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Review

A State-of-the-Art Comprehensive Review on Maximum Power Tracking Algorithms for Photovoltaic Systems and New Technology of the Photovoltaic Applications

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Abstract

Various maximum power point tracking (MPPT) techniques have been proposed to optimize the efficiency of solar photovoltaic (PV) systems. These techniques differ in several aspects such as design simplicity, convergence speed, implementation types (analog or digital), decision optimal point accuracy, effectiveness range, hardware costs, and algorithmic modes. Choosing the most suitable MPPT controller is crucial in PV system design, as it directly impacts the overall cost of PV solar modules. This paper presents a comprehensive exploration of 64 MPPT techniques for PV solar systems, covering optimization, traditional, intelligent, and hybrid methodologies. A comparative analysis of these techniques, considering cost, tracking speed, and system stability, indicates that hybrid approaches exhibit higher efficiency albeit with increased complexity and cost. Amidst the existing PV system review literature, this paper serves as an updated comprehensive reference for researchers involved in MPPT PV solar system design.

Keywords: convergence speed; photovoltaic (PV); renewable energy; system efficiency; maximum power point tracking (MPPT); maximum power point (MPP)

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1. Introduction

Globally, the escalating demand for electricity has spurred researchers to focus on developing clean and highly efficient electrical power sources, considering both production and cost [1–3]. The adverse environmental impacts of fossil fuel-fired power plants emphasize the urgent need to transition toward sustainable and secure renewable energy alternatives [4,5]. Hybrid models of electricity generation have emerged as promising solutions, offering enhanced system reliability [6,7]. However, the intermittent nature of renewable energy sources, such as wind and solar, alongside fluctuating weather conditions, poses challenges to consistent stability [8,9]. In addition, solar photovoltaic (PV) modules, reliant on solar panels and integrated systems to harness solar energy, encounter limitations in extracting maximum power [10,11].

To address these challenges, various mechanisms are employed to track the maximum power point (MPP) in PV systems given the variation in irradiance and temperature [12]. Achieving the MPP, a crucial determinant of the output power (P_{out}) in PV systems, necessitates the continuous tracking of the operating point, which is a task entrusted to the maximum power point tracking (MPPT) algorithms [13]. MPPT facilitates optimal power extraction from PV systems by dynamically adjusting parameters to match the impedance [14–16].

One of the main difficulties associated with the MPPT algorithms pertains to voltage monitoring and duty ratio variation when aiming to achieve the PV maximum output power (P_{max}) from the PV system. Figures 1 and 2 illustrate variations in voltage (V), current (I), and power (P) in a conventional solar panel in response to changes in irradiance and temperature [12,17]. As can be seen in Figure 1, the temperature variations impact the V_{out} as compared to I_{out}, while Figure 2 demonstrates the influence of irradiance on the I and V of a PV system.

Accordingly, the PV panel's Pout also varies [18]. In addition, the I-V curve is never identical under full irradiance or at partial sun shading, as the Vout and PV power (PPV) change with variations in irradiance and temperature [19–21].

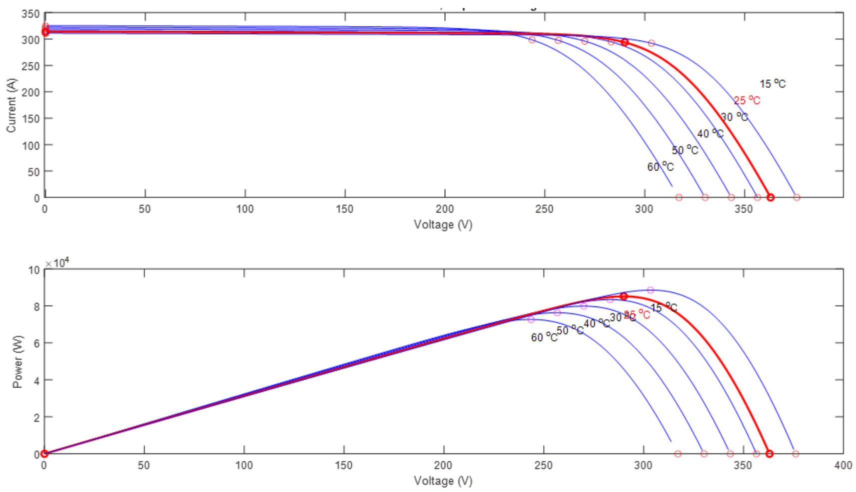

Figure 1. I-V and P-V characteristics at different temperature levels.

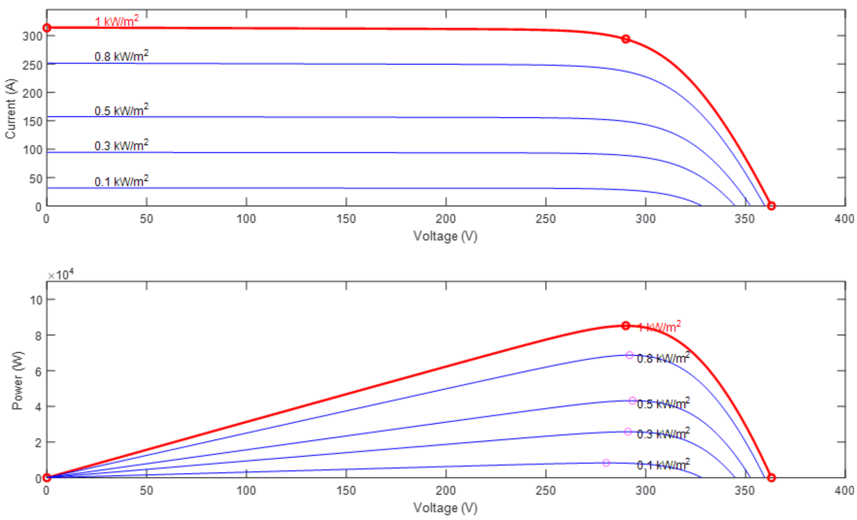

Figure 2. Characteristic curves at different irradiances.

This paper aims to provide a comprehensive review of prevalent MPPT techniques published in the recent literature and currently employed in industry practices [22]. The main contributions of this paper can be summarized as follows:

- Classification of MPPT algorithms based on their efficiency, accuracy, cost, convergence speed, and complexity using a multi-criteria decision-making algorithm.

- Evaluate the efficiency performance of each MPPT technique.
- Compare PV applications' dependency on the MPPT technique.
- Distinguish MPPT accuracy based on their precision to reach the peak point.
- Illustrate the parameters influencing the MPPT algorithms.

2. Classification, Ranking and Selection of MPPT Methods

2.1. Family-Based Classification

MPPT algorithms can be broadly classified into conventional (deterministic), intelligent (soft computing), and hybrid (composite) families. While all aim to continuously extract the maximum power from PV systems under varying environmental conditions, their underlying mechanisms, dynamic behaviors, and computational requirements differ substantially. In this paper, MPPT algorithms are hierarchically classified based on their families from top to bottom, as shown in Figure 3.

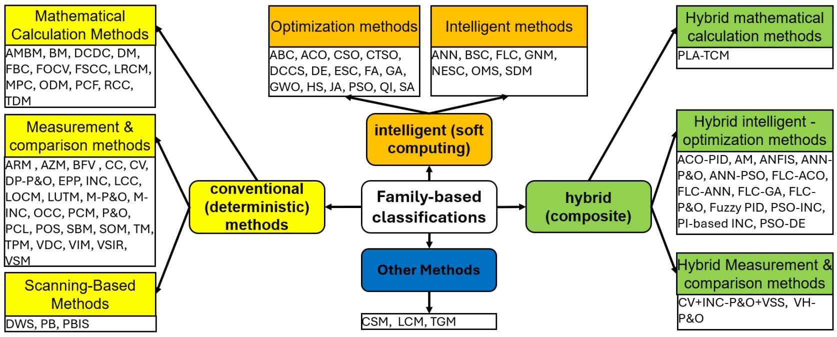

Figure 3. Family based classification of MPPT techniques.

The conventional algorithms include the following main groups:

- Measurement and Comparison Methods (e.g., P&O, INC, etc.), in which they use a direct comparison between current and voltage measurements or incremental changes to locate the MPP.
- Scanning-Based Methods (e.g., hill climbing, curve scanning), in which they rely on periodic or continuous voltage scanning to detect the MPP; they are deterministic and model-free but relatively slow.
- Mathematical Calculation Methods (e.g., methods based on current–voltage curve fitting, derivative-based computation, or model-based estimation of the MPP). These methods rely on analytical or empirical equations rather than intelligent inference. However, when coupled with adaptive tuning or estimation (e.g., using ANN or fuzzy inference), they may evolve into hybrid strategies.

On the other hand, Intelligent (Soft Computing) algorithms use advanced computational and artificial intelligence techniques to enhance tracking performance, particularly under partial shading conditions where multiple local power maxima exist. They generally have higher computational complexity and require tuning or training. They include the following groups:

- Intelligent methods (Learning and Adaptive) utilize techniques that involve learning, pattern recognition, or rule-based systems derived from artificial intelligence to control the PV converter. They often rely on input/output data relationships rather than a purely iterative mathematical search. Fuzzy Logic and ANNs are some examples of the intelligent MPPT algorithms.
- Optimization methods are a specific subset of advanced MPPT techniques that are primarily designed to solve a mathematical optimization problem: finding the global maximum

of the power curve—especially under partial shading conditions where multiple peaks exist. Genetic Algorithm and PSO are some examples of the optimization methods.

Then, the hybrid methods in MPPT techniques combine two or more different algorithms to leverage the strengths of each, thereby overcoming the limitations typically associated with single, standalone methods. The primary goal of a hybrid MPPT method is usually to achieve reliable Global maximum power point (GMPP) tracking under partial shading conditions (PSC) while maintaining fast convergence and low steady-state oscillation under uniform conditions. In this paper, the hybrid methods include the following groups:

- The hybridization of conventional algorithms is considered the simplest form, combining two traditional, simple MPPT methods to improve specific performance aspects. The main goal is to improve speed or eliminate oscillation without high computational cost. These hybrid methods use the strength of one method to compensate for the weakness of the other. An example is the P&O-INC, which is an algorithm that starts with P&O, for fast initial tracking, and then switches to INC when close to the MPP in order to eliminate oscillation and increase accuracy.
- Hybridization for global tracking between optimization and conventional methods is the most common and effective classification, which was designed specifically to solve the PSC problem. They combine sophisticated global search methods with simpler and faster local search methods. These types of algorithms are usually fast and reliable for tracking the GMPP by combining global exploration with local exploitation. An example is the PSO-P&O, which periodically explores the entire curve to find the GMPP voltage, and then P&O fine-tunes the tracking locally until the next PSO cycle.
- Finally, the hybridization with intelligent methods (model-based/predictive) uses an intelligent technique (like a learned model) to rapidly provide a precise starting point, significantly speeding up the convergence of a simpler search algorithm. Their main goal is to maximize speed and improve performance during rapid transients by using system knowledge. In this case, some intelligent methods (often a trained ANN) provide a prediction or starting point for the duty cycle or voltage, and search algorithms then take over for fine-tuning.
- An example is the ANN-P&Om in which an ANN is trained on irradiance/temperature data to output a rough estimate of the MPP voltage, which serves as the initial condition for the P&O algorithm. Then, the P&O algorithm performs the local fine tuning.

In summary, hybrid methods offer the best overall performance by addressing the classic trade-off between tracking speed (local search) and global search capability (PSC performance).

2.2. Novel Classification Based on Tracking Methods Considering Multiple Criteria

In this section, the authors present a novel way of classifying more than 60 different MPPT methods into a single figure stating the different tracking methods and comparing many criteria such as (1) complexity, (2) convergence speed, (3) accuracy, (4) cost, (5) efficiency, and (6) stability, as presented in Figure 4. The letters represent the MPPT method: for example, AZM stands for the Azab Method, while the numbers represent the criteria as mentioned above. The number in a green circle (1) represents an advantage, such as low cost, high efficiency, etc. The number in red color (1) represents a moderate value, such as medium cost or moderate efficiency. Meanwhile, the number in a black circle (1) represents a disadvantage, such as high cost or low efficiency. By arranging and comparing the five above-mentioned criteria of the MPPT algorithms into a single figure, it becomes much easier to select the method that meets specific requirements. Additionally, to opt for an algorithm marked by low expense, high precision, moderate effectiveness, and reliability, it is vital to validate the values that show the following sequence color. 3 4

5 6. After reviewing the figure, seek to determine the algorithms that show the greatest performance resemblance. In this particular instance, the AM (Analytic Method) algorithm.

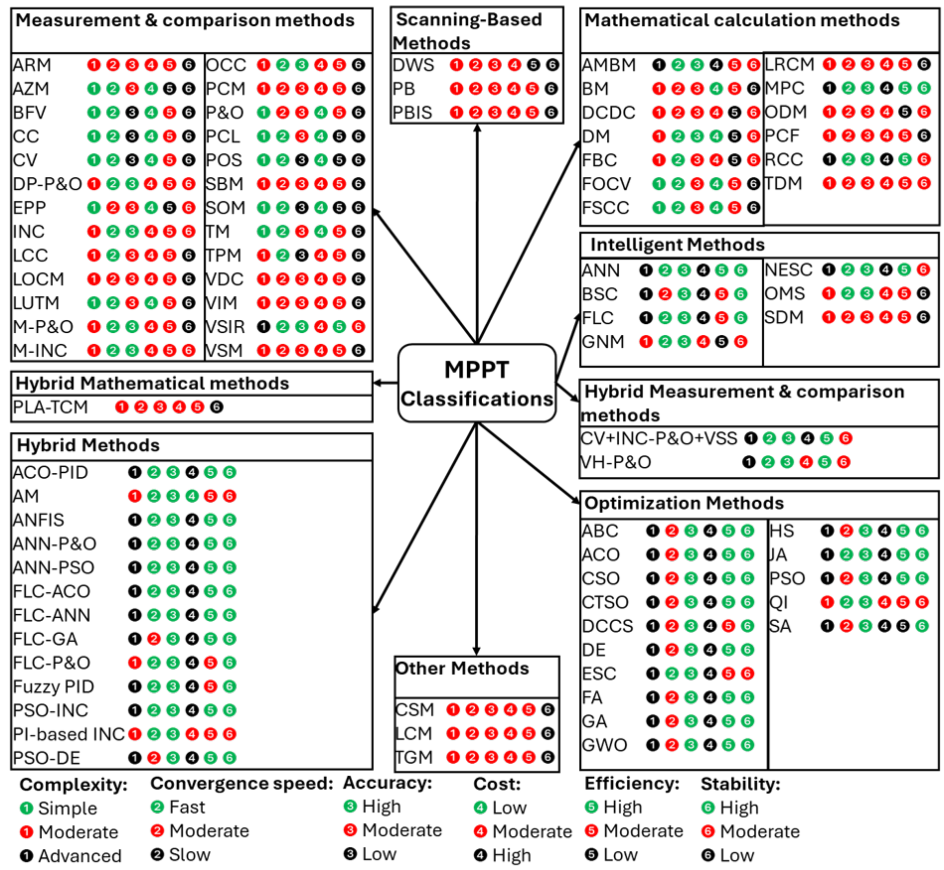

Figure 4. Classification of MPPT techniques.

A detailed description of the classification criteria for MPPT algorithms is presented in Table 1.

Table 1. Classification criteria for MPPT algorithms.

Parameter	Description
Complexity	Refers to the computational effort required to execute the MPPT algorithm. This includes the computational load, the ease of implementation on microcontrollers and the performance in dynamic conditions.
Convergence Speed	Refers to how quickly the algorithm reaches the true maximum power point.
Accuracy	Refers to how close the algorithm comes to the actual MPPT. A high-accuracy method minimizes energy loss.
Cost	Involves both direct and indirect cost factors, which vary depending on the complexity of the algorithm (computational load and performance), hardware requirements (simple/powerful processors), sensor requirements (cheap/expensive sensors, number of involved sensors (e.g., current, voltage, irradiance, temperature, etc.)), and operational cost (energy consumption, maintenance, installation cost, etc.).
Efficiency	Evaluates the efficiency of an MPPT method, which involves measuring how effectively the algorithm extracts the maximum available power from a PV system under varying environmental conditions.
Stability	Refers to the stability of MPPT techniques, which often relates to their performance under partial shading conditions and their tendency to oscillate around the maximum power point in steady state. In general, the classification in this paper is a simplification, as actual stability can depend heavily on implementation, tuning, and specific operating conditions.

2.3. Proposed Rank–Weigh–Rank (RWR) Algorithm for Selecting and Ranking MPPT Methods for Specific Applications

For the advanced selection and ranking of the appropriate MPPT methods for very specific applications with strict requirements and criteria, a novel multi-criteria decision-making algorithm is proposed in this paper. The algorithm named Rank–Weigh–Rank (RWR) is used to rank and select the best MPPT methods for specific applications considering many criteria and weighting factors. The main goal of the proposed algorithm is to help decision-makers select the best MPPT method that meets their requirements and specifications.

The algorithm is described in Figure 5, which is mainly divided into three sections. The first section involves collecting MPPT data such as the efficiencies, accuracies, convergence speed, etc. as well as the associating criteria for each required dataset. The second section sorts and ranks the criteria in descending order. Additionally, weighting factors are associated with each criterion to provide different weights for each criterion based on its importance in the decision making and selection. The third section calculates the average rank of each attribute (MPPT method). The algorithm then sorts all attributes based on their final ranking to assist decision-makers in selecting the best MPPT method that meets their expectations.

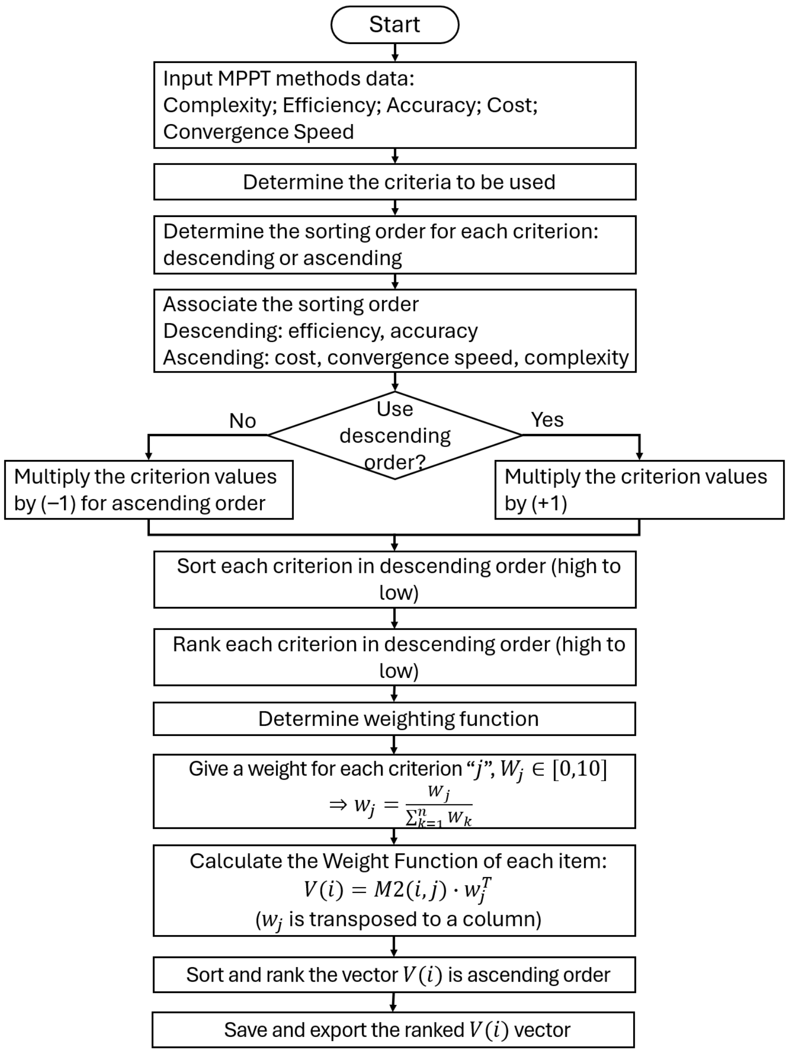

Figure 5. Proposed multi-criteria decision-making optimization algorithm for ranking, sorting and selecting the best MPPT methods for specific applications.

2.4. Comparison Between the Proposed RWR Algorithm and TOPSIS

To illustrate the importance of the suggested algorithm for identifying the optimal MPPT methods, a comparison is made with the renowned MCDM technique known as TOPSIS. In this paper, TOPSIS serves as a standard for comparison.

TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) is a popular multi-criteria decision-making method (MCDM) that ranks alternatives based on their relative closeness to an ideal solution. The core idea is to identify both an ideal solution, which has the best values for all criteria, and a negative-ideal solution, which has the worst. Each alternative is then evaluated by calculating its Euclidean distance from these two reference points. The alternative closest to the ideal and furthest from the negative-ideal is considered the most preferable. The process involves normalizing the decision matrix to eliminate scale differences, applying weights to reflect the importance of each criterion, and computing a closeness coefficient for each option. TOPSIS is valued for its simplicity, logical structure, and ability to handle both benefit and cost criteria effectively.

Both TOPSIS and RWR are used to provide quantitative comparisons of different MPPT techniques for the same dataset and for the following criteria: complexity, efficiency, accuracy, cost, convergence speed, and stability. In this section, three examples are selected for visualization purposes, in which different weighting factors are provided for the attributes; refer to Table 2. For simplicity, 20 different MPPT techniques are chosen and compared: ARM, AZM, BFV, DP-P&O, EPP, INC, LOCM, LUTM, ACO-PID, AM, ANFIS, ANN-P&O, FLC-GA, FLC-P&O, Fuzzy PID, PSO-INC, PI-based INC, CSM, ANN, and PCL.

Table 2. Examples of weighting factors used to weight criteria.

	Weighting Factor					
	Complexity	**Convergence Speed**	**Accuracy**	**Cost**	**Efficiency**	**Stability**
Example 1	5	10	10	10	10	10
Example 2	2	2	1	10	10	2
Example 3	4	1	1	0	5	3
Example 4	2	10	5	9	0	5

A value = 10 means that the criterion is of high importance in the selection; A value = 0 means that the criterion is of low importance in the selection.

For the first example (Figure 6a), one is interested in having high convergence speed, accuracy, efficiency and stability, and low cost, while showing less interest in the complexity of the used techniques. By supplying the preferences to the algorithm, RWR selected AM, and TOPSIS selected BFV as the best alternatives, respectively. The main reason for these large discrepancies is that the dataset for the criteria was not detailed enough for the algorithms to select the most appropriate techniques. Therefore, the average difference in ranking between RWR and TOPSIS is 3.9. However, on the other hand, both algorithms agreed on the second-best alternative, which is ACO-PID. In the second example (Figure 6b), there is a greater emphasis on achieving high efficiency and a low-cost MPPT method with other factors being considered to a lesser extent. By supplying our preferences to the algorithm, both RWR and TOPSIS agreed on the same best alternative, which is the AM method. For the second example, the average difference in ranking is 2.7. In the third example (Figure 6c), the main interest lies in attaining high efficiency and lower complexity with less regard for additional factors. In this example, both RWR and TOPSIS agreed on the same best alternative, which is the ACO-PID method. The average difference in ranking is 1.6. Regarding the fourth examples (Figure 6d), the main interest lies in ensuring a swift convergence rate and low costs with diminished focus on other factors. By supplying our preferences to the algorithm, RWR selected AM and TOPSIS selected BFV as the best alternatives, respectively. However, both RWR and TOPSIS agreed that AZM is the second-best alternative. In this case, the average difference in ranking is 1.5.

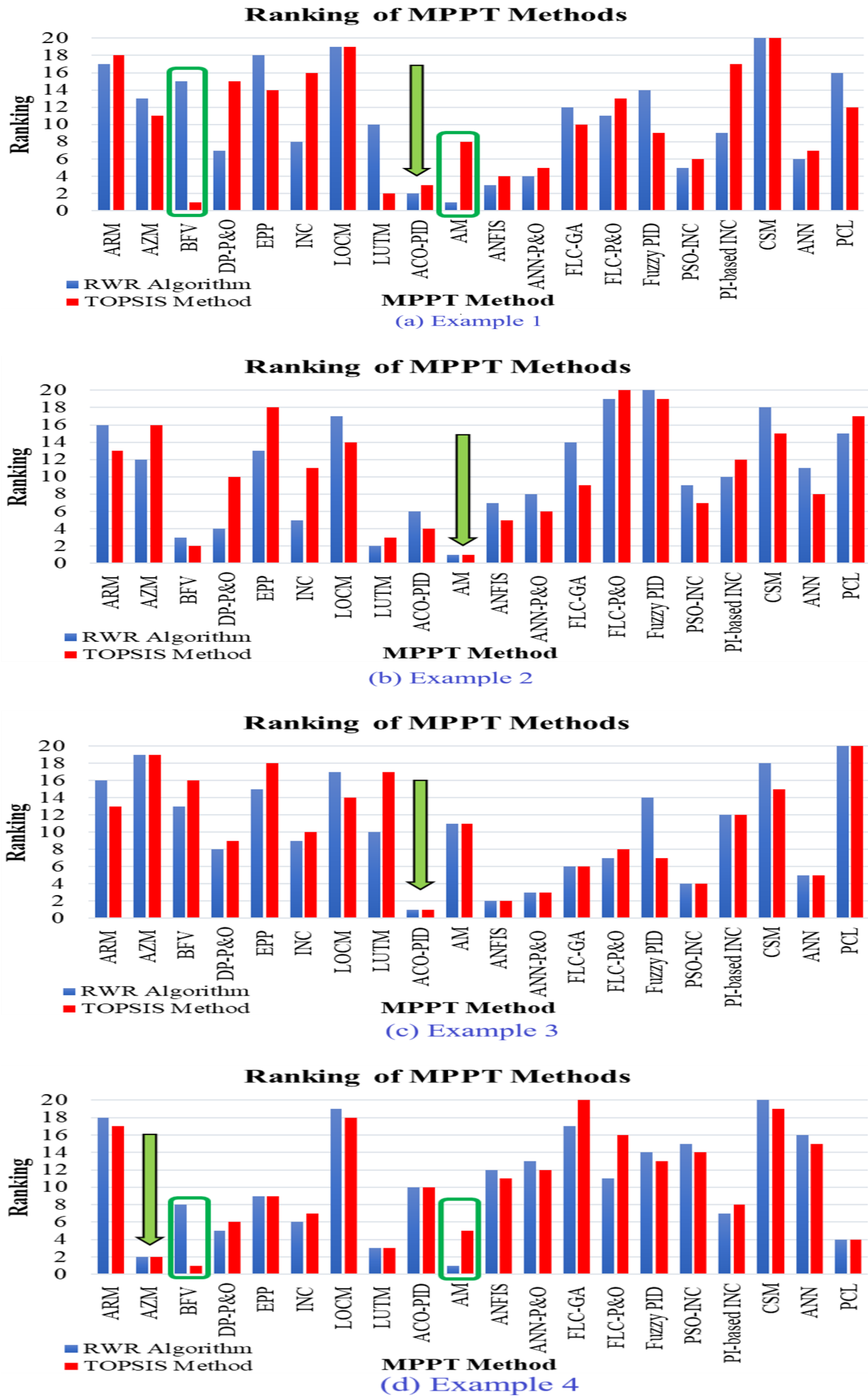

Figure 6. Comparison between RWR and TOPSIS algorithms to rank and select the best MPPT methods considering different weighting factors for (**a**) example 1, (**b**) example 2, (**c**) example 3, and (**d**) example 4.

Figure 7 presents the difference in ranking the best alternatives between the RWR and TOPSIS methods. For example, RWR and TOPSIS select the same best alternative in 25% of the cases, while 19% of the cases show a difference equal to only 1. In other terms, if RWR ranked the "A" method as the best and TOPSIS ranked it as second, the difference in ranking is equal to 1.

Figure 8 shows the similarities in ranking the best alternative between the RWR and TOPSIS methods. It can be seen that in 44% of the cases, RWR and TOPSIS select the same MPPT techniques with more than 90% similarities. Moreover, in 61% of the cases, both methods select MPPT techniques with more than 80% similarities.

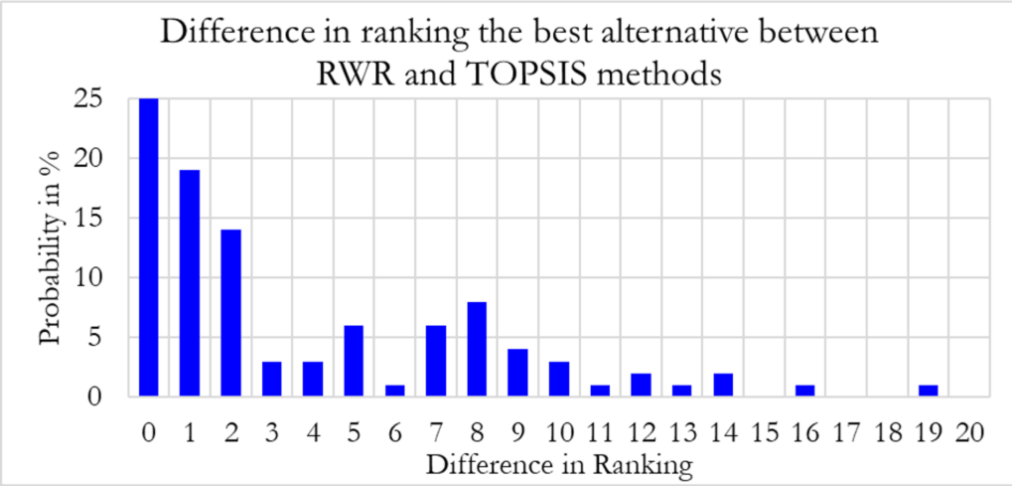

Figure 7. Different in ranking the best alternative using RWR and TOPSIS methods.

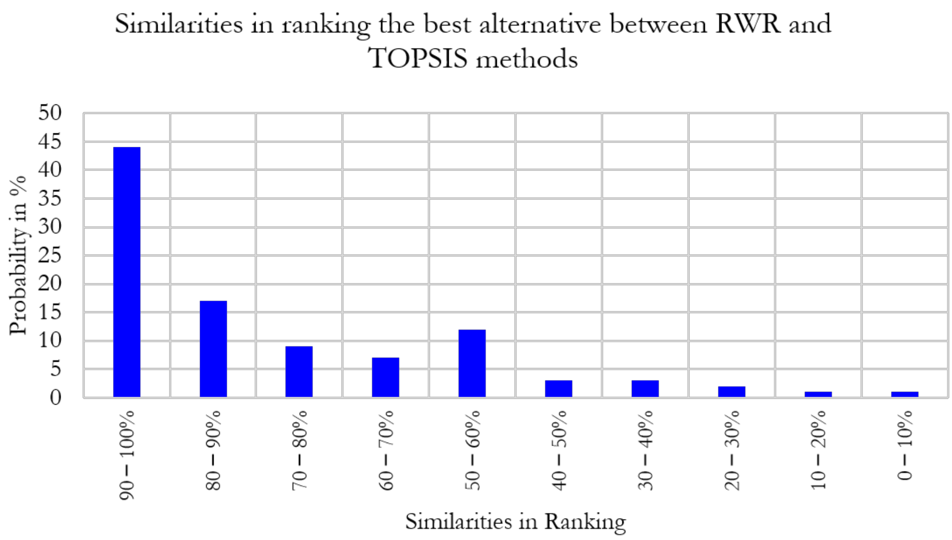

Figure 8. Similarities in ranking the best alternative between RWR and TOPSIS methods.

3. Scanning-Based MPPT Algorithms

An essential component of the scanning-based method is the utilization of iterative decremented step-size scanning-based MPPT algorithms. The variability in partial shading circumstances presents a major issue in photovoltaic structures. The power curves of these structures feature not only a global maximum power point but also several local maximum power points [23–27].

Furthermore, these curves are subject to alterations based on climate environment, which have a direct influence on the partial shading settings [28–31]. To address this challenge, three iterative scanning-based MPPT algorithms have been introduced: decremented window scanning, the peak bracketing (PB) method, and PB with initial scanning [32–36].

3.1. Decremented Window Scanning (DWS)

DWS is an algorithm employed to track the global MPP of a PV system by progressively decreasing the scanning domain range in each iteration. The duty cycle percentage of the pulse signal for the DC/DC converter is used as the unit for the scanning domain, while the converter's output power is measured in Watts as the co-domain unit [32]. By dividing the scanning domain into an ND number of scan points, an equivalent number of domain segments is established [37]. A segmented domain with the MPP within its range is then chosen as the new decremented scanning domain. Through a process of iteratively identifying and decreasing segmented scanning domains, the optimal perturbing duty cycle, which leads to the global peak power point, is ultimately determined [38–40].

3.2. Peak Bracketing (PB)

The PB algorithm employs a bisection method to trace the global maximum power point. This is achieved when the peak power point is being bracketed with three duty cycle points denoted as follows: a left duty cycle point, a right duty cycle point, and a center duty cycle point [32,41,42]. Through iterative reduction of the searching domain, the algorithm identifies the ultimate perturbing duty cycle point that corresponds to the global MPP [36,43,44].

3.3. Peak Bracketing with Initial Scanning (PBIS)

The PBIS is developed as a combination of the DWS and PB algorithms, which is specifically designed to decrease the cycling periods associated with locating the global maximum power point (GMPP). The initial step involves the implementation of the DWS algorithm to identify a segmental reductional window scanning. Subsequently, the PB algorithm is applied to identify the optimal perturbing duty cycle point (D), which ultimately leads to the discovery of the GMPP [32,35,45].

4. MPPT Intelligent Control Techniques

4.1. Neural Network

Deep learning suites are rooted in a specific branch of machine learning called neural networks, which are also referred to as Artificial Neural Networks (ANNs) or in many literatures as Simulated Neural Networks (SNNs). These networks are designed to mimic the structuring and functioning of the human brain, replicating the intricate communication patterns observed in real neurons. In general, the neural network consists of different sets of layers. Three layers are commonly used as shown in Figure 9: input, output, and hidden layers. At each layer, the number of nodes can vary depending on the user. Input variables are selected for photovoltaic system parameters such as irradiance, temperature I_{SC}, V_{OC} or any combination of those [46–50], whereas an output selection may be selected for photovoltaic system parameters such as the duty cycle. As per the hidden layer, this can be related to the distance of an operating point approaching the MPP and how effective a neural network is trained. Note that all links are using a weight. For example, nodes i and j have the link W_{ij}, as shown in [51]. The term W_{ij} is determined to be as accurate as possible using a training process to precisely detect the MPP.

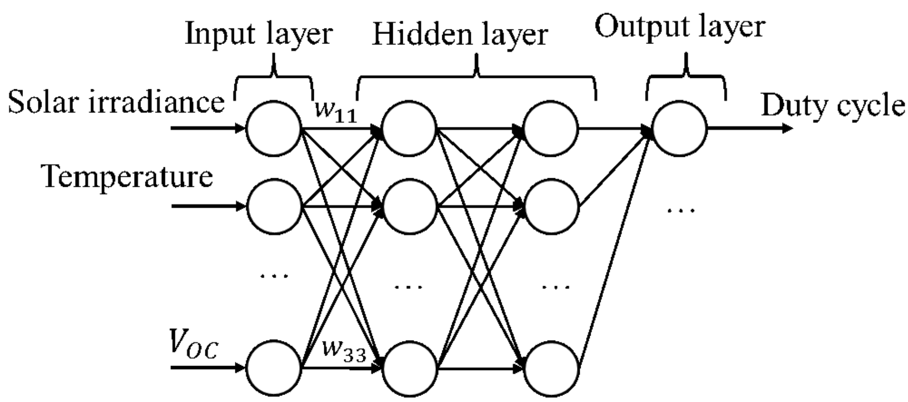

Figure 9. The structure of an Artificial Neural Network for MPPT.

4.2. Fuzzy Logic Controller (FLC)

FLC is well applied in PV systems especially in dealing with imprecise inputs. Furthermore, it does not need to be based on a precise model or an exact mathematical model, making it able to cope with non-linear system issues [52–54]. It can also achieve MPPT under varying climatic and environmental conditions. FLC consists of four different sections; fuzzification, inference engine, rule-base and defuzzification. A numerical value at the input is transformed into a linguistic variable constructed using membership functions (MFs) [54–56], as shown in Figure 10. Five membership functions are used in FLC for an MPPT scenario with two inputs and an output. The two input variables are denoted as the error (E) and change of error (E) at sampling time k. The following equations represent these inputs [55–58].

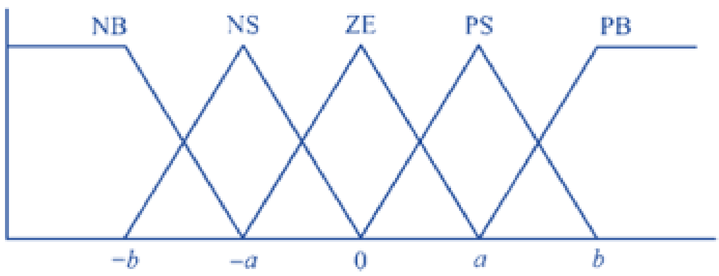

Figure 10. MF in a Fuzzy Logic.

$$E(K) = \frac{P_{PH}(K) - P_{PH}(K-1)}{V(K) - V(K-1)} \tag{1}$$

$$\Delta E(K) = E(K) - E(K-1) \tag{2}$$

Based on Equation (1), it can be determined if the operating point at time k is to the right or left of the maximum power point MPP on the PV curve. Equation (2) describes the direction of movement for the operating point on the P-V curve [59–61].

4.3. Artificial Neural Network (ANN) Based on the Technique of Perturb & Observe (P&O)-MPPT

The role of the ANN is to predict the power value in the next cycle. There is an observed difference between the ANN output value and the measured power [62–65]. This is used to adjust the step value for the next cycle using Equation (3):

$$\Delta V_{i+1} = k\frac{\Delta P_r}{\Delta V_i} f(I_r / I_p) \tag{3}$$

where V_i is the perturbation step at the ith cycle, k is a constant, P_r is the reel power, f is a function of input/output characteristic, I_r is the reel current, and I_p is the predicted value.

4.4. Gauss–Newton Method

The Gauss–Newton method is a faster mechanism compared to P&O. It applies the 1st and 2nd derivatives of parameter value changes in an attempt to approximate the distance and direction a program should go through to approach an enhanced point. The calculation of the operating point in tracking the MPP is shown in Equation (4) [66–74].

$$V_{K+1} = V_K - \frac{\frac{dp}{dv}\Big|_{V=V_K}}{\frac{d^2p}{dv^2}\Big|_{V=V_K}} \tag{4}$$

where dp/dv is the power derivation.

4.5. Steepest-Descent Method

The steepest-descent method is used to search for the closest local MPP under the condition where a function's gradient is calculated. MPPT tracking is shown by Equation (5).

$$V_{K+1} = V_K - \frac{\frac{dp}{dv}\Big|_{V=V_K}}{K_\epsilon} \tag{5}$$

Knowing the K_ϵ value will determine the steepness of each step—or in other words, the gradient direction. Power derivation is computed as follows:

$$\frac{dP}{dV} = F(V,P) \tag{6}$$

$$F(V_K, P_K) = \frac{P_{K+1} - P_{K-1}}{2\Delta V} + O(\Delta V^3) \tag{7}$$

where $O(\Delta V^3)$ is the local truncation error considered for center differentiation, which designates the 2nd order accuracy. Controllers are required to search for a point where $F(V,P)$ is equal to zero in an MPPT context [75–79].

4.6. Newton-like Extremum Seeking Control Method

To ensure the practicality of an MPPT control system, it is often necessary to have control over the convergence of the controller. This requirement can be met by employing the Newton-based extremum seeking approach. When equipped with knowledge of the power map, the Newton optimization algorithm can be utilized to successfully identify the maximum power point. It utilizes the panel characteristic's gradient and Hessian in estimating the operating point's optimal value, and it requires the Hessian approximation of the P-V characteristic, as shown in Figure 11 [80–85].

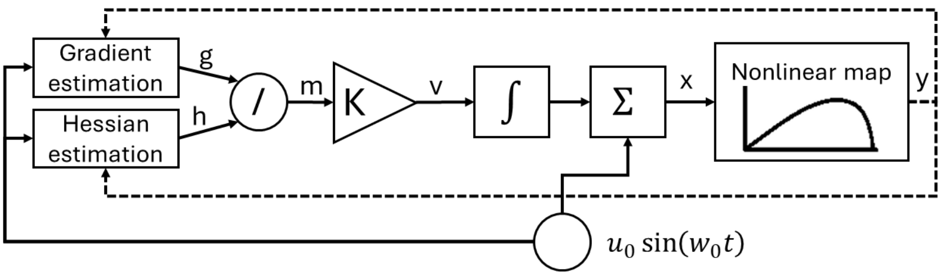

Figure 11. Block diagram representing Newton-like extremum seeking control method.

4.7. Online MPP Search Algorithm

The online MPP search algorithm works by finding a reference value of maximum power, where a comparison with the current power is achieved as shown in Figure 12 [86]. This mechanism results in a difference, which is named the maximum power error. The error should be close to zero in order to reach the MPP. When a referenced value for the

MPP changes due to changes in temperature or irradiance levels, this method adjusts the voltage array and searches for a new MPP. If the power/current at the load is lower than that for the MPP power, this method cannot execute the search and regulate the MPP. In this case, more loads need to be connected to increase the Ipv to allow the system to operate at the MPP [86,87].

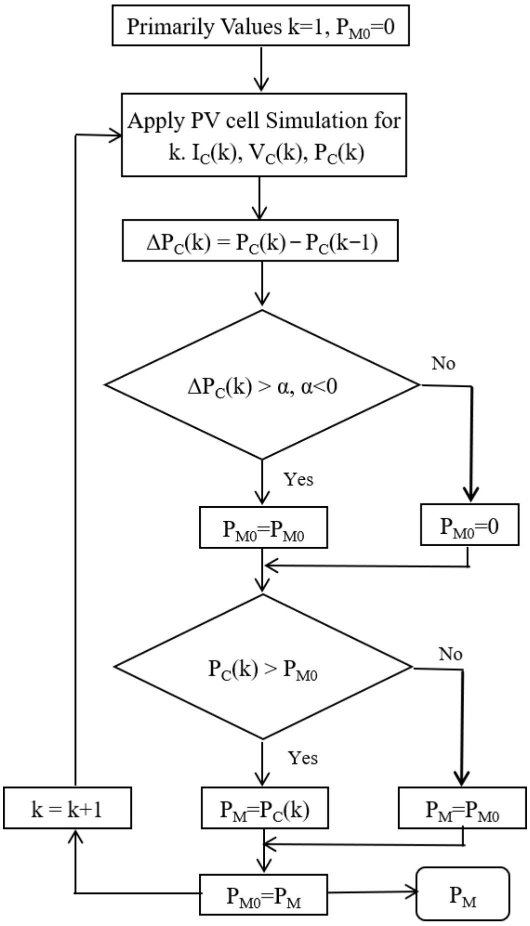

Figure 12. Flowchart of the online MPP search algorithm.

4.8. Particle Swarm Optimization (PSO) Algorithm

Decentralized schemes are at the core of swarm intelligence, which is an artificial intelligence technique that explores the study of collective behavior. Among the various paradigms within swarm intelligence, PSO has gained significant popularity. By simulating the social behavior observed in bird grouping, PSO has been developed as a worldwide optimization algorithm. This algorithm effectively addresses problems where the best solution is represented by a surface or point in an N-dimensional space. In these types of algorithms, its primary usage is to improve the performance of MPPT. Each segment is considered a particle, and the MPP is used as the target. In this scenario, a PV module can search for the MPP, as shown in Figure 13 [88–91].

The PSO algorithm's effectiveness and applications exist in numerous local MPPs. PSO uses particles with fitness and cost values that are assessed to be minimized by the function. Particles move through the search space by following the optimal particles. This technique relies on the collaboration of multiple agents, where they exchange information resulting from their individual search processes [54,92–94]. The state of the algorithms is shown in (8) and (9).

$$V_i^{K+1} = wV_i^k + c_1\, r_1(P_l X_i^{K+1k} - X_l^k) + c_2\, r_2(P_g^k - X_l^k) \quad (8)$$

$$X_i^{K+1} = X_i^k + X_i^{k+1} \quad (9)$$

where V_i^{K+1} is the velocity of the particle, X_i^{K+1} is the particles' position, P_i^k is the best local position, P_g^k is the best global position, r_1 and r_2 are numbers randomly taken between [0–1], and c_1 and c_2 are learn factors.

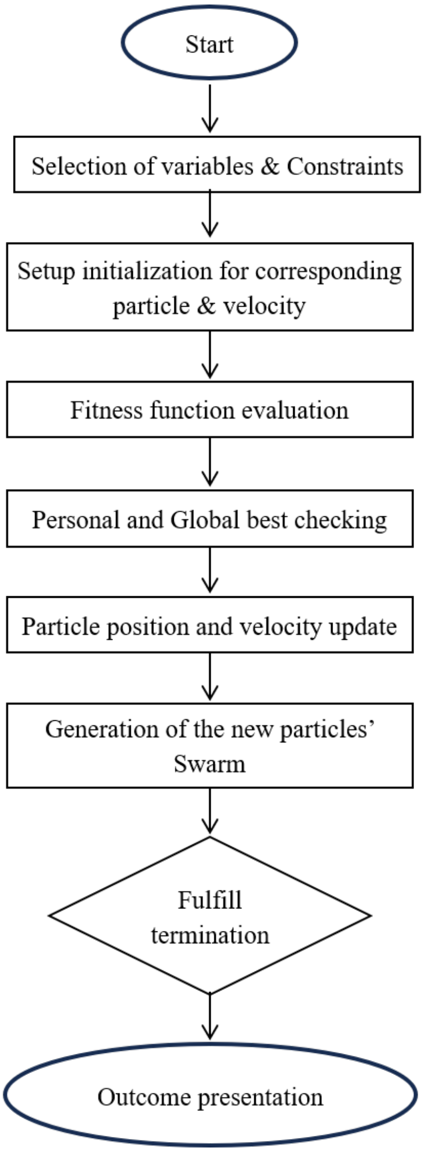

Figure 13. Flowchart of the PSO-based MPPT method.

5. Hybrid Intelligent Control Algorithms

5.1. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The integration of Artificial Neural Networks and Fuzzy Logic in a hybrid system has proven to be advantageous in various modeling and forecasting issues. This approach has found particular application in predicting the maximum power point (MPP) based on the exposure of solar data and neighboring temperature [95–97]. This method offers several benefits, including rapid response, non-invasive sampling, reduction in total harmonic distortion, improved utilization of the photovoltaic system, and straightforward training of the ANFIS algorithm [98–101].

The neuro-fuzzy method plays a crucial role in the development of a fuzzy expert scheme. However, it is essential to carefully select the rules, the total number, the type sort, and other various parameters of the membership functions in the fuzzy system to achieve optimal performance [102,103]. Trial and error are often employed to fine-tune these settings and attain the minimal desired level of performance. This highlights the significance of configuring the fuzzy systems appropriately. ANFIS, as a Sugeno network embedded within adaptive systems, simplifies learning and training processes [104,105]. This framework enhances the systematic nature of models and leverages expert knowledge, thereby enabling non-experts to utilize the system effectively [106,107].

5.2. Hybrid Genetic Algorithmic

Among the various evolutionary algorithms, genetic algorithms hold a prominent position in research applications. This algorithm is highly effective in exploring complex solution spaces to identify optimal or near-optimal solutions. Genetic algorithms are commonly utilized in optimizing fuzzy controllers or neural networks for the management control of the maximum power point (MPP) [108–113]. The fundamental concept guiding genetic algorithms is to replicate the principles of evolution theory, leading to the determination of an optimal parameter set through the application of the "survival of the fittest" principle [114–117].

5.3. Fuzzy-PID

The PID controller, an acronym for Proportional–Integral–Differential controller, is a conventional controller widely employed in various control applications [118,119]. Its output is determined by three constants: one for the proportional term, one for the integral term, and one for the differential term. To tune the PID controller and determine the appropriate proportional, integral, and differential gains, several methods exist. Among these methods, the Ziegler–Nichols tuning formula is the most commonly used [120–122]. In control systems, there are directions addressed that involve the utilization of fuzzy logic and the PID block. One entails employing the FL block as a tuning mechanism for the PID controller [120,123,124]. This allows for the online tuning of the PID controller using the fuzzy block. Additionally, a novel adaptive fuzzy PID controller has been introduced for maximum power point tracking. Through this method, the fuzzy block is utilized to fine-tune the PID controller. Numerous studies have conducted a comparative analysis between the fuzzy-tuned PID controller and other traditional PID control schemes. These studies have demonstrated the algorithm's exceptional tracking capabilities, highlighting the advantages of the fuzzy-tuned PID controller [125–128].

5.4. Ant Colony Optimization

The Ant Colony Optimization (ACO) algorithm is a probabilistic method utilized for determining the optimal path, as shown in Figure 14. In the context of MPPT, Ant Colony Optimization is employed in two distinct manners: initially, it is used as a direct controller aimed at identifying the optimal power point rather than the optimum path, and secondly, it can be utilized as an optimization tool for fuzzy controllers or PI controllers [129–133].

During the search mechanism of MPP, the path-seeking information is performed by using pheromone density as a first practice and an idea function and then sorting out the ultimate answer in accordance with the density of pheromones.

A dispersed field establishes an ant colony, whereas the PV output curve of a system in practice is a succeeding curve. In a continuous field, this technique is used to present Gaussian mutation for optimizing the algorithm and achieving (MPP) tracking. This is accomplished by considering practical situations of PV electrical production [134,135].

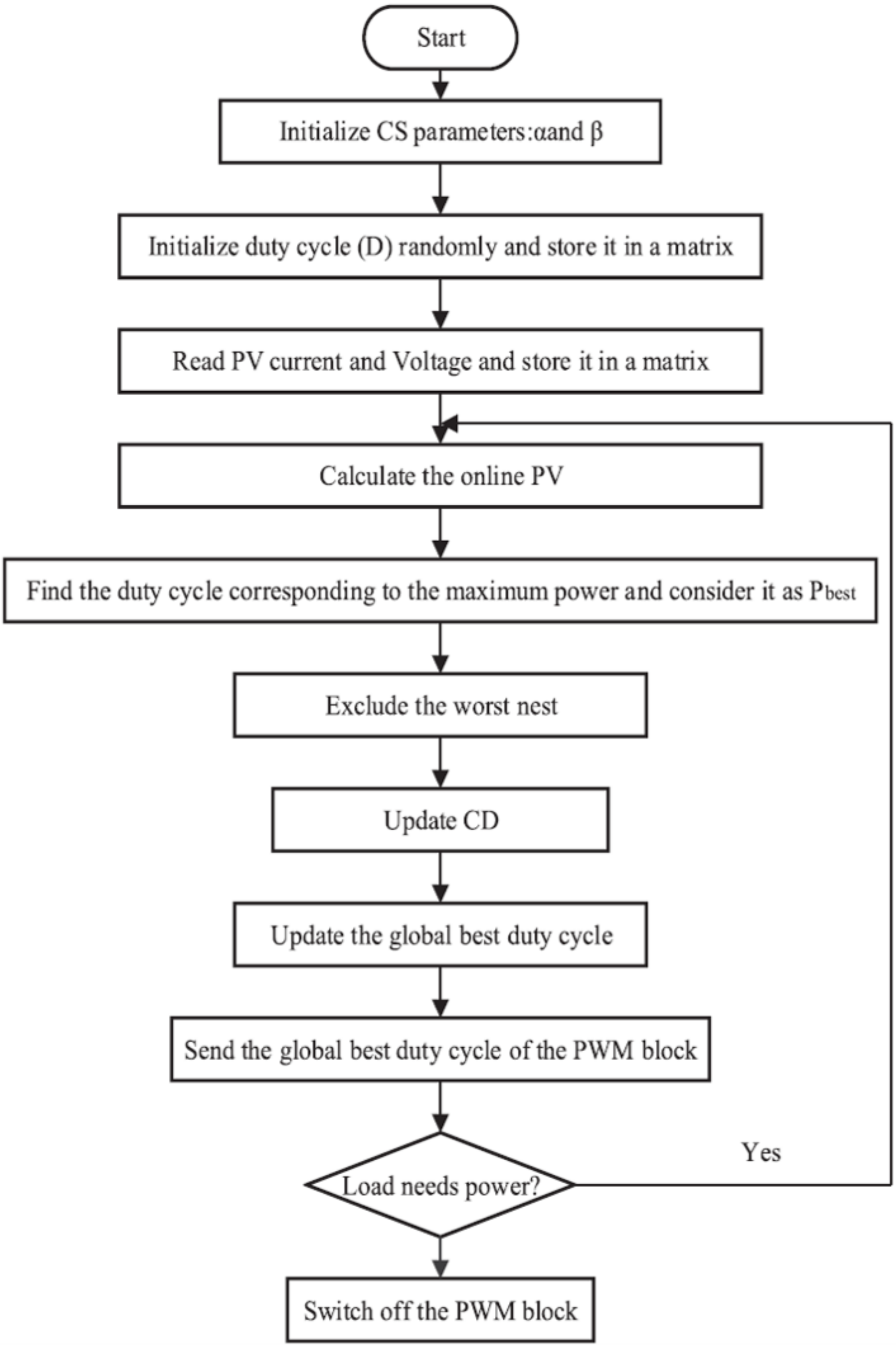

Figure 14. Flowchart of the ACO-based MPPT method.

5.5. Fuzzy-Neural Network

In place of using ANFIS controllers, there is an alternative hybrid technique that combines neural network and fuzzy control. Such hybridization methods are commonly referenced in the literature using two distinct structures [109,136–138]. The first method involves using the neural network to estimate a specific variable for the fuzzy logic controller. On the other hand, the second method involves using fuzzy logic in conjunction with the Hopfield neural network to govern the maximum power point [47,139,140].

5.6. Analytic Method

The field of MPPT for PV modules heavily relies on analytical methods. These methods often encompass a combination of theoretical control, mathematical modeling, and optimization methods. By employing these approaches, an algorithm can be derived to effectively determine the optimal operating point, thereby achieving the maximum power output. This method depends on experimental/observational results, providing analytical clarification to photovoltaic MPP problems. It is based on the real analysis theorem (mean value theorem). The precise manifestation of the neighborhood's MPP is acquired and demonstrated to be within a small radius ball, which also handles the MPP [141,142].

5.7. PI Based Incremental Conductance (INC)

Implementing a PI controller through an INC is beneficial for minimizing the difference between true conductance and the INC. The compensator updates the system's requirements, providing an advantage at the steady state as a PI controller minimizes ripple oscillations [143,144].

5.8. PSO-INC Structure

The performance of the INC algorithm in efficiently tracking the maximum power point (MPP) under different environmental conditions is enhanced by optimizing its parameters, such as the step size or perturbation value, using the Particle Swarm Optimization (PSO) algorithm. This hybrid model utilizes PSO to dynamically fine-tune the parameters of the INC algorithm, aiming to improve the overall efficiency and adaptability of maximum power point tracking (MPPT) in photovoltaic (PV) systems.

The PSO approach is employed to refine the parameters associated with the INC algorithm, particularly the perturbation step size/value necessary for effectively tracking the MPP. Through an iterative methodology, PSO systematically navigates the parameter space to discover the most suitable three values that enhance the performance of the INC algorithm in accurately tracking the MPP even when faced with varying environmental conditions [145–147].

6. Measurement MPPT Methods and Comparison

6.1. Perturb and Observe (P&O)

To start with, one of the simplest and easiest to implement algorithms, along with low cost, is the P&O algorithm, which is also referred to in many studies as "hill climbing." In addition to the above features, P&O is popular due to its simple structure and the minimal required parameters that need to be addressed for measurement. The measured values are related to a PV array set and include the current (I) and voltage (V).

Figure 15 The text addresses a flowchart of the P&O algorithm operation [9,148–150]. In this method, the voltage of the module is perturbed periodically in accordance with the requirement of driving the operating point through a set of fixed step size perturbations, and the Pout of the module is compared with the Pout from the previous perturbation cycle. In this algorithm, a slight but fixed perturbation step size is applied to the system. This perturbation causes the solar power to vary based on the variation of the perturbation step size applied [9,151]. When an increase in power is observed, it is due to the effects of the perturbation. If the perturbation leads to an increment in power, the next perturbation will continue in the same direction. The main goal is to reach the MPP, which is achieved when the MPP power is zero. During the next available instant, the power decreases, and then the perturbation will start to go in the other reversed direction, as shown in Figure 16.

Note that the P&O keeps perturbing in an effort to approach the MPP by decreasing and increasing perturbation steps [150]. This algorithm has the disadvantage of oscillation that occurs around the MPP as well as a slower response time due to dynamic changes in climatic parameters such as temperature and irradiance [152].

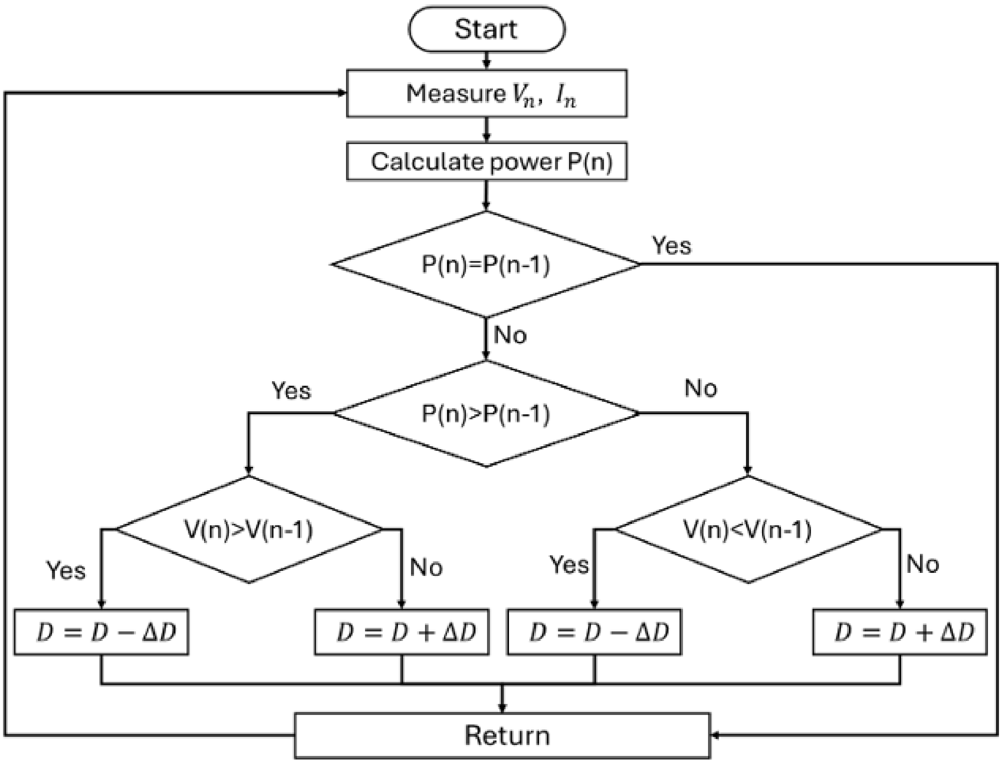

Figure 15. P&O MPPT algorithm.

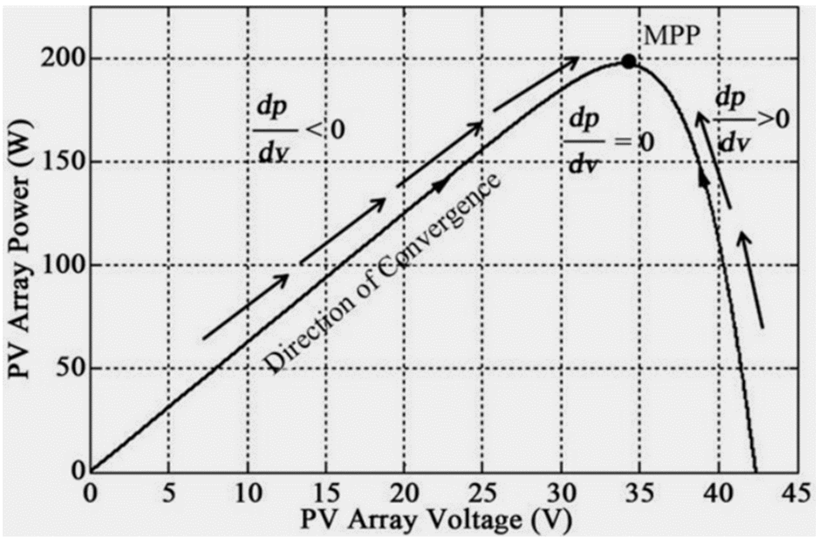

Figure 16. P&O algorithm principle.

6.2. Incremental Conductance Algorithm

The incremental conductance (INC) MPPT algorithm is used in PV systems due to its simplicity and ease of implementation, and it has the benefit of providing satisfactory performance in instances of decreased irradiance levels and when it is affected by dynamic changes due to climatic conditions. INC utilizes current/voltage sensors to detect the current (I) and voltage (V) generated by the photovoltaic array [153–156].

INC operates as follows: the PV voltage (V_{pV}) adjustment is performed based on the array voltage of the PV system around the maximum power point (MPP). The concept of operation of INC is illustrated in the flowchart shown in Figure 17 [157–159].

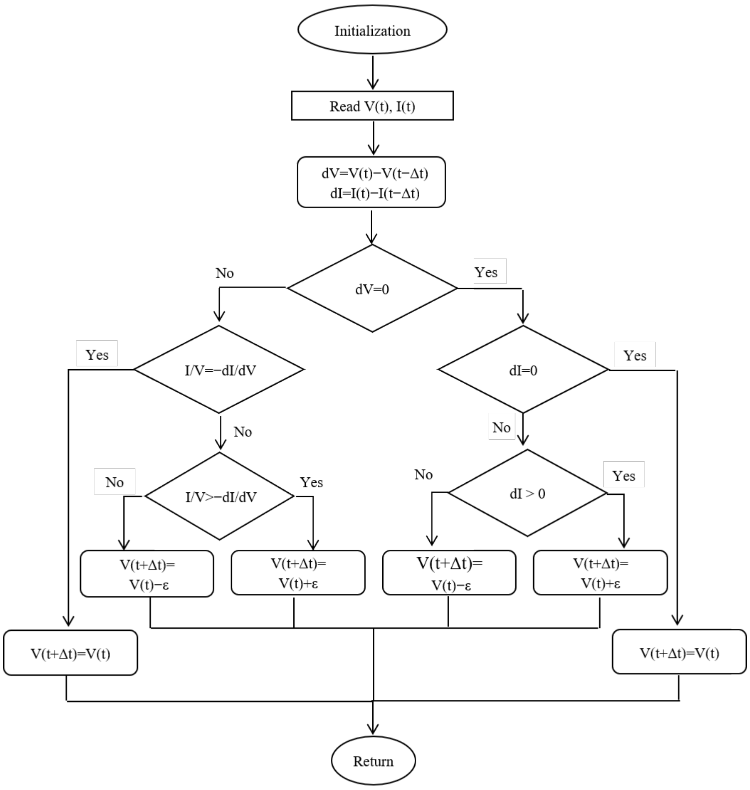

Figure 17. INC flowchart.

6.3. Short Circuit Current Method

In many studies, the short circuit current method is well known as the constant current method. The short circuit current (I_{sc}) has a linear relationship with the maximum power point current (I_{MPP}) as illustrated in (10) [160,161].

$$I_{\mathrm{MPP}} = I_{\mathrm{sc}}\left[1 - e^{\frac{(V_{\mathrm{MPP}} - V_{\mathrm{OC}})}{A}}\right] \quad (10)$$

Figure 18 shows that there is a linear relationship between both the between both the I_{MPP} and I_{sc} at various climatic conditions (irradiance/temperature) [160,161]. The relationship between I_{MPP} and (I_{sc}) does not change significantly under irradiance and temperature variations even when the temperature changes. The short circuit current (I_{sc}) technique is a very basic MPPT method that compares the photovoltaic current I_{Pv} with a reference constant current referred to as I_{MPP}. To minimize errors in the steady state, the error signal is used in a basic controller with integral action [160,162].

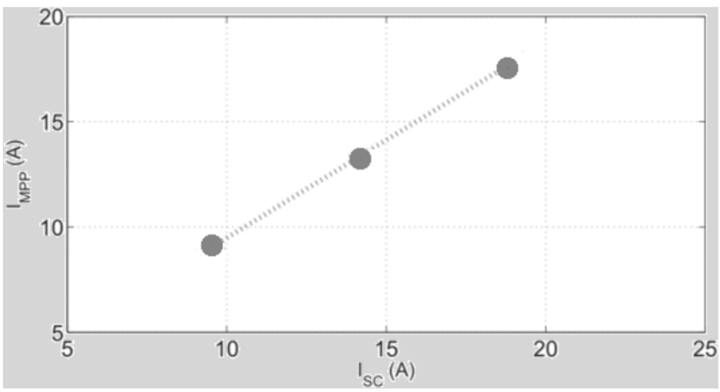

Figure 18. Relationship between IMPP and ISC.

6.4. Open Circuit Voltage Method

The open circuit voltage method is also known as the constant voltage method. The PV solar voltage has a proportional relationship with the open circuit voltage (V_{OC}). At the maximum power point (MPP), it is considered a reference voltage for different levels of irradiation and temperature. The applied voltage can be adjusted based on the measurement of a battery's open circuit voltage V_{OC}. To determine the MPP, the following equation can be used [163,164]:

$$V_{\text{Max}} = M_V \times V_{\text{OC}} \tag{11}$$

However, determining the value of the constant Mv is challenging, as it can range between 0.71 and 0.8 based on the features of the photovoltaic array, according to the literature. An estimated value of 0.76 is recommended for this technique [163–166].

6.5. Parasitic Capacitances (C_p)

The parasitic capacitances algorithm operates similarly to the INC algorithm, but it takes into account the parasitic effects of capacitance (C_p). A setup for C_p is added in parallel at the terminals of the preceding models, where it is included in the observation of the diode equation. The observed current (I_{ob}) is described in the following equation [167,168]:

$$I_{\text{obs}} = I - I_{\text{PC}} \tag{12}$$

$$I_{\text{obs}} = I_{\text{PH}} - I_{\text{S}}\left[\exp\left(\frac{q(V + R_S I)}{AV_{\text{Th}}}\right) - 1\right] - \frac{(V + R_S I)}{R_{\text{SH}}} - C_p \frac{dV}{dt} \tag{13}$$

$$I_{\text{obs}} = F(V) - C_p \frac{dV}{dt} \tag{14}$$

The current in C_p is denoted as $C_p(dv/dt)$. The maximum power point (MPP) occurs when $dP/dV = 0$. By multiplying the equations by the panel's voltage (V), the array's power can be determined, and differentiation can be applied to the result. This approach is used to analyze the power array [168].

$$\frac{dF(V)}{dV} + F(V)V = \frac{dI_{\text{obs}}}{dV} + I_{\text{obs}}V + C_p(\dot{V}V + \ddot{V}\dot{V}) = 0 \tag{15}$$

There are three parameters to address: (1) parasitic capacities, (2) observed instantaneous conductance, and (3) incremental conductance. We know that the 1st and 2nd derivations of the voltage's array would consider ripple effects. The drawback of this algorithm is related to the parasitic capacitance at the minimal in each module, thus increasing the effective capacitance accounted for during MPPT [167,169].

6.6. Temperature Method

Temperature method allows avoiding changes that may take place at MPP due to temperature changes. This is implemented through a low cost temperature sensor that varies the MPP algorithm function, and upholding the appropriate MPP track [170]. A major drawback for this technique is the irregularity formation of PV distribution of array's temperature. such sensors may not be accurately calibrated due to its quality that may generate false and inaccurate PV's temperature measurements. The following equation is used to direct the temperature method [170–172].

$$V_{\text{MPP}}(t) = V_{\text{MPP}}(T_{\text{ref}}) + TK_{VOC}(T - T_{\text{ref}}) \tag{16}$$

where V_{MPP} is the voltage of the maximum power point, T is the temperature of the surface panel, T_{KVOC} is the temperature coefficient of V_{MPP}, and T_{ref} is the temperature of the standard test condition.

6.7. System Oscillation Method

To identify the maximum power point (MPP), a perturbation-based maximum power point tracker incorporates the use of system oscillation. Rather than relying on an explicit perturbation source, the controller of the tracker is specifically engineered to induce self-oscillation within the entire system. As a result, the main switch's duty cycle at a power conversion stage is modulated with a tiny variation in amplitude at a defined frequency around the desired steady-state value. This method relies on using a Cuk converter in the middle between the solar panel and the load. It depends on calculating the MPP based on the switching frequency along with a portion of sinusoidal signal variation [173,174].

6.8. Constant Voltage Method

The constant voltage method assumes a fixed voltage value for the maximum power point, which aligns with the voltage observed under the manufacturing Standard Test Conditions. This fixed voltage value typically varies between 72 and 80 percent of V_{OC}, as shown in Figure 19. Subsequently, V_{ref} is utilized to modulate the MPPT converter's duty cycle through a feedback control loop. In general, constant voltage depends on using a voltage sensor. The DC-DC converter's duty cycle is modified to maintain an output voltage (at PV) and relies on the characteristic of temperature. The algorithm has the benefit of using a sole sensor, easy implementation and its advantage in tracking [172,175–178].

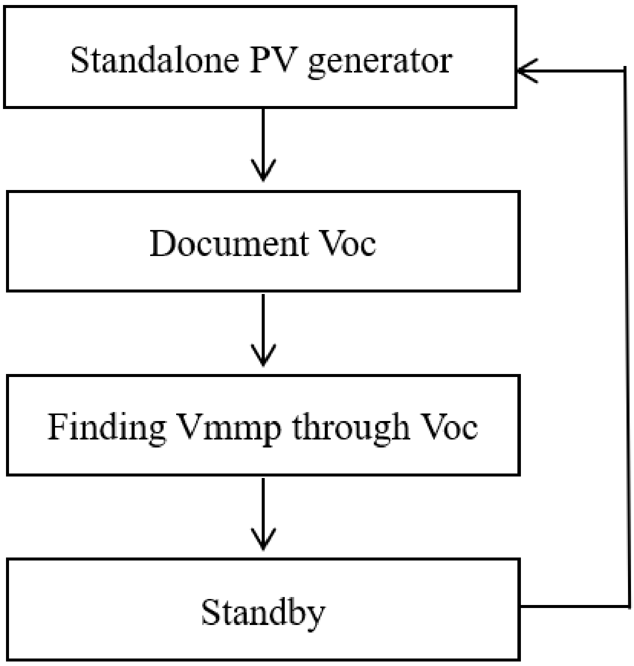

Figure 19. Flowchart of the constant voltage MPPT method.

6.9. Method of Look-Up Table

The process of locating the maximum power point (MPP) in this method requires prior knowledge of the PV panel material, technical data, and panel characteristics under different normal circumstances. This information is stored for future reference. The controller, considering the measured temperature and insolation values, compares them with the data stored in the look-up table to determine a new voltage for each cycle. The look-up table is generated based on the specifications provided by the manufacturer or through experimental examinations conducted on the PV panel under various climatic conditions. This offline method is primarily used in MPP tracking. Information about technical specifications and panel characteristics for different climatic conditions is necessary. The measured voltage and current of the PV generator will be compared to the values stored in the control system, which correspond to the MPP [179,180]. A drawback of this algorithm is the need for large memory capacities to store the data [180].

6.10. Array Reconfiguration Method

The main purpose of PV array reconfiguration strategies is to enhance the power output when there are imperfections in irradiance parameters. The primary goal of this method is to regulate the currents flowing through various electrical lines. This MPPT technique is used in partially shading, where the solar units are arranged in a set of series/parallel combinations to allow the MPP to meet the requirements of the load. The disadvantage is the time consumption required to track the MPP. There are three ways of arrangements: series, parallel, and parallel–series arrangements [181–184].

6.11. State-Based MPPT Method

In the realm of photovoltaic (PV) systems, state-based MPPT is utilized to optimize the output power by continuous adjustment of the operating point in solar panels, depending on the system's current state. This approach takes into consideration a range of environmental parameters and electrical status to find the maximum power point (MPP) and ensures that the module functions at or close to this point. State space represents a model in this method. The literature shows that it is reliable and non-sensitive to fluctuations in the parameters of a system, and the MPP can be attained regardless of PV partial shading [94,185–187].

6.12. One-Cycle Control (OCC) Method

The OCC method involves a non-linear control theory specifically designed for the regulation of switching converters through the utilization of a solitary switching cycle. By employing this controller, it becomes possible to achieve instantaneous dynamic control over the average value of the switching variables following a transient event. This technique boasts numerous benefits, such as its minimal complexity and cost-effective implementation, its ability to effectively reject disturbances, its robustness, its capacity for maintaining stability, and its swift dynamic response. It is a type of inverter in which the output current can be regulated by a PV voltage to obtain P_{max}. The topology of OCC consists of the following functions: it adjusts Pout based on irradiance, and it outputs an AC current into the grid. The advantages of OCC include a power factor at the highest level, its easy-to-implement circuit, and cost efficiency [188–191].

6.13. Best Fixed Voltage (BFV) Algorithm

The BFV algorithm searches for statistical data regarding sunlight and temperature over a period of time and finds the BFV conforming to the MPP. The applying controller can set the operating point to the BFV or can set the output voltage toward the load voltage [192,193]. To explain the algorithm in more detail, over a period of time, comprehensive statistical data are gathered to analyze the irradiance and temperature levels. These data are crucial in identifying the Best Fit Voltage (BFV) that serves as a representation of the maximum power point (MPP). Subsequently, the controller adjusts either the operating point of the PV module to align with the BFV or sets the Vout to match the nominal load voltage. As a result, the operation is never precisely at the MPP, necessitating the collection of diverse data for different geographical regions. Simplicity and ease of implementation are the main benefits of this algorithm. However, its efficiency is limited and requires an analysis of mathematical statistics in locating the BFV to increase the PV array power [192–194].

6.14. Three-Point Method

The three-point method is used to suppress oscillation problems in the P&O algorithm where it compares only two points (current and perturbation point). In this three-point method, it periodically perturbs the PV voltage and compares output power. The method works on avoiding any operating point moving rapidly during varying irradiance. The points are (A) the present operating point, and (B) perturbation starting at points "A" and "C" through the opposite direction from "A", as shown in Figure 20 [195–197].

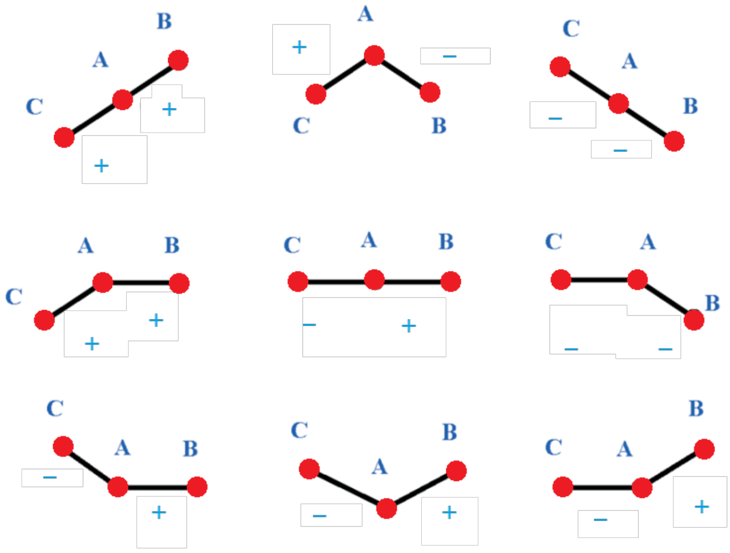

Figure 20. Three perturbation points of possible states.

6.15. The Method of PV Output Senseless (POS)

The primary benefit of employing the PV Output Senseless (POS) approach lies in the fact that the sole significant factor to be considered is the current that flows into the load. When dealing with a large photovoltaic (PV) generation system, it can be operated with a significantly higher level of safety compared to a conventional system. In this context, it is necessary to focus solely on the current flowing through the load. The source and load power are proportional in a PV system. When the current increases, the load power increases, and thus the current at the load is proportional to the power at the source, which is the solar cell output power. Power in this method is controlled by PWM. Incrementing the duty ratio leads to an increase in current output at the converter [198,199].

6.16. Variable Inductor MPPT Method

The variable inductor MPPT method introduces a novel MPPT topology controller for solar power applications, incorporating adjustable inductance based on current characteristics. It has been demonstrated that under steady processes, the output inductor exhibits a characteristic where the inductance decreases as the current increases, corresponding to the increase in solar radiation incident. This technique utilizes a variable inductor slope airgap, which gradually saturates with a cumulative increase in current to meet this requirement. This design offers the advantage of reducing the overall size of the inductor by almost 60% and expanding the operational range of the entire tracker, enabling the extraction of solar energy even under low irradiance conditions. It introduces variable inductance to enhance the operable range of the tracking method to extract P_{max} even at lower irradiance levels. This technique is recommended for use in low-irradiance scenarios [192,200].

6.17. Variable Step-Size Incremental Resistance (INR) Method

A variable step-size algorithm is proposed to overcome the issue of a fixed step size for dynamic environmental conditions. An advantage of this algorithm is the ability to switch the points and values of the threshold function, as shown below [91,138,201]:

$$C = P_n \times \left| \frac{dP}{dI} \right| \tag{17}$$

where n is assumed to be an index. Furthermore, it is assumed that the curve's power slope reaches a value of zero at the MPP, which is positive when it is to the left and eventually negative when it is moving to the right of the MPP. The MPP is tracked through a comparison of instantaneous resistance (V/I) and incremental resistance ($\Delta V/\Delta I$).

6.18. DP-P&O MPPT

DP-P&O MPPT applies additional power measuring in the center of the sampling MPPT period where no perturbation occurs, as shown below [202]. Figure 21 shows P_x and P_{k+1} when they have a change in their power. This change reflects only the power changes due to weather conditions and other variations. Differentiation between P_x and P_k indicates a power change initiated by an MPPT perturbation and irradiance variation. dP is computed [203–205]:

$$dP = dP_1 - dP_2 = (P_x - P_k) - (P_{k+1} - P_x) \tag{18}$$

$$dP = 2P_x - P_{k+1} - P_k \tag{19}$$

Thus, (dP) is the result of modifying the MPPT algorithm.

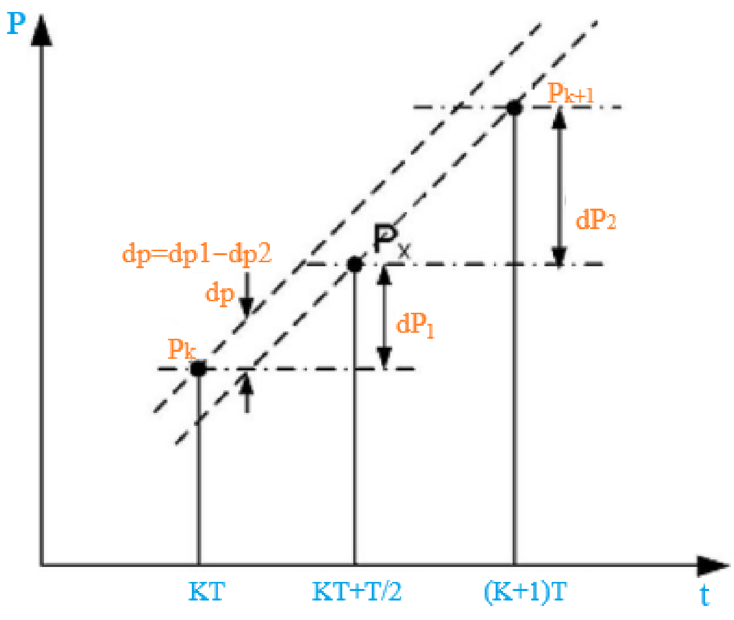

Figure 21. Power measurement between sampling of two MPPT values.

6.19. Pilot Cell

In the pilot cell scheme, the pilot cells are operated at their MPP to eliminate any photovoltaic power losses during pilot cell MPP measurements. However, there is an issue with a missing constant value "K". The pilot cell parameters need to be precisely matched to the parameters of the arrays represented by the pilot cell, which increases the system's energy cost. This method allows MPPT to operate a PV system at the MPP without power losses in the pilot cell measurements. Nevertheless, the issue of the missing constant value "K" remains. The pilot cell parameters must be accurately calibrated to match the parameters of the arrays represented by the pilot cell, leading to an increase in the system's energy cost [163,206–208].

6.20. Modified Perturb and Observe

The modified perturb and observe method works well in a non-dynamic changing environment but has issues detecting the MPP in rapidly changing climatic conditions, leading to inaccurate MPP tracking. To address these issues, a modified P&O (M-P&O) method is used to separate the variations caused by perturbation from those caused by irradiance or weather changes. The tracking speed of the modified P&O method is approximtely 50% of the conventional method [209–215].

6.21. Estimate Perturb and Perturb (EPP)

The EPP approach utilizes an extended P&O method with one estimate mode and two perturb modes. The perturb process addresses the high non-linearity of PV specifications, while the estimate process compensates for irradiance variations during perturbation. Despite its complexity, this technique offers superior tracking speed compared to the conventional P&O method. It improves speed while maintaining the key characteristics of the M-P&O algorithm. Compared to M-P&O algorithm, this method relies on a single estimation mode for every two perturb approaches, significantly increasing the tracking speed of MPPT without sacrificing tracking accuracy. Compared to M-P&O, the EPP is 1.5 times faster in tracking speed but has almost the same time delay between estimation and perturb processes [216–219].

6.22. CVT + INC-CON (P&O) + VSS Method

The CVT + INC-CON (P&O) + VSS method shows improvements in tracking performance but has a complex initial start-up process. The control algorithm is straightforward, checking if V_{out} is greater than the voltage instruction of the PV array. However, the voltage change is unidirectional, leading to a power increase in one direction and oscillation suppression [220,221].

6.23. VH-P&O MPPT Algorithm

The VH-P&O MPPT algorithm halts conventional perturbation during irradiance changes before exceeding the MPP voltage, holding V_{ref} to the capacitor voltage of the PV system, which is a crucial tracking factor. When the MPP is reached and the irradiance changes stop, the step size tracking is gradually reduced to zero. If there is a change in the PV power, the step size tracking is reset to the original value to maintain fast tracking. This technique ensures a linear tracking performance in response to irradiance changes and suppresses oscillation at the MPP [222–226].

6.24. Variable DC-Link Voltage

The variable DC-link voltage algorithm aims to expand the MPPT range and reduce total harmonic distortion (THD) by selecting a suitable DC-link V_{ref}, which is adjusted based on the sorted input voltage. This adjustment helps overcome limitations in the design of PV systems caused by the impact of input voltage and current on the PV cell connection structure, especially during specific environmental conditions [223–230].

6.25. Modified INC Algorithm

The modified INC algorithm focuses on the current rather than the voltage of the PV array. It simplifies the calculation of the reference current I_{ref} based on the linear variation of dP/dV_{pv}, which is easier to calculate compared to the non-linear variation of V against dP/dV. By neglecting voltage variations through two sampling times, the algorithm improves tracking efficiency, especially on the right MPP side where V_{pv} changes slowly [231–234].

6.26. Azab Method

The Azab method is a modified P&O algorithm that tracks the MPP power extracted from the PV system. It continues to reduce the calculated MPP power until the error in both P_{MPP} and P_{ACT} falls within predefined upper and lower limits [235–237].

6.27. Voltage Scanning-Based MPPT Method

The voltage scanning-based MPPT method uses a three-step process to identify the global MPP (GMPP). By systematically increasing the reference voltage of the system at a predetermined rate, MPPs and their corresponding voltage values are identified through the resulting power changes. By comparing MPPs with the previous MPP, the local MPP (LMPP) is eliminated, and a new GMPP is determined at each MPP. This iterative process continues until all voltage levels have been examined with the voltage at the GMPP established as the module's reference voltage for optimized power generation [32,38,238–240].

7. Mathematical Calculation MPPT Methods

7.1. Model-Based MPPT

The model-based MPPT approach enhances PV module tracking under fast-varying irradiance conditions by using a PV mathematical model to predict the MPP systematically. The inverse PV model is used to compute the irradiance value based on current and voltage measurements [241–244]. While the current's inverse PV model may not be found in a closed form, simple interpretations can impact the accuracy of irradiance estimation, leading to imprecise tracking. Introducing a shunt PV model with a closed-form inverse can improve the accuracy of irradiance estimation, resulting in better tracking accuracy and increased energy extraction compared to existing model-based trackers [242,243,245,246].

7.2. Piecewise Linear Approximation with Temperature-Compensated Method

The Piecewise linear approximation with temperature compensated method rapidly tracks the PV's MPP and addresses temperature drifting issues. This method has shown high tracking efficiency at various irradiances and temperatures ranging from $(-5\ °C$ to $55\ °C)$ with less than 1% tracking efficiency loss [160,247,248].

7.3. Beta Method

The Beta method is based on the I-V curve of the PV system and provides accurate and fast tracking of the MPP using an intermediate variable (β) [52,174,249].

$$\beta = \ln(IV) - C \times V = \ln(I_S \times C) \tag{20}$$

$$C = \frac{qAKT}{N_s} \tag{21}$$

where I_s denotes the reverse saturated current, q is the electronic charge, A is the ideality factor, k is the Boltzmann constant, T is the temperature and N_s is the number of cells connected in series. When operating settings change, β stays constant. β calculations can be made at any time through the (I) and (V) of the panel and fed to the conventional closed loop through a constant reference.

7.4. Ripple Correlation Control (RCC)

Due to the ripples involved in a PV system, this method reconsiders using ripples to accomplish MPPT. RCC works in the following structure: if (I) or (V) increases, it causes an increase in power where the operating point location is to the left of the MPP ($V < V_{MPP}$ and $I < I_{MPP}$). When either the current or voltage is increasing and power (P) is decreasing, the operating point is observed to be located to the right of the MPP ($V > V_{MPP}$ and $I > I_{MPP}$). Controlling the duty cycle ratio in this method allows for reference to the equations that follow [250–254];

$$d(t) = -K_3 \int p \cdot v \, dt \tag{22}$$

$$d(t) = K_3 \int p \cdot i \, dt \tag{23}$$

where K_3 is a positive constant.

7.5. Current Sweep

The current sweep applies a sweep waveform to the current of the PV array system, where an I-V curve (PV module) is attained accordingly within a set of fixed intervals of time [255]. The same computation can be made to ensure that the sweep looks for and searches the highest possible peak when multiple peaks exist. This method is likely to be achieved if tracking power consumption is less than the increased power delivered to the system [192,256].

7.6. DC-Link Capacitor Droop Control

The DC-link capacitor droop control method operates in a cascading fashion within the PV system. The duty ratio D is shown below:

$$D = 1 - \frac{V}{V_{\text{link}}}. \tag{24}$$

Through this approach, it is possible to increase the power of the PV system [257–259].

7.7. Feedback Control

In the realm of power systems, the expressions dP/dV and dP/dI pertain to the power derivatives in relation to voltage (V) and current (I), respectively. These derivatives are frequently employed in the examination of the power–voltage (P-V) and power–current (P-I) characteristics of electrical systems. The utilization of feedback control is essential in computing the slope dP/dV or dP/dI in the P-V curve and feeding it to the power converter. Slope calculations and signs are used for past cycles where the duty ratio's incremental or decremental power conversion is applied to reach the ultimate MPP [260,261].

7.8. The Method of Linear Current Control

The main purpose of PV array reconfiguration strategies is to enhance the power output when there are imperfections in irradiance parameters. The primary goal of this method is to regulate the currents flowing through various electrical lines. Depending on interpretational graphics of two algebraic equations, the intersecting points of two curves on the phase plane are applied [199].

7.9. Linear Reoriented Coordinates Method (LRCM)

LRCM works by iteratively solving the MPP equation and is employed to find a symbolic approximation of the MPP. It measures (I_{SC}, V_{OC}) and additional parameters of the P-V curve to discover an approach of the maximum error by adopting LRCM to estimate the MPP [262,263].

7.10. Slide Mode Control Method

The voltage derivative slope to current ratio is utilized for finding the MPP. A mathematical model can be created for many DC-DC converters such as boost, buck, etc., to find the MPP. The parameter u is considered as the converter's switching function, where u is articulated as [264–267]

$$u = \begin{cases} 0 & \text{if } S \geq 0, \\ 1 & \text{if } S < 0. \end{cases} \tag{25}$$

If $u = 0$ (open switch) and when u = 1 (closed switch). S is expressed as

$$S = \frac{dP}{dV} = I + V\frac{dI}{dV} \tag{26}$$

7.11. Polynomial Curve Fitting (PCF)

PCF is known as an offline technique. It is based on mathematical equations and describes the electric characteristics of PV modules. A 3rd order polynomial function can be applied to accurately fit a P-V curve using (27) [268,269].

$$p_{pv} = aV_{PV}^3 + \beta V_{PV}^2 + \gamma V_{PV} + \delta \tag{27}$$

where $\alpha, \beta, \gamma, \delta$ are found through V_{pv} sampling and power intervals. The MPP is at the optimal value when $dP/dV = 0$, and is computed by

$$V_{\text{MPP}} = \frac{-\beta \pm \sqrt{\beta^2 - 3\alpha\gamma}}{3\alpha} \tag{28}$$

Curve fitting is easy to use, since differentiation calculations are not involved. However, it requires prior knowledge of mathematical equations and coefficients. Additionally, it requires a large memory capacity due to the high number of computations, which increase rapidly [270].

7.12. Differentiation Method (DM)

Numerical differentiation is the basis for the DM. It involves finding the numerical value of the derivative of a function at a specific point [271,272].

7.13. MPP Locus Characterization

MPP locus characterization aims to establish a linear relationship between current (I&V) and the MPP (MPP locus). This relationship is represented by a tangent line to the MPP locus curve for the current, Ipv with sensitivity being highest at minimal irradiance conditions [174,273–275]. This method is described by Equation (29). It provides reliable results at high irradiances compared to traditional methods.

$$T_L = (A \cdot V_T I_{\text{MPP}} - N_S R_S) \cdot I_{\text{MPP}} + \{V_{\text{OC}} - A[V_{\text{DO}} + V_T]\} \tag{29}$$

where A is the ideality factor, and V_{Do} is the differential voltage.

8. MPPT Optimization Methods

8.1. IMPP and VMPP Computation Method

The optimization of power output in PV systems heavily relies on the implementation of MPPT technology. This essential technology enables solar panels to consistently operate at their MPP despite changes in environmental conditions. By continuously adjusting the operating point of the solar panels, the MPPT controller ensures that the power output is maximized. The computational approach encompasses perturbing the operating point, either by modifying the voltage or current, and then examining the consequent variation in power. Subsequently, the controller adapts the operating point to converge to the MPP. The measurement of photovoltaic power relies on the irradiance/temperature measured by a systematic photovoltaic. A disadvantage of this method is the need for additional measurements, which are sometimes hard to obtain, and the need for an exact photovoltaic array model. The advantage of this method is that the MPP is accurately monitored even in varying atmospheric conditions [194,276–278].

8.2. Numerical Method–Quadratic Interpolation (QI)

The QI method is new and uses numerical calculation in PV power production systems. It creates a parabolic scheme along quadratic interpolation. This is achieved by applying the (V&I) parameters from a set of three sampling points. The peak of the parabolic model is found by calculating the voltage value of the MPP [279–282]. The basis function technique is used to construct the quadratic function:

$$L_2(X) = l_0(X)y_0 + l_1(X)y_1 + l_2(X)y_2 \tag{30}$$

where $L2(X)$ is a quadratic interpolation polynomial, while $l_o(X)$, $l_1(X)$, and $l_2(X)$ refer to the quadratic interpolation functions. The MPP is achieved at a zero derivative of Equation (30). This algorithm enhances MPPT accuracy, stability and speed [118,119].

8.3. Extremum Seeking Control Method (ESC)

Non-linear dynamic system and adaptive feedback optimizations are involved in this method. ESC is designed for PV systems during the process of tracking the MPP. Some of its advantages are maximizing power and dynamic adaptation-based feedback control, which is an important factor used in the optimization problem in sinusoidal perturbation [283–285].

8.4. Dual Carrier Chaos Search Algorithm

The effectiveness of the chaos search algorithm is enhanced by incorporating the dual carrier approach, which effectively addresses the limitations of the conventional chaos search method. As a result, the search efficiency is significantly enhanced. Empirical evaluations demonstrate that the suggested technique enables the rapid and precise tracking of the step response, leading to superior optimization outcomes. A logistic and $y_{n+1} = \mu(\pi y_n)$ mapping is added to generate a carrier in this method and incorporate it into a step of stochastic searching [286,287].

8.5. Algorithm for Simulated Annealing (SA)

Simulated annealing, which involves the establishment of crystals using high-temperature heating and low-temperature cooling, is referred to as stimulated crystal formation. This can be further elucidated for the behavior of semiconductors using solid-state device theory [288].

System stability increases before heating. A comparison between the energy and cost function of the MPPT algorithm can be performed. This reflects an inverse of the P_{out} (panel) that is required to minimize it. At high temperature, the likelihood of finding a duty cycle matching the garbage P_{out} is higher. However, when the temperature is low, the likelihood of selecting a duty cycle matching the higher P_{out} increases. When the temperature is low enough, the likelihood of picking a duty cycle matching the maximum power is unity [289–292].

9. Comparison of MPPT Techniques

There are many differences between the MPPT techniques, which may assist in selecting a system suitable for specific applications. There are multiple parameters, including the overall implementation, types of sensor, total cost, what sort of applications can be applied, and other factors. The number of sensors matters when selecting an MPPT algorithm. Thus, sensors play an important role in achieving the most precise MPPT, where increasing the number of sensors would provide better results [207,293,294]. Sensing voltage can be easy as measuring current. Hitting the MPP during a specific time is called convergence speed, according to Walker et al. [295]. The convergence of the voltage or current required shall be low in order to achieve a high performance. Power losses have been observed after decreasing the period of time taken to reached the MPP. At partial shading conditions, power losses reach 70% when the local maximum tracking is reached as compared to the actual MPP [296,297]. Performance cost is an additional factor concerning users, since using an analog system is cheaper than using a digital system. PV selection depends on the type of applications used. For instance, in the case of large-scale space satellite and orbital station applications, the cost and complication of MPPT are the least essential in accordance with (performance/ dependability). The MPPT module may come as direct or indirect depending on the parameters of arrays. In the direct type, either the V or I of the photovoltaic is used. Direct methods do not depend on the previous understanding of the PV array configuration. Therefore, the P-V curve operating point does not depend on whether the parameters conditions may change during a period of time. Indirect methods have a parametric database which includes data of various irradiances and temperatures as well as estimations of the MPP using a series of functions derived from empirical data [298].

This study conducted a literature review of current maximum power point tracking (MPPT) algorithms. A theoretical analysis was performed on previously published papers, identifying a set of important parameters as shown in Table 3. A total of 64 different algorithms were collected, showing some of their variations compared to those listed in Table 4, expanding on the findings of Ali et al. [194]. Among all the algorithms reviewed, the most commonly used ones were perturb and observe P&O, "hill climbing", and the incremental conductance algorithm. Table 4 provides an overview of the known algorithms.

Table 3. Parameters definition for the MPPT efficiency performance comparison.

Parameter	Description
PV array dependencies	No specific configurations required or a predefined parameters value
MPPT accuracy	When the actual MPPT is compared to an inaccurate one, Pout will decrease with respect to the actual value.
Type of operation	Relies on the circuit category.
Tuning over periodic sets of time	Any oscillation involved in this scenario.
Convergence speed	How fast to converge and reach MPP.
Complexity	Describes the complexity of the module.
Parameters	Relies on variables' factors.

Table 4. Evaluation of MPPT algorithms (D: Digital, A: Analogue, Ir: Irradiance, T: Temperature, V: Voltage, I: Current).

Algorithm	PV Array Dependency	MPPT Accuracy	Type (D/A)	Periodic Tuning	Convergence Speed	Complexity	Parameters
P&O/ HCS [299–302]	No	Yes	D and A	No	Different	Simple	V, I
INC Algorithm [168,277,301–304]	No	Yes	D	No	Different	Simple	V, I
Fractional Isc [301,302,305,306]	Yes	No	D and A	Yes	Moderate	Moderate	I
Fractional Voc [301,302,305,306]	Yes	No	D and A	Yes	Moderate	Simple	V
Parasitic Capacitances (Cp) [15,168,307]	No	Yes	A	No	Fast	Simple	V, I
FLC [194,301,302,308]	Yes	Yes	D	Yes	Fast	High	Diverse
Temperature Methods [174,194]	Yes	Yes	D	Yes	Moderate	Simple	V, T
Beta Method [194]	Yes	Yes	D	No	Fast	High	V, I
Neural Network [194,302]	Yes	Yes	D	Yes	Fast	High	Diverse
RCC [194,301,309]	No	Yes	A	No	Fast	Simple	V, I
Current Sweep [194]	Yes	Yes	D	Yes	Low	High	V, I
DC Link Capacitor Droop Control [194]	No	No	D and A	No	Medium	Simple	V
dP/dV or dP/dI Feedback Control [194]	No	Yes	D	No	Fast	Moderate	V, I
System Oscillation Method [194]	Yes	No	A	No	N/A	Simple	V
Constant Voltage Tracker [172,194]	Yes	No	D	Yes	Moderate	Simple	V
Lookup Table Method [172,194,300]	Yes	No	D	Yes	Fast	Moderate	V, I
Online MPP Search Algorithm [194]	No	Yes	D	No	Fast	High	V, I
Array Reconfiguration [194]	Yes	No	D	Yes	Low	High	V, I
Linear Current Control [194]	Yes	No	D	Yes	Fast	Moderate	Ir
IMPP and VMPP Computation	Yes	Yes	D	Yes	N/A	Moderate	Ir, T
State-Based MPPT [194]	Yes	Yes	D and A	Yes	Fast	High	V, I
OCC MPPT [194]	Yes	No	D and A	Yes	Fast	Moderate	I
BFV [194]	Yes	No	D and A	Yes	N/A	Low	None
LRCM	Yes	No	D	No	N/A	High	V, I
Slide Control [172,194,300,306,308]	No	Yes	D	No	Fast	Moderate	V, I
Three-Point Weight Comparison [194]	No	Yes	D	No	Low	Simple	V, I
POS Control [194]	No	Yes	D	No	N/A	Simple	Current
Biological Swarm Chasing MPPT [194]	No	Yes	D	No	Varies	High	V, I, Ir, T
Variable Inductor MPPT [194]	No	Yes	D	No	Different	Moderate	V, I
INR method [194]	No	Yes	D	No	Fast	Moderate	V, I
dP-P&O MPPT [202]	No	Yes	D	No	Fast	Moderate	V, I
Pilot Cell [310]	Yes	No	D and A	Yes	Moderate	Simple	V, I
Modified Perturb and Observe [219]	No	Yes	D	No	Fast	Moderate	V, I
Estimate, Perturb and Perturb EPP [219]	No	Yes	D	No	Fast	Moderate	V, I

Table 4. *Cont.*

Algorithm	PV Array Dependency	MPPT Accuracy	Type (D/A)	Periodic Tuning	Convergence Speed	Complexity	Parameters
Numerical Method–Quadratic Interpolation (QI) [279]	No	Yes	D	No	Fast	Moderate	V, I
MPP Locus Characterization [273]	N/A	Yes	N/A	N/A	Fast	Simple	V, I
CVT + INC-CON (P&O) + VSS Method [220]	Yes	Yes	D and A	No	Fast	Moderate	V
Piecewise Linear Approximation with Temp Compensation [311]	Yes	Yes	D and A	Yes	Fast	Simple	V, I, Ir, T
PSO Algorithm [145,309]	Yes	Yes	D	Yes	Fast	Moderate	V, I
PSO-INC Structure [145]	No	Yes	D	No	Fast	Simple	V, I
Dual Carrier Chaos Search Algorithm [286,309]	No	Yes	D	No	Fast	Moderate	V, I
Algorithm for Stimulated Annealing (SA) [309,312]	Yes	Yes	D	No	Fast	High	V, I
Artificil Neural Network (ANN)-Based P&O MPPT [63,302]	No	Yes	D and A	No	Fast	Moderate	V, I
VH-P&O MPTT Algorithm [222]	No	Yes	D	No	Moderate	Moderate	V
Ant Colony Algorithm [313]	No	Yes	D	No	Fast	Moderate	V, I
Variable DC-Link Voltage Algorithm [227]	No	Yes	D	No	Moderate	Moderate	V
ESC Method [314]	No	Yes	D and A	No	Fast	Moderate	V, I
Gauss–Newton Method [76]	No	Yes	D	No	Fast	Simple	V, I
Steepest-Descent Method [[76,315]	No	Yes	D	No	Fast	Moderate	V, I
Analytic Method [315]	Yes	No	D and A	Yes	Moderate	High	V, I
PCF [268]	Yes	No	D	Yes	Low	Simple	V
DM [316]	No	Yes	D	Yes	Fast	High	V, I
IC Based on PI [174,309]	No	Yes	D	No	Fast	Moderate	V, I
Azab Method [235]	Yes	Yes	D	Yes	Moderate	Simple	N/A
Modified INC Algorithm [202]	No	Yes	D	No	Moderate	High	V, I
Newton-Like Extremum Seeking Control Method [82]	No	Yes	D and A	No	Fast	Hogh	V, I

10. Future Trends

Much concerns should be paid to the following research topics:

- Bifacial panels: bifacial panels preform the normal panels by many factors such as output power, cost and efficiency. in terms of power, it reported in [317] that the output power bifacial panels is 10% higher than traditional panels. The efficiency could be enhanced by several tens of percentage points. Thanks to the albedo conditions [318]. However, the pollution and the environmental change are the major drawbacks of the PV industry. Thus, producing a friendly environment bifacial panel is an open research issue. Organic bifacial panels are suggested solution. In addition, the thickness of the substrate is a challenging issue and needs further investigation [319].

- Transparent Panels: This technology could turn any glass sheet to a PV cell. Therefore, this technology could be integrated in buildings, electronic devices and vehicles. Simply the screen of a phone or the window of a vehicle or a building could be replaced by a solar screen or window [320]. The drawbacks of such technology are the cost and the efficiency. The efficiency may improve from 9% for fully transparent medium to 13-15 % for 80% transparency [321].

11. Conclusions

The exploration of numerous MPPT techniques in the context of solar PV systems presented in this paper unveils the diverse methodologies available for enhancing the efficiency of solar PV systems. The comparison of MPPT techniques, considering factors such as cost, tracking speed, and system stability, underscores the trade-offs inherent in MPPT controller selection. Our findings highlight that hybrid approaches, while demonstrating higher efficiency, entail increased complexity and higher costs. A notable contribution of this paper lies in the synthesis of efficiency performance metrics for MPPT algorithms, emphasizing their accuracy in reaching the optimal point. The MPPT algorithms have been classified based on their dependencies, highlighting those that prioritize simplicity, and assessing their convergence speed in response to peak point detection in the power curve. In conclusion, this comprehensive study serves as a decisive reference for the MPPT algorithms crucial to companies engaged in the production of PV systems and power charge controllers. This study also holds significant value for both researchers and practitioners, offering valuable guidance for the judicious selection of MPPT controller algorithms for PV applications.

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Abbreviations

The following abbreviations are used in this manuscript:

ABC	Artificial Bee Colony
ACO	Ant Colony Optimization
ACO-PID	Ant Colony Optimization (ACO) + Proportional–Integral–Derivative (PID) controller
AM	Analytic method
AMBM	Adaptive model-based methods
ANFIS	Adaptive neuro-fuzzy inference system
ANN	Artificial Neural Network
ANN-P&O	Artificial Neural Network + Perturb and Observe
ANN-PSO	Artificial Neural Network + Particle Swarm Optimization
ARM	Array reconfiguration method
AZM	Azab method
BFV	Best fixed voltage method

BM	Beta method
BSC	Biological swarm chasing method
CC	Constant current (also known as short circuit current method)
Cp	Parasitic capacitances
CSM	Current sweep method
CSO	Cuckoo Search Optimization
CTSO	Cat Swarm Optimization
CV	Constant voltage (also known as open circuit voltage method)
CV+INC-P&O+VSS	Constant Voltage Tracking + Incremental Conductance with Perturb and Observe + Variable Step Size
D	Duty cycle point
DCDC	DC-link capacitor droop control
DCCS	Dual carrier chaos search
DE	Differential evolution
DM	Differentiation method
DP-P&O	Dual Perturb and Observe MPPT method
DWS	Decremented window scanning
EPP	Estimate perturb and perturb
ESC	Extremum seeking control
FA	Firefly Algorithm
FBC	Feedback control
FLC	Fuzzy Logic Controller
FLC-ACO	Fuzzy Logic Controller + Ant Colony Optimization
FLC-ANN	Fuzzy Logic Controller + Artificial Neural Network
FLC-GA	Fuzzy Logic Controller + Genetic Algorithm
FLC-P&O	Fuzzy Logic Controller + Perturb and Observe
FOCV	Fractional open circuit voltage
FSCC	Fractional Short Circuit Current Fuzzy PID (Fuzzy Logic + Proportional–Integral–Derivative)
HS	Harmony search
GA	Genetic Algorithm
GMPP	Global maximum power point
GNM	Gauss–Newton method
GWO	Gray Wolf Optimization
INC	Incremental conductance
Isc	Short circuit current
IMPP	Maximum power point current
JA	Jaya Algorithm
LCM	Load current maximization
LCC	Linear current control method
LMPP	Local maximum power point
LOCM	Locus characterization MPP method
LRCM	Linear reoriented coordinates method
LUTM	Look-up table method
MF	Membership functions
M-INC	Modified INC method
MPC	Model Predictive Control
M-P&O	Modified Perturb and Observe
MPP	Maximum power point
MPPT	Maximum power point tracking
NESC	Newton-based extremum seeking control method
OCC	One-cycle control method
ODM	One-diode model
OMS	Online MPP search

P	Power
PB	Peak bracketing method
PBIS	Peak bracketing with initial scanning method
PCL	Pilot cell method
PCF	Polynomial curve-fitting method
PCM	Parasitic capacitance method
PI	Proportional Integral
PID	Proportional Integral Differential
PI-based INC	(Proportional–Integral + Incremental conductance)
PLA-TCM	Piecewise linear approximation with temperature compensated method
P&O	Perturb and observe
POS	PV output senseless method
PPV	PV power
PSO	Particle Swarm Optimization
PSO-INC	(Particle Swarm Optimization + Incremental Conductance)
PSO-DE	(Particle Swarm Optimization + Differential Evolution)
PV	Photovoltaic
QI	Quadratic interpolation
RCC	Ripple correlation control
SA	Stimulated annealing
SBM	State-based MPPT method
SDN	Steepest-descent method
SI	System identification
SNNs	Simulated neural networks
SOM	System oscillation method
TDM	Two-diode model
TGM	Temperature gradient method
THD	Total harmonic distortion
TM	Temperature method
TPM	Three-point method
V	Voltage
VDC	Variable DC-link voltage
VSM	Voltage scanning-based MPPT method
VH-P&O	Variable Hill-climbing Perturb and Observe maximum power point tracking
VIM	Variable inductor MPPT method
VSIR	Variable step-size incremental resistance method

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