# A state of the art a hybrid intelligent strategies of maximum power point tracking: a systematic contemporary

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**ABSTRACT**

Renewable energy sources are among the best substitute sources to fossil fuel due to it is very suitable for mitigating global warming; solar energy is considered the main causes of renewable energy, and solar photovoltaic (PV) generation systems have gained importance worldwide due to several characteristics, including cheap maintenance, low noise, and low fuel costs. However, one of the most difficult challenges facing solar energy systems is changing weather circumstances. The robust control approach stabilizes the PV system's output and maximizes harvested energy. In this study, several maximum power point tracking (MPPT) performances have been presented. Among them, artificial intelligence (AI) based on MPPT methods demonstrates the ability to capture the MPP point. There are several ways to apply AI to MPPT, and this paper presented various intelligent MPPT methods in detail with their benefits and drawbacks and comparison among them to select which technique is suitable and can be used to change weather conditions with horse optimization method (HOM) plus neural artificial system (NAS).



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## 1. INTRODUCTION

Because of the increase in demand for electric power and the increase in environmental problems, traditional energy causes with coal, oil, and natural gas are being sought to be replaced or minimize their use by utilizing other energy sources in the modern context of electricity generation [1]. Among the several available alternative sources of electrical generation. Photovoltaic (PV) energy has proven to be a particularly significant and important role because the sun provides an infinite energy supply with minimal maintenance and is easy to construct [2]. Because of the dynamic behavior of PV system production that depends on changing weather conditions, it is required to employ a mechanism for tracking the highest power point to maximize the PV systems' efficiency. There are two common types of traditional MPPT techniques: INC plus (P&O) because they are easy to operate and have fast convergence to MPP in uniform weather conditions, sometimes the solar array can be partially shaded under a variety of operational conditions.

The maximum power point tracking (MPPT) method allows tracking a LMPP rather than a GMPP. However, these methods have drawbacks that reduce their performance, such as suggesting a fixed and small step size of duty cycle and which causes slow tracking under rapid weather conditions, high fluctuations under MPP, and tracking the LMPP rather than GMPP under partial protecting environments [3]–[5]. There are several traditional MPPT methods, such as open circuit voltage ($V_{OC}$ ),short circuit current( $I_{SC}$ ),hill climbing (HC), Pilot cell algorithm. In order to result the issues of the traditional MPPT system, artificially intelligent MPPT performances are used, such as artificial neural system (ANS) and fuzzy logic controller (FLC) [6]. Various articles in the literature have developed optimization strategies using meta-heuristics algorithms to solve the partial shading issues in PV arrays. Particle swarm optimization (PSO), grey wolf optimization (GWO), ant colony optimization (ACO), artificial bee colony (ABC), cuckoo search (CS), and several optimization algorithms [7], [8] take inspiration from animal and insect behavior in the nature.

On the other hand, compared to traditional methods, the computational complexity-based drawbacks of these approaches limit their practical implementation. Such as, for correct training, ANN-based MPPT methods require a lot of information (different irradiation levels, temperature levels, and partial shadings conditions). Therefore, they can only be used with big PV panels. Because of its relative superiority in managing imprecision and parameter variations, AI-based techniques have been widely employed and coupled with other techniques for MPPT [9].

The major aim of this article is to offer an efficient MPPT based intelligent strategy. To capture maximum power from PV systems and overcome many issues the traditional MPPT like P&O, and INC and comparison among them in terms of the No of sensors, difficulty, cost, speed convergence and precise tracking under irradiance and temp. variants to select which technique is better for application of PV system. The main focus of this work is to provide an operative intelligent technique based on MPPT. The MPPT extracts maximum power from PV systems while mitigating several problems. Different MPPT methods are compared regarding the No of sensors needed, cost, convergence speed, and precise tracking under irradiance and temp. variations. The content of this work is structured survey of: section 2 covers the modelling of the PV system that impact of partial shading on PV cells. In addition, while section 3 the MPPT operation under PSC with intelligent MPPT method, and section 4 led to the supposition of this study.

## 2. METHODS AND MATERIALS

Due to the varying weather conditions that solar panels are exposed to, PSC is a nonlinear relationship between V and I when estimating the O\P power in the structures designed to extract the MPP point. Some PV systems are coupled in series or parallel to procedure an array, the series connection leading to an increase in voltage and the parallel connection leading to an equivalent rise in current [10]. This model includes series and parallel resistance, such as demonstrated in Figure 1.

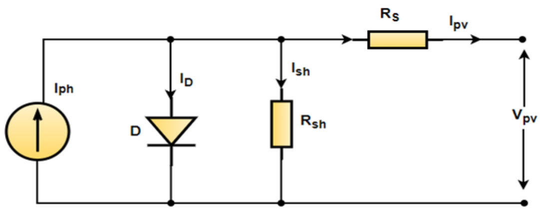


Figure 1. The physical model of solar cell [10]

### 2.1. Modelling of the PV system and intelligent MPPT methods survey

The traditional MPPT method performs well under normal operation tests or uniform irradiation and temperature. However, under continuously changing weather conditions, this MPPT method faces many significant issues: partial shadowing and rapid irradiance change and These strategies (P&O), (HC), and (INC) are the three most common method applied and there are many lists the typical equations, characteristics, and measured variables for these three strategies [11].

#### 2.1.1. Partial shading condition

Partial shading from clouds or nearby buildings and trees causes the reverse bias of the shaded cells, which means that they act as a load rather than a power source and dissipate their energy as heat. As a result of the temperature rise, the panel deteriorates and the damaged cells transition from producing to consuming energy. When the panel's temperature rises, its output power drops; the dust can also be caused by dust, reducing the panel's efficiency. The cell becomes an electrical resistance that consumes that power. As a result, to overcome this issue, a (bypass diode) is associated to separately string independently, as illustrated in Figure 2. the use of (the bypass diode) came because it is linked to the PV module, and the generated current flows through it to the unshaded PV module. When the cell's power generation weakens, the bypass diode prevents current from entering the cell, mitigating electrical energy loss [12]. A blocking diode is also employed to prevent reverse current from passing from the battery to the photovoltaic panels, which can damage them [13].

#### 2.1.2. Rapid change climatic

The radiation and temperature fluctuate during the day, but the radiation change is instantaneous, so it is considered the most influential on the photovoltaic system from gradually descending temperature. Therefore, in the event of radiation descending, the current decreases because the proportionality is direct, and thus the power decreases. So, the traditional method (P&O and INC) has slow tracking under critical weather environments due to its suggestion of a fixed step change of the duty cycle(D) and sending it to the DC-DC. In another part the rapid changes in radiation, accumulating the fixed period through the different stage proceeds a long time, resulting in significant power loss [14].

### 2.2. Intelligent MPPT method

In this category, Intelligent algorithm MPPT is divided into two main types: the first type is based on swarm intelligent techniques that mimic the behavior of animals or insects in the natural, which includes PSO, ACO and artificial optimization algorithm (ABC), while the second type such as ANN, FLC, sliding mode controller (SMC) and Fibonacci series depend on MPPT as shown in Figure 3. A number of MPPT methodologies, with particular factors measured, paving the way for a lot more studies. For each MPPT system, the current study includes a complete reason of working measures and the flow demonstration development. It is challenging to control which plan is superior from the numerous approaches existing in this work.

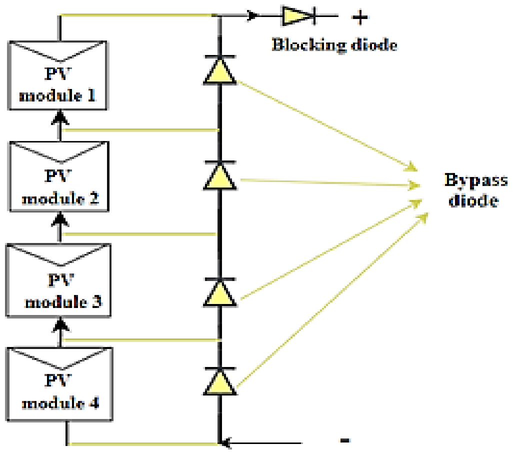


Figure 2. Physical model of PV array [13]

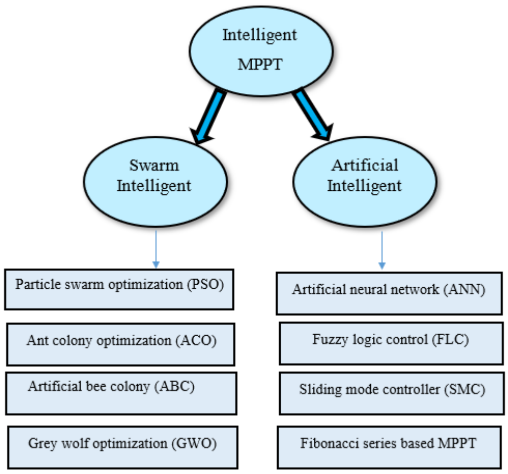


Figure 3. Classification of intelligent MPPT

#### 2.2.1. Swarm intelligent techniques

There are various strategies under the name intelligent methods, and the following subsections briefly explain some of these methods:

a) Particle swarm optimization (PSO)

PSO is an effective calculating performance. This method depends on the velocity and position to determine each particle. Each individual is the best solution, but the leader is global, and all particles follow the leader alpha to find the best performance. In the search space, particle distribution is random. Particles use two best values to update themselves in each iteration. The value estimate of the solution is best personal value; another technique is the collective estimate of the solution, best global value [15]. Particles' velocity and location are updated in relation to the next equations:

$$V_n(k+1) = wV_n(k) + s_1\rho_1(P_{p,best-k} - X_n(k)) + s_2\rho_2(P_{g,best} - X_n(k) \quad (1)$$

n=1, 2, 3, N. Where: k is the number of iterations; $X_n$ denotes the nth particle's position; $V_n$ this means the nth particle's velocity; and w indicates the inertia burden. The social and cognitive acceleration factors are denoted by $s_1$ and $s_2$, respectively; The arbitrary variables $\rho_1$, $\rho_2$ are uniformly distributed between 0&1; $P_{p,best-i}$ is the nth particle's optimal position at the kth iteration; $P_{g,best}$ Denotes the swarm–optimum position [16]. If an extempore scenario, such as the initialization requirement in (3), was studied, the technique update is in line with Equs. The Ft indicates the board purpose that must be maximized [17].

$$\mathrm{Ft}(X_{n-k}) > Ft(P_{p,best-k}) \tag{2}$$

$$P_{p,best-k} = X_{n-k} \tag{3}$$

b) Ant colony optimization (ACO)

ACO simulators the searching behavior of ants to optimize the path in a diagram. Ants search the trail unsystematically and place down pheromones for other ants to follow, and begins a positive feedback loop. The ACO approach is based on ants' trail-laying and trail-following behavior. Ants initially walk in a random direction. Ants communicate with each other through pheromones. Pheromones are synthetic compounds delivered by living beings to communicate with other members of the same species. If additional ants find this road, they follow it to the food source rather than drifting aimlessly. They leave pheromones behind when they return to their province, enhancing the current pheromone intensity [18].

c) Artificial bee colony (ABC)

The ABC methodology is depending on honey bees' foraging intelligence. Honey bees reside inside the province's boundaries (i.e., in the hives). Honey bees use pheromones (chemical exchange) and the waggle dance to communicate with one another. If a bee finds a food source and takes it back to the province. The waggle dance's power and length show the opulence of the food source discovered. The waggling movements change from one species to the next [7].

Waggling movements differ from one species group to another. The artificial bees are divided into three classes using the ABC strategy: employed bees, observer bees, and scouts. Employed bees make up half of the honey bee province, while spectator bees make up the other half. The ant colony aims to find the best nectar supply, representing food. Firstly, employed honey bees seek a food source, return to the hive, and discuss their findings through waggle dance movements. Onlooker honey bees try to find a food source by following the employed honey bee's waggle dance, whereas scout honey bees haphazardly look for new food sources [19]. To track the GMPP, the ABC algorithm used the following steps:

- Initialization phase: Make Ns food sources randomly in the search space. The algorithm's show progresses with each resolution $X_i$ is an n-dimensional direction from (4).

$$X_{i,j} = X_{min,i} + rand[0,1](X_{max,i} - X_{min,i}) \tag{4}$$

  Where, i=1,2,3,…,$N_s$, j=1,2, 3…, n: denotes the No of optimization factors, $X_{max,i}$ and $X_{min,i}$: denote the nth dimension's max& min values, respectively.
- Employed bee phase: The objective is to follow the food source position in the search area with the nectar available (GMPP). As shown in (5), each employed bee advances its new position ($V_{i,j}$) in the closeness space while keeping the old position value ($X_i$) in memory.

$$V_{i,j} = X_{i,j} + \propto_{i,j} (X_{i,j} - X_{k,j})$$
$$k=1,2,3,\dots..N_s \tag{5}$$

  $X_k$: denotes a food source other than $X_i$ That was chosen at random, i.e. (k) should not be the same as (i), $\propto_{i,j}$: represents a random number between the numbers [-1, 1]. When the employed honey bee searches for a new food source, it employs the greedy selection method [19].
- Onlooker bee phase: Onlooker bees undertake the probabilistic assortment procedure for selecting food sources based on the data given by the employed bees to the onlooker bees via a waggle dance (solutions). The (6) calculates the chance of selecting each food source.

$$\beta_i = \frac{f(X_i)}{\sum_{n=1}^{N_s} f(X_i)} \tag{6}$$

  i=1,2,3,…,$N_s$ , f(x): indicates the fitness factor concerning the dietary source.
- Finishing Phase: The method stops when the output power does not improve. The procedure, however, will restart if the output power fluctuates. Changes in radiation could cause the fluctuation effect. The inequality condition, as shown in the equation, represents such changes in radiation (7).

$$\left|\frac{P_{pv}-P_{pv,old}}{P_{pv,old}}\right| \geq \Delta P_{pv}\% \tag{7}$$

If the requirement mentioned above in (11) is met, the GMPP search will begin again. As a result, regardless of partial shade situations, the ABC approach can track the global MPP.

d) Grey wolf optimization (GWO)

The GWO method is based on the social structure and hunting behavior of grey wolves in the wild. Grey wolves, on the whole, prefer to live in packs. The typical size of a grey wolf pack is around (5,12) the sequence indicated in Figure 4 grey wolves are categorized addicted to 4 classes depend on their social dominance. Alpha (∝) wolves are the pioneers at the top and are regarded as the fittest solution for a particular optimization problem. Beta (β) wolves pursue the '∝ wolves' and assist them in fulfilling their tasks. As a result, if ∝ wolves die, β wolves can take their place [20]. The delta (δ) wolves, who make up the pack's hunters, keepers, and explorers, make up the second last category. Omega (Ω) wolves are the last group. *Ω* wolves are the pack's youngest members and represent the remaining options. The Figure 5 depicts the major flowchart of the GWO strategy. The tracking performance, power conversion efficiency, hardware implementation, and other performance indices of the swarm intelligent-based MPPT method can be summarized in Table 1.

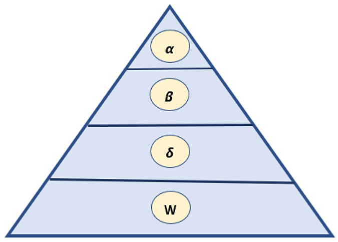


Figure 4. The grey wolf's hierarchical order [20]

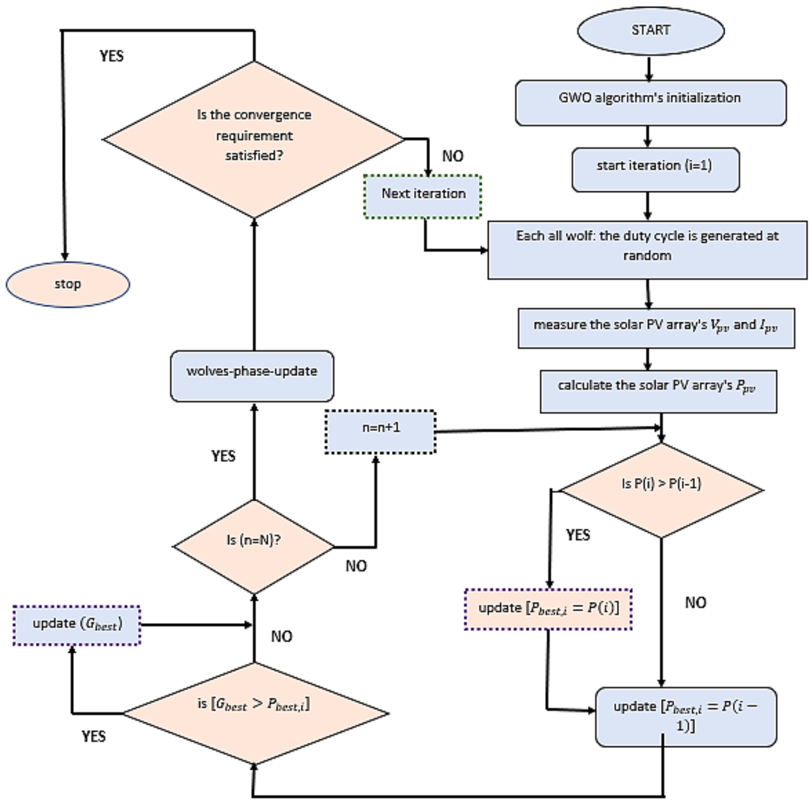


Figure 5. The flowchart of GWO-MPPT [20]

Table 1. Comparison among swarm intelligent MPPT

| Performance parameter | PSO | ACO | ABC | GWO |
|---|---|---|---|---|
| Speed of tracking | Fast | Fast | Fast | Fast |
| Complexity | Simple | Simple | Medium(M) | M |
| Cost | Very expensive | affordable | Expensive | affordable |
| System efficiency | 99.89% [21] | --- | 99.78% [7] | 99.91% [22] |
| Implementation | M | M | M | Difficult |
| Tracking accuracy | Very H | High(H) | H | H |
| Ability to track under PSC | H | H | H | H |

## 3. PROPOSED METHOD AND ALGORITHMS

Various strategies come under "intelligent MPPT," as outlined in the following subcategories.

### 3.1. Artificial neural network (ANN)

A neural network is a collection of nodes that imitate brain neurons. The nodes calculate the input signal's weighted sum and output the activation function's result with the weighted sum. The single-layer neural system has only a few uses. Therefore, the multilayer neural network was recognized to solve the single-layer neural network's important limitations. Most neural networks are constructed with layered nodes. Neural network learning is adjusting the weights and decreasing the differences between the proper o\p and the neural network's output. Figure 6 shows the structure of ANN [23].

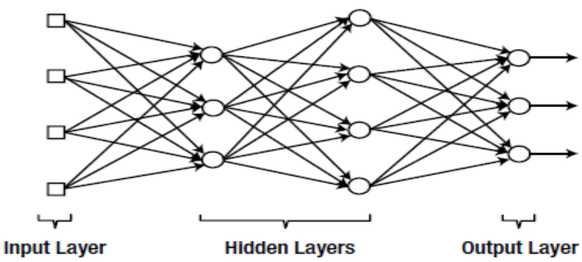


Figure 6. A layered structure of nodes [23]

The interconnection of neurons in the (I\P, hidden, and O\P) layers are considered by the weights $W^o$ and $W^i$ .

$$F = 1 - \frac{2}{1-e^{-x}} \tag{8}$$

$$Y^{na}(k) = W^o{}_i Y_i(k) \tag{9}$$

$$Y_i(k) = f\left(S_j(k)\right) = \frac{1}{1+expexp\left(-S_j(k)\right)} \tag{10}$$

$$S_j(k) = W^o{}_i Y_i(k) \tag{11}$$

$$S_j(k) = \sum_{j=1}^{me} \quad W^o{}_i(k) Y_i(k) \tag{12}$$

Where $m_e, m_c$ = the neurons in the hidden and output layers, $I_r = is\ the\ irradiance,$ and T= temperature.

### 3.2. Fuzzy logic control (FLC)

FLC is one some general methods, and it is cheaper to develop, covers a wider range of operating conditions, and is more robust. While it is a drawback is complex control rules. The flowchart is shown in Figure 7. The key mechanisms of the FLC are russification, defuzzification, fuzzy interference, membership function, and fuzzy rule base. These elements are illustrated in Figure 8. The following is a breakdown of the Fuzzy system's constituent parts [24], [25].

- Input vector: crisp values may be transformed into fuzzy sets using the russification block.
- Fuzzification is a method for converting the crisp values (input variable) into the fuzzy band.

- Membership function: indicates the goal function compared with the result; if it reaches, the operation is terminated. If not, the process keeps working toward the goal.
- Fuzzy rule base: a set of statements using relative terms like old, young, far, near, little, big, and long.
- Defuzzification: convert the data into something meaningful.
- Fuzzy inference: creates a process of fuzzy reasoning by integrating data from Fuzzification with information from a rule base.
- Output vector: reflect the values produced by defuzzification, which restores precision to a previously fuzzy collection.
- The following equations show the input parameters to the system [25].

$$E(n) = \frac{P_{PV}(n) - P_{PV}(n-1)}{V_{PV}(n) - V_{PV}(n-1)} \tag{13}$$

$$CE(n) = E(n) - E(n-1) \tag{14}$$

Where E act as the error and CE is the change of error. The below equation is the output from the defuzzification act as a duty cycle(D) [26].

$$D = \frac{\sum_{i=1}^{n} \quad \mu(D_i) - D_i}{\sum_{i=1}^{n} \quad \mu(D_i)} \tag{15}$$

Where, I is iteration; $\mu$ is the membership function.

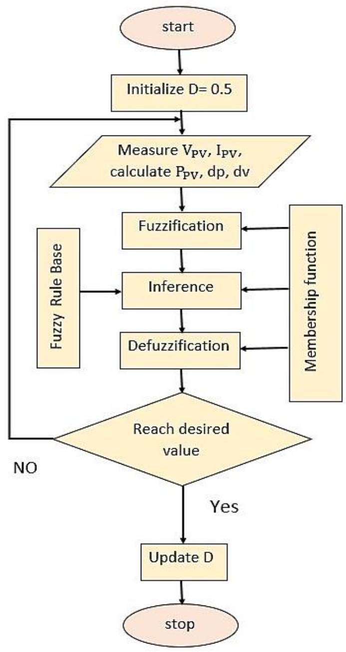


Figure 7. Flowchart of FLC method [25]

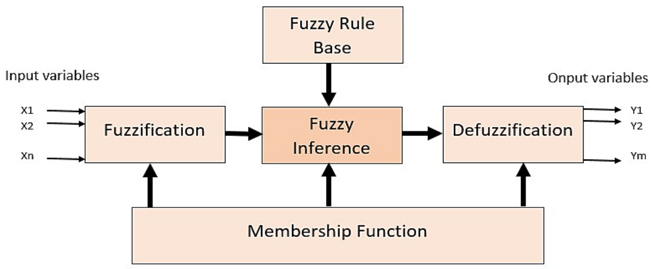


Figure 8. The component of the fuzzy system [26]

### 3.3. Sliding mode controller (SMC)

SMC is a kind of intelligent technique utilized with the PV system to suggest a fitting D for the DC-DC converter switch and increase the PV system's efficiency. Three steps illustrate the methodology of SMC as the following travers ability, reachability and equivalent control. The SMC is a nonlinear method that controls a nonlinear system to enhance its performance and makes it more robust under rapid changes in environmental and weather conditions [27]. The main merits of the SMC algorithm are fast response, lower ripple and oscillation, and low cost. In addition, the disadvantage of the SMC method is that it is complex to implement [28]. The Figure 9 is shown of the SMC algorithm. Using the following equation, we can determine how much power will change when the PV voltage changes, which is the basis of this approach [29].

$$S = \frac{dp_{pv}}{dv_{pv}} = I_{pv} + V_{pv} \times \frac{dI_{pv}}{dv_{pv}} \tag{16}$$

Where S will determine the precise value of the operational Vi\p based on the MPP's location.

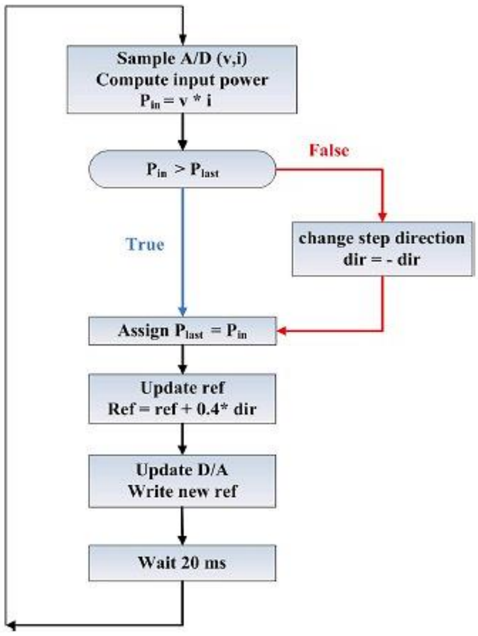


Figure 9. The flowchart of the SMC method [30]

### 3.4. Fibonacci series based MPPT

This method performs a comprehensive scan of the search space to specify the optimal point to enhance the PV system's performance by proposing a suitable duty cycle for the DC-DC converter [31]. The benefits of this technique are fast response, high convergence speed, easy tracking MPPT, high accuracy, and high efficiency [32]. Nevertheless, the demerit of the search strategy is that if there is a sudden shift in insolation, the search radius will be flipped [33]. To address this issue provides a workaround by tuning the power ripple and expanding the search area via precise approximation at the outset, according to Harrag and Messalti [30]. The principle of operation of the Fibonacci series is shown in Figure 10. The two approximations $V_1$, $V_2$ between $V_{min}$ and $V_{max}$ determine the direction of the required change [34]. The following equations illustrate the principle of operation of the Fibonacci series. Table 2 as shown the comparison among artificial intelligent-based MPPT other performance indices of the swarm intelligent

$$R_{n+2} = R_{n+1} + R_n \tag{17}$$

Where (n=1,2,3,…); $R_1 = R_2 = 1$, the following Equation expresses the calculated sequence:

$$R_3 = 2;\ R_4 = 3;\ R_5 = 5;. \tag{18}$$

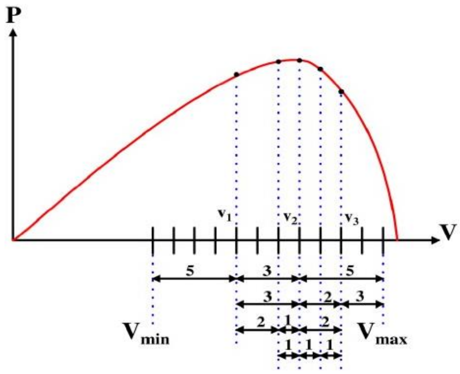


Figure 10. The principle of operation of the Fibonacci series [30]

Table 2. Comparison among artificial intelligent-based MPPT

| Performance parameter | ANN | FLC | SMC | Fibonacci series |
|---|---|---|---|---|
| Speed of tracking | M | Fast | Very fast | Very fast |
| Complexity | Simple | M | H | M |
| Cost | Expensive | Affordable | Expensive | affordable |
| System efficiency | 98% [35] | 97.87% [36] | -- | -- |
| Tracking accuracy | H | H | M | M |
| Capability to track under PSC | H | H | H | H |

## 4. RESULTS AND DISCUSSION (HYBRID MPPT)

In general, when selecting the efficient technique, the hybrid MPPT was considered the best solution to track GMPP under critical weather environments in terms of fast-tracking, accuracy tracking, power conversion effectiveness, and lower fluctuation around max point due to it is the combination of the benefits of two techniques. The hybrid techniques based on MPPT are divided into two types: traditional and intelligent methods or intelligent MPPT and optimization MPPT. Recently, hybrid techniques have been the most common and effective [37]. In this section, three various hybrid techniques are discussed and summarized in Table 3.

### 4.1. FLC and PSO

This hybrid is between fuzzy logic control and particle swarm optimization (FPSO), this combination was chosen because it involves less parameter tuning and reduces mathematical calculations. These two controlling factors, which generate membership functions, form the system's foundation (MFs). Give the best MF distribution possible to reach the optimal resolution, the fuzzy-PSO MPPT [38].

Mamdani-based fuzzy MFs enhance the converter's(D), rapidly boosting the converter, resulting in output convergence and harvesting the max power under climatic weather environments. The Figure 11 was shown a hybrid system, due to the PSO method's efficiency depending on the particle's velocity and position, it is essential to initialize of position to get optimal values. The fitness function assesses the system's overall performance. This function is given by (19).

$$\int_0^{T_f} \quad [P_{peak}(T) - P_{PV}(T)]^2 dT \tag{19}$$

Table 3. The benefits and drawbacks of this hybrid MPPT method

| Technique | Advantages | Disadvantages |
|---|---|---|
| FPSO MPPT | The switching losses are significantly reduced. Due to its ability to automatically fine-tune the association purposes and control rules, PSO can be used instead of the standard PI controller. | Despite the fact that planning the fuzzy procedures and rule base, artificial intelligence must incorporate some approximation and trial and error. |
| ANFIS MPPT | Power stability and better efficiency under PSCs are generally applicable to nonlinear systems. | Extensive and complicated algorithm-based calculation |
| GWO-P&O MPPT | increased efficiency, fewer oscillations, and a better convergence rate. This combined approach disregards the tuning procedure and its inherent complexity. | The only real drawback to this MPPT configuration is the required extensive mathematical computations. |
| PSO&P&O MPPT | A lot less complexity in designing algorithms and coding them into hardware | High fluctuation near the MPP. |
| HC-ANFIS MPPT | Improving tracking speed while maintaining a minimal circuit architecture is a key design goal. Eliminates the requirement for complicated mathematical modelling of the system. | Designing a membership function is more difficult. Training a neural network takes much time. |

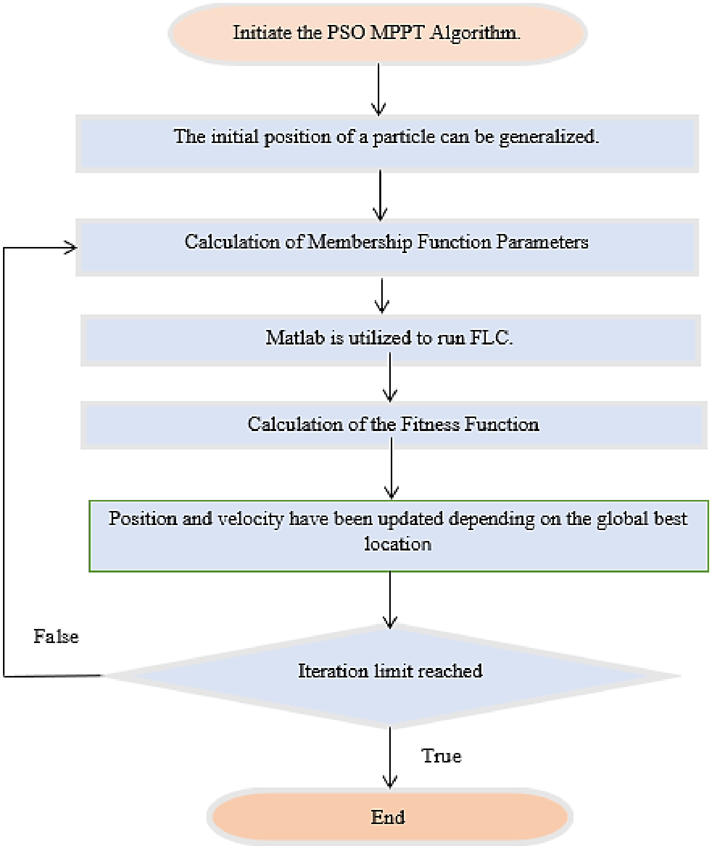


Figure 11. The flowchart of the hybrid FPSO method [39]

### 4.2. ANFIS technique

The optimal structure and position of MFs must adapt dynamically to the data available, so this hybrid is designed to get the optimal MF distribution. The tracking of GMPP from the PV array can be very rapidly based on the adaptive neuro-fuzzy interface rule. The MFs' design can be obtained from the iterative process of trial and error. The structure of ANFIS MPPT has six layers, two input parameters, and three MFs that have been carefully trained using the ANFIS technique. After an input/output mapping has been performed, nine fuzzy rules are developed to maximize output. Base widths for triangular MF distribution are used as inputs in the working process. Since each input consists of three neurons, nine fuzzy rules will be produced [39] as presented in Figure 12.

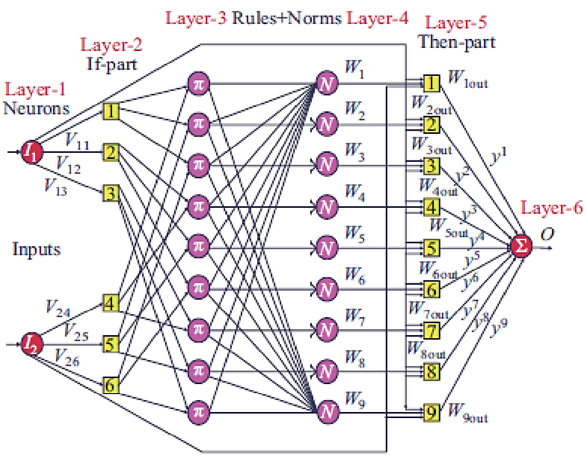


Figure 12. The structure of ANFIS [40]

### 4.3. PSO-P&O MPPT

The traditional MPPT methods cannot trajectory the MPP under PSCs. Consequently, this inspired the development of more effective methods for solving the problem. P&O is the most popular choice for tracking due to its easy-to-implement algorithm and superior efficiency. The first LMPP is identified using this method, initial GMPP is obtained using P&O, and then the actual result is obtained using PSO. Only fixed-step P&O is utilized to reduce computational complexity, which is suitable for this hybrid technique [40].

### 4.4. MCM and NAS MPPT

In order to prevent convergence at one of the LPs and to limit oscillation around the GP under steady-state circumstances, the MPPT needs excellent exploration performance at the beginning of the optimization iteration. The innovative suggested MCA technique may be used to build a large sum of examine agents at the commencement of the iteration and subsequently decrease the number of search agents with further iterations in order to meet these requirements [22], [31]. In PV systems, ANN MPPT control has been extensively studied. Under both stable and unstable air circumstances, then MCM & NAS MPPT. From Table 3 gives the information a hybrid MPPT. The Table 4. presents the cooperation among the hybrid MPPT method.

Table 4. Cooperation among the hybrid MPPT method

| Performance factors | FPSO | ANFIS | PSO&P&O | GWO&P&O | HC-ANFIS | HOM-ANS |
|---|---|---|---|---|---|---|
| Speed of tracking | H | H | M | H | H | H |
| Accuracy of tracking | H | M | H | M | H | H |
| System stability | Very stable | stable | stable | stable | Very stable | Very stable |
| System efficiency | -- | 99.562% | 99.77% | 100% | -- | 98% |
| Cost | Costly | Cheap | Affordable | Affordable | Cheap | Very Costly |
| Tracking under PSCs | H | H | H | H | H | More stable |
| Complexity | S | M | M | M | S | Easy with MPPT. |

## 5. CONCLUSION AND FUTURE WORK

There is various type of MPPT method, including traditional MPPT, intelligent MPPT, optimization MPPT, and hybrid MPPT. This paper presented a literature survey about intelligent MPPT to offer the superior technique which can be harvested Pmax. from PV systems under PSCs and rapidly varying weather conditions taking into account some variables parameters such as complexity, cost power conversion effectiveness, tracking speed, and tracking accuracy. This article classified the intelligent MPPT algorithm into two major types: swarm intelligence, which mimics the natural behavior of animals or insects, and artificially intelligent. The advantages and disadvantages of these technologies have been discussed in detail and compared in tables. Artificial intelligence strategies are effective for MPP tracking under varying radiation conditions because they fast-track, sense, and store huge amounts of data. The system can be simplified without depending on complex mathematical equations. Furthermore, swarm intelligence works best with any system without understanding PV panel factors. The nicest part about this method is that it is a bio-inspired algorithm that may be applied to any PV system minus previous information of its nature.

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