobaid, et al. [119] 2012	ANN	Boost converter / Duty Cycle	99.15	V, I	No	ANN is trained with the training function and a Levenberg Marquardt (LM) activation function (AF), and ANN-based MPPT is evaluated in MATLAB with two dynamic changes. The results show that ANN is competent in following the MPP in PSCs. We collect information from 35 P-V plots.
T. L. Nguyen, et al. [120], 2010	Direct Search	Boost converter / Duty Cycle	99.85	V, I	Yes	This study introduces dividing rectangles for tracking MPP. The new method seeks global maxima, improving on perturb-and-observe. This is vital in partly shaded systems. Experiments show the method works. The proposed method tracks moving targets reliably and quickly.

TABLE 5. *(Continued.)* **Analysis of different MPPT algorithms implemented by different authors.**

Reference	MPPT Method	Converter Type/ Control Variable	Efficiency (%)	Inputs	Experimental Setup Included	Remarks
Soufyane Benyoucef et al. [121], 2015	ABC	Boost converter / Duty Cycle	99.35	V, I	Yes	The direct duty cycle control ABC approach outperforms PSO in tracking time and accuracy. Enhanced fluctuations are detrimental.
Pilakkat and Kanthalakshmi, [122], 2018	ABC	Boost converter / Duty Cycle	97.75	V, I	No	There is no comparison with other MPPT algorithms to indicate that the proposed ABC is superior, however it is stated that it effectively monitors the GMPP with high efficiency and fast response time.
Sundareswaran et al. [123], (2014)	FA	Boost converter / Duty Cycle	99.57	V, I	Yes	Both P&O and PSO are not even close to the limits of tracking speed and efficiency. However, there are significant delays between oscillations at start-up and settling down.
Priyadarshi et al. [124], 2019	ACO	Cuck converter / Duty Cycle	98.87	V, I	Yes	The proposed method outperforms the PSO, ABC, and FFA MPPT algorithms by a factor of seven in terms of convergence speed and tracking efficiency.
Jegha et al. [125], 2020	GWO	Luo converter / Duty Cycle	97.8	V, I	Yes	An improved PV system, using a LUO converter and BLDC motor drive, is designed for a water pumping application. There is a recommendation to expand the project to include a three-phase brushless DC (BLDC) pumping motor.
Mohanty et al. [126], 2017	GWO	Boost converter / Duty Cycle	99.8	V, I	Yes	Compared to P&O and PSO, a GWO performs better. Uniform performance curves. The algorithms with identical features are used for the comparison.
Brindha et al. [127], 2020	CSA	Zeta converter / Duty Cycle	High	V, I	No	When a BLDC motor is used to drive a centrifugal pump, a CSA is required for the motor.
J. Ahmed, et al. [128], 2013	Cuckoo Search	Buck-Boost converter / Voltage	High	V, I	No	An algorithm based on Cuckoo Search is modelled in MATLAB and compared to P&O. Convergence speeds between CS and P&O are much shorter, according to the results.
Hugues Renaudineau, et al. [129], 2015	PSO	Boost converter / Duty Cycle	98.1	V, I	Yes	It has been proposed to implement a global optimization technique into a PV generation system that uses distributed generation. PV power generation also uses a PSO-based distributed MPPT technique.
S. Lyden, M. E. Haque, et al. [130], 2014	SA	Boost converter / Duty Cycle	High	V, I	No	This study describes a Simulated Annealing-based GMPPT method for PV systems that are partially shadowed (PSC). The proposed method is tested with Particle Swarm Optimization GMPPT and Perturb and Observe MPPT.
Liang-Rui Chen, et al. [131], 2010	Biological Swarm Chasing	Buck converter / Duty Cycle	High	V, I	Yes	To improve the MPPT performance for a module integrated PV power system, a new method of photovoltaic (PV) maximum power point tracking (MPPT) is suggested, inspired by the swarm pursuing behavior of biological swarms.
P. Kofinas, et al. [132], 2015	BB-BC with ANN	Buck converter / Current	High	I	Yes	The ANN is trained using a new learning-based approach called backpropagation with backward correction (BB-BC).
Al-wesabi Ibrahim et al. [133], 2020	M-PSO	Boost converter / Duty Cycle	99.87	V, I	Yes	The MPSO-based algorithm increases PV system output power in abnormal situations. Partial shading conditions and non-uniform irradiance levels are simulated in MATLAB to evaluate the suggested method and compared to neural network results. This comparison helps evaluate the proposed method's efficacy. Verify the outcomes using an experiment.
J. Ahmed, et al. [134], 2014	Cuckoo search and PSO	Buck-Boost converter / Voltage	V. High	V, I	No	In order to examine and analyses how well the CS technique operates in typical (uniform), intermediate (step), and extreme (abrupt) variations in the weather, MATLAB is utilized.

TABLE 5. ***(Continued.)*** **Analysis of different MPPT algorithms implemented by different authors.**

Reference	MPPT Method	Converter Type/ Control Variable	Efficiency (%)	Inputs	Experimental Setup Included	Remarks
H. Rezk, et al. [135], 2017	Teaching-learning-based optimization	Boost converter / Duty Cycle	High	V, I	No	This newly developed optimization-based approach, known as TLBO, is examined, and analyzed to determine how effective it is.
A. Fathy, et al. [136], 2016	Mine blast optimization (MBO)	Boost converter / Duty Cycle	High	V, I	No	This article examines the mine blast analogy as a means of understanding the Nature-inspired approach known as MBO.
Kok Soon Tey, et al. [137], 2014	M-INC	Boost converter / Duty Cycle	High	V, I	Yes	This work presents a multifaceted duty cycle control mechanism for Inc Cond, allowing for more efficient use of the periodic P-V features of partially shaded circumstances.
Azadeh Safari, et al. [138], 2010	Direct control-INC	Cuck converter / Duty Cycle	Good	V, I	Yes	In this work, an additional control loop was avoided by adopting the INC MPPT with fixed-step-size direct control.
A. S. Mahdi, et al. [139] 2020	ANFIS	Boost converter / Duty Cycle	V. High	V, I	No	The MPPT system is simulated using a boost DC-DC converter and an MSX-64 PV module. The ANFIS controller reacts dynamically to climatic changes. ANFIS performance is compared to traditional methods at 50% and 25% shading.
Vivek Nandan Lal, et al. [140], 2016	M-PSO	VSI/ Vref	99.5	V, I	No	A modified PSO algorithm is proposed to maintain MPP for single-stage PV grid connection. PV voltages are used as PSO agents, and the PSO MPPT controller computes the dc-link controller's voltage reference to follow the MPP regardless of shading.
K. L. Lian, et al. [141], 2014	P&O-PSO	Interleaved Boost converter / Duty Cycle	99.2	V, I	Yes	In this study, P&O and PSO are combined. In the first stage, P&O 23assigns the closest local maximum. We utilize PSO to find the GMP using the previous step's results. With the hybrid technique, the PSO's search space is shrunk, speeding up convergence.
Xiaoling Yuan, et al. [142], 2015	AIW-PSO	Boost converter / Duty Cycle	99.4	V, I	No	This study designs and implements the adaptive inertial weight particle swarm optimization (AIWPSO) algorithm. As a result, the MPPT potential of a PV system is enhanced in partially shaded environments.
S. M. Mirhassani, et al. [143], 2015	Improved particle swarm optimization	Boost converter / Duty Cycle	High	V, I	Yes	Using the variable sampling approach, traditional PSO is optimized to better follow the MPP in less time.
N. Sangawong, et al. [144], 2015	Fuzzy-PSO	Boost converter / Duty Cycle	V. High	V, I	Yes	This Fuzzy-PSO approach optimizes the D used to regulate the converter by automatically modifying the fuzzy rules, making the system adaptive.
Manickam et al. [145], 2016	PSO-P&O	Boost converter / Duty Cycle	V. High	V, I	Yes	An improved algorithm that combines PSO and P&O is used to dampen power fluctuations in string inverters. The settling time is significant, however.
Nugraha et al. [146], 2018	CSA–GSS	Boost converter / Duty Cycle	99.87	V, I	Yes	Comparatively, a hybrid CSA-GSS requires less time to track than PSO or traditional CSA. Oscillations and the need for additional settling time remain problems.
Safarudin et al. [147], 2015	FA-P&O	Buck converter / Duty Cycle	99.67	V, I, T	Yes	Hybrid FA-P&O systems outperform both traditional FA and P&O systems in terms of tracking speed and convergence accuracy. However, significant delays between oscillations at start-up and settling down.
Ajiatmo and Robandi, [148], 2017	FLC-FA	Boost converter / Duty Cycle	99.98	V, I	No	In order to get MP out of the PV system, a hybrid FLC-FA algorithm is implemented for the solar automobile. It is more efficient than both P&O and FLC.
Catalina González-Castaño et al. [149], 2021	ABC -PI	Boost converter / Duty Cycle and Current	99.9	V, I	Yes	The artificial bee colony algorithm is used to find the outer PI loop voltage reference to maximize PV system power. This algorithm's double loop control with inner current control provides fast tracking power, efficiency, flexibility, no parameters knowledge, and simplicity. The ABC algorithm's effectiveness will be tested using experimental setups.
K. Sundareswaran, et al. [150], 2015	PSO-P&O	Boost converter / Duty Cycle	99.89	V, I	Yes	The 6S (6 series) and 3S2P (3 series) shading arrangements both successfully verify the hybrid approach (3 series and 2 parallel). The overall performance outstrips that of both PSO and P&O approaches taken separately.

TABLE 5. *(Continued.)* **Analysis of different MPPT algorithms implemented by different authors.**

Reference	MPPT Method	**Converter Type/ Control Variable**	Efficiency (%)	**Inputs**	**Experimental Setup Included**	Remarks
S. Mohanty, et al. [151], 2017	GWO-P&O	Boost converter/ Duty Cycle	99.98	V, I	Yes	Different shading patterns are simulated, including 3S (3 series) and 3S2P (3 series and two parallel), and the performance characteristics of distinct optimization techniques such GWO, hybrid PSO-P&O, and GWO - P&O are analyzed. In a 3S shading pattern, this hybrid MPPT operated at full efficiency.
Nishant Kumar, et al. [152], 2017	Jaya-DE	Boost converter/ Duty Cycle	99.98	V, I	Yes	In variable weather, Jaya-DE is used for MPPT in fully and partially shaded conditions. The performance of Jaya-DE in GMPP tracking under uniformly and partially shaded settings in steady state and dynamic conditions was compared to several prominent approaches (FPA, ACOPO, and PSO).
Macaulay et al. [156], 2018	FLC-IC and FLC-P&O	Buck-Boost converter/ Duty Cycle	V. High	V, I	Yes	This article models two different hybrid MPPT methods and evaluates them in terms of efficiency, tracking speed, and convergence time. Each hybrid MPPT method's efficiency is analyzed as it stands up to a quick and consistent change in irradiance.
Eltamaly et al. [153], 2019	Grey wolf-FLC	Boost converter/ Duty Cycle	High	V, I	No	The soft computing MPPT methods experience excessive steady-state oscillation during MPP and lose track of MPP if the GMPP is modified. The article suggests a grey wolf-FLC to monitor the global MPP as a solution.
Priyadarshi, N. et al. [154], 2022	Grey wolf-FLC	Multilevel Boost converter/ Duty cycle	High	V, I	Yes	A hybrid GWO-FLC based MPPT technique offers zero oscillation tracking of the GMPP as well as high PV power tracking in the face of quick weather changes. By acquiring GMPP and offering soft tuning of fuzzy parameters, the GWO technique achieves high PV power tracking with no oscillations around GMPP. The experimental results validate the changes in the environment.
(Kchaou et al. [155], 2017	Second order sliding mode control	Boost/ Duty Cycle	V. High	V, I	No	The paper recommends a reliable MPPT method that employs a sliding mode control strategy of the second order. The outcomes demonstrate the algorithm's quick response and reduced background noise in dynamic environments.

P&O algorithms. If shading is occurring in that case, move towards the GWO algorithms and determine the best duty cycle (D_{best}). If the wolf position does not differ by more than 1%, then proceed to the next iteration and repeat all steps. When we obtain the D_{best}, we return to the traditional P&O algorithms [154].

VII. DISCUSSION ON REVIEW FINDINGS

There are a variety of methods for locating the maximum power point that have been published. This research reviewed the literature on MPPT methods for both uniform and non-uniform (shading) solar irradiation circumstances. Conventional MPPT methods, Intelligence-based MPPT methods, Optimization-based MPPT methods, and Hybrid MPPT methods are the four primary categories that categories these strategies. All MPPT methods strive for the same goal of reaching the maximum power point under all circumstances. We address the sense parameters, efficiency, efficiency in PCS, convergence speed, tracking accuracy, tracking speed, design complexity, economy, and sensitivity to environmental changes in Tables 1, 2, 3 and 4, respectively. The Table 5 below classifies and reviews the various MPPT strategies applicable under variable environment or partial shading conditions by different researchers. Also, compare the efficiency of different algorithm for different environmental condition. This work provides an in-depth review of over fifty MPPT methods from various works of literature, evaluating their features and drawbacks. The following discussion is based on an examination of the literature surrounding the various solar PV system MPPT methods, and it may prove helpful when deciding which method best meets the needs of both corporations and customers.

- ➢ Most of the conventional MPPT method is not complex in nature also hardware implementation is easy but main disadvantage of this algorithm is less accuracy, time taken to reach the MPP is more, oscillation around MPP point in rapid change environment condition. In this study some modification in conventional algorithm using intelligence or optimization techniques is discussing.
- ➢ Among the all traditional MPPT method discussed in this study. in which, some algorithms have providing good results in variable environmental condition. for selecting the best traditional MPP method algorithm based on requirement you can follow the comparison chart discuss in Table 1.

TABLE 6. Comparison chart in between different category of MPPT algorithms.

MPPT Method	Pros	Cons
Conventional MPPT Method	➢ Simple and cost effective ➢ Easy to implement ➢ High reliability	➢ Low efficiency ➢ Slow tracking ➢ Sensitive to changes in environment
Intelligent MPPT Method	➢ Fast response time ➢ High efficiency ➢ Robust against environmental changes	➢ Complex control system ➢ Higher cost
Optimization Based MPPT Method	➢ High efficiency ➢ Fast tracking time ➢ Medium complexity	➢ High cost ➢ Sensitive to environmental changes
Hybrid MPPT Method	➢ Fast response time ➢ Very High efficiency ➢ Robust against environmental changes ➢ Medium complexity	➢ Higher cost ➢ Sensitive to changes in power source

- ➢ OCV, CV, SSC, and CC are four examples of classic MPPT algorithms that are based on constant parameters and are significantly faster than many other classic or intelligent algorithms. due to the absence of derivative calculations in these algorithms. The implementation is also very straightforward.
- ➢ Current-based methods are more accurate than voltage-based methods but require more expensive and complex hardware to implement, leading to higher losses.
- ➢ There is no need for a precise mathematical model when using the intelligent MPPT methods like FLC, ANN, and the resulting tracking efficiency is striking. Despite their effectiveness, these algorithms have yet to be widely adopted for tracking MPP from PV sources. One of the primary drawbacks of these algorithms is the high implementation cost.
- ➢ Under the partial shading condition, the optimization techniques based MPPT algorithms are best option to extract the maximum power from the PV panels. There are various evolutionary optimization techniques based MPPT techniques is available in which some important techniques discuss in this study.
- ➢ To overcomes the issues in traditional and intelligence MPPT algorithm many researchers move towards hybrid MPPT algorithms basically its combination of two algorithm for overcomes the drawbacks of each other's algorithms. Hybrid algorithm is more efficient in PSC as well as rapid changed environmental condition. but implantation complexity is high. Some Currently emerging hybrid MPPT algorithm is discuss in this study. Also, more than 30 hybrid algorithms are discussed in Table 5.

VIII. CONCLUSION

Solar energy is one of the suitable sustainable energy sources that has demonstrated a remarkable potential in meeting the world's energy requirements. But since the output of PV systems depends on sun-oriented irradiance, it is crucial to use the right maximum power extraction techniques. To improve the effectiveness of PV systems, numerous researchers all over the world have been diligently exploring and developing novel MPPT methods. This review article thoroughly examines about 50 different MPPT techniques under four different categories, including classical, intelligent, optimization, and hybrid techniques. Classical techniques are appropriate for uniformly shaded PV systems, whereas intelligent techniques are more appropriate for partially shaded PV systems. For both uniform and partial shading conditions, optimization-based approaches to enhancing tracking efficiency and convergence speed are described. Recent developments in hybrid methods, which combine classical, intelligent, and optimization techniques to effectively track the global maximum power, are made in response to rapidly changing environmental conditions. The results are broken down in a comparative summary at the conclusion of each discussion in accordance with the important benchmarks for selection, such as sensor type, efficiency, tracking speed, complexity, convergence speed, and implementation cost. So, this discussion review will be very useful in comprehending the MPPT requirements and putting them into practice. Finally, a comparison chart highlights the benefits and drawbacks of each category of MPPT algorithms. The overall study assists in determining the best MPPT algorithm for various scenarios.

REFERENCES

[1] M. H. Ahmadi, M. Ghazvini, M. Sadeghzadeh, M. Alhuyi Nazari, R. Kumar, A. Naeimi, and T. Ming, "Solar power technology for electricity generation: A critical review," *Energy Sci. Eng.*, vol. 6, no. 5, pp. 340–361, Oct. 2018.

[2] A. K. Pandey, V. V. Tyagi, J. A. Selvaraj, N. A. Rahim, and S. K. Tyagi, "Recent advances in solar photovoltaic systems for emerging trends and advanced applications," *Renew. Sustain. Energy Rev.*, vol. 53, pp. 859–884, Jan. 2016.

[3] J. T. Bialasiewicz, "Renewable energy systems with photovoltaic power generators: Operation and modeling," *IEEE Trans. Ind. Electron.*, vol. 55, no. 7, pp. 2752–2758, Jul. 2008.

[4] P. Bhatnagar and R. K. Nema, "Maximum power point tracking control techniques: State-of-the-art in photovoltaic applications," *Renew. Sustain. Energy Rev.*, vol. 23, pp. 224–241, Jul. 2013.

[5] T. Tafticht and K. Agbossou, "Development of a MPPT method for photovoltaic systems," in *Proc. Can. Conf. Electr. Comput. Eng.*, May 2004, pp. 1123–1126.

[6] B. Subudhi and R. Pradhan, "A comparative study on maximum power point tracking techniques for photovoltaic power systems," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 89–98, Jan. 2013, doi: 10.1109/TSTE.2012.2202294.

[7] P. K. Sorte, K. P. Panda, and G. Panda, "Current reference control based MPPT and investigation of power management algorithm for grid-tied solar PV-battery system," *IEEE Syst. J.*, vol. 16, no. 1, pp. 386–396, Mar. 2022.

[8] X. Li, Q. Wang, H. Wen, and W. Xiao, "Comprehensive studies on operational principles for maximum power point tracking in photovoltaic systems," *IEEE Access*, vol. 7, pp. 121407–121420, 2019.

[9] M. Mao, L. Cui, Q. Zhang, K. Guo, L. Zhou, and H. Huang, "Classification and summarization of solar photovoltaic MPPT techniques: A review based on traditional and intelligent control strategies," *Energy Rep.*, vol. 6, pp. 1312–1327, Nov. 2020.

[10] N. A. Kamarzaman and C. W. Tan, "A comprehensive review of maximum power point tracking algorithms for photovoltaic systems," *Renew. Sustain. Energy Rev.*, vol. 37, pp. 585–598, Sep. 2014.

[11] A. Reza Reisi, M. Hassan Moradi, and S. Jamasb, "Classification and comparison of maximum power point tracking techniques for photovoltaic system: A review," *Renew. Sustain. Energy Rev.*, vol. 19, pp. 433–443, Mar. 2013.

[12] N. Karami, N. Moubayed, and R. Outbib, "General review and classification of different MPPT Techniques," *Renew. Sustain. Energy Rev.*, vol. 68, pp. 1–18, Feb. 2017.

[13] A. Ali, K. Almutairi, S. Padmanaban, V. Tirth, S. Algarni, K. Irshad, S. Islam, M. H. Zahir, M. Shafiullah, and M. Z. Malik, "Investigation of MPPT techniques under uniform and non-uniform solar irradiation condition-a retrospection," *IEEE Access*, vol. 8, pp. 127368–127392, 2020, doi: 10.1109/ACCESS.2020.3007710.

[14] E. Koutroulis and F. Blaabjerg, "Overview of maximum power point tracking techniques for photovoltaic energy production systems," *Electr. Power Compon. Syst.*, vol. 43, no. 12, pp. 1329–1351, Jul. 2015.

[15] K. P. Panda, A. Anand, P. R. Bana, and G. Panda, "Novel PWM control with modified PSO-MPPT algorithm for reduced switch MLI based standalone PV system," *Int. J. Emerg. Electr. Power Syst.*, vol. 19, no. 5, pp. 1–17, Oct. 2018.

[16] S. Kumar Dash, S. Nema, R. K. Nema, and D. Verma, "A comprehensive assessment of maximum power point tracking techniques under uniform and non-uniform irradiance and its impact on photovoltaic systems: A review," *J. Renew. Sustain. Energy*, vol. 7, no. 6, Nov. 2015, Art. no. 063113.

[17] A. K. Podder, N. K. Roy, and H. R. Pota, "MPPT methods for solar PV systems: A critical review based on tracking nature," *IET Renew. Power Gener.*, vol. 13, no. 10, pp. 1615–1632, Jul. 2019.

[18] M. Seyedmahmoudian, B. Horan, T. Kok Soon, R. Rahmani, A. Muang Than Oo, S. Mekhilef, and A. Stojcevski, "State of the art artificial intelligence-based MPPT techniques for mitigating partial shading effects on PV systems—A review," *Renew. Sustain. Energy Rev.*, vol. 64, pp. 435–455, Oct. 2016.

[19] K. Yung Yap, C. R. Sarimuthu, and J. Mun-Yee Lim, "Artificial intelligence based MPPT techniques for solar power system: A review," *J. Mod. Power Syst. Clean Energy*, vol. 8, no. 6, pp. 1043–1059, 2020, doi: 10.35833/MPCE.2020.000159.

[20] Z. Salam, J. Ahmed, and B. S. Merugu, "The application of soft computing methods for MPPT of PV system: A technological and status review," *Appl. Energy*, vol. 107, pp. 135–148, Jul. 2013.

[21] M. A. S. Masoum, H. Dehbonei, and E. F. Fuchs, "Theoretical and experimental analyses of photovoltaic systems with voltageand current-based maximum power-point tracking," *IEEE Trans. Energy Convers.*, vol. 17, no. 4, pp. 514–522, Dec. 2002, doi: 10.1109/TEC.2002.805205.

[22] N. Femia, D. Granozio, G. Petrone, G. Spagnuolo, and M. Vitelli, "Predictive & adaptive MPPT perturb and observe method," *IEEE Trans. Aerosp. Electron. Syst.*, vol. 43, no. 3, pp. 934–950, Jul. 2007, doi: 10.1109/TAES.2007.4383584.

[23] S. K. Kollimalla and M. K. Mishra, "Variable perturbation size adaptive P&O MPPT algorithm for sudden changes in irradiance," *IEEE Trans. Sustain. Energy*, vol. 5, no. 3, pp. 718–728, Jul. 2014, doi: 10.1109/TSTE.2014.2300162.

[24] N. Kumar, I. Hussain, B. Singh, and B. K. Panigrahi, "Self-adaptive incremental conductance algorithm for swift and ripple-free maximum power harvesting from PV array," *IEEE Trans. Ind. Informat.*, vol. 14, no. 5, pp. 2031–2041, May 2018, doi: 10.1109/TII.2017.2765083.

[25] S. B. Kjær, "Evaluation of the 'Hill climbing' and the 'incremental conductance' maximum power point trackers for photovoltaic power systems," *IEEE Trans. Energy Convers.*, vol. 27, no. 4, pp. 922–929, Dec. 2012, doi: 10.1109/TEC.2012.2218816.

[26] M. A. Elgendy, B. Zahawi, and D. J. Atkinson, "Assessment of the incremental conductance maximum power point tracking algorithm," *IEEE Trans. Sustain. Energy*, vol. 4, no. 1, pp. 108–117, Jan. 2013, doi: 10.1109/TSTE.2012.2202698.

[27] S. H. Hanzaei, S. A. Gorji, and M. Ektesabi, "A scheme-based review of MPPT techniques with respect to input variables including solar irradiance and PV arrays' temperature," *IEEE Access*, vol. 8, pp. 182229–182239, 2020, doi: 10.1109/ACCESS.2020.3028580.

[28] M. Kermadi and E. M. Berkouk, "Artificial intelligence-based maximum power point tracking controllers for photovoltaic systems: Comparative study," *Renew. Sustain. Energy Rev.*, vol. 69, pp. 369–386, Mar. 2017, doi: 10.1016/j.rser.2016.11.125.

[29] A. Singhal, N. S. Benibal, S. Roy, and S. Pal, "A survey of intelligent algorithms used for MPPT of photovoltaic systems," in *Proc. AIP Conf.*, vol. 2452, 2022, Art. no. 090005, doi: 10.1063/5.0114856.

[30] H. Rezk, M. Aly, M. Al-Dhaifallah, and M. Shoyama, "Design and hardware implementation of new adaptive fuzzy logic-based MPPT control method for photovoltaic applications," *IEEE Access*, vol. 7, pp. 106427–106438, 2019, doi: 10.1109/ACCESS.2019.2932694.

[31] M. N. Ali, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "An efficient fuzzy-logic based variable-step incremental conductance MPPT method for grid-connected PV systems," *IEEE Access*, vol. 9, pp. 26420–26430, 2021, doi: 10.1109/ACCESS.2021.3058052.

[32] S. Chahar and D. K. Yadav, "Performance analysis of soft computing ANN based MPPT technique for solar PV generator," in *Proc. IEEE World Conf. Int. J. Speech Technol. Comput. (AIC)*, Jun. 2022, pp. 98–102, doi: 10.1109/AIC55036.2022.9848876.

[33] M. Elsisi, K. Mahmoud, M. Lehtonen, and M. M. F. Darwish, "An improved neural network algorithm to efficiently track various trajectories of robot manipulator arms," *IEEE Access*, vol. 9, pp. 11911–11920, 2021.

[34] A. B. G. Bahgat, N. H. Helwa, G. E. Ahmad, and E. T. El Shenawy, "Maximum power point traking controller for PV systems using neural networks," *Renew. Energy*, vol. 30, no. 8, pp. 1257–1268, 2005.

[35] R. B. Bollipo, S. Mikkili, and P. K. Bonthagorla, "Critical review on PV MPPT techniques: Classical, intelligent and optimisation," *IET Renew. Power Gener.*, vol. 14, no. 9, pp. 1433–1452, 2020.

[36] R. B. Bollipo, S. Mikkili, and P. K. Bonthagorla, "Hybrid, optimal, intelligent and classical PV MPPT techniques: A review," *CSEE J. Power Energy Syst.*, vol. 7, no. 1, pp. 9–33, Jan. 2021, doi: 10.17775/CSEEJPES.2019.02720.

[37] N. Priyadarshi, P. Sanjeevikumar, M. Bhaskar, F. Azam, I. M. Taha, and M. G. Hussien, "An adaptive TS-fuzzy model based RBF neural network learning for grid integrated photovoltaic applications," *IET Renew. Power Gener.*, vol. 16, no. 14, pp. 3149–3160, 2022.

[38] H. S.-H. Chung, K. K. Tse, S. Y. R. Hui, C. M. Mok, and M. T. Ho, "A novel maximum power point tracking technique for solar panels using a SEPIC or Cuk converter," *IEEE Trans. Power Electron.*, vol. 18, no. 3, pp. 717–724, May 2003.

[39] J. Zhang, T. Wang, and H. Ran, "A maximum power point tracking algorithm based on gradient descent method," in *Proc. IEEE Power Energy Soc. Gen. Meeting*, Jul. 2009, pp. 1–5, doi: 10.1109/PES.2009.5275737.

[40] X. Weidong, W. G. Dunford, P. R. Palmer, and C. Antoine, "Application of centered differentiation and steepest descent to maximum power point tracking," *IEEE Trans. Ind. Electron.*, vol. 54, no. 5, pp. 2539–2549, Oct. 2007.

[41] J. Zhang, T. Wang, and H. Ran, "A variable step maximum power point tracking algorithm based on gradient descent method," in *Proc. Int. Conf. Sustain. Power Gener. Supply*, Apr. 2009, pp. 1–6, doi: 10.1109/SUPERGEN.2009.5348202.

[42] P. Sahu and R. Dey, "Maximum power point tracking for photovoltaic systems using ripple correlation control," in *Proc. Int. Conf. Control, Autom., Power Signal Process. (CAPS)*, Dec. 2021, pp. 1–6, doi: 10.1109/CAPS52117.2021.9730626.

[43] A. M. Bazzi and P. T. Krein, "Concerning 'maximum power point tracking for photovoltaic optimization using ripple-based extremum seeking control,'" *IEEE Trans. Power Electron.*, vol. 26, no. 6, pp. 1611–1612, Jun. 2011, doi: 10.1109/TPEL.2010.2093605.

[44] A. Costabeber, M. Carraro, and M. Zigliotto, "Convergence analysis and tuning of a sliding-mode ripple-correlation MPPT," *IEEE Trans. Energy Convers.*, vol. 30, no. 2, pp. 696–706, Jun. 2015, doi: 10.1109/TEC.2014.2371873.

[45] H. A. Sher, A. F. Murtaza, A. Noman, K. E. Addoweesh, K. Al-Haddad, and M. Chiaberge, "A new sensorless hybrid MPPT algorithm based on fractional short-circuit current measurement and P&O MPPT," *IEEE Trans. Sustain. Energy*, vol. 6, no. 4, pp. 1426–1434, Oct. 2015, doi: 10.1109/TSTE.2015.2438781.

[46] M. Metry and R. S. Balog, "An adaptive model predictive controller for current sensorless MPPT in PV systems," *IEEE Open J. Power Electron.*, vol. 1, pp. 445–455, 2020, doi: 10.1109/OJPEL.2020.3026775.

[47] M. Metry, M. B. Shadmand, R. S. Balog, and H. Abu-Rub, "MPPT of photovoltaic systems using sensorless current-based model predictive control," *IEEE Trans. Ind. Appl.*, vol. 53, no. 2, pp. 1157–1167, Mar./Apr. 2017, doi: 10.1109/TIA.2016.2623283.

[48] X. Li, H. Wen, Y. Zhu, L. Jiang, Y. Hu, and W. Xiao, "A novel sensorless photovoltaic power reserve control with simple real-time MPP estimation," *IEEE Trans. Power Electron.*, vol. 34, no. 8, pp. 7521–7531, Aug. 2019, doi: 10.1109/TPEL.2018.2880461.

[49] J.-E. Hernández-Díez, C.-F. Méndez-Barrios, S.-I. Niculescu, and E. Bárcenas-Bárcenas, "A current sensorless delay–based control scheme for MPPT–boost converters in photovoltaic systems," *IEEE Access*, vol. 8, pp. 174449–174462, 2020, doi: 10.1109/ACCESS.2020.3024566.

[50] J.-L. Kuo, K.-L. Chao, and L.-S. Lee, "Dual mechatronic MPPT controllers with PN and OPSO control algorithms for the rotatable solar panel in PHEV system," *IEEE Trans. Ind. Electron.*, vol. 57, no. 2, pp. 678–689, Feb. 2010, doi: 10.1109/TIE.2009.2034680.

[51] H. Fathabadi, "Novel online sensorless dual-axis sun tracker," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 1, pp. 321–328, Feb. 2017, doi: 10.1109/TMECH.2016.2611564.

[52] K. Bataineh, "Improved hybrid algorithms-based MPPT algorithm for PV system operating under severe weather conditions," *IET Power Electron.*, vol. 12, no. 4, pp. 703–711, Apr. 2019.

[53] M. Kumar and D. V. K. Shiva Krishna Rao, "Modelling and parameter estimation of solar cell using genetic algorithm," in *Proc. Int. Conf. Intell. Comput. Control Syst. (ICCS)*, Madurai, India, May 2019, pp. 383–387, doi: 10.1109/ICCS45141.2019.9065759.

[54] M. R. Vincheh, A. Kargar, and G. A. Markadeh, "A hybrid control method for maximum power point tracking (MPPT) in photovoltaic systems," *Arabian J. Sci. Eng.*, vol. 39, no. 6, pp. 4715–4725, Jun. 2014.

[55] M. Sarvi and A. Azadian, "A comprehensive review and classified comparison of MPPT algorithms in PV systems," *Energy Syst.*, vol. 13, no. 2, pp. 281–320, May 2022.

[56] M. R. Al-Soeidat, A. Cembrano, and D. D.-C. Lu, "Comparing effectiveness of hybrid MPPT algorithms under partial shading conditions," in *Proc. IEEE Int. Conf. Power Syst. Technol. (POWERCON)*, Sep. 2016, pp. 1–6, doi: 10.1109/POWERCON.2016.7754024.

[57] D. Khodair, M. S. Salem, A. Shaker, H. E. A. El Munim, and M. Abouelatta, "Application of modified MPPT algorithms: A comparative study between different types of solar cells," *Appl. Sol. Energy*, vol. 56, no. 5, pp. 309–323, Sep. 2020.

[58] P. Gaur, "The survey of MPPT under non-uniform atmospheric conditions for the photovoltaic generation systems," *Int. J. Inf. Technol.*, vol. 13, no. 2, pp. 767–776, Apr. 2021.

[59] C. C. W. Chang, T. J. Ding, M. A. S. Bhuiyan, K. C. Chao, M. Ariannejad, and H. C. Yian, "Nature-inspired optimization algorithms in solving partial shading problems: A systematic review," *Arch. Comput. Methods Eng.*, vol. 30, no. 1, pp. 223–249, Jan. 2023.

[60] H. Wang, L. Vinayagam, H. Jiang, Z. Q. Cai, and H. Li, "New MPPT solar generation implemented with constant-voltage constant-current DC/DC converter," in *Proc. 51st Int. Universities Power Eng. Conf. (UPEC)*, Sep. 2016, pp. 1–6, doi: 10.1109/UPEC.2016.8114047.

[61] Y.-Y. Chen and Y.-K. Man, "Constant current-based maximum-power-point tracking for photovoltaic power systems," in *Proc. Chin. Control Decis. Conf.*, Jun. 2009, pp. 3422–3425.

[62] S. Jain and V. Agarwal, "A new algorithm for rapid tracking of approximate maximum power point in photovoltaic systems," *IEEE Power Electron Lett.*, vol. 2, no. 1, pp. 16–19, Mar. 2004, doi: 10.1109/LPEL.2004.828444.

[63] X. Li, H. Wen, Y. Hu, L. Jiang, and W. Xiao, "Modified beta algorithm for GMPPT and partial shading detection in photovoltaic systems," *IEEE Trans. Power Electron.*, vol. 33, no. 3, pp. 2172–2186, Mar. 2018, doi: 10.1109/LPEL.2004.828444.

[64] V. Salas, E. Oliás, A. Barrado, and A. Lázaro, "Review of the maximum power point tracking algorithms for stand-alone photovoltaic systems," *Sol. Energy Mater. Sol. Cells*, vol. 90, no. 11, pp. 1555–1578, 2006.

[65] A. M. Farayola, A. N. Hasan, and A. Ali, "Curve fitting polynomial technique compared to ANFIS technique for maximum power point tracking," in *Proc. 8th Int. Renew. Energy Congr. (IREC)*, Mar. 2017, pp. 1–6, doi: 10.1109/IREC.2017.7926047.

[66] D. Baimel, S. Tapuchi, Y. Levron, and J. Belikov, "Improved fractional open circuit voltage MPPT methods for PV systems," *Electronics*, vol. 8, no. 3, p. 321, Mar. 2019, doi: 10.3390/electronics8030321.

[67] S. Malathy and R. Ramaprabha, *Maximum Power Point Tracking Based on Look Up Table Approach*, vol. 768. Germany: AMR, 2013, pp. 124–130.

[68] J. K. Udavalakshmi and M. S. Sheik, "Comparative study of perturb & observe and look-up table maximum power point tracking techniques using MATLABISimulink," in *Proc. Int. Conf. Current Trends Towards Converging Technol. (ICCTCT)*, Mar. 2018, pp. 1–5.

[69] J. Ahmad, "A fractional open circuit voltage based maximum power point tracker for photovoltaic arrays," in *Proc. 2nd Int. Conf. Softw. Technol. Eng.*, Oct. 2010, doi: 10.1109/ICSTE.2010.5608868.

[70] Y.-P. Huang, "A rapid maximum power measurement system for high-concentration photovoltaic modules using the fractional open-circuit voltage technique and controllable electronic load," *IEEE J. Photovolt.*, vol. 4, no. 6, pp. 1610–1617, Nov. 2014.

[71] A. Sandali, T. Oukhoya, and A. Cheriti, "Modeling and design of PV grid connected system using a modified fractional short-circuit current MPPT," in *Proc. Int. Renew. Sustain. Energy Conf. (IRSEC)*, Oct. 2014, pp. 224–229, doi: 10.1109/IRSEC.2014.7059859.

[72] N. Femia, G. Petrone, G. Spagnuolo, and M. Vitelli, "Optimization of perturb and observe maximum power point tracking method," *IEEE Trans. Power Electron.*, vol. 20, no. 4, pp. 963–973, Jul. 2005, doi: 10.1109/TPEL.2005.850975.

[73] M. Kumar, R. Bharti, and D. V. S. K. K. Rao, "Conventional and hybrid perturb & observe based maximum power point tracking for solar system," in *Proc. Int. Conf. Vis. Towards Emerg. Trends Commun. Netw. (ViTECoN)*, Mar. 2019, pp. 1–5, doi: 10.1109/ViTECoN.2019.8899412.

[74] D. Sera, L. Mathe, T. Kerekes, S. V. Spataru, and R. Teodorescu, "On the perturb-and-observe and incremental conductance MPPT methods for PV systems," *IEEE J. Photovolt.*, vol. 3, no. 3, pp. 1070–1078, Jul. 2013.

[75] S. Khadidja, M. Mountassar, and B. M'hamed, "Comparative study of incremental conductance and perturb & observe MPPT methods for photovoltaic system," in *Proc. Int. Conf. Green Energy Convers. Syst. (GECS)*, Mar. 2017, pp. 1–6, doi: 10.1109/GECS.2017.8066230.

[76] M. I. Bahari, P. Tarassodi, Y. M. Naeini, A. K. Khalilabad, and P. Shirazi, "Modeling and simulation of Hill climbing MPPT algorithm for photovoltaic application," in *Proc. Int. Symp. Power Electron., Elect. Drives, Automat. Motion (SPEEDAM)*, Jun. 2016, pp. 1041–1044, doi: 10.1109/SPEEDAM.2016.7525990.

[77] K. M. Tsang and W. L. Chan, "Maximum power point tracking for PV systems under partial shading conditions using current sweeping," *Energy Convers. Manage.*, vol. 93, pp. 249–258, Mar. 2015.

[78] F. Silva, F. L. Tofoli, P. d. Santos Vicente, and E. Moreira Vicente, "Maximum power point tracking based on the curve sweep method," in *Proc. 14th IEEE Int. Conf. Ind. Appl. (INDUSCON)*, Aug. 2021, pp. 38–45, doi: 10.1109/INDUSCON51756.2021.9529667.

[79] P. Midya, P. T. Krein, R. J. Turnbull, R. Reppa, and J. Kimball, "Dynamic maximum power point tracker for photovoltaic applications," in *Proc. 27th Annu. IEEE Power Electron. Spec. Conf.*, Jun. 1996, pp. 1710–1716.

[80] Y. Chen and K. M. Smedley, "A cost-effective single-stage inverter with maximum power point tracking," *IEEE Trans. Power Electron.*, vol. 19, no. 5, pp. 1289–1294, Sep. 2004.

[81] B. M. T. Ho, H. S. H. Chung, and W. L. Lo, "Use of system oscillation to locate the MPP of PV panels," *IEEE Power Electron Lett.*, vol. 2, no. 1, pp. 1–5, Mar. 2004, doi: 10.1109/LPEL.2004.828443.

[82] J. M. Riquelme-Dominguez and S. Martinez, "Systematic evaluation of photovoltaic MPPT algorithms using state-space models under different dynamic test procedures," *IEEE Access*, vol. 10, pp. 45772–45783, 2022, doi: 10.1109/ACCESS.2022.3170714.

[83] D. Shmilovitz, "On the control of photovoltaic maximum power point tracker via output parameters," in *IEE Proc.-Electr. Power Appl.*, vol. 152, no. 2, pp. 239–248, Mar. 2005.

[84] S. Mumtaz, S. Ahmad, L. Khan, S. Ali, T. Kamal, and S. Hassan, "Adaptive feedback linearization based neurofuzzy maximum power point tracking for a photovoltaic system," *Energies*, vol. 11, no. 3, p. 606, Mar. 2018.

[85] K. Javed, H. Ashfaq, and R. Singh, "An improved MPPT algorithm to minimize transient and steady state oscillation conditions for small SPV systems," *Int. J. Renew. Energy Develop.*, vol. 7, no. 3, pp. 191–197, Dec. 2018.

[86] X. Li, H. Wen, and W. Xiao, "A modified MPPT technique based on the MPP-locus method for photovoltaic system," in *Proc. 43rd Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Beijing, China, Oct. 2017, pp. 2338–2343.

[87] E. M. Ahmed and M. Shoyama, "Novel stability analysis of variable step size incremental resistance INR MPPT for PV systems," in *Proc. 37th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Melbourne, VIC, Australia, Nov. 2011, pp. 3894–3899.

[88] R. F. Coelho, F. M. Concer, and D. C. Martins, "A MPPT approach based on temperature measurements applied in PV systems," in *Proc. IEEE Int. Conf. Sustain. Energy Technol. (ICSET)*, Dec. 2010, pp. 1–6, doi: 10.1109/ICSET.2010.5684440.

[89] R. Faranda and S. Leva, "Energy Comparison of MPPT techniques for PV Systems," *J. Electromagn. Anal. Appl.* , vol. 3, no. 6, pp. 446–455, Jun. 2008.

[90] M. Boztepe, F. Guinjoan, G. Velasco-Quesada, S. Silvestre, A. Chouder, and E. Karatepe, "Global MPPT scheme for photovoltaic string inverters based on restricted voltage window search algorithm," *IEEE Trans. Ind. Electron.*, vol. 61, no. 7, pp. 3302–3312, Jul. 2014, doi: 10.1109/TIE.2013.2281163.

[91] E. Koutroulis and F. Blaabjerg, "A new technique for tracking the global maximum power point of PV arrays operating under partial-shading conditions," *IEEE J. Photovolt.*, vol. 2, no. 2, pp. 184–190, Apr. 2012.

[92] A. Al Nabulsi and R. Dhaouadi, "Efficiency optimization of a DSP-based standalone PV system using fuzzy logic and dual-MPPT control," *IEEE Trans. Ind. Informat.*, vol. 8, no. 3, pp. 573–584, Aug. 2012, doi: 10.1109/TII.2012.2192282.

[93] S. Moustapha, N. Fatou, E. F. Marie, D. Saliou, and S. M. Amadou, "A comparative study of maximum power point tracker approaches based on artificial neural network and fuzzy controllers," *Int. J. Phys. Sci.*, vol. 13, no. 1, pp. 1–7, Jan. 2018.

[94] S. Touil, N. Boudjerda, A. Boubakir, and K. E. K. Drissi, "A sliding mode control and artificial neural network based MPPT for a direct grid-connected photovoltaic source," *Asian J. Control*, vol. 21, no. 4, pp. 1892–1905, Jul. 2019.

[95] M. Uoya and H. Koizumi, "A calculation method of photovoltaic array's operating point for MPPT evaluation based on one-dimensional Newton–Raphson method," *IEEE Trans. Ind. Appl.*, vol. 51, no. 1, pp. 567–575, Jan./Feb. 2015, doi: 10.1109/TIA.2014.2326083.

[96] R. Pradhan and B. Subudhi, "A steepest-descent based maximum power point tracking technique for a photovoltaic power system," in *Proc. 2nd Int. Conf. Power, Control Embedded Syst.*, Dec. 2012, pp. 1–6, doi: 10.1109/ICPCES.2012.6508050.

[97] R. Storn and K. Price, "Minimizing the real functions of the ICEC'96 contest by differential evolution," in *Proc. IEEE Int. Conf. Evol. Comput. (ICEC)*, May 1996, pp. 842–844.

[98] X.-S. Yang and S. Deb, "Cuckoo search via Lévy flights," in *Proc. World Congr. Nature Biol. Inspired Comput. (NaBIC)*, Dec. 2009, pp. 210–214, doi: 10.1109/NABIC.2009.5393690.

[99] S. Hadji, J.-P. Gaubert, and F. Krim, "Real-time genetic algorithms-based MPPT: Study and comparison (theoretical an experimental) with conventional methods," *Energies*, vol. 11, no. 2, p. 459, Feb. 2018.

[100] Z. Cheng, H. Zhou, and H. Yang, "Research on MPPT control of PV system based on PSO algorithm," in *Proc. Chin. Control Decis. Conf.*, May 2010, pp. 887–892, doi: 10.1109/CCDC.2010.5498097.

[101] S. Mohanty, B. Subudhi, and P. K. Ray, "A grey wolf optimization based MPPT for PV system under changing insolation level," in *Proc. IEEE Students' Technol. Symp. (TechSym)*, Sep. 2016, pp. 175–179, doi: 10.1109/TechSym.2016.7872677.

[102] K. Socha and M. Dorigo, "Ant colony optimization for continuous domains," *Eur. J. Oper. Res.*, vol. 185, no. 3, pp. 1155–1173, 2008.

[103] K. Sundareswaran, P. Sankar, P. S. R. Nayak, S. P. Simon, and S. Palani, "Enhanced energy output from a PV system under partial shaded conditions through artificial bee colony," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 198–209, Jan. 2015.

[104] X.-S. Yang, *Nature-Inspired Metaheuristic Algorithms*. Beckington, U.K.: Luniver Press, 2008, pp. 242–246.

[105] L.-L. Li, G.-Q. Lin, M.-L. Tseng, K. Tan, and M. K. Lim, "A maximum power point tracking method for PV system with improved gravitational search algorithm," *Appl. Soft Comput.*, vol. 65, pp. 333–348, Apr. 2018.

[106] X.-S. Yang, "Flower pollination algorithm for global optimization," in *Unconventional Computation and Natural Computation* (Lecture Notes in Computer Science), vol. 7445. Berlin, Germany: Springer, 2012, pp. 240–249.

[107] J. P. Ram and N. Rajasekar, "A novel flower pollination based global maximum power point method for solar maximum power point tracking," *IEEE Trans. Power Electron.*, vol. 32, no. 11, pp. 8486–8499, Nov. 2017, doi: 10.1109/TPEL.2016.2645449.

[108] C. Huang, L. Wang, R. S.-C. Yeung, Z. Zhang, H. S. Chung, and A. Bensoussan, "A prediction model-guided Jaya algorithm for the PV system maximum power point tracking," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 45–55, Jan. 2018, doi: 10.1109/TSTE.2017.2714705.

[109] T. Nagadurga, P. V. R. L. Narasimham, and V. S. Vakula, "Global maximum power point tracking of solar photovoltaic strings under partial shading conditions using cat swarm optimization technique," *Sustainability*, vol. 13, no. 19, p. 11106, Oct. 2021.

[110] T. K. Soon and S. Mekhilef, "Modified incremental conductance MPPT algorithm to mitigate inaccurate responses under fast-changing solar irradiation level," *Sol. Energy*, vol. 101, pp. 333–342, Mar. 2014.

[111] B. N. Alajmi, K. H. Ahmed, S. J. Finney, and B. W. Williams, "Fuzzy-logic-control approach of a modified Hill-climbing method for maximum power point in microgrid standalone photovoltaic system," *IEEE Trans. Power Electron.*, vol. 26, no. 4, pp. 1022–1030, Apr. 2011, doi: 10.1109/TPEL.2010.2090903.

[112] M. A. Ghasemi, H. M. Foroushani, and F. Blaabjerg, "Marginal power-based maximum power point tracking control of photovoltaic system under partially shaded condition," *IEEE Trans. Power Electron.*, vol. 35, no. 6, pp. 5860–5872, Jun. 2020, doi: 10.1109/TPEL.2019.2952972.

[113] H. Fathabadi, "Novel highly accurate universal maximum power point tracker for maximum power extraction from hybrid fuel cell/photovoltaic/wind power generation systems," *Energy*, vol. 116, pp. 402–416, Dec. 2016.

[114] M. Q. Yu, "Parameter identification of photovoltaic cell model based on perturbation and observation and modified Gauss-Newton method," in *Proc. 37th Chin. Control Conf. (CCC)*, Jul. 2018, pp. 6127–6131.

[115] C.-S. Moo and G.-B. Wu, "Maximum power point tracking with ripple current orientation for photovoltaic applications," *IEEE J. Emerg. Select. Topics Power Electron.*, vol. 2, no. 4, pp. 842–848, Dec. 2014, doi: 10.1109/JESTPE.2014.2328577.

[116] J. H. Zhang, X. Y. Wei, L. Hu, and J. G. Ma, "A MPPT method based on improved Fibonacci search photovoltaic array," *Tehnički Vjesnik*, vol. 26, no. 1, pp. 163–170, Feb. 2019.

[117] A. Kihal, F. Krim, A. Laib, B. Talbi, and H. Afghoul, "An improved MPPT scheme employing adaptive integral derivative sliding mode control for photovoltaic systems under fast irradiation changes," *ISA Trans.*, vol. 87, pp. 297–306, Apr. 2019.

[118] X. Li, H. Wen, Y. Hu, and L. Jiang, "A novel beta parameter based fuzzy-logic controller for photovoltaic MPPT application," *Renew. Energy*, vol. 130, pp. 416–427, Jan. 2019.

[119] L. M. Elobaid, A. K. Abdelsalam, and E. E. Zakzouk, "Artificial neural network based maximum power point tracking technique for PV systems," in *Proc. 38th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Montreal, QC, Canada, Oct. 2012, pp. 937–942.

[120] T. L. Nguyen and K.-S. Low, "A global maximum power point tracking scheme employing DIRECT search algorithm for photovoltaic systems," *IEEE Trans. Ind. Electron.*, vol. 57, no. 10, pp. 3456–3467, Oct. 2010, doi: 10.1109/TIE.2009.2039450.

[121] A. S. Benyoucef, A. Chouder, K. Kara, S. Silvestre, and O. A. Sahed, "Artificial bee colony based algorithm for maximum power point tracking (MPPT) for PV systems operating under partial shaded conditions," *Appl. Soft Comput.*, vol. 32, pp. 38–48, Jul. 2015.

[122] D. Pilakkat and S. Kanthalakshmi, "An improved P&O algorithm integrated with artificial bee colony for photovoltaic systems under partial shading conditions," *Sol. Energy*, vol. 178, pp. 37–47, Jan. 2019.

[123] K. Sundareswaran, S. Peddapati, and S. Palani, "MPPT of PV systems under partial shaded conditions through a colony of flashing fireflies," *IEEE Trans. Energy Convers.*, vol. 29, no. 2, pp. 463–472, Jun. 2014.

[124] N. Priyadarshi, V. Ramachandaramurthy, S. Padmanaban, and F. Azam, "An ant colony optimized MPPT for standalone hybrid PV-wind power system with single Cuk converter," *Energies*, vol. 12, no. 1, p. 167, Jan. 2019.

[125] A. Darcy Gnana Jegha, M. S. P. Subathra, N. Manoj Kumar, U. Subramaniam, and S. Padmanaban, "A high gain DC–DC converter with grey wolf optimizer based MPPT algorithm for PV fed BLDC motor drive," *Appl. Sci.*, vol. 10, no. 8, p. 2797, Apr. 2020.

[126] S. Mohanty, B. Subudhi, and P. K. Ray, "A new MPPT design using grey wolf optimization technique for photovoltaic system under partial shading conditions," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 181–188, Jan. 2016, doi: 10.1109/TSTE.2015.2482120.

[127] R. Brindha, A. A. Christy, P. Kumar, and A. Sarkar, "Photovoltaic based brushless DC motor using cuckoo algorithm as a maximum power point tracking," in *Proc. Int. Conf. Comput. Intell. Smart Power Syst. Sustain. Energy (CISPSSE)*, Jul. 2020, pp. 1–6.

[128] J. Ahmed and Z. Salam, "A soft computing MPPT for PV system based on cuckoo search algorithm," in *Proc. 4th Int. Conf. Power Eng., Energy Electr. Drives*, Istanbul, Turkey, May 2013, pp. 558–562.

[129] H. Renaudineau, F. Donatantonio, J. Fontchastagner, and G. Petrone, "A PSO-based global MPPT technique for distributed PV power generation," *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 1047–1058, Feb. 2015, doi: 10.1109/TIE.2014.2336600.

[130] S. Lyden, M. E. Haque, and D. Xiao, "Application of a simulated annealing technique for global maximum power point tracking of PV modules experiencing partial shading," in *Proc. 40th Annu. Conf. IEEE Ind. Electron. Soc. (IECON)*, Oct. 2014, pp. 1977–1983, doi: 10.1109/IECON.2014.7048773.

[131] L.-R. Chen, C.-H. Tsai, Y.-L. Lin, and Y.-S. Lai, "A biological swarm chasing algorithm for tracking the PV maximum power point," *IEEE Trans. Energy Convers.*, vol. 25, no. 2, pp. 484–493, Jun. 2010, doi: 10.1109/TEC.2009.2038067.

[132] P. Kofinas, A. I. Dounis, G. Papadakis, and M. N. Assimakopoulos, "An intelligent MPPT controller based on direct neural control for partially shaded PV system," *Energy Buildings*, vol. 90, pp. 51–64, Mar. 2015.

[133] A.-W. Ibrahim, M. B. Shafik, M. Ding, M. A. Sarhan, Z. Fang, A. G. Alareqi, T. Almoqri, and A. M. Al-Rassas, "PV maximum power-point tracking using modified particle swarm optimization under partial shading conditions," *Chin. J. Electr. Eng.*, vol. 6, no. 4, pp. 106–121, Dec. 2020, doi: 10.23919/CJEE.2020.000035.

[134] J. Ahmed and Z. Salam, "A maximum power point tracking (MPPT) for PV system using cuckoo search with partial shading capability," *Appl. Energy*, vol. 119, pp. 118–130, Apr. 2014.

[135] H. Rezk and A. Fathy, "Simulation of global MPPT based on teaching–learning-based optimization technique for partially shaded PV system," *Elect. Eng.*, vol. 99, no. 3, pp. 847–859, Sep. 2017.

[136] A. Fathy and H. Rezk, "A novel methodology for simulating maximum power point trackers using mine blast optimization and teaching learning based optimization algorithms for partially shaded photovoltaic system," *J. Renew. Sustain. Energy*, vol. 8, no. 2, Mar. 2016, Art. no. 023503.

[137] K. S. Tey and S. Mekhilef, "Modified incremental conductance algorithm for photovoltaic system under partial shading conditions and load variation," *IEEE Trans. Ind. Electron.*, vol. 61, no. 10, pp. 5384–5392, Oct. 2014, doi: 10.1109/TIE.2014.2304921.

[138] A. Safari and S. Mekhilef, "Simulation and hardware implementation of incremental conductance MPPT with direct control method using Cuk converter," *IEEE Trans. Ind. Electron.*, vol. 58, no. 4, pp. 1154–1161, Apr. 2011, doi: 10.1109/TIE.2010.2048834.

[139] A. S. Mahdi, A. K. Mahamad, S. Saon, T. Tuwoso, H. Elmunsyah, and S. W. Mudjanarko, "Maximum power point tracking using perturb and observe, fuzzy logic and ANFIS," *Social Netw. Appl. Sci.*, vol. 2, no. 1, p. 89, Jan. 2020.

[140] V. N. Lal and S. N. Singh, "Modified particle swarm optimisation-based maximum power point tracking controller for single-stage utility-scale photovoltaic system with reactive power injection capability," *IET Renew. Power Gener.*, vol. 10, no. 7, pp. 899–907, 2016.

[141] K. L. Lian, J. H. Jhang, and I. S. Tian, "A maximum power point tracking method based on perturb-and-observe combined with particle swarm optimization," *IEEE J. Photovolt.*, vol. 4, no. 2, pp. 626–633, Mar. 2014, doi: 10.1109/JPHOTOV.2013.2297513.

[142] X. Yuan, D. Yang, and H. Liu, "MPPT of PV system under partial shading condition based on adaptive inertia weight particle swarm optimization algorithm," in *Proc. IEEE Int. Conf. Cyber Technol. Autom., Control, Intell. Syst. (CYBER)*, Jun. 2015, pp. 729–733, doi: 10.1109/CYBER.2015.7288032.

[143] S. M. Mirhassani, S. Z. M. Golroodbari, S. M. M. Golroodbari, and S. Mekhilef, "An improved particle swarm optimization based maximum power point tracking strategy with variable sampling time," *Int. J. Elect. Power Energy Syst.*, vol. 64, pp. 761–770, Jan. 2015.

[144] N. Sa-ngawong and I. Ngamroo, "Intelligent photovoltaic farms for robust frequency stabilization in multi-area interconnected power system based on PSO-based optimal Sugeno fuzzy logic control," *Renew. Energy*, vol. 74, pp. 555–567, Feb. 2015.

[145] C. Manickam, G. R. Raman, G. P. Raman, S. I. Ganesan, and C. Nagamani, "A hybrid algorithm for tracking of GMPP based on P&O and PSO with reduced power oscillation in string inverters," *IEEE Trans. Ind. Electron.*, vol. 63, no. 10, pp. 6097–6106, Oct. 2016.

[146] D. A. Nugraha and K.-L. Lian, "A novel MPPT method based on cuckoo search algorithm and golden section search algorithm for partially shaded PV system," in *Proc. IEEE Electr. Power Energy Conf. (EPEC)*, Oct. 2018, pp. 173–182.

[147] Y. M. Safarudin, A. Priyadi, M. H. Purnomo, and M. Pujiantara, "Combining simplified firefly and modified P&O algorithm for maximum power point tracking of photovoltaic system under partial shading condition," in *Proc. Int. Seminar Intell. Technol. Appl. (ISITIA)*, vol. 1, May 2015, pp. 181–186.

[148] D. Ajiatmo and I. Robandi, "A hybrid fuzzy logic controller-firefly algorithm (FLC-FA) based for MPPT photovoltaic (PV) system in solar car," in *Proc. IEEE Int. Conf. Power Renew. Energy (ICPRE)*, Oct. 2016, pp. 606–610.

[149] C. Gonzalez-Castano, C. Restrepo, S. Kouro, and J. Rodriguez, "MPPT algorithm based on artificial bee colony for PV system," *IEEE Access*, vol. 9, pp. 43121–43133, 2021, doi: 10.1109/ACCESS.2021.3066281.

[150] K. Sundareswaran, V. Kumar, and S. Palani, "Application of a combined particle swarm optimization and perturb and observe method for MPPT in PV systems under partial shading conditions," *Renew. Energy*, vol. 75, pp. 308–317, Mar. 2015.

[151] S. Mohanty, B. Subudhi, and P. K. Ray, "A grey wolf-assisted perturb & observe MPPT algorithm for a PV system," *IEEE Trans. Energy Convers.*, vol. 32, no. 1, pp. 340–347, Mar. 2017.

[152] N. Kumar, I. Hussain, B. Singh, and B. K. Panigrahi, "Rapid MPPT for uniformly and partial shaded PV system by using JayaDE algorithm in highly fluctuating atmospheric conditions," *IEEE Trans. Ind. Informat.*, vol. 13, no. 5, pp. 2406–2416, Oct. 2017.

[153] A. M. Eltamaly and H. M. Farh, "Dynamic global maximum power point tracking of the PV systems under variant partial shading using hybrid GWO-FLC," *Sol. Energy*, vol. 177, pp. 306–316, Jan. 2019.

[154] N. Priyadarshi, S. Padmanaban, M. S. Bhaskar, F. Azam, B. Khan, and M. G. Hussien, "A novel hybrid grey wolf optimized fuzzy logic control based photovoltaic water pumping system," *IET Renew. Power Gener.*, Nov. 2022, doi: 10.1049/rpg2.12638.

[155] A. Kchaou, A. Naamane, Y. Koubaa, and N. M'sirdi, "Second order sliding mode-based MPPT control for photovoltaic applications," *Sol. Energy*, vol. 155, pp. 758–769, Oct. 2017, doi: 10.1016/J.SOLENER.2017.07.007.

[156] J. Macaulay and Z. Zhou, "A fuzzy logical-based variable step size P&O MPPT algorithm for photovoltaic system," *Energies*, vol. 11, no. 6, p. 1340, 2018.

[157] M. Lasheen and M. Abdel-Salam, "Maximum power point tracking using Hill climbing and ANFIS techniques for PV applications: A review and a novel hybrid approach," *Energy Convers. Manage.*, vol. 171, pp. 1002–1019, Sep. 2018.

[158] A. Harrag and S. Messalti, "Variable step size modified P&O MPPT algorithm using GA-based hybrid offline/online PID controller," *Renew. Sustain. Energy Rev.*, vol. 49, pp. 1247–1260, Sep. 2015.
[159] H. M. El-Helw, A. Magdy, and M. I. Marei, "A hybrid maximum power point tracking technique for partially shaded photovoltaic arrays," *IEEE Access*, vol. 5, pp. 11900–11908, 2017, doi: 10.1109/ACCESS.2017.2717540.
[160] N. Priyadarshi, M. S. Bhaskar, P. Sanjeevikumar, F. Azam, and B. Khan, "High-power DC–DC converter with proposed HSFNA MPPT for photovoltaic based ultra-fast charging system of electric vehicles," *IET Renew. Power Gener.*, early access.
[161] M. Kumar and G. Panda, "Analysis of conventional and interleaved boost converter with solar photovoltaic system," in *Proc. Int. Conf. Intell. Controller Comput. Smart Power (ICICCSP)*, Hyderabad, India, Jul. 2022, pp. 1–6, doi: 10.1109/ICICCSP53532.2022.9862351.
[162] S. K. Prince, K. P. Panda, and G. Panda, "Kalman filter variant intelligent control for power quality improvement in photovoltaic active power filter system," *Int. Trans. Electr. Energy Syst.*, vol. 30, no. 3, Mar. 2020, Art. no. e12239, doi: 10.1002/2050-7038.12239.
[163] N. Priyadarshi, P. K. Maroti, F. Azam, and M. G. Hussien, "An improved Z-source inverter-based sensorless induction motor-driven photovoltaic water pumping with Takagi–Sugeno fuzzy MPPT," *IET Renew. Power Gener.*, early access.

MADHAV KUMAR received the B.Tech. degree in electrical and electronics engineering from Techno India, West Bengal, India, in 2017, and the M.Tech. degree in power electronics and drives specialization from the Birla Institute of Technology (BIT) Mesra, Ranchi, India, in 2019. He is currently pursuing the Ph.D. degree with the National Institute of Technology Meghalaya, Shillong, India. From March 2021 to January 2022, he was a Teaching Assistant and a Research Assistant (TRA) with the Department of Electrical Engineering, Vellore Institute of Technology (VIT), Vellore, India. His current research interests include power-electronic converters, DC microgrids, renewable energy sources, solar photovoltaic systems, optimization techniques, and electric vehicles.

KAIBALYA PRASAD PANDA (Member, IEEE) received the B.Tech. degree in electrical and electronics engineering from Dr. M. G. R. University, Chennai, India, in 2011, the M.Tech. degree in power electronics and drives specialization from KIIT University, Bhubaneswar, India, in 2013, and the Ph.D. degree in electrical engineering from the Department of Electrical Engineering (EE), National Institute of Technology Meghalaya, Shillong, Meghalaya, in 2021.

From 2013 to 2017, he was with the C. V. Raman College of Engineering, Bhubaneswar, India, as an Assistant Professor. From 2021 to 2022, he was with NIT Andhra Pradesh, Tadepalligudem, India, as an Ad Hoc Faculty. He is currently an Assistant Professor with the Department of EE, School of Energy Technology, Pandit Deendayal Energy University (PDEU), Gandhinagar, India. He was also with the University of Warwick, U.K., funded by the Joint U.K.–India Clean Energy Program, from January 2019 to March 2019. He was a recipient of several travel grants. He has authored/coauthored over ten IEEE TRANSACTIONS and reputed journals and also filed two patents. Recently, he has been listed in the World's Top 2% of Researchers under the energy category as per the Stanford University list. His research interests include efficient multilevel inverters design, high-gain converters, photovoltaic systems, and power quality.

Dr. Panda received the Institute Best Research Award for Outstanding Research during his Ph.D. He is a regular reviewer of several IEEE, IET, and Wiley journals.

JULIO CESAR ROSAS-CARO (Senior Member, IEEE) received the B.S. degree in electronics and the M.S. degree in sciences in electrical engineering from Instituto Tecnologico de Ciudad Madero, Madero, Mexico, in 2004 and 2005, respectively, and the Ph.D. degree in sciences in electrical engineering from Cinvestav del IPN, Guadalajara, Mexico, in 2009.

He was a Visiting Scholar with Michigan State University, University of Colorado Denver, and Ontario Tech. He is currently a Professor with Universidad Panamericana, Zapopan, Mexico. His research interests include power electronics including DC–DC converters, flexible alternating current transmission system devices, and power converter topologies and applications.

ANTONIO VALDERRABANO-GONZALEZ (Senior Member, IEEE) received the B.S. degree in industrial electronics from Instituto Tecnológico de Puebla, México, the M.Sc. degree in electronics from Instituto Nacional de Astrofísica, Óptica y Electrónica, México, and the Ph.D. degree in electrical engineering from Cinvestav, Guadalajara, México, in 2010. He is currently a Professor with Universidad Panamericana, Guadalajara. His research interests include power electronics, control of power electronic converters, FACTS devices, and power quality.

GAYADHAR PANDA (Senior Member, IEEE) received the B.E. degree in electrical engineering from the Institute of Engineers, Kolkata, India, in 1996, the master's degree in power electronics from Bengal Engineering College (currently IIEST), Shibpur, India, in 1998, and the Ph.D. degree in electrical engineering from Utkal University, Bhubaneswar, India, in 2007. Since 2013, he has been with the Department of Electrical Engineering, National Institute of Technology (NIT) Meghalaya, Shillong, India, where he is currently a Professor. He has more than 20 years of teaching experience. He was the head of the department and the chairperson of various committees at the institute level. He is currently heading the National Institute of Technology Meghalaya, India, as the Director, since January 2023. He has published more than 80 technical papers in national and international conference proceedings/journals. His current research interests include automatic generation control, stability improvements using flexible alternating current transmission system devices, power quality, power electronic converters, and distributed power generation. He has received the Institution Medal for obtaining the highest marks in graduation and the Power Medal for one of his research papers.