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Review on Classical and Emerging Maximum Power Point Tracking Algorithms for Solar Photovoltaic Systems

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ABSTRACT

The sun serves as the primary energy source, providing our planet with the essential energy for sustaining life. To efficiently harness this energy, photovoltaic cells, commonly known as PV cells, are employed. These cells convert the solar energy they receive into electrical energy. The operational point of the solar cell, delivering maximum output power, is referred to as the maximum power point (MPP). However, as light availability and temperature fluctuate throughout the day, the MPP also varies accordingly. To maintain constant operation at the MPP, Maximum Power Point Tracking (MPPT) algorithms are employed to trace the MPP during module operation. These algorithms can be categorized into four groups: classical, intelligent, optimization, and hybrid, based on the tracking algorithm utilized. Each MPPT algorithm, existing in these categories, comes with its own set of advantages and limitations. This paper extensively reviews fifteen algorithms categorized under different groups. The review concludes with a comparative analysis of these algorithms, considering various parameters such as cost, complexity, tracking accuracy, and sensed parameters in a succinct manner. The paper focuses on elucidating the necessity of MPPT algorithms, their classification as per existing literature, and a comparative assessment of the studied MPPT algorithms. This comprehensive review aims to address advancements in this field, paving the way for further research.

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1. INTRODUCTION

With the current scenario of a rapid increase in population, the demand for energy is rising day by day. Conventional sources of energy, such as coal, natural gas, and petroleum, are age-old and limited. It takes millions of years for these sources to form, and they are inevitably depleting (Nnadi, 2012 ; Uddin et al., 2023). Renewable energy emerges as a potential solution to this crisis. Energy generated from natural resources, including sunlight, wind, and water, is termed renewable energy. Wind energy, solar energy, and geothermal energy are examples of renewable sources considered inexhaustible. Solar power, in particular, stands out as a significant and vital source of energy. Given India's proximity to the equator, it enjoys a favorable geographical location for solar energy utilization (Catherine, 2013; Sumathi et al., 2015). To harness solar energy, photovoltaic (PV) cells come into play. These electrical devices convert solar energy into electrical energy. When light strikes the n-p junction, it creates an electric field, facilitating the flow of electrons. PV cells are connected in series to yield high-voltage output, and this arrangement is then connected in parallel to increase current output, forming a PV array. A typical PV cell is often represented by a current source with a diode connected in parallel. The resistance offered by the p-n junction to the electron flow is denoted by series resistance, while parallel resistance accounts for leakage current. Figure 1 illustrates a model of a photovoltaic cell composed of a single diode (Sumathi et al., 2015). The mathematical model of a PV cell is expressed by Equation (1):

$$I = I_{ph} - I_D \left(e^{\frac{qV}{nKT}} - 1\right) \qquad (1)$$

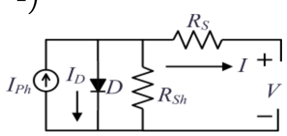

Figure 1. Single diode model for PV cell.

A standard solar panel can convert approximately 30% of incident solar energy into electrical energy (Xu et al. ,2021). The concept of Maximum Power Point Tracking (MPPT) is employed to improve solar panel efficiency. The maximum power supplied by PV is influenced by load parameters, irradiance, and ambient temperature. The properties of a PV array are non-linear, as illustrated in Figure 2, and these characteristics vary based on temperature and irradiance (Gupta et.al., 2017). The simulated array has a peak capacity of 10 kW and is designed with an open-circuit voltage of 350 V and a short-circuit current of 315 A.

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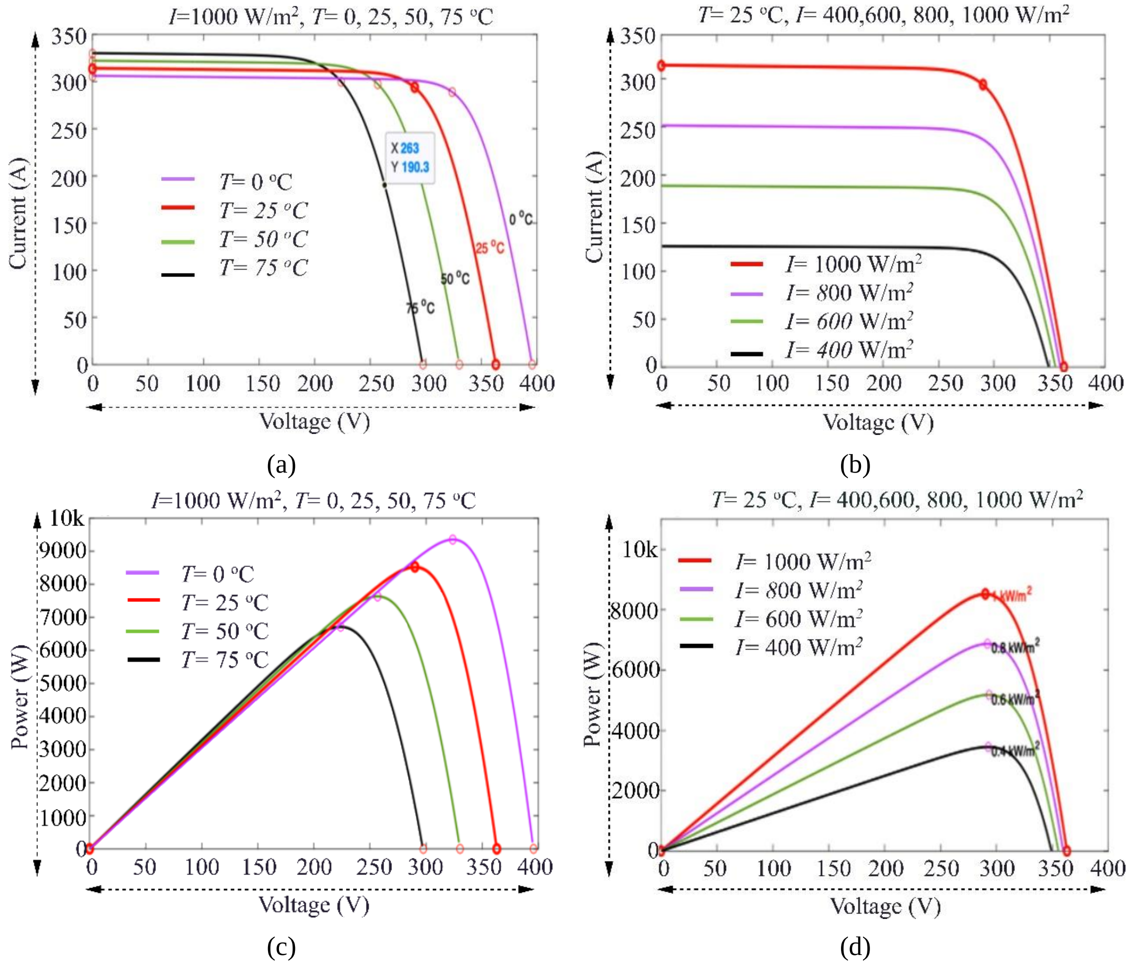

Figure 2. Characteristics of PV array for (a) I-V characteristics at different temperature levels; (b) I-V characteristics at different irradiation levels; (c) P-V characteristics at different temperature levels; and (d) P-V characteristics at different irradiation levels.

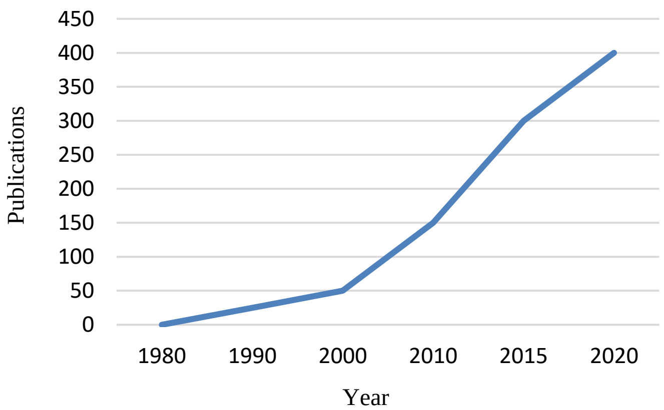

Figure 3. Statistics of MPPT publication in past three decades.

The MPPT algorithms play a crucial role in tracking the MPP and ensuring that the array consistently delivers maximum output. At the MPP, the load impedance closely aligns with the source impedance, allowing the system to extract the maximum power from the source. To achieve this optimal condition, MPPT is employed to adjust the load impedance presented to the array to match that of the source impedance. The MPPT automatically monitors the fluctuating load conditions of the PV array. Various algorithms for tracking the MPPT are documented in the literature (Tajjour & Chandel, 2023; Kumar et.al., 2023; Kundu et al., 2016; Sera et al., 2006; Shinde et al., 2016; Esram et al., 2007; Belkaid et al., 2017). Figure 3 illustrates the number of papers published on MPPT in the past decades.

This article elucidates the fundamental principles governing the optimal functioning of photovoltaics to achieve maximum power extraction. Additionally, it provides insights into the operation of Maximum Power Point Tracking (MPPT) algorithms in a general context. The significance and necessity of MPPT are explored, considering the growing importance of renewables in clean power generation. Given the widespread availability of solar power, the paper concentrates on elucidating advancements in algorithms for power point tracking in Photovoltaics (PVs), along with their associated advantages and drawbacks.

Section 1 of this article offers a concise introduction to PV characteristics and the imperative need for MPPT methods. In Section 2, the various methods are categorized and explained based on the field's advancements, namely classical (Loukriz et al., 2016; Ahmad et al., 2010; Sher et al., 2015; Casadei et al., 2006) intelligent (Cheng et al., 2021; Kottas et al., 2006; . Elobaid et. al., 2012) optimization (Miyatake et al., 2007; Mohanty et al., 2015; Jiang et al., 2013; Kumar et al., 2017), and hybrid (Sundareswaran et al., 2015) accompanied by their respective flowcharts. Section 3 summarizes the comparison of all methods discussed in the article, utilizing tabular and graphical representations. This allows readers to obtain a compact and precise understanding of these algorithms, facilitating the selection of the most appropriate one for their project and area of interest. Finally, Section 4 concludes the presented work, providing a comprehensive overview of the discussed topics and findings.

2. MAXIMUM POWER POINT TRACKING ALGORITHMS

The MPPT algorithms track the MPP and ensure that the array always provides maximum output.
There are different sorts of MPPT algorithms, which are classified below and also shown in Figure4:

- Classical MPPT;
- Intelligent MPPT;
- Optimization Based MPPT;
- Hybrid MPPT.

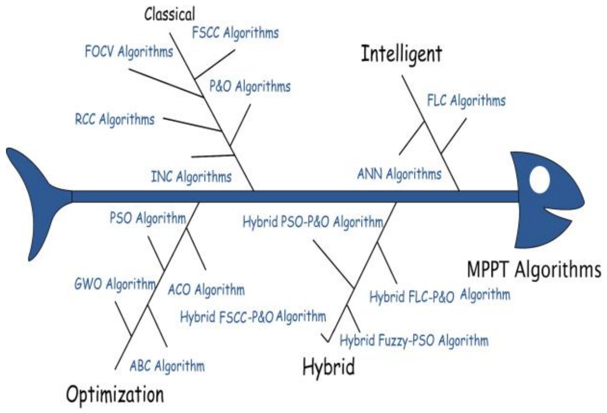

Figure 4. Classification of various MPPT algorithms in fishbone Structure.

The reduced complexity of traditional Maximum Power Point Tracking (MPPT) algorithms makes them simpler to implement. Classical MPPTs considered in the paper include Perturb and Observe (Loukriz et al., 2016) Fractional Open Circuit Voltage (Ahmad, 2010) Fractional Short Circuit Current and Ripple Correlation Control (Sher et al., 2015). The intelligent MPPT algorithms discussed in this paper are Fuzzy Logic Control (Kottas et al., 2006) and Artificial Neural Networks (Elobaid et al., 2012). These algorithms are designed for use in dynamic environmental conditions with high accuracy. The optimization MPPT utilizes evolutionary algorithms inspired by the search behavior of animals seeking food. Additionally, these algorithms can be easily executed with the assistance of a low-cost microcontroller. Optimization algorithms featured in the paper comprise Particle Swarm Optimization (Miyatake et al., 2007) Grey Wolf Optimization (Mohanty et al., 2015) Ant Colony Optimization (Jiang et.al., 2013) and Artificial Bee Colony (Kumar et al., 2017).
Hybrid MPPT algorithms combine classical MPPT algorithms with intelligent or optimization MPPT algorithms. At times, a combination of intelligent and optimization MPPTs is employed to create a hybrid MPPT. In hybrid MPPTs, the Maximum Power Point (MPP) estimation is initially determined using classical methods, and then the estimated point is fine-tuned using advanced algorithms to achieve the actual MPP. The hybrid algorithms detailed in the paper are Hybrid FSCC-P&O MPPT, Hybrid FLC-P&O MPPT, Hybrid PSO-P&O MPPT, and Hybrid FLC-PSO MPPT algorithms (Kumar et al., 2017). These algorithms are explained in the following.

2.1 Classical MPPT

2.1.1. Perturb and Observe method (P&O)

The P&O algorithm operates based on the hill-climbing principle. The algorithm flowchart is depicted in Figure 5. To identify the maximum power point, the operating voltage of the PV panel is continuously perturbed, and the change in power is compared to previous data. Consequently, the operating point on the P-V curve is adjusted (Pandey and Srivastava, 2019). The P&O algorithm finds extensive applications due to its ease of implementation. However, a notable drawback of this method is that, due to the fixed step size, once it approaches the Maximum Power Point (MPP), the system's operating point oscillates around the MPP (Blange et al., 2015). While this approach ensures convergence to the MPP, its performance is slow and susceptible to rapid changes in environmental conditions (Podder et al., 2019; Bollipo et al., 2021; Fapi et al., 2019).

2.1.2. Incremental Conductance method (INC)

The INC approach is grounded in the observation that at Maximum Power Point (MPP), the gradient of the power-voltage curve is zero. The slope to the left of the curve is positive, while to the right, it is negative (Sera et al., 2013). Figure 6 illustrates the algorithm flowchart of the INC method. The slope of the PV curve is expressed as follows:

$$\frac{dP}{dV} = \frac{d(V.I)}{dV} = I + V\frac{dI}{dV} = I + V\frac{\Delta I}{\Delta V} \quad (2)$$

After determining ΔV, ΔI and by using V, I and the above equation, instantaneous conductance (I/V) and incremental conductance ($\frac{\Delta I}{\Delta V}$) are compared to determine which side of the PV curve point of operation is to be moved to obtain the MPP (Huynh and Dunnigan, 2016). This approach, like P&O, employs step size to shift the operating point and identify the MPP, and it oscillates around the MPP. This can be enhanced by using variable- step size, which changes as the slope varies, but it makes the algorithm complex and time-consuming.

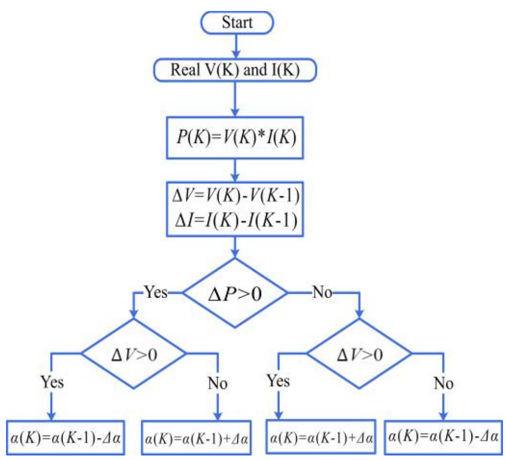

Figure 5. Algorithm for Perturb and Observe method.

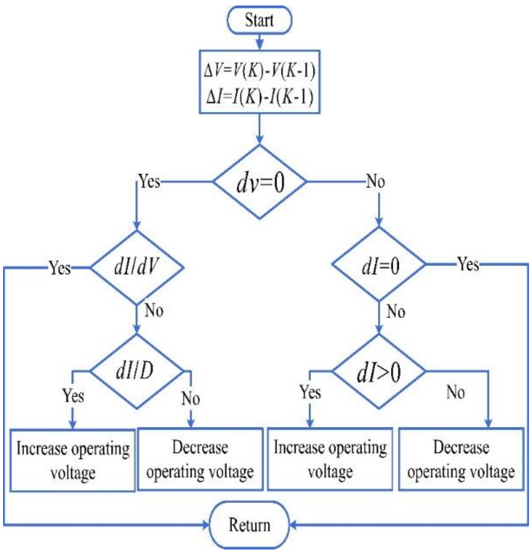

Figure 6. Algorithm for Incremental Conductance method.

2.1.3. Fractional Open Circuit Voltage (FOCV)

This is an approximation and does not provide the real MPP. Figure7 depicts the FOCV method's algorithm flowchart. The algorithm is based on the fact that the open-circuit voltage (V_{OC}) and the maximum power point voltage (V_{MPP}) are proportional to each other and the relationship is given by(Baimel et al., 2019).

$$V_{MPP} \approx K_{OC} * V_{OC} \tag{3}$$

Here, K_{OC} is the voltage proportionality constant, which ranges from 0.71 to 0.78. The drawback of this algorithm is that V_{OC} must be measured every now and then. To do so, the load is disconnected from the PV, which results in power loss.

2.1.4. Fractional Short Circuit Current (FSCC)

This method is identical to FOCV in the sense that it uses current parameters instead of voltage. Figure 8 depicts the FSCC method's algorithm flowchart. The algorithm functions based on the fact that the short-circuit current (I_{SC}) and the maximum power point current (I_{MPP}) are proportional to each other and the relationship is given by

$$I_{MPP} \approx K_{SC} * V_{SC} \tag{4}$$

where K_{SC} is the current proportionality constant, which ranges from 0.64 to 0.85 (Sher et al.,2015). Here, the current I_{SC} changes as the environmental conditions vary, and so the I_{SC} must be measured at periodic intervals, which requires disconnecting the load from the PV panel (Sher et al., 2015; Masoum et al., 2002).

2.1.5. Ripple Correlation Control (RCC)

A PV module is ultimately going to be connected to the power electronic converter, and with the introduction of the power converter, a ripple is introduced in both the PV current and voltage. This ripple is then reflected in the power output of the converter. The algorithm utilizes this ripple to track the MPP. Since the ripple is naturally present due to switching in converters, there is no need for artificial perturbation (Spiazzi, 2009). Figure 9 illustrates the algorithm flowchart of the RCC method. RCC correlates *dp/dt* with *dv/dt* or *di/dt*, and using the equations below, it checks whether the voltage or current of PV is greater or less than that of the MPP. RCC eventually aims to minimize this ripple to zero and adapt the operating voltage and current of the panel to that of the MPP, ensuring that the predicted gradient of the curve is zero (Boonmee and Kumsuwan, 2013; Srinivas & Sreeraj 2016; Moo and Wu 2014; Brunton et al., 2010).

When the operational point on the power curve is to the left of MPP, we have:

$$\frac{dV}{dt} > 0 \text{ or } \frac{dI}{dt} > 0 \text{ and } \frac{dP}{dt} > 0 \tag{5}$$

When the operational point on the power curve is to the right of MPP, we have:

$$\frac{dV}{dt} > 0 \text{ or } \frac{dI}{dt} > 0 \text{ and } \frac{dP}{dt} < 0 \tag{6}$$

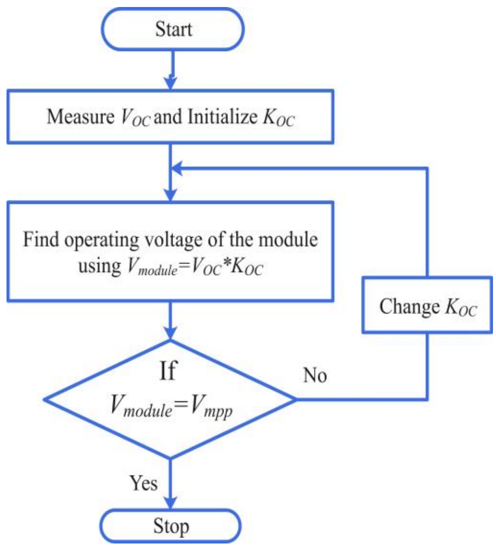

Figure 7. Algorithm for Fractional Open Circuit Voltage

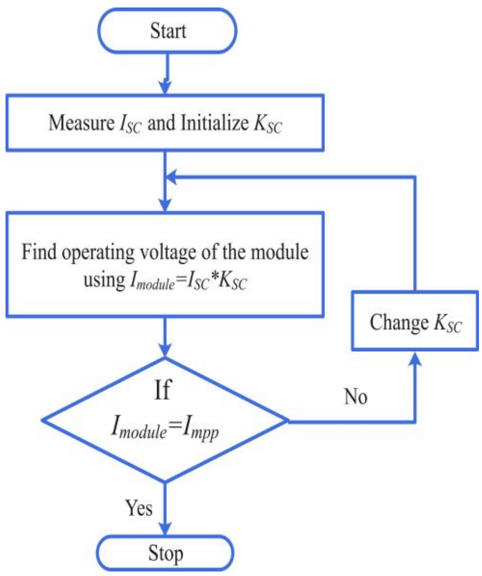

Figure 8. Algorithm for Fractional Short-Circuit Current.

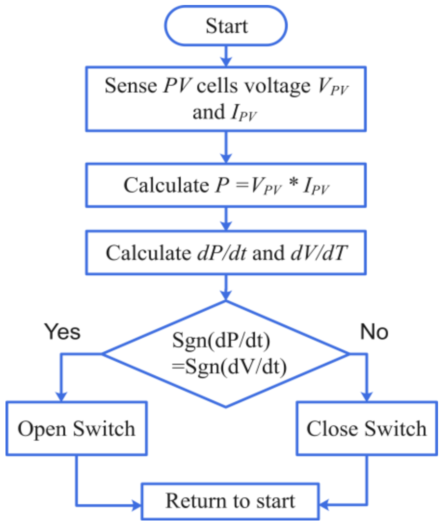

Figure 9. Algorithm for Ripple Correlation Control method.

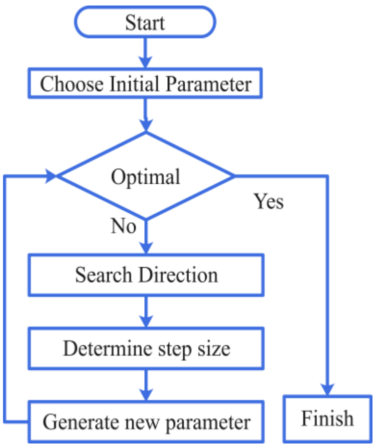

Figure 10. Algorithm for Fuzzy Logic Control method.

2.2. Intelligent MPPT

2.2.1. Fuzzy Logic Control (FLC)

In the FLC algorithm, fuzzy logic theory is employed to determine the MPP. This approach eliminates the need for a detailed mathematical model of the system. Fuzzy logic operates not on absolute values of true and false (i.e., 0 and 1) but is grounded in degrees of truth and falsity. Figure 10 illustrates the algorithm flowchart of the FLC method. Fuzzification, fuzzy rule-based table inference, and defuzzification constitute the three essential processes in Fuzzy Logic control (Priyadarshi et al., 2020). During fuzzification, each variable used in control rules is expressed in terms of fuzzy set notation, transforming them into linguistic-based variables. For instance, two numerical variables, error and change in error, can be inputted and subsequently translated into linguistic-based variables using membership functions. In the subsequent step, the fuzzy-rule-based table is employed to map potential outputs corresponding to the inputs forming the fuzzy set. In the defuzzification process, the fuzzy inference result is converted into crisp values. A decision-making algorithm is then utilized to select the optimal crisp value from the potential solutions within the fuzzy set (Li et al., 2019). This method enables swift tracking of MPP and is adaptable to diverse environmental conditions. However, it is important to note that the controller requires periodic tuning to account for varying atmospheric conditions (Datta and Senjy, 2013).

2.2.2. Artificial Neural Networks (ANN)

The computation of Maximum Power Point (MPP) based on Artificial Neural Networks (ANN) is also an intelligent algorithm. Similar to Fuzzy Logic Control (FLC), ANN does not require detailed information about the Photovoltaic (PV) system in operation. The ANN is established on the workings of neural networks in the human brain. It comprises three layers: the output layer, the hidden layer, and the input layer, all made up of interlinked nodes (kumar et al., 2020). The weight between i^{th} and the j^{th} node is defined as W^{ij}. The values of the weights between nodes are determined by simulation and training (Kumar et al., 2022; Dogra et al., 2022). This approach is suitable for complex problem-solving where results need to be computed based on the mapping of input and output (Balzani and Reatti, 2005). Figure 11 depicts the ANN method's algorithm flowchart. The input to the ANN could be panel voltage, current, I_{SC}, V_{OC}, irradiance, temperature, or a combination of these. The output is the signal that optimizes the panel to operate at V_{MPP}. The ANN learns to associate inputs with required outputs and assigns values to weights to better compute the output for variable inputs. The process of training the algorithm of the hidden layer is the reason for the speed and efficiency of this algorithm. ANN-based tracking is widely applied to various conditions, including variables like PV module, configuration, and partial shading conditions. If the configurations are altered, then retraining of the artificial neural network needs to be done for the new configuration before use. This method provides fast-tracking of MPP and has a higher rate of convergence. The only limitation is the training required by the ANN before connecting it to the system (Ramana and Jena, 2015; Giraud and Salameh, 1999; Karami et al., 2017).

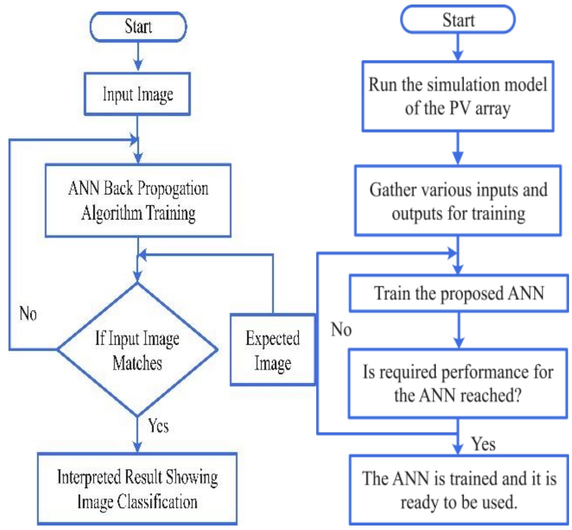

Figure 11. Algorithm for Artificial Neural Networks method.

2.3. Optimization-Based MPPT

2.3.1. Particle Swarm Optimization (PSO)

The initial suggestion for this method originated from Eberhart and Kennedy in 1995. Figure 12 illustrates the algorithm flowchart of the PSO method. The PSO algorithm draws inspiration from the social behavior of animals, specifically swarms (Ghita and Ahmed, 2018). The fundamental concept behind this approach is to establish connections between evolutionary principles and artificial life, linking the life patterns of animals to artificial theories.

Swarms, akin to insects, move collectively in large numbers to seek food and adapt their patterns based on experiential learning. The PSO algorithm boasts merits such as simple realization and fast convergence. It is particularly effective for locating maxima and minima in a function defined within a multi-dimensional vector space. However, a notable drawback of PSO is its susceptibility to falling into local optima, especially in higher-dimensional spaces (Fahad, 2018). Additionally, it exhibits a lower rate of convergence during the iterative process.

2.3.2. Grey Wolf Optimization (GWO)

The GWO algorithm is grounded in the hunting patterns of grey wolves, making it a widely utilized swarm intelligence approach. Figure 13 illustrates the algorithm flowchart of the GWO method. GWO draws inspiration from the social structure of grey wolf families, which typically consist of 5–12 members that collaborate in both living and hunting. Key advantages of GWO include its rapid seeking speed, ease of implementation, and high search precision (Mosavi and Gharahopog, 2020). In a wolf pack, there are male and female leaders known as alphas, responsible for decisions such as choosing hunting locations, determining sleeping places, and setting wake-up times. The entire pack signals their acknowledgment of the alpha by holding their tails down. The alpha wolf takes charge of all decisions, and beta wolves are expected to show respect to the alpha. Omega, the wolf with the lowest rank, communicates information to the other prevailing wolves. The remaining grey wolves are categorized as delta and prevail in the omega group (Mirjalili & Mirjalili, 2014). However, GWO does have its drawbacks, including a slow coverage rate and low solving accuracy (Mohanty et al., 2016).

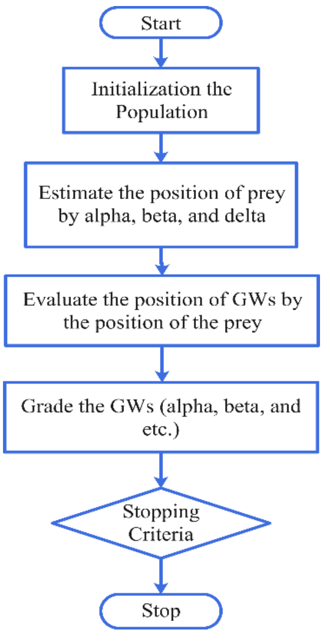

Figure 12. Algorithm for Particle Swarm Optimization method.

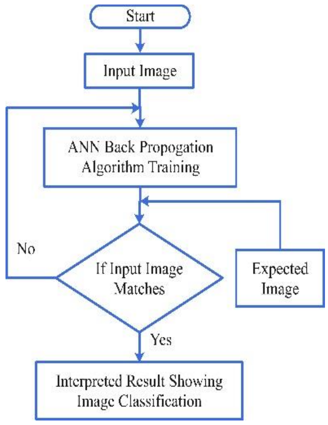

Figure 13. Algorithm for Grey Wolf Optimization method.

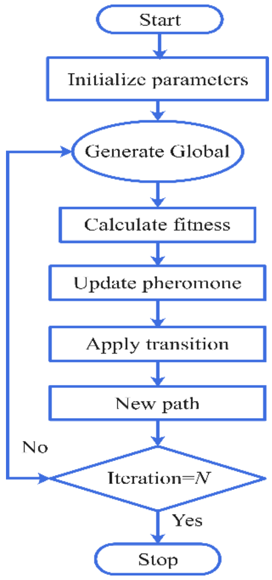

Figure 14. Algorithm for Ant Colony Optimization method.

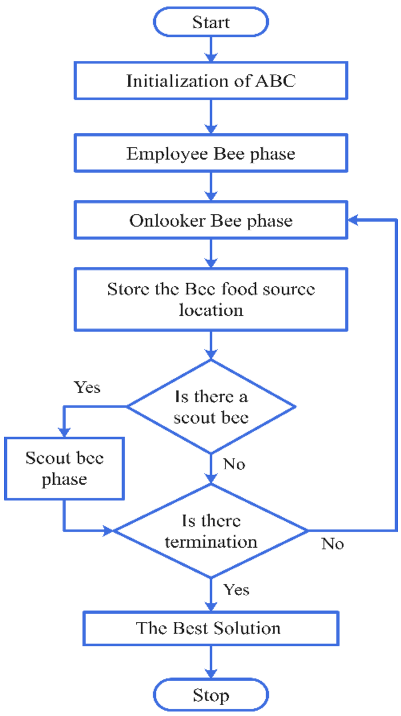

Figure 15. Algorithm for Artificial Bee Colony method.

2.3.3. Ant Colony Optimization (ACO)

The foundation of the ACO algorithm lies in the hunting and gathering (foraging) behavior exhibited by ant colonies. Marco Dorigo initially proposed this concept in 1990. Ants, being biomass insects, exhibit a preference for communal living in large colonies rather than leading solitary lives. A key advantage of the ACO algorithm is its enhancement of efficiency in high-speed data transmission (Krishnan et al., 2020). Ants employ sounds and pheromones as communication tools to convey vital information. Pheromones, chemical compounds secreted by ants, serve as directional cues for other ants to follow. Consequently, the primary focus of ACO is to investigate how ants efficiently transport food back to their colonies by choosing the shortest routes possible.

Figure 14 illustrates the algorithm flowchart of the ACO method. In the quest for food, multiple routes exist from the colony to the food source. Upon locating food sources, ants transport portions of the food back to the colonies while depositing essential pheromones along the return path. Ants select specific paths based on the pheromone trails left by fellow worker ants. In essence, when a worker ant discovers a shorter path to a specific food source within the colony, other ants subsequently follow it, guided by the pheromone trail. Simulated ants traverse a graph, mimicking the behavior of real ants to determine the optimal solution on the graph (Dorigo et al., 1996; Adly and Besheer, 2012). The primary drawback is the time-consuming nature of laying pheromones on trails used for ant communication, making it susceptible to falling into the trap of local optima.

2.3.4. Artificial Bee Colony (ABC)

Swarm intelligence stands as one of the rapidly expanding research fields, drawing inspiration from the collaborative behaviors observed in social animals such as bees and birds. These creatures harness collective intelligence for activities like searching for food. In Figure 15, the algorithm flowchart for the ABC method is illustrated. The ABC algorithm specifically mimics the foraging behavior of bees in the collection of nectar and subsequent processing. Bees employ a dance language as a means of communication to convey crucial information about food quality to the entire group. Artificial bees are categorized into three types: employed, onlooker, and scout bees. Each employed bee is assigned to a specific food source. These bees travel to their respective food cradles, assess the quality of the food, and then communicate their findings through dance within the hive (Sharma and Agarwal, 2013). Onlooker bees observe the dances of employed bees and select one based on the dance to explore the neighborhood and evaluate the quantity of nectar. The superior food source is then recorded, and any new food sources discovered by scout bees replace the abandoned ones. Employed bees without a food source transition into the role of scout bees, actively searching until they locate a new food source (Li et al., 2019).

2.4. Hybrid MPPT

Hybrid MPPT algorithms comprise a blend of two or more MPPT algorithms. The primary objective of a hybrid algorithm is to address a drawback of one algorithm by concurrently utilizing another algorithm. Hybrid MPPT algorithms aim to alleviate the computational load on hardware and enhance the speed of achieving Maximum Power Point (MPP), all while maintaining a high level of accuracy (Sundareswaran et al., 2014). The efficient tracking of the Global Maximum Power Point (GMPP) among various Local Maximum Power Points (LMPP) is not effectively managed by optimized or intelligent MPPT algorithms individually. Therefore, to leverage the strengths of both algorithm types, intelligent and optimization algorithms are employed in parallel for precise GMPP tracking. Hybrid MPPT algorithms encompass the hybridization of classical control algorithms (such as FSCC with P&O), the fusion of classical control algorithms with intelligent algorithms (FLC with P&O), the integration of classical control algorithms with optimization algorithms (PSO and P&O), and the combination of intelligent and optimization algorithms (FLC and PSO).

2.4.1. Hybrid FSCC-P&O MPPT

this approach, the P&O algorithm is hybridized with the FSCC algorithm. The FSCC algorithm demonstrates quick convergence speed but lacks accuracy, a deficiency addressed by the P&O algorithm (Batarseh and Zater, 2018; Mohapatra et al., 2017). Therefore, combining these two approaches results in immediate and accurate tracking of the MPP. The hybrid algorithm is initiated with the FSCC process, bringing it closer to the MPP through the offline process. Subsequently, the system progresses to the next step, i.e., P&O. The P&O approach gains an advantage by being able to choose small step sizes, as the algorithm is already operating near the MPP. This leads to fewer power oscillations and, consequently, improved efficiency and accuracy. Figure 16 illustrates the flowchart of the Hybrid FSCC-P&O method.

2.4.2. Hybrid FLC-P&O MPPT

In this method, the P&O algorithm is hybridized with a widely used artificial intelligence algorithm, the FLC algorithm. FLC improves the operating point position to the ideal one, thereby maximizing performance. However, FLC lacks one dimension: the inputs are selected by the users, making the actual performance of the algorithm user-dependent. Users create and select the membership functions and the rule base for the algorithm to work. The P&O algorithm suffers from issues such as oscillations and a lengthy settling time. The hybrid algorithm can overcome the shortcomings of both (Batarseh and Zater, 2018). The hybrid algorithm is designed to overcome the shortcomings of both methods (Batarseh and Zater, 2018). It starts with the FLC process, bringing it closer to the MPP. The system then proceeds to the next step, i.e., P&O, where the power values of two successive points are compared, and the required perturbation is determined. The duty cycle is adjusted in every iteration, bringing the system closer to the MPP. Figure 17 depicts the algorithm flowchart of the Hybrid FLC-P&O method.

2.4.3. Hybrid PSO-P&O MPPT

Figure 18 depicts the algorithm flowchart of the Hybrid PSO-P&O method. Classical MPPT, such as the P&O method, tracks the initial LMPP and then converges on it. However, optimization MPPT algorithms, like PSO, have been suggested to trace the GMPP. The demerit of the PSO algorithm is that for large search spaces, the time taken to converge at the GMPP is comparatively long. This results in a hybrid algorithm that tracks GMPP using both P&O and PSO side by side. Due to the lesser complexity and higher tracking efficiency of P&O, it is initially used to track the LMPP. Afterward, PSO is employed to hunt for the GMPP. The advantage of using the hybrid PSO-P&O is that P&O is initially used to reduce the search space for

PSO. This leads to a reduction in the time required by PSO to reach convergence (Figueiredo et al., 2021; Lian et al., 2014).

2.4.4. Hybrid Fuzzy - PSO MPPT

In this approach, PSO is hybridized with FLC. This combination is advantageous because it requires fewer parameter adjustments and less mathematical calculations. This reduced need for parameter adjustments leads to the design of membership functions with better-optimized base rules (Ishaque et al., 2012).

The system's non-linearities are overcome with the help of fuzzy rules. Furthermore, to obtain optimized solutions, it is imperative to design the membership functions to function under PSCs. In this approach, PSO assists in the formation of the membership functions and the fine-tuning of the control rules (Mahdi et al., 2020). This enables us to avoid the use of a PI controller, thus reducing switching losses. One consideration is that some areas for trial and error and approximation must be considered while designing fuzzy logic rules, which are to be inferred from human intelligence. The algorithm flowchart of the Hybrid Fuzzy-PSO method is depicted in Figure 1

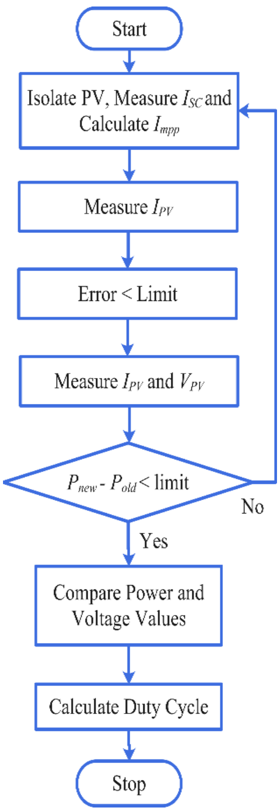

Figure 16. Algorithm for Hybrid FSCC-P&O MPPT method.

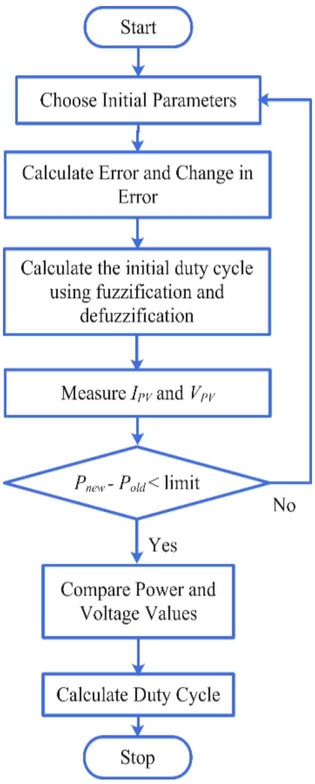

Figure 17. Algorithm for Hybrid FLC-P&O MPPT method

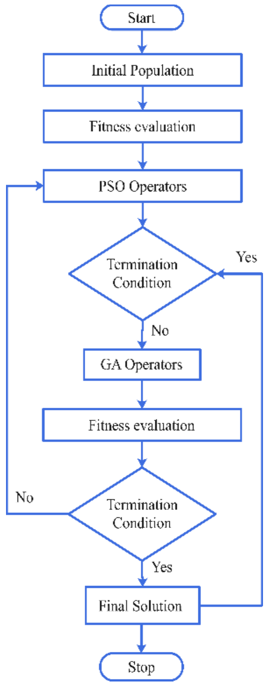

Figure 18. Algorithm for Hybrid PSO-P&O MPPT method.

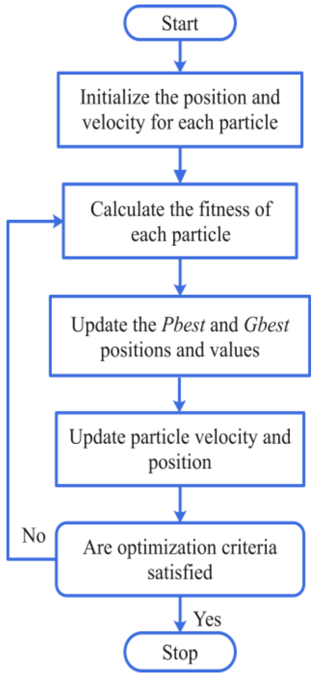

Figure 19. Algorithm for Hybrid Fuzzy - PSO MPPT method

3. DISCUSSION AND RECOMMENDATIONS

PV systems necessitate MPPT controllers to maximize power harvest, making the selection of the appropriate controller crucial due to its associated advantages and disadvantages. Various algorithms exhibit distinct features, and the aspects chosen for comparison in this review are pivotal considerations in decision-making. Table 1 presents a comparative analysis of the algorithms explored in this study, focusing on cost, complexity level, tracking accuracy, and the number of sensed parameters. In Figure 20, a graphical representation offers a relative comparison of all algorithms in terms of cost, complexity level, and tracking accuracy. The primary objective of this grading system is to streamline the selection of methods based on common parameters. The analysis indicates that Perturb and Observe (P&O), Incremental Conductance (INC), Fractional Open Circuit Voltage (FOCV), Fractional Short Circuit Current (FSCC), and Ripple Correlation Control (RCC) fall under the classical classification of MPPT algorithms, exhibiting lower accuracy under partial shading conditions. Intelligent, optimization, and hybrid MPPT algorithms prove more adept at tracking GMPP and LMPP in partial shading scenarios. Moreover, Fractional Open Circuit Voltage (FOCV) and Fractional Short Circuit Current (FSCC) algorithms emerge as cost-effective and straightforward, requiring fewer parameters for sensing. On the other hand, algorithms like Ripple Correlation Control (RCC), Fuzzy Logic Control (FLC), Artificial Neural Networks (ANN), Grey Wolf Optimization (GWO), and Hybrid Fuzzy-PSO MPPT demonstrate high tracking accuracy. The study suggests further research into simplifying MPPT algorithms beyond classical methods to mitigate production costs and enhance commercial implementation.

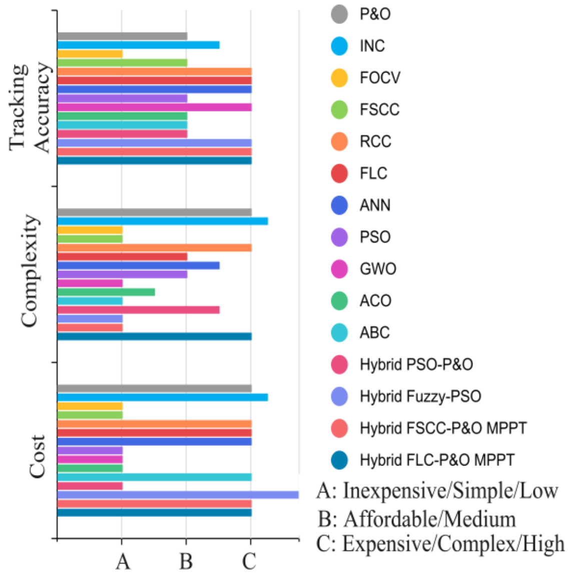

Figure 20. Relation of cost, complexity level, and tracking accuracy for Various MPPT algorithms.

Table 1. Comparative analysis of various Classical, Intelligent, Optimization Based and Hybrid MPPT algorithms.

MPPT Algorithms	Cost	Complexity Level	Tracking Accuracy	Sensed Parameters
P&O (Perturb and Observe method	Expensive	Complex	Medium	Voltage, Current
INC (Incremental Conductance method)	Expensive	Complex	Medium	Voltage, Current
Fractional Open Circuit Voltage (FOCV)	Inexpensive	Simple	Low	Voltage
Fractional Short Circuit Current (FSCC)	Inexpensive	Simple	Medium	Current
Ripple Correlation Control (RCC)	Expensive	Complex	High	Voltage, Current
Fuzzy Logic Control (FLC)	Expensive	Medium	High	Voltage, Current
Artificial Neural Networks (ANN)	Expensive	Medium	High	Irradiation, Temperature
Particle Swarm Optimization (PSO)	Affordable	Medium	Medium	Voltage, Current
Grey Wolf Optimization (GWO)	Affordable	Simple	High	Voltage
Ant Colony Optimization (ACO)	Affordable	Simple	Medium	Voltage, Current
Artificial Bee Colony (ABC)	Expensive	Simple	Medium	Voltage, Current
Hybrid FSCC-P&O MPPT	Expensive	Simple	High	Voltage, Current
Hybrid FLC-P&O MPPT	Expensive	Complex	High	Voltage, Current
Hybrid PSO-P&O MPPT	Affordable	Medium to Complex	Medium	Voltage, Current
Hybrid Fuzzy-PSO MPPT	Very Expensive	Simple	High	Voltage, Current

4. CONCLUSIONS

This paper reviewed fifteen MPPT algorithms across different categories, comparing them on various parameters in a concise manner. Additionally, the paper emphasizes the necessity of MPPT algorithms, driving extensive research in the field. The detailed review study explains procedures using flowcharts for each MPPT algorithm, along with their respective benefits and drawbacks.

Out of all the algorithms in the literature, fifteen distinct MPPT algorithms were investigated, classified, and compared for faster and more efficient Maximum Power Point (MPP) tracking. The analysis concludes that P&O, INC, FOCV, FSCC, and RCC fall under the classical classification of MPPT algorithms and are less accurate and reliable under uniform irradiation conditions only. To overcome this limitation, intelligent MPPT algorithms like FLC and ANN were introduced, demonstrating higher accuracy in various irradiation conditions but requiring extensive data storage. Furthermore, Optimization MPPT algorithms such as GWO, ACO, ABC, and PSO were introduced, utilizing bio-inspired algorithms that could work without the need for large system studies, unlike intelligent algorithms. However, these algorithms come with their own set of disadvantages, such as slower tracking speed compared to intelligent algorithms. To address the drawbacks of both intelligent and optimization algorithms, a recent introduction is hybrid algorithms, which merge two or more of these algorithms. This study aims to highlight advancements in this area, promoting further research and providing a guide for individuals working in the field to select suitable MPPT algorithms for specific applications.

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6. CONFLICT OF INTEREST

On behalf of all authors, the corresponding author states that there is no conflict of interest.

NOMENCLATURE

PV	Photovoltaic

MPP	Maximum power point
MPPT	Maximum power point tracking
I_{ph}	Photon current
I_D	Diode current
R_S	Series resistance
R_{Sh}	Shunt resistance
D	Diode
V	PV cell output voltage
I	PV cell output current
P	PV cell output power
T	Temperature
α	Duty Cycle
K	Iteration
V_{oc}	Open circuit voltage
V_{module}	Module voltage
V_{mpp}	Maximum power point voltage
I_{sc}	Short circuit current
I_{module}	Module current
I_{mpp}	Maximum power point current
P&O	Perturb and Observe method
INC	Incremental Conductance method
FOCV	Fractional Open Circuit Voltage
FSCC	Fractional Short Circuit Current
RCC	Ripple Correlation Control
FLC	Fuzzy Logic Control
ANN	Artificial Neural Networks
W^{ij}	Weights in ANN
PSO	Particle Swarm Optimization
GWO	Grey Wolf Optimization
ACO	Ant Colony Optimization
ABC	Artificial Bee Colony
GMPP	Global maximum power point
LMPP	Local maximum power points

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