mathematics

Review

Role of Metaheuristic Approaches for Implementation of Integrated MPPT-PV Systems: A Comprehensive Study

Amit Kumar Sharma [1], Rupendra Kumar Pachauri [2], Sushabhan Choudhury [2], Ahmad Faiz Minai [3], Majed A. Alotaibi [4,5,*], Hasmat Malik [6,*] and Fausto Pedro García Márquez [7]

1 Electrical Engineering Department, Savitri Bai Phule Government Girls Polytechnic, Saharanpur 247001, Uttar Pradesh, India
2 Electrical and Electronics Engineering Department, SOE, University of Petroleum and Energy Studies, Dehradun 248007, Uttarakhand, India
3 Electrical Engineering Department, Integral University, Lucknow 226026, Uttar Pradesh, India
4 Department of Electrical Engineering, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
5 K.A. CARE Energy Research and Innovation Center at Riyadh, Riyadh 11451, Saudi Arabia
6 Department of Electrical Power Engineering, Faculty of Electrical Engineering, University Technology Malaysia (UTM), Johor Bahru 81310, Malaysia
7 Ingenium Research Group, Universidad Castilla-La Mancha, 13071 Ciudad Real, Spain
* Correspondence: majedalotaibi@ksu.edu.sa (M.A.A.); hasmat.malik@gmail.com (H.M.)

Abstract: An effective MPPT approach plays a significant role in increasing the efficiency of a PV system. Solar energy is a rich renewable energy source that is supplied to the earth in surplus by the sun. Solar PV systems are designed to utilize sunlight in order to meet the energy needs of the user. Due to unreliable climatic conditions, these PV frames have a non-linear characteristic that has a significant impact on their yield. Moreover, PSCs also affect the performance of PV systems in yielding maximum power. A significant progression in solar PV installations has resulted in rapid growth of MPPT techniques. As a result, a variety of MPPT approaches have been used to enhance the power yield of PV systems along with their advantages and disadvantages. Thus, it is essential for researchers to appraise developed MPPT strategies appropriately on regular basis. This study is novel because it provides an in-depth assessment of the current state of MPPT strategies for PV systems. On account of novelty, the authors analyzed the successive growth in MPPT strategies along with working principles, mathematical modeling, and simplified flow charts for better understanding by new learners. Moreover, the taxonomy and pro and cons of conventional and AI-based MPPT techniques are explored comprehensively. In addition, a comparative study based on key characteristics of PV system of all MPPT algorithms is depicted in a table, which can be used as a reference by various researchers while designing PV systems.

Keywords: MPPT; solar PV system; optimization techniques

MSC: 68W50

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1. Introduction

As our civilization advances in technology, it necessitates a greater use of energy in today's world. Renewable energy sources have the potential to cater the increasing demand for energy in various forms. In near future, demand for renewable energy will rise in all sectors, including heating, power, and transportation, etc. Solar power is more admired than other renewable energy sources due to its widespread availability and well-established technology. This is because of recent developments in increasing accuracy and tracking speed for maximum energy harvesting [1].

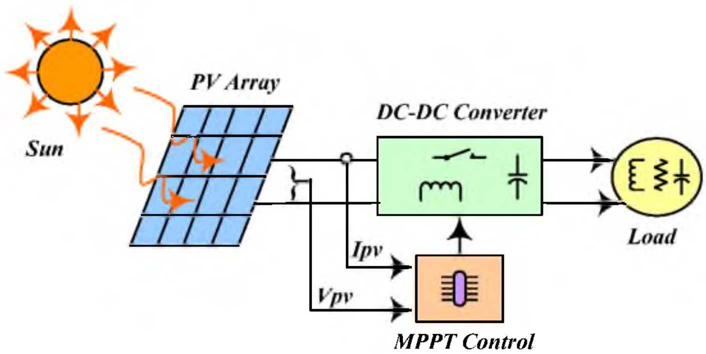
Direct current is generated when photons from sunlight strike the solar cells. A series-parallel combination of these cells gives rise to a PV module, which when further combined together forms a PV array. The literature reveals that the characteristics of solar cells are non-linear [2], which degrades their conversion efficiency. Therefore, it is required to extract all the power accessible from the PV module. Moreover, a PV module does not supply power constantly on account of various factors such as temperature, irradiance, geographical conditions, and so on [3].

The P–V curve of any solar module has an optimal point, i.e., the global maximum power point (GMPP), that varies depending on temperature and solar irradiance. The PV module produces the most power at that point [4]. To confirm that the PV module is always operating at GMPP, MPPT techniques come into picture. MPPT techniques are algorithms that are implemented via software and power electronics hardware combination in any solar controller. These algorithms aid in ensuring that the output of solar array is always at its peak. MPPT techniques perform this task by continuous power tracking methodology to determine the best operating power point from solar array. Since the maximum power of a solar array varies in accordance with many environmental conditions, tracking this power is crucial for utmost utilization of solar energy. The MPPT system's aim is to sample the output of the PV array and apply the appropriate resistance to obtain maximum power for any given environmental conditions. Thus, these techniques function as an impedance-matching device between the array and load with the help of varying the duty cycle of the DC-DC converter. The whole process is controlled by software and a micro-controller. MPPT-equipped controllers have numerous advantages over other controllers, such as the following:

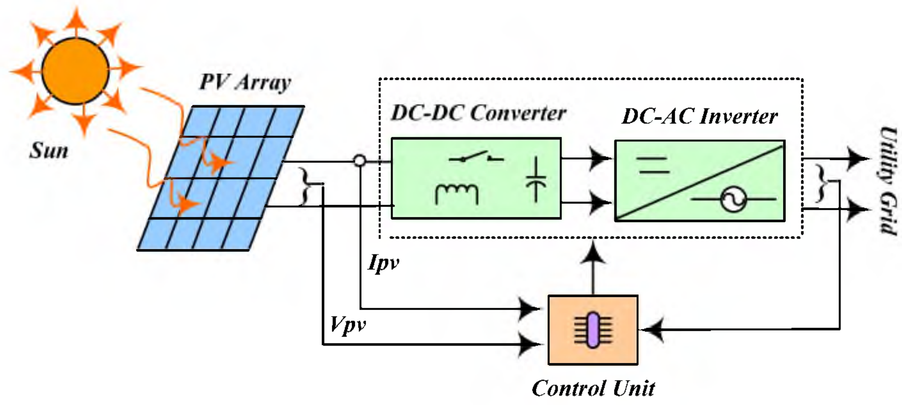
- More efficiency;
- Capability of optimizing voltage differences as well as DC load optimization;
- Best for larger systems where solar panel output exceeds battery voltage by a significant margin;
- Enhances the system's output and hence its capacity.

There are several approaches to achieving MPPT, which are discussed in this article.

Many researchers have published their findings on MPPT algorithms. Refs. [5–7] compare various MPPT approaches for uniform irradiance and PSCs for solar PV systems, whereas [8,9] focus specifically on PSCs. Traditional MPPT techniques such as P&O [10], INC [11], and HC [12] are proficient for uniform irradiance with a unique peak. They are unsuitable when the PV system is subjected to PSCs. The researchers attempted to improve on traditional MPPT algorithms by combining them with advanced strategies [13–15]. Figure 1a,b show a generalized block diagram of standalone and grid-connected PV systems.



(a)



(**b**)

Figure 1. Generalized block diagram of (**a**) standalone PV system and (**b**) grid-connected PV system.

However, the choice of a specific MPPT approach is still an ambiguity. As a result, there is strong need to investigate and reassess the developed strategies on regular basis, as this will help in the selection of a specific technique based on the context. Different conventional and AI-based meta-heuristic MPPT techniques are reviewed and compared in this article based on a variety of factors such as tracking time, complexity, oscillations around GMPP, implementation cost, and so on. BI [16,17], SI [18,19], ANN, FLC, and ECI are explained and reviewed by authors on various parameters.

The novelty of this work can be summarized as an approach to presenting qualitative comparative analysis and set-theoretic research, with emphasis on tabular presentation (technical datasheet presentation) of the chief attributes of conventional and AI-based MPPT techniques.

This data positioning approach is most appropriate format for reading and understanding the data. Quantifying these data helps in comprehensive analysis and comparing different data sets, thereby bringing out the most important and widely used conventional, metaheuristic, and other AI-based MPPT techniques, wherein various parameters such as array size, irradiance levels, techniques considered, % boost in GMPP using best technique, and tracking time, etc., are considered.

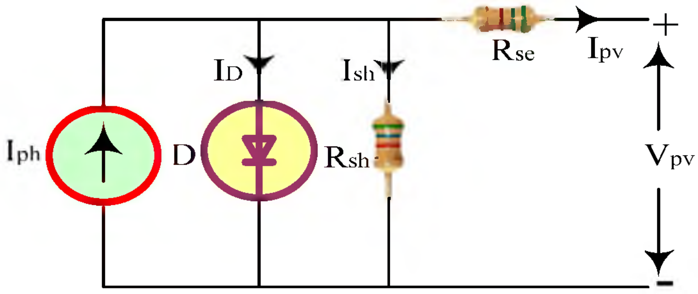
This research work is novel from other aspects as well, such as the following:

- Ease of representation: In distinct sections, the work summarizes the main characteristics of traditional and AI-based metaheuristic techniques in a simplified style using simplified flowcharts;
- Ease of analysis: A technical datasheet was created after reviewing all the major attributes required to design any PV system of recently reported conventional MPPT techniques, AI-based metaheuristic approaches, and other AI-based MPPT techniques. This datasheet provides a bare-bones description that facilitates even a new learner to understand the performances of these metaheuristic MPPT techniques, particularly PV systems in PSCs;
- Ease of modification: The technical datasheet highlights the pros and cons of all reviewed works of each category, which enables the user to identify the research gap as discussed above and helps them to modify a particular algorithm to meet the requirement of good PV system;
- Qualitative comparative analysis: The technical datasheet facilitates comparison of all MPPT approaches based on the key characteristics required while incorporating them in any PV system, which helps the readers to select the most suitable technique for any particular application.

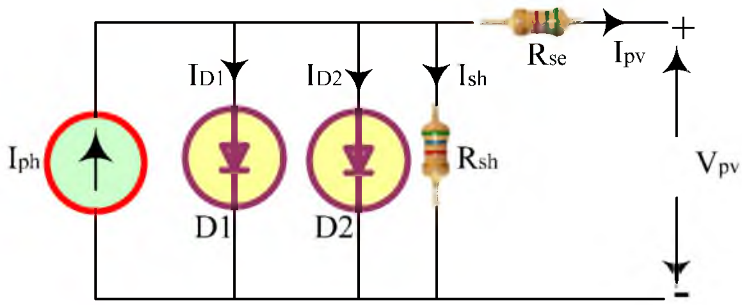
Structure of this work is as follows: The modeling of the PV cell is elaborated upon in Section 2 along with the effects of environmental factors. The partial shading effect is discussed in Section 3. MPPT techniques and their classification are elaborated upon in Section 4. Research gap findings are reported in Section 5. Challenges and further scope of the conducted effort are pointed out in Section 6, and paper is concluded in Section 7.

2. Modeling of PV Cell

Ideally, a parallel combination of a current source and a diode represents a solar cell. For practical applications, the model also incorporates shunt and series resistances to take into account manufacturing defects and contact resistances [20], as illustrated in Figure 2a.



(a)



(b)

Figure 2. Solar cell: (**a**) single-diode model and (**b**) double-diode model.

The current generated by the solar cell can be computed by Equation (1).

$$I_{pv} = I_{ph} - I_D - I_{sh} \tag{1}$$

The Shockley equation and Ohm's law can be used to calculate the current through a diode and shunt resistor, as shown in Equations (2) and (3), respectively.

$$\mathrm{I_D} = \mathrm{I_0}\left[\exp\left(\frac{q}{N_{cs}\dot{K}T}(V_{pv} + I_{pv}R_{se})\right) - 1\right] \tag{2}$$

$$\mathrm{I_{sh}} = \frac{V_{pv} + I_{pv}\,R_{se}}{R_{sh}} \tag{3}$$

Thus, the distinctive Equation of solar cell output current can be written as

$$\mathrm{I_{pv}} = \mathrm{I_{ph}} - \mathrm{I_0}\left[\exp\left(\frac{q}{nkT}(V_{pv} + I_{pv}R_{se})\right) - 1\right] - \frac{V_{pv} + I_{pv}\,R_{se}}{R_{sh}} \tag{4}$$

The ideality factor "n" is assumed to be constant in single-diode model, but this factor is a function of voltage at the device terminals. Its value is close to one at high voltages and becomes two at low voltages because of recombination in junction. This effect can be modelled by connecting another diode in parallel with the first diode, giving rise to the double-diode model, as shown in Figure 2b. The ideality factor is set to "2" for the double-diode model.

Figure 3 shows the PV module (I–V) and (P–V) characteristic curves. It details the solar energy conversion capability and efficiency for a particular atmospheric condition. Since short- and open-circuit circumstances have no effect on power generation, there must be a point somewhere in the middle where the solar module produces most power and is located close to the bend in the characteristic curves. P_{max} is generated by a specific combination of voltage and current, and the combination's coordinates represent the MPP.

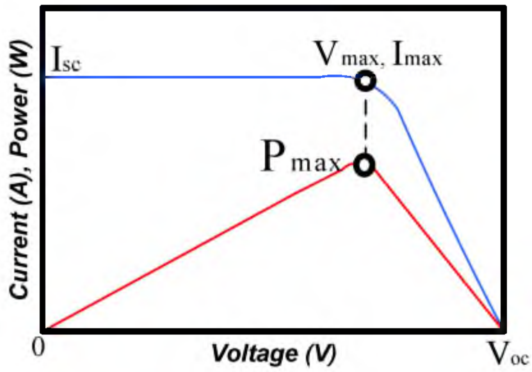
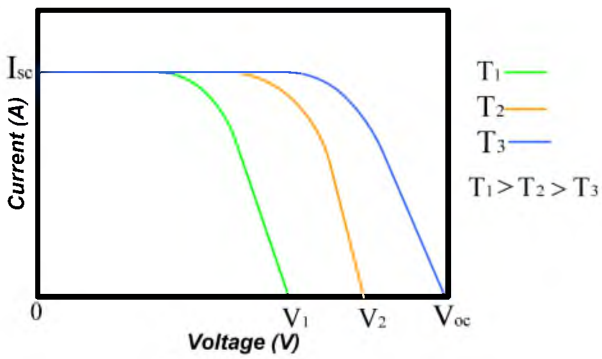
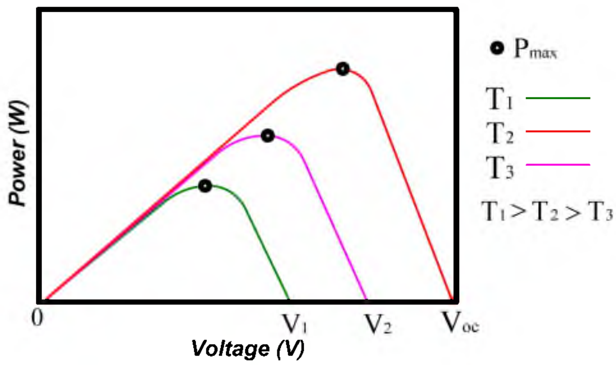


Figure 3. PV module characteristic curves (I–V) and (P–V).

A slight change in atmospheric temperature and irradiance affects the module's performance. Since module Voc decreases as temperature rises [21], the power output yield of the PV system will decrease. Figure 4a,b show the temperature variation effect on PV module (I–V) and (P–V) curves.



(**a**)



(**b**)

Figure 4. Temperature variations effect on PV module: (**a**) I–V curve and (**b**) P–V Similarly, the output of PV modules is also affected by the change in solar irradiance "W w/m^2", as the output current of PV module depends on irradiance. As irradiance increases, the PV module output current also increases. Thus, the PV module can generate more output power. Figure 5a,b show the effect of irradiance change on PV module (I–V) and (P–V) curves.

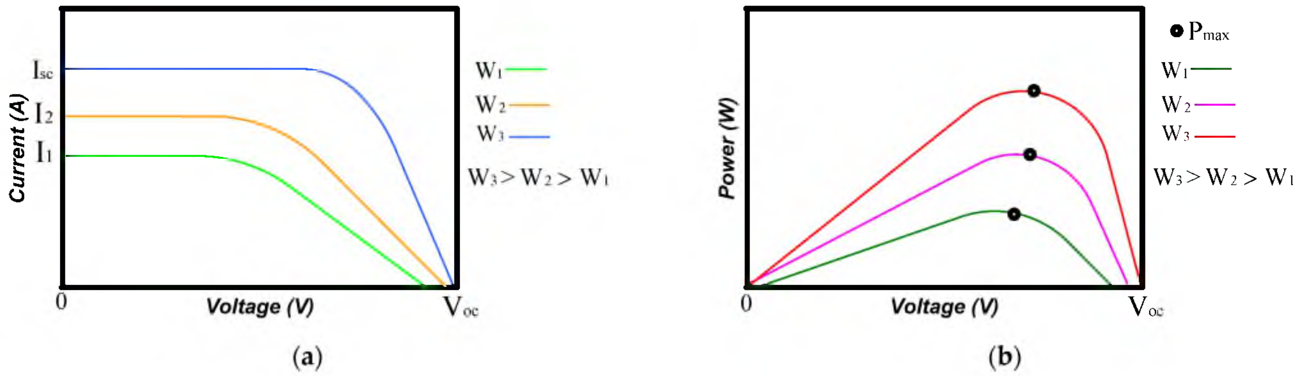


Figure 5. Irradiance variation effect on PV module: (**a**) I–V curve and (**b**) P–V curve.

3. Partial shading Effect

PV systems are extremely susceptible to partial shading. On account of various environmental conditions such as rain, clouds, and storms, it is not possible to obtain uniform irradiance at all times. In addition, PV array also suffers shading from nearby buildings and trees. This shading effect leads the PV module to yield less output power [22]. PSCs can lead to the following:

- Non-linear PV module (I–V) characteristic curve with multiple LMPP. As a result, shading causes hot spots and damages the solar cells;
- Current and voltage mismatch in PV array;
- Many peaks in the (P–V) characteristic curve with an increase in shading conditions.

Shading one cell results in a drop of current flowing through it when compared to the unshaded cells of its string. As a result, unshaded cells are forced to carry high current, and shaded cells will be restricted to the string current. This leads to a drop in the output power of the PV string. A bypass diode is connected across the shaded cell string to moderate the effect of shading. Through this, unidirectional flow of current is achieved. Figure 6a,b shows the effect of partial shading on (I–V) and (P–V) characteristics of PV system.

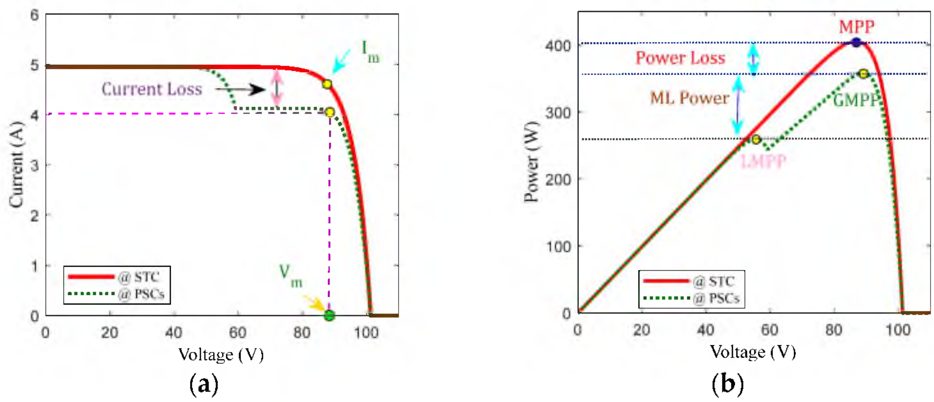


Figure 6. Characteristics of (**a**) I–V and (**b**) P–V under PSCs.

4. MPPT Algorithms

Each PV module has a different MPP in different atmospheric conditions. Thus, to extract maximum power from it, MPPT algorithms are used. These algorithms are imposed through electronic converters. Though these techniques enhance the performance of PV system, designers are generally concerned about tracking GMPP under PSCs. These algorithms are implemented through microcontrollers. The duty ratio of the DC converter employed is adjusted by these algorithms after frequent sampling of some PV module parameters. This changes the impedance seen by the PV module, resulting in achieving maximum power. These MPPT techniques are classified as shown in Figure 7. The following sections explain the basics of these techniques comprehensively, while recent advancements in each are listed in the tables at the end of each classification separately.

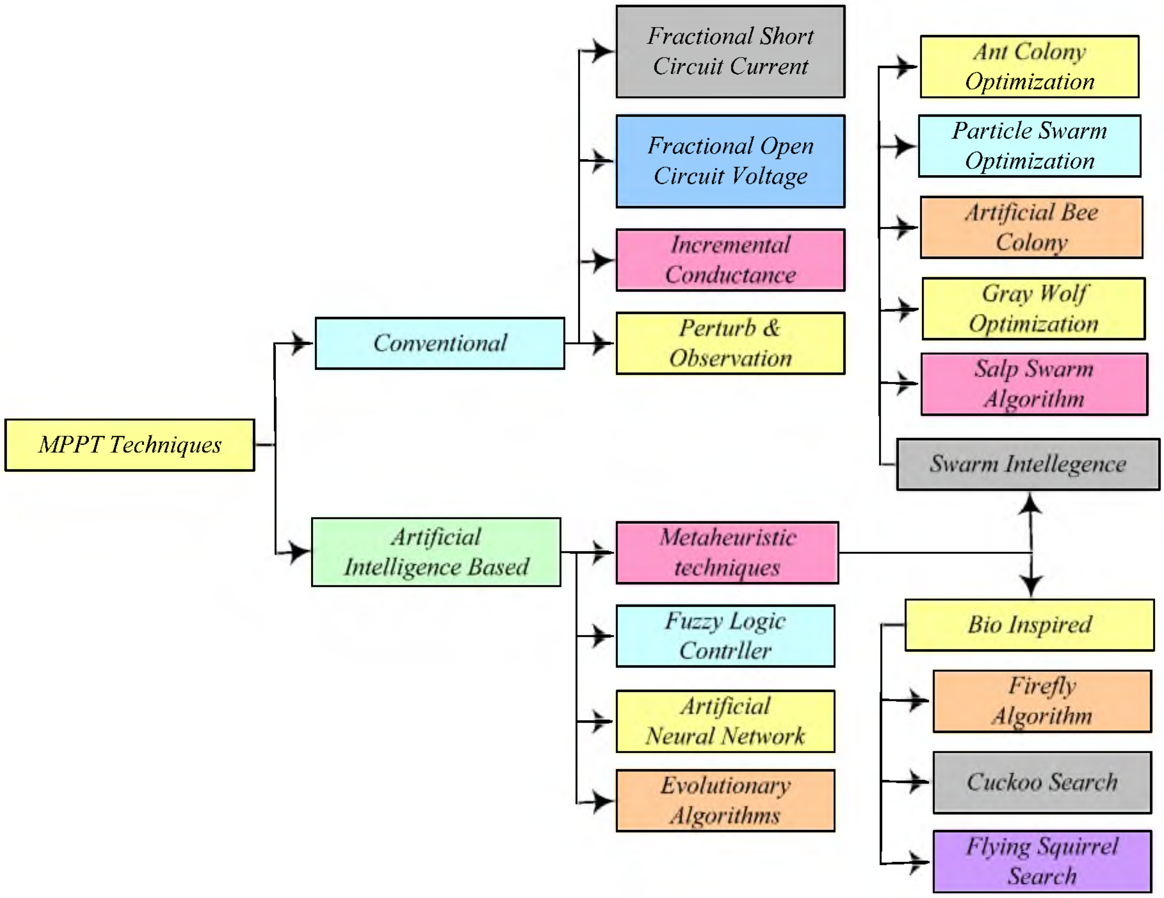


Figure 7. MPPT Techniques Classifications.

4.1. Conventional MPPT Techniques

4.1.1. Perturb and Observe

The P&O MPPT technique is widely used due to its simplicity, ease of implementation, fewer sensor requirements, and low actualized costs [23,24]. It is an iterative method of tracking MPP. This technique works on the principle of minor change in PV array voltage and monitors the resulting impact on power. This is achieved by varying the duty cycle of the DC–DC converter employed in the system. With these perturbations, the change in power can be determined. If power is increased by increasing the voltage, the operating point of the PV module is on the left side of the P–V curve. If, on the other hand, power is reduced with the increase in voltage, the PV module operating point is on the right side of the P–V curve. As a result, for tracking MPP, the direction of perturbation must be such that it converges towards a precise end. Thereafter, this iteration process is continued until MPP is reached. Though the conventional P&O technique works well in stable environmental conditions, it fails to track MPP in PSCs [25]. To overcome this drawback, P&O are modified, as reported in [26]. Steps to demonstrate the working of this technique are shown in Figure 8.

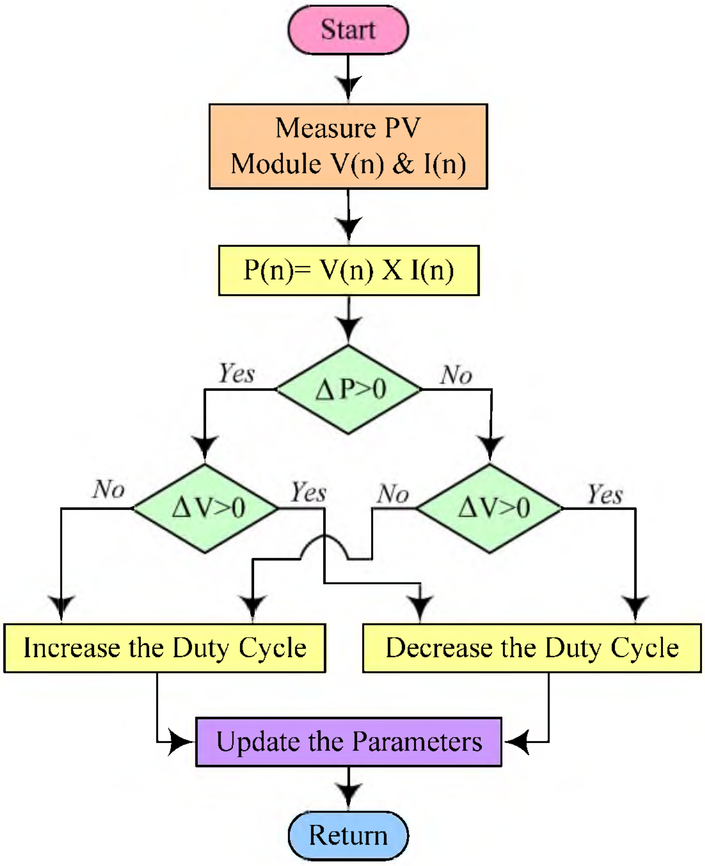


Figure 8. P&O-based MPPT technique [24].

4.1.2. Incremental Conductance

This technique is an improved version of P&O and can track MPP in a rapidly changing environment [27,28]. The principle fact of this technique is based on computing the slope of power "p" on the P–V curve. Since instantaneous power is given as the product of instantaneous voltage and current,

$$p = v \times i \tag{5}$$

The P–V curve slope can be computed as

$$\begin{aligned} \partial p/\partial v &= \frac{\partial(v \times i)}{\partial v} \\ &= i + v\left(\frac{\partial i}{\partial v}\right) \end{aligned} \tag{6}$$

The following conditions can be drawn from Equation (6):

If $\partial i/\partial v = -v/i$	$\partial p/\partial v = 0$	At MPP
If $\partial i/\partial v < -v/i$	$\partial p/\partial v < 0$	At the right side of MPP
If $\partial i/\partial v > -v/i$	$\partial p/\partial v > 0$	At the left side of MPP

As a result, the INC approach tracks MPP by comparing incremental conductance with instantaneous one [28]. Although INC can show zero oscillations in steady state, it acts the same as the P&O technique in transition states. Figure 9 shows the flowchart of the INC approach for tracking MPP.

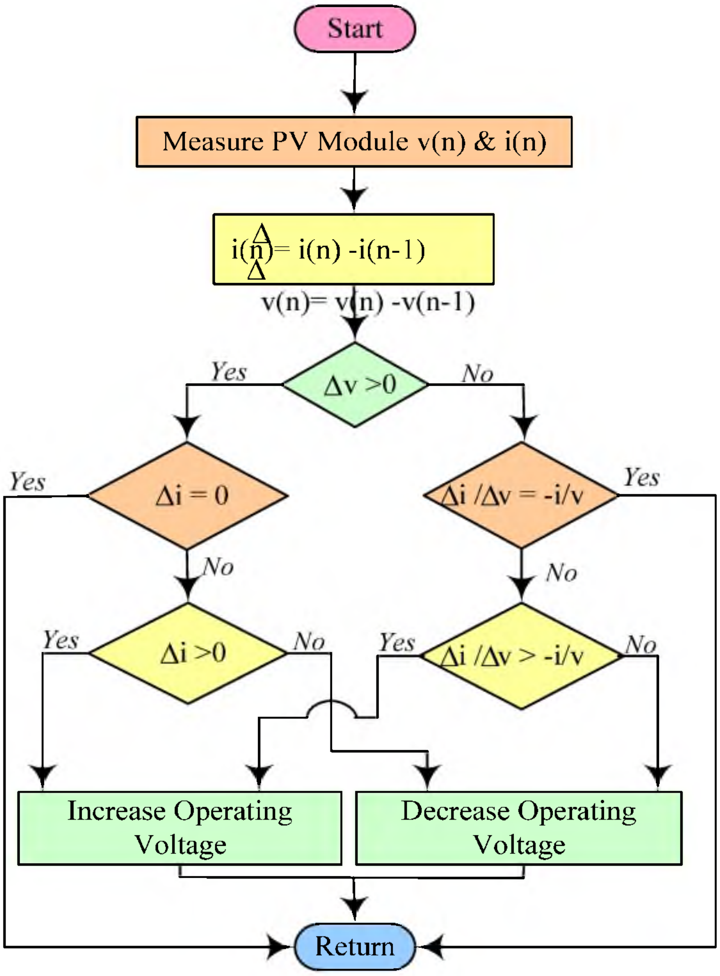


Figure 9. INC-based MPPT technique [27].

4.1.3. Fractional Open-Circuit Voltage Technique

FOCV MPPT technique is an indirect scheme to track MPP and can be utilized for low-power functions. This technique utilizes the principle that shows linear relationship between V_{mpp} and V_{oc}:

$$V_{mpp} \approx b \times V_{oc} \tag{7}$$

"b" lies in a range of 0.71 < b < 0.78 [29]. Its value is mainly dependent on module and environmental conditions. Although the technique is simple, FOCV suffers from power loss while sampling V_{oc}. A flowchart of the FOCV method is shown in Figure 10.

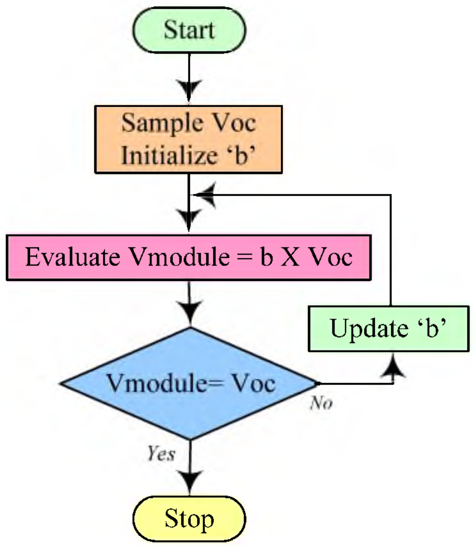


Figure 10. FOCV-based MPPT technique [29].

4.1.4. Fractional Short-Circuit Current Technique

This technique is also an indirect method for tracking MPP and is similar to FOCV. The FSCC technique utilizes the fact that there exists a linear association between I_{mpp} and I_{sc}:

$$I_{mpp} \approx d \times I_{sc} \tag{8}$$

The range of "d" lies in 0.78 < d < 0.92 [30]. This technique also suffers from the drawback of power loss while measuring I_{sc} during MPPT. A flowchart of the FSCC technique is shown in Figure 11.

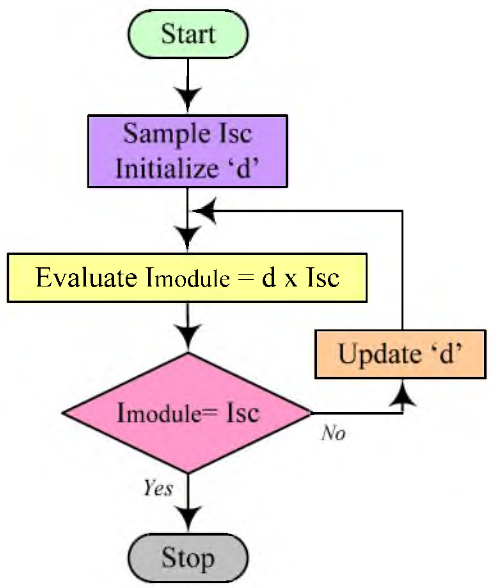


Figure 11. FSCC-based MPPT technique [30].

These conventional techniques are still used as a baseline for tracking GMPP in PSCs. Table 1 summarizes recently reported works based on these principles, followed by a discussion of their pros and cons in Table 2.

Table 1. Taxonomy on recent reported work on conventional techniques to track GMPP.

Authors [Reference No.]	Optimization Techniques	Best optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Numan BA et al. [31]	P&O Variable-step P&O	Variable-step P&O	71.8	2 PV module in series	29.22, 116.1, 106.2	0	200, 700, 800	Uniform	2, 4.8
Gil-Velasco A et al. [32]	P&O, ACO, ACO-P&O, Proposed	Proposed	250	5 PV module in series	44.97, 30.49	102.9, 35.15	1000–200	Uniform	1.12
Efendi MZ et al. [33]	P&O, Modified P&O	Modified P&O	50	3 PV module in series	6037, 5387, 7051, 7385,6322	8.30, 31.19, 61.42, 31.63, 27.69	946–828	Uniform	NA
Shang L et al. [34]	Conventional INC Proposed INC	Proposed INC	49.8	1 PV module	25.1, 40.18 25.1, 27.61	0.039, 0.424, 0.199, 0.217	800–300	Uniform	0.3, 0.35, 0.16, 0.05
Zand SJ et al. [35]	INC SP-INC	SP-INC	100.17	1X1	98.981, 94.097, 81.292	1.811, 1.179, 1.615	1000–800	Uniform	NA
Baimel D et al. [36]	FOCV PC SPC	SPC	NA	NA	27.11, 15.76, 04.83	0.93, 11.01, 0.89 10.98, 0.83, 11.03	1000–200	Uniform	NA
Hua C et al. [37]	CSAM Proposed	Proposed	60	4 PV module in series	470.95	7.27	1000–300	Uniform	0.043, 0.049
Nadeem A et al. [38]	Analytical FOCV Offline FOCV, Proposed	Proposed	245.328	3 PV module in series	438.15	89.67, 0.51	1000–600	Uniform	NA
Fapi CBN et al. [39]	FSCC, Proposed	Proposed	145	1PV module	85	13.33	NA	NA	0.7
Sarika EP et al. [40]	Proposed, VSS P&O, VSS fuzzy	Proposed	100	1PV module	76.50, 65.27	4.08, 2.99	1000–600	Non uniform	0.01
Li C et al. [41]	Proposed INC Fixed-step INC Variable-step INC	Proposed INC	178.4	NA	175.6	1.738	1000–0	Non uniform	0.38, 0.14, 0.165
Owusu-Nyarko I et al. [42]	Proposed, Variable-step-size methods	Proposed	60	NA	596.9	0.285	1000–400	Non uniform	0.0126
Sarwar S et al. [43]	PSO, DFO, INC, Hybrid, CS, FA, ACO	Hybrid	315.072	4X1	511.4, 780.4	57.35, 9.6	1000–200	Non uniform	0.48, 0.20
Hafeez M A et al. [44]	Hybrid, DFO, ACS, WCA, PSO, P&O.	Hybrid	NA	4 PV module in series	1259.9, 794.8, 593.2, 1077.0	1.933, 0.353, 7.32, 0.937	1000–200	Non uniform	0.16, 0.25, 0.4, 0.17
González-Castaño C et al. [45]	SPF-P&O, P&O	SPF-P&O	200	4 PV module in series	405.63, 331.85	4.59, 30.53	1000–120	Uniform & Non uniform	NA

Table 2. Pros and cons of recent work based on conventional techniques.

Authors [Reference No.]	Pros	Cons
Numan BA et al. [31]	• Less computationally complex	• Oscillations around GMPP • Power loss while tracking GMPP • High tracking time
Gil-Velasco A et al. [32]	• High convergence time • High tracking efficiency	• Oscillations around GMPP • Power loss due to oscillations around GMPP
Efendi MZ et al. [33]	• Additional current Voltage sensors are required	• No record of tracking time is given
Shang L et al. [34]	• Ability to judge the correct direction of disturbance • High tracking accuracy	• Low oscillations around GMPP results in power loss • Significant boost in GMPP is observed
Zand SJ et al. [35]	• Simple to implement • High tracking efficiency	• Oscillations are GMPP cannot be removed • Tracking time is not recorded
Baimel D et al. [36]	• Improves overall system efficiency	• Power loss include switching loss, switches loss, and output power of semi pilot cell
Hua C et al. [37]	• Accurate tracking • Low tracking time	• Additional sensor is required • Low oscillations around MPP
Nadeem A et al. [38]	• Can continuously measure Voc without disconnecting PV module • High tracking efficiency	• Three sensors are required to sense Voc • Computationally more complex • No record of tracking time
Fapi CBN et al. [39]	• Low ripples in output power • Improved tracking efficiency	• Two sensors are required for current and irradiance measurement • Initial setting of more parameters are required
Sarika EP et al. [40]	• Low tracking time • Low ripples in output current	• Oscillations around GMPP •
Li C et al. [41]	• Automatically regulated step size enhances the tracking performance • Fast dynamic response	• Oscillations in steady state • Highly intricate in design
Owusu-Nyarko I et al. [42]	• Dynamic performance is enhanced by adjusting scaling factor in accordance with irradiance. • Low overshoot.	• Oscillations in steady state •
Sarwar S et al. [43]	• High tracking efficiency • Low settling time.	• Oscillations around GMPP • Highly intricate in design.
Hafeez M A et al. [44]	• High tracking efficiency • Ability to handle complex partial scenarios	• Oscillations around GMPP • Computationally more complex
González-Castano C et al. [45]	• Robust and fast tracking response • No oscillations in steady state under PSCs	• Low tracking factor at the time of system start up • High settling time

4.2. Swarm Intelligence MPPT Techniques

This section of the paper explains various swarm intelligence MPPT techniques in detail and reports the recent work done with these techniques to enhance MPPT along with their pros and cons in Tables 3 and 4 respectively.

4.2.1. Ant colony Optimization

Ants' cooperative search behavior for the shortest path between source food and their colony motivates ACO. Firstly, ants scurry about aimlessly. When any ant finds a food source, they return to their home along with the food, leaving pheromone trails at their back. This pheromone is composed of particular artificial compounds that are received by living organisms to send messages or codes to other members of the same class. If other colony ants come across such a route, they will follow it to the food source rather than roaming randomly.

They leave pheromones when they return to their territory, boosting the existing pheromone strength. The potency of the pheromone is condensed as pheromone dissipates over time. The ants ultimately regulate and find the shortest path to the food source.

The procedure starts with a single colony of (artificial) ants that has been randomly positioned in that colony. Suppose ants are represented by N parameters. Each ant in the colony uses its magnetic power to entice another ant. They travel from the lower potency zone to the higher potency zone on the basis of attractive force. The attractive power resolute after each iteration cycle and the ants travel in the direction of the best option based on the results.

Consider a problem in which "n" artificial ants (parameters) must be tuned so that $A \geq n$. The solution register stores "A", which represents the primarily created arbitrary solutions. The result afterwards sited according to their fitness significance, f (si), is shown in Equation (9):

$$f(s_1) \leq f(s_2) \leq f(s_3) \leq f(s_4) \ldots\ldots\ldots\ldots\ldots \leq f(s_n) \tag{9}$$

Similarly, fresh arrangements are created to determine the placements of these ants with the help of Gaussian kernel function sampling for ith dimensions and kth solution as [46]

$$\hat{G}_i(x) = \sum_{k=1}^{A} w_k g_k^i(x) = \sum_{k=1}^{A} w_k \frac{1}{\sqrt{2\pi}\widetilde{\alpha}_k^i} e^{\left[-\frac{(x-\hat{\mu}_k^i)^2}{2(\hat{\alpha}_k^i)^2}\right]} \tag{10}$$

$\widetilde{\alpha}_k^i$, $\hat{\mu}_k^i$, and w_k can be evaluated as

$$\widetilde{\alpha}_k^i = \epsilon \sum_{k=1}^{A} \frac{\left|s_k^i - s_k^i\right|}{A-1} \tag{11}$$

$$\hat{\mu}_k^i = \left[\hat{\mu}_1^i, \hat{\mu}_2^i, \ldots\ldots \hat{\mu}_k^i, \ldots\ldots, \hat{\mu}^i{}_A\right] = \left[s_1^i, s_2^i, \ldots\ldots s_k^i, \ldots\ldots s^i{}_A\right] \tag{12}$$

$$w_k = \frac{1}{\varnothing A\sqrt{2\pi}} e^{\left[-\frac{(k-1)^2}{2(\varphi A)^2}\right]} \tag{13}$$

The investigative cycle will be continual depending on the quantity of parameters that needs to be improved. First, we generate "B" novel solutions that sum up the initial "A" solutions. Afterwards, A + B solutions must be placed in the search box. Soon after, A's most effective arrangements are re-established. The entire cycle is thus re-hashed for the required amount of iterations [47]. Effective tracking of GMPP, high convergence rate, and a lesser number of iteration makes ACO more advantageous than traditional MPPT techniques. A flowchart of ACO is shown in Figure 12.

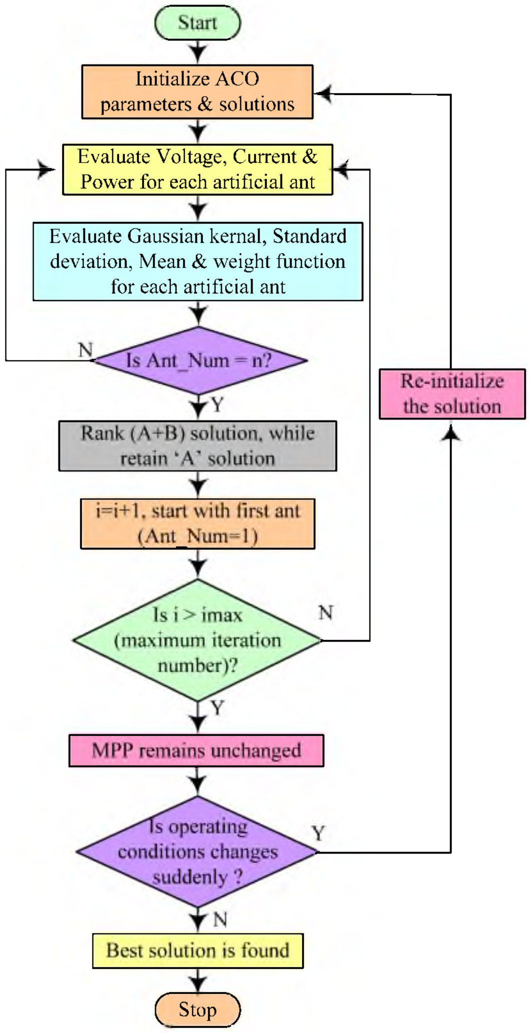


Figure 12. ACO-based MPPT technique [47].

4.2.2. Particle Swarm Optimization

PSO is a random search technique. It utilizes the principle of maximizing nonlinear continuous function. It follows the rules of natural manner of fish schooling and flock gathering. Several combined birds are used in this technique, each of which represents a particle. In search space, every particle has a fitness value mapped by a vector of position and velocity. The direction and steps of every particle are determined by their fitness value. Following that, all particles present a solution by combining the information gathered during their own search process to arrive at the optimal solution. This technique starts with random solution groups based on particles position and velocity in the search area. With the help of cerebral and social trade-off, the fitness value of particles is adjusted after each iteration. Because of the trade off, shifts in individual and community best position are obtained. Individual particles' best position is also remembered by every particle while also accumulating the global best position [48].

After each cycle, the swarm tries to determine the optimum solution by stimulating the position and velocity. Following that, a global maximum is swiftly achieved by each particle. For the kth cycle, the nth molecule refreshes the condition with position "Y" and velocity "v" as given below

$$v_n(k+1) = \omega v_n(k) + \alpha_1 \mu_1 \left(p_{p,best-k} - Y_n(k) \right) + \alpha_2 \mu_2 \left(p_{g\ ,best} - Y_n(k) \right) \tag{14}$$

$$Y_n(k+1) = Y_n(k) + v_n(k+1) \tag{15}$$

$$n = 1, 2, 3, \ldots\ldots\ldots\ldots, N$$

If, with an improvised scenario as in Equation (16), the initialization requirement is satisfied, the technique update is in line with Equation (17):

$$ft(Y_{n-k}) > ft\left(p_{p,\ best-k} \right) \tag{16}$$

$$p_{p,\ best-k} = Y_{n-k} \tag{17}$$

"ft" must be maximized. Figure 13 shows the flowchart of the PSO algorithm to track GMPP.

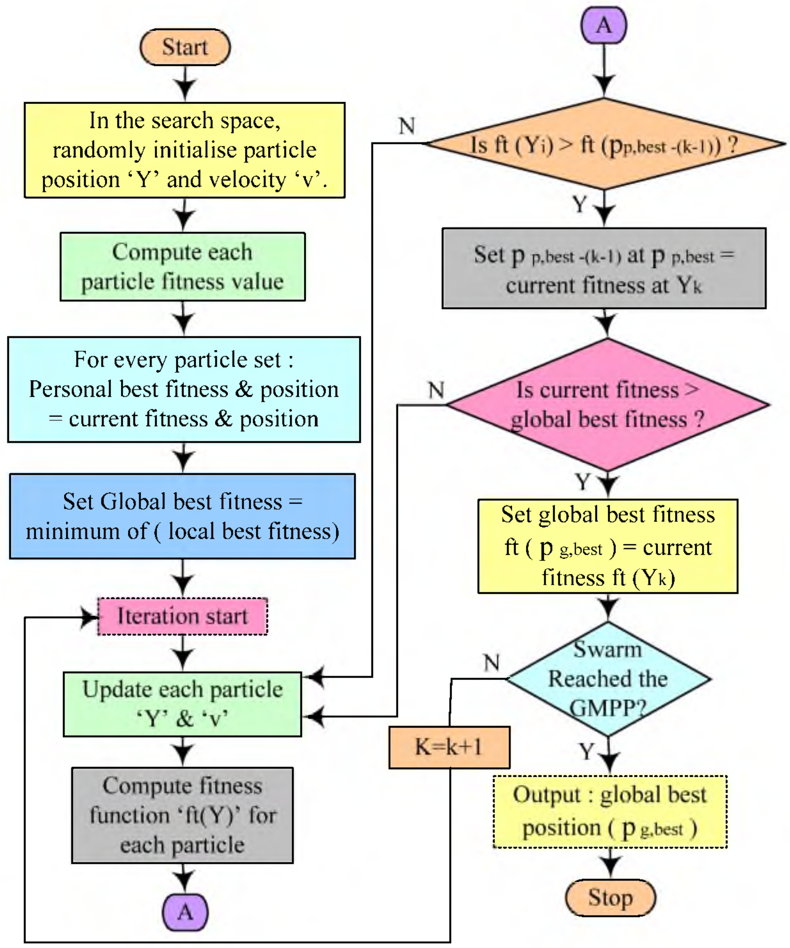


Figure 13. PSO-based MPPT technique [48].

4.2.3. Artificial Bee Colony

The ABC approach is based on honey bees' foraging intelligence. This approach is a sensible, modern, and speculative global optimization technique. Honey bees reside inside their hives and use a chemical exchange (pheromones) and the shake dance for their communication. If a bee finds a honey source (food), it takes food back to its hive by performing a shake dance to trade off the food-source site. The potency and duration of the shake dance show the richness of the food source discovered.

Three classes of artificial bee are formed by ABC algorithm, i.e., employed, scouts, and spectator bees. The hive is divided equally between employed and spectator bees. The main aim of whole bees group is to find the best honey source. Employed bees seek out a honey source (food) initially. They revisit their hive and communicate their findings with other groups of bees through shake dance movements. By carefully examining the shake dance of employee bees, spectator bees try to find the food source, while scout bees imprecisely search for new food sources. Thus, with this communication and coordination amongst them, artificial honey bees arrive at ideal solutions in the possible shortest time [49,50]. The ABC algorithm uses five phases to track GMPP as discussed below.

Phase 1: Initialization phase

First, create N_s food sources at random in the hunt arena. The algorithm's performance improves with the increase in size of the group. Each solution Y_i is an n-dimensional vector that dispenses the entire employed bee equivalent to each distinctive source of food as per Equation (18) with n optimization parameter numbered as

$$Y_{i\ ,k} = Y_{min,i} + rand[0,1](Y_{max,i} - Y_{min,i}) \tag{18}$$

$$i = 1,2,3,\ldots\ldots N_S \& \ k = 1,2,3,\ldots\ldots\ldots n$$

Phase 2: Employed bee phase

The goal is to chase the food source location in the exploration region with the most nectar accessible (i.e., GMPP). Every employed bee progresses to its new position (X_i, k) in the immediate space by means of the previous position value (Y_i) to maintain the previous position value (Y_i) securely in memory according to Equation (19):

$$X_{i,k} = Y_{i,k} \ + \alpha_{i,k}\left(Y_{i,k} - Y_{j,k}\right);\ \ j = 1,2,3,\ldots\ldots\ N_s \tag{19}$$

Y_j is other than Y_i, i.e., $i \neq j$, and $\alpha_{i,k}$ ranges from $[-1, 1]$.

A gluttonous assortment method is adopted by employed bees after they search a new food source. The quantity of nectar present at the previous and latest sites is compared in this technique. As a result, a better option is preserved.

Phase 3: Spectator bee phase

On the basis of the information of the food source obtained by spectator bees from employed bees with their shake dance, spectator bees use a probabilistic selection mechanism in order to identify food sources (solutions) with f(x) fitness factor according to Equation (20).

$$\hat{p}_i = \frac{f(x_i)}{\sum_{n=1}^{N_s} f(x_i)}; i = 1,2,3,\ \ldots\ldots, N_s \tag{20}$$

Phase 4: Scout bee phase

Scout bees can locate fresh feasible solutions on the basis of Equation (20) in the vicinity of the chosen food source. In any event, even after a thorough investigation of the entire investigated area by employed and spectator bees, the food-source fitness value remains unaffected for the existing step. The same employed bees turn into scout bees, and the scout bees use Equation (18) to hunt for new possible solutions in the next step.

Phase 5: Conclusion phase

In case that output power does not show any further improvement, the method comes to an end. The procedure, on the other hand, will restart when there is a fluctuation in output power on account of various factors. Irradiance variation is one amongst them, and such changes can be represented as

$$\left| \frac{P_{pv} - P_{pv\ old}}{P_{pv\ old}} \right| \geq \Delta P_{pv}\% \tag{21}$$

If Equation (21) is satisfied, ABC again starts searching GMPP. Hence, ABC works well in PSCs. Figure 14 shows a flowchart of the ABC technique.

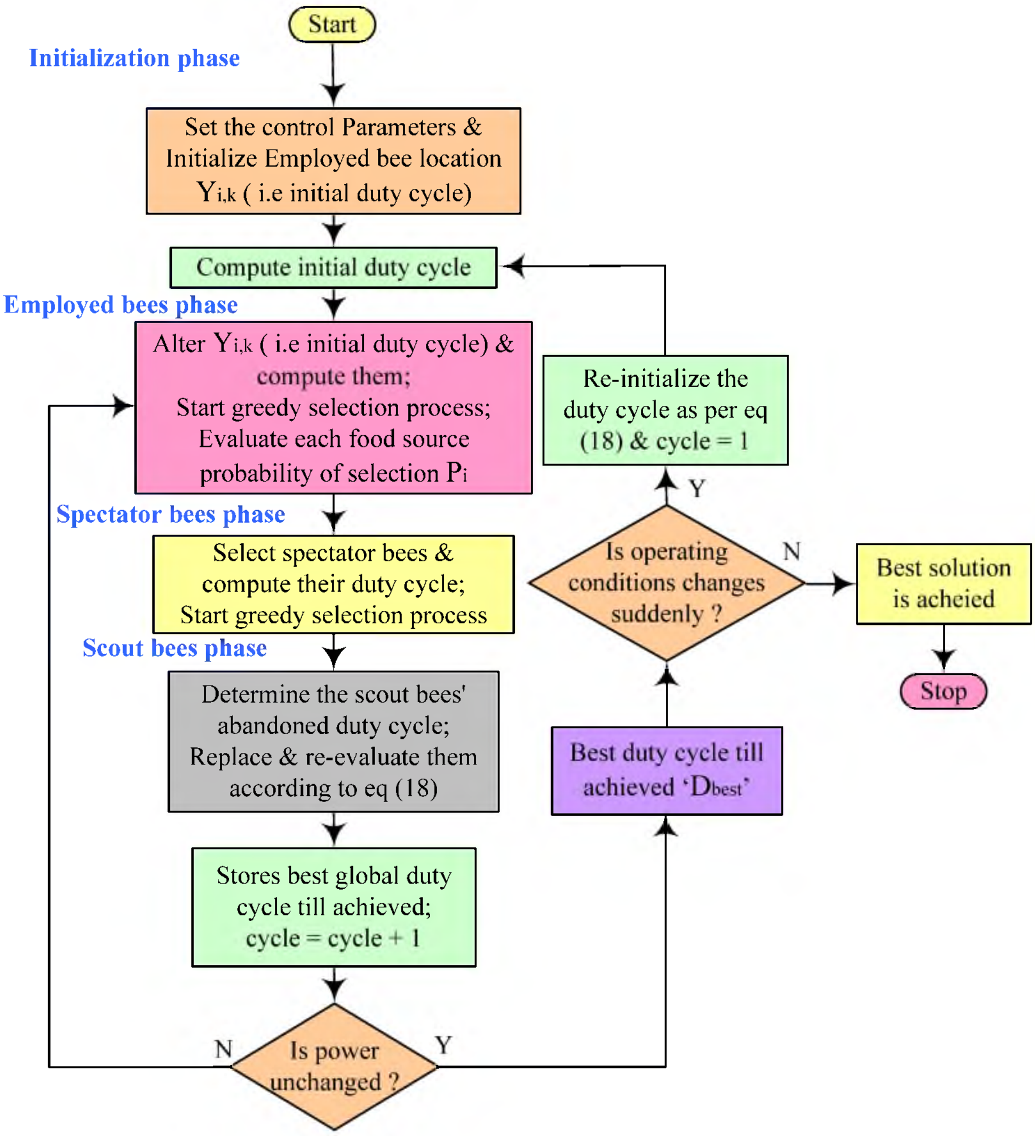


Figure 14. ABC-based MPPT technique [50].

4.2.4. Grey Wolf Optimization

The GWO technique was proposed in 2014. It is motivated by social stratification and the gray wolf's behavioral hunting personality [51]. Grey wolves, as a whole, live in packs with typical size of around 5–12. According to the hierarchical chain shown in Figure 15, grey wolves are classified into four categories based on their community supremacy. Alpha (α) wolves are the pioneer at the peak and are thus regarded as the best sources of solutions for a given optimization problem. Beta (β) wolves pursue the (α) and assist them in fulfilling their tasks. They take (α) wolves' position if the (α) wolves die. The delta (δ) wolves make up the pack's hunters, keepers, and explorers and are the second end-class. As a result, (β) and (δ) wolves represent the second- and third-best solutions, correspondingly. Omega (ω) wolves are the last group, which make up the youngest members and therefore stand for the residual solution [52].

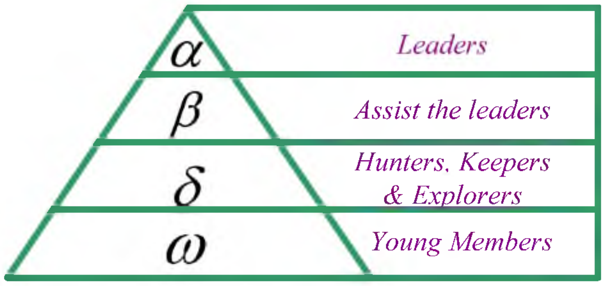


Figure 15. Grey wolves hierarchy sequence.

The supremacy of wolves is reduced as the position of the wolves lowers in the hierarchical order from top to bottom. Aside from the community order of wolves, the grey wolf's social behavior is also heavily influenced by aggregation hunting. On the basis of this, the GWO algorithm's mathematical model analyzes the following measure [52]:

Step-1: Social Hierarchy

The GWO technique presumes (α) as the fittest solution, followed by (β) and (δ) as the second- and third-finest solutions, to simulate the hierarchical system of wolves. (ω) is thought to represent the left-over contender solutions. Thus α, β and δ wolves guide the hunting process with ω wolves trailing behind.

Step-2: Tracking and Encircling the Prey

Grey wolves frequently encircle prey all through the hunting phase, expressed mathematically by Equations (22) and (23) (with iteration "i"). Equation (22) calculates a wolf's distance vector $\vec{d}$ from prey with current iteration.

$$\vec{d} = \left| \vec{B}.\vec{X}_{P_{GW}}(i) - \vec{X}_P(i) \right| \tag{22}$$

$$\vec{X}_P(i+1) = \vec{X}_{P_{GW}}(i) - \vec{A}.\vec{d} \tag{23}$$

$$\vec{A} = 2\vec{a}.\vec{r}_1 - \vec{a} \tag{24}$$

$$\vec{B} = 2\vec{r}_2 \tag{25}$$

$\vec{r}_1$&$\vec{r}_2$ ranges between [0, 1], and $\vec{a}$ = linearly decreases from 2 to 0 during each iteration.

Step-3: Hunting

Using arbitrary vectors $\vec{r}_1$ and $\vec{r}_2$, any place in between the points can be reached by a wolf. The first three best solutions (i.e., α, β, and δ wolves' locations) are initially saved. Other probing wolves alter their locations based on the top solution knowledge. As a result, a grey wolf can use this technique to improve its position in any arbitrary direction.

Step-4: Attack the Prey

Since in each cycle, the $\vec{a}$ drops linearly from 2 to 0, therefore, when $|A| < 1$ is achieved, the prey comes to a standstill in an unchanging position, and the grey wolves attack it.

Step-5: Searches for Prey

If condition $|A| > 1$ is achieved, grey wolves are compelled to look for the prey. The exploration approach is depicted in this procedure where the wolves wander away from each other in search of prey, then return to attack the prey.

In addition to this, a flowchart to explain the operation of the GWO-based MPPT technique is depicted in Figure 16.

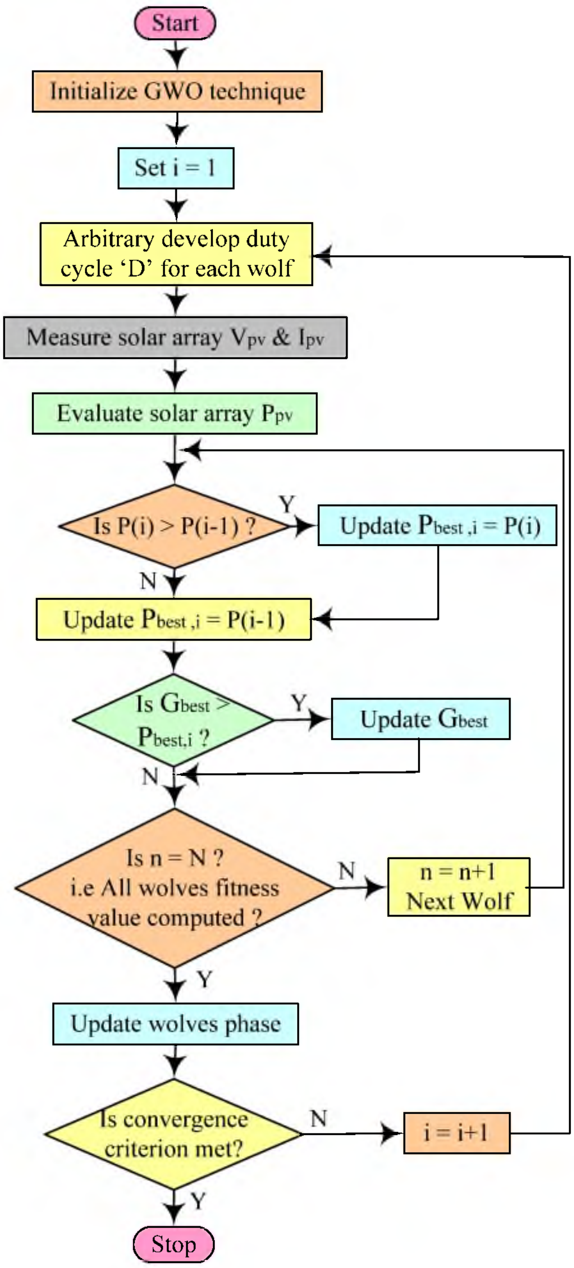


Figure 16. GWO-based MPPT technique [52].

4.2.5. Salp Swarm Algorithm (SSA)

SSA was proposed in 2017 and mimics the salps' swarm behavior. Salps are barrel-shaped, jellylike zooplankton with jellylike bodies, and they live in the deep, warm waters of the ocean. It moves by swimming with its gelatinous body, which pumps water all the way through it. It moves by constructing a chain formation of one leader, and rest follow in the chain [53]. Figure 17 shows its flowchart.

At first, a candidate solution for the leader is updated and then for the followers with the solutions found for the leaders. Let the entire chain's primary solution be given by $X_{m,n}$, where $m = 1, 2, 3, \ldots\ldots., M$ and $n = 1, 2, 3, \ldots\ldots, N$ represent salp chain size and verdict variable numbers, respectively. The leader's candidate solutions are rationalized by

$$X_{m,n}^{new} = P_n + a_1\{(X_n^+ - X_n^-)a_2 + X_n^-)a_3 \geq 0.5 \quad (26)$$

$$X_{m,n}^{new} = P_n - a_1\{(X_n^+ - X_n^-)a_2 + X_n^-)a_3 < 0.5 \quad (27)$$

Random numbers a_2 and a_3 are distributed evenly between [0, 1], as per the following Equation:

$$a_1 = 2e^{-(4i/I)^2} \tag{28}$$

where i= current iteration, and I= iterations maximum count.

This solution aids in updating the followers' candidate solutions:

$$X_{m,n}^{new} = \frac{X_{m,n} + X_{m-1,n}}{2} \tag{29}$$

If, after modifying the candidate solutions as recommended in Equations (26), (27), and (29), the entire chain candidate solutions still breach the minimum and maximum standards of verdict variables, the candidate solutions must be reinitialized at the appropriate minimum and maximum values of verdict variables.

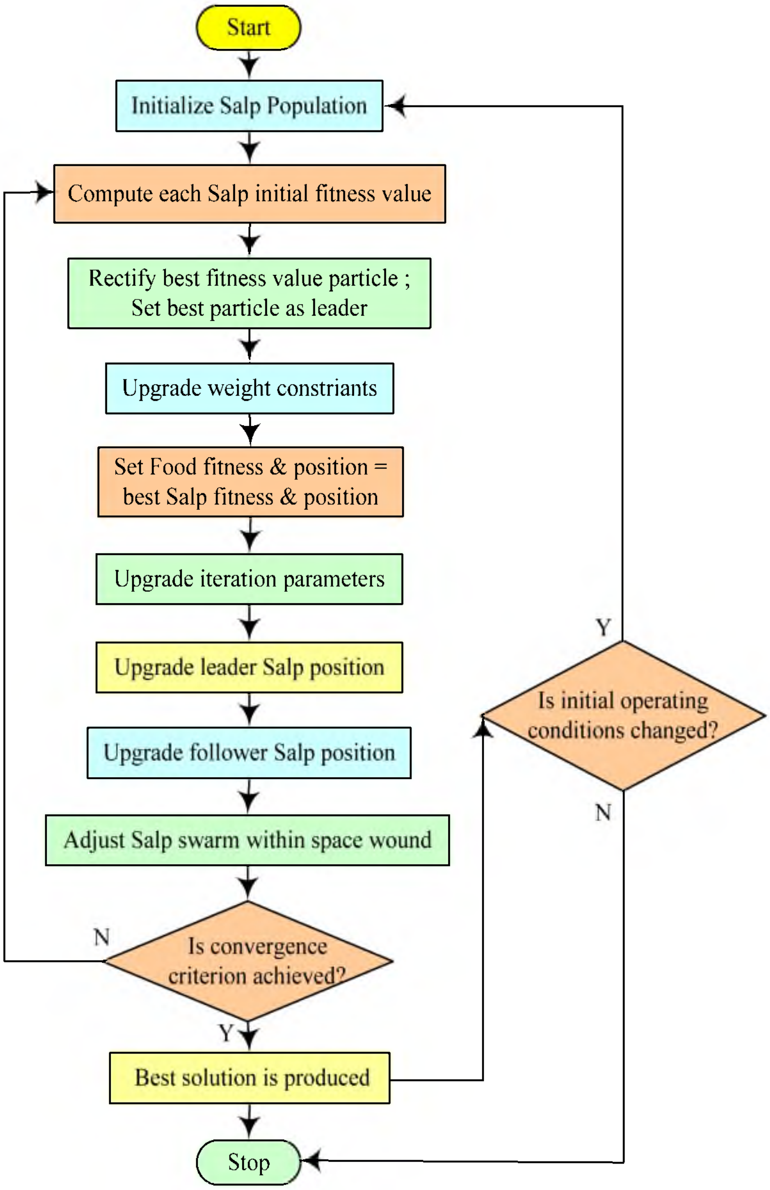


Figure 17. SSA-based MPPT technique [46].

Table 3. Taxonomy on recent reported work on swarm intelligence techniques to track GMPP.

Authors [Reference No.]	Optimization Techniques	Best Optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Krishnan SG et al. [54]	Proposed, ACO, PSO, P&O	Proposed ACO	20	4 × 4 3 × 6	63, 48.75	1.00, 32.29	NA	Non uniform	1.5, 1.56
Sridhar R et al. [55]	ACO, P&O	ACO	NA	3 PV module in series	61.4	261.1	NA	Non uniform	0.076
Alshareef M et al. [56]	APSO, PSO, P&O	APSO	NA	NA	40.56, 73.33, 76.51	13.07, 4.29, 73.49	NA	NA	1.9–2.4
Panda KP et al. [57]	Modified PSO PSO, P&O	Modified PSO	60	4 × 1	116.4	105.3	1000–400	Non uniform	0.9
Gopalakrishnan SG et al. [58]	Proposed PSO PSO, P&O	Proposed PSO	20	4 × 4 3 × 6	56.25, 48.75	18.42, 32.29	NA	Non uniform	1.9, 1.7
Mao M et al. [59]	Proposed, PSO	Proposed	83.2824	3 × 1	245.31, 60.8, 148.38	−0.28, 32.83, 1.54	1000–300	Non uniform	0.012–0.016
Koad RBA et al. [60]	LIPSO, P&O INC, PSO	LIPSO	NA	4 × 1	60.64, 48.76, 36.58, 24.29, 11.67	4.98, 12.79, 8.80, 16.23	1000–200	Uniform	NA
Belghith OB et al. [61]	PSO Fuzzy_TS P&O	PSO	150	1 PV module	148.46, 122.81, 55.67	1.48, 2.36, 5.69	1000–400	Non uniform	0.003–0.043
Obukhov S et al. [62]	VCPSO, CFPSO	VCPSO	320.4	3 PV module in series, 4 PV module in series, 8 PV module in series	960.2, 478.8, 477.8, 312.3	0.376, 0.041, 0.378, 0.192	1000–100	Non uniform	0.48–0.66
Li H et al. [63]	OD-PSO Firefly, P&O-PSO	OD-PSO	101.3	3 PV module in series	112.85, 110.85	−10.48, 4.00	1000–300	Non uniform	1.64, 2.08
Suhardi D et al. [64]	GWO INC	GWO	200	NA	203.2, 142.2, 35.9	112.19, 54.76, −50.72	1000–400	Non uniform	0.55
Kumar CS [65]	EGWO GWO PSO	EGWO	200	4 PV module in series, 2 × 2	522.629, 401.044, 522.763, 401.027	0.938, 2.707, −0.05, 7.91	1000–400	Non uniform	3.6–4.8
Shi JY et al. [66]	P&O, PSO GWO, GWO-P&O GWO-GSO	GWO-GSO	60	4 × 1	100.72	100.95	1000–300	Non uniform	0.64
Ilyas M [67]	Modified GWO GWO	Modified GWO	100	4 PV module in series, 2 × 2	444.65, 435.76	0.234, 0.045	NA	Non uniform	0.189, 0.21
Kraiem H et al. [68]	PSO, GWO	PSO	249	4 PV module in series	645.6, 633.9, 359.1	0.077, 0.939, 0.447	1000–200	Non uniform	0.0561–0.071
Jamaludin MNI et al. [69]	SSA PSO GOA GWO BOA HC	SSA	59.85	4 × 1	136.3, 114.3, 176.9	23.5, 107.7, 58.93	1000–500	Non uniform	0.22, 2.3, 4.2
Dagal I et al. [70]	Hybrid SSPSO P&O FA DE ISSA	SSPSO	60	4 PV module in series	124.09	6.55	1000–400	Non uniform	0.29

Table 3. *Cont.*

Authors [Reference No.]	Optimization Techniques	Best Optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Krishnan S et al. [71]	SSO WOA GWO	SSO	220.5	3 PV module in series 2X2	294.8, 41.8, 525.4, 38.5, 445.2, 02.7	5.58, 10.04, 39.92, 14.67, 14.97, 28.43	750–500	Non uniform	0.0245–0.0749
Farzaneh J et al. [72]	P&O, FFA, PSO, DE, SSA, ISSA	ISSA	60	4 PV module in series	115.59	6.53	1000–400	Non uniform	1.22
Ali MHM [73]	P&O, SSO	SSO	NA	NA	843.5	2.55	200	Uniform	0.72
Balaji V et al. [74]	Hybrid SSPO SS, PO	Hybrid SSPO	50	4 PV module in series	50.3, 85.1, 78.2, 96.1	27.66, 0.09, 24.32, 51.10	1000–200	Non uniform	0.52–0.57
Restrepo C et al. [75]	ABC-P&O GMPPT P&O	ABC-P&O	200.143	4 PV module in series	597.95	54.19	900–120	Non uniform	NA
Sawant PT et al. [76]	ABC, PSO	ABC	75	NA	74, 61	2.77, 3.38	1000–800	Non uniform	NA
Li N et al. [77]	P&O, PSO ABC, MABC	Modified MABC	NA	2 PV module in series	850	70.68	1000–800	Non uniform	0.39
Wan Y et al. [78]	SSA-GWO, P&O, PSO, SSA	SSA-GWO	35	3 PV module in series	104.88, 44.55, 69.32	0.788, 28.60, 1.612	1000–300	Non uniform	0.46, 0.53, 0.47
Hayder W et al. [79]	IPSO, PSO-P&O, ANN-PSO	IPSO	120	NA	119.9720, 69.9888, 94.9073, 45.3924	NA	1000–400	Non uniform	1.5
Almutairi A et al. [80]	OGWO, P&O	OGWO	60	NA	60, 47.8, 23	32.77	NA	Non uniform	0.5, <1,
Sharma A et al. [81]	TSA-PSO, FPA, GWO, TSA, PSO, P&O	TSA-PSO	85	3 PV module in series	103.36, 122.88, 156.84	22.20, 5.97, 13.11	1000–300	Non uniform	0.38, 0.54, 0.40
Chao K-H et al. [82]	I-ABC, PSO, P&O, ABC	I-ABC	20	4×3	246.6, 198.6, 148.8, 107.1, 77.1	0.08, 2.00, 0.881, 17.43, 66.88	NA	Non uniform	0.38, 0.63, 0.89, 1.48, 1.14
Alaraj M et al. [83]	HGWO, PSO, INC	HGWO	450	5×5	8256, 6441, 6347, 5567	13.23, 13.09, 20.50, 22.86	1000–400	Non uniform	0.08, 0.07
Windarko N A et al. [84]	Proposed, DE, FF, PSO, GWO	Proposed	100	3 PV module in series	172.9, 170.9, 80.9	5.81, 65.60, 226.2	1000–100	Non uniform	0.45, 0.41, 0.52
Chawda G S et al. [85]	ICPSO, P&O, INC, GA-based FLC, PSO-based FLC PSO-GA-FLC	ICPSO	NA	NA	97.3, 60, 94.2	7.955, 11.77	1000–300	Non uniform	0.1

Table 4. Pros and cons of recent work based on swarm intelligence techniques.

Authors [Reference No.]	Pros	Cons
Krishnan SG et al. [54]	• High tracking efficiency • Less iterations are required to achieve GMPP • Less ripples in output power	• Convergence time can further be reduced • Computationally complex
Sridhar R et al. [55]	• Ability to achieve high GMPP in PSCs	• Tracking time is high when compared with conventional technique • Required more numbers of iterations
Alshareef M et al. [56]	• Can distinguish between LMPP and GMPP • Fast dynamic response	• Tracking time can further be improved • Oscillations around GMPP
Pandal KP et al. [57]	• No oscillations in steady state • Both good and worst position of particle is considered	• High computational complexity • Required more number of iterations
Gopalakrishnan SK et al. [58]	• Ability to achieve true GMPP in PSCs	• Oscillations in steady state • High tracking time
Mao M et al. [59]	• With adaptive inertia factor, tracking time is improved • Low MPP tracking error in PSCs	• Computationally more complex • Oscillations around GMPP • Require more number of iterations
Koad RBA et al. [60]	• High tracking efficiency • Less iterations are required to reach at GMPP	• Algorithm estimates three sets of duty cycle making it more intricate in design
Belghith OB et al. [61]	• Takes less time to reach at MPP • High accuracy	• Cannot track GMPP in some changing irradiance condition
Obukhov S et al. [62]	• Optimal parameters of PSO is conveniently selected	• Time to track GMPP can be further improved
Li H et al. [63]	• Required less number of iterations • Low power fluctuations	• High tracking time • Trapped in LMPP is some cases when tested on hardware

Table 4. *Cont.*

Authors [Reference No.]	Pros	Cons
Suhardi D et al. [64]	• Low power loss while tracking GMPP	• Cannot achieve GMPP is some shading conditions • Tracking time can further be improved
Kumar CS et al. [65]	• Low standard deviation	• Very high tracking time • Trapped in local GMPP
Shi JY et al. [66]	• Highly accurate • Hunting process is accelerated by varying decision weight	• Comparatively more iterations are required results in power loss • Intricate to design
Ilyas M et al. [67]	• High tracking efficiency • Algorithm modified the surrounding and hunting behavior that finds the optimum solution correctly	• Oscillations around GMPP • Computationally more complex
Kraiem H et al. [68]	• Low tracking time • Low oscillations around GMPP	• High computational complexity •
Jamaludin MNI et al. [69]	• High accuracy • Zero steady state oscillations • High convergence speed	• Inability to deal with rapidly changing environment conditions • Information regarding change in landscape fitness is not considered while tracking GMPP • Required periodic tuning
Dagal I et al. [70]	• High tracking efficiency	• Not tested on hardware setup
Krishnan S et al. [71]	• No periodic tuning is required • Low computational complexity in comparison to other metaheuristic approaches	• Oscillations around GMPP • Requires large number of iterations
Farzaneh J et al. [72]	• No oscillations around GMPP • High tracking efficiency	• High tracking time • Computationally more complex to design
Ali MHM [73]	• High tracking efficiency	• Oscillations around GMPP

Table 4. *Cont.*

Authors [Reference No.]	Pros	Cons
Balaji V et al. [74]	• fewer initializations of parameters • reduced oscillations in initial stage of tracking	• Hardware validation is not done •
Restrepo C et al. [75]	• Rapid control loops • Quick response	• High computational constraint
Sawant PT et al. [76]	• Highly accurate	• Intricate to design • Hardware validation is not done
Li N et al. [77]	• High tracking efficiency	• Computationally more complex to design
Wan Y et al. [78]	• Accurate GMPP tracking • Low power fluctuations	• Parameter initialization is required • Low oscillations in steady state
Hayder W et al. [79]	• High accuracy	• Temperature effect is neglected in testing
Almutairi A et al. [80]	• Low fluctuation of power in steady state around MPP	• High tracking time • More number of iterations are required
Sharma A et al. [81]	• Fast tracking capability • Less number of iteration is required	• High computational complexity
Chao K-H et al. [82]	• Low power losses during power-generation process	• High tracking time in complex PSCs
Alaraj M et al. [83]	• Low convergence factor • Low rise and settling time	• Highly intricate to design
Windarko N A et al. [84]	• High energy tracking capability • Random calculations are avoided which minimize unnecessary duty cycle	• High cost of implementation
Chawda G S et al. [85]	• Low tracking time • INC is utilized to update particle position and velocity, resulting in high dynamic response	• Computationally more complex

4.3. Bio Inspired Techniques

This part of the paper elaborates various MPPT techniques inspired by biological behavior of different organism. Additionally, various recent works done to track MPP incorporating these techniques are tabulated in Tables 5 and 6.

4.3.1. Firefly MPPT Algorithm

Fireflies are beetles emitting light in the night and communicate amongst themselves using a special light pattern. The light color formed by each species is unique. The FFA's hunting tactic is governed by firefly attraction, which is equivalent to brightness. A dimmer firefly approaches a brighter one, and if their brightness level is the same as that of a certain firefly, it will shift at random [86]. The key purpose of flashing in the FFA tactic is to allure other fireflies and attract their target. The charm of fireflies is governed by the intensity of the firefly along with the objective function value. The value of attraction "μ" is resolute by the evaluation of other fireflies and is diverge on the basis of "i" and "j" fireflies' distance "D_{ij}". Both can be evaluated as per Equations (30) and (31), with "D" as the distance between two fireflies, "β" as an arbitrary constant that lies between 0.1 and 10, and "n" as the dimension number.

$$\mu = \mu_0 \; e^{-\beta D^2} \tag{30}$$

$$D_{ij} = |x_i - x_j| = \sqrt[2]{\sum_{y=1}^{n} (x_{i,y} - x_{j,y})^2} \tag{31}$$

D = 1 is taken in MPPT problems because it is a one-dimensional case. A flowchart of FFA is shown in Figure 18.

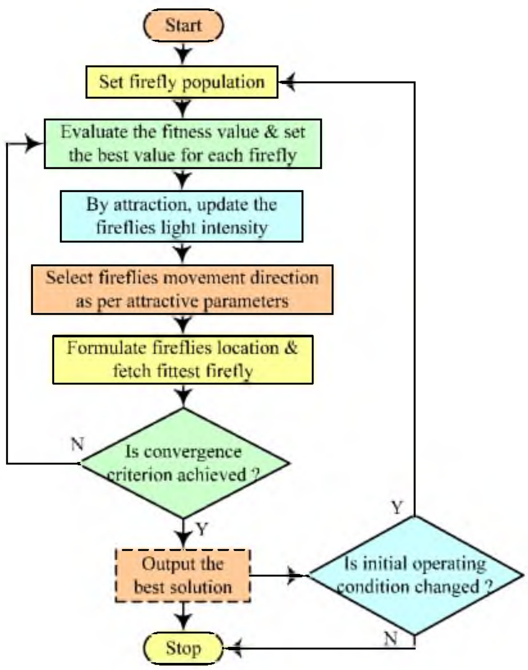


Figure 18. FFA-based MPPT technique [46].

4.3.2. Cuckoo Search

This bio-inspired technique was reported in 2009 and is inspired by the cuckoo species' parasitic imitation tactic (brood-parasitism) [87]. Certain birds, such as cuckoos (Tapera), engage in social parasitism. The Tapera is a knowledgeable winged creature that fits in with the host fowls, and with this tactic, next-generation endurance is encouraged. Rather than building its own nest, the cuckoo places its eggs in the nests of other flying species. Primarily, the cuckoo bird (female) flies erratically in search of a nest with similar egg characteristics to their own. After finding the best nest, cuckoo eggs have the utmost opportunity of hatching, ensuring the new generation. The cuckoo makes a few attempts by assisting the incubating bird in laying their eggs in a suitable location and hence gives itself a better chance. The cuckoo may occasionally throw the eggs of the host species from the nest because host birds could be readily duped into recognizing the strange eggs. If the host bird comes to know about the foreign eggs, the eggs will definitely be dumped outside the nest. The host bird may even demolish the nest.

For optimization objectives, the CS approach is an effective meta-heuristic method. Three idealized principles used to accomplish this strategy are as follows:

- Every cuckoo bird merely lays one egg at a time in a hastily chosen host nest;
- The cuckoos' subsequent generation will be carried on by the superior eggs' nest (i.e., the best solutions);
- In the hunt area, the entire number of reachable host nests is fixed.

Cuckoo birds represent the particles relegated to find the solution in the CS strategy implementation, and their eggs indicate the current iteration's solution to an optimization problem. Searching for a nest is comparable to searching for food, and in CS, it is described by Levy flight. A Levy flight "y" is an arbitrary stride where Levy distribution is used to evaluate sizes of steps by using a power law [88]:

$$y = L^{-\gamma}\ ;\ (1 < \gamma < 3) \tag{32}$$

Thus, "y" has an infinite variance. The new cuckoo solution $\left(\mathrm{x}^{\mathrm{i}+1}\right)$ for ith iteration cycle "i" and the nth particle "n" can be generated as

$$x_n^{i+1} = x_n^i + z(\ levy\ (\gamma)) \tag{33}$$

"z" is a mathematical operator that represents the multidimensional problem's entry-wise multiplication.

In each iteration cycle, all particles transmit Levy flights until they find GMPP. Figure 19 shows the flowchart of the CS algorithm to track GMPP.

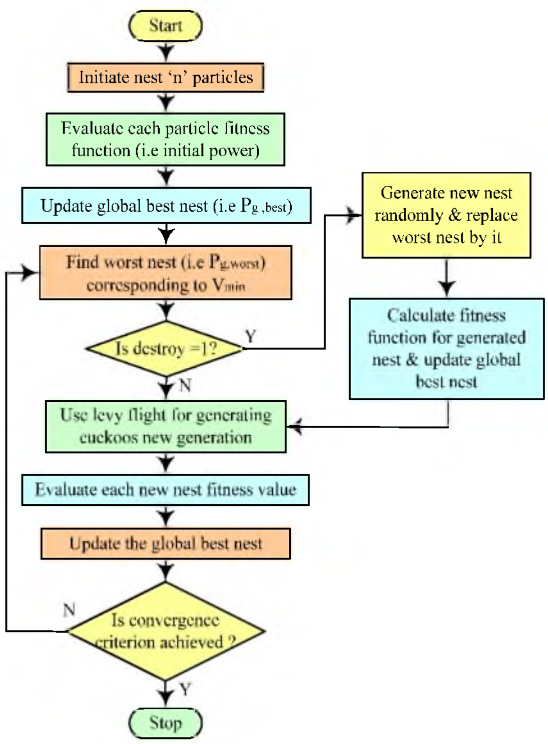


Figure 19. CS-based MPPT technique [87].

4.3.3. Flying Squirrel Search Optimization

This bio-inspired optimization approach to track GMPP was introduced in 2020 and mimics the highly effective hunting tactic used by southern flying squirrels [89]. This approach also mimics the squirrels' manner of buoyant headways in the air. The posture of FS is referenced to as the feasible outcome vector and the comparable wellness is typical food source, respectively.

The posture is divided into three districts addressing sets based on wellness value:

- BS (hickory nut tree);
- CBS (acorn nut tree);
- US (ordinary tree).

Following assumptions are made while incorporating FSSO [89] in tracing GMPP:

The food supply point is similar to the power yield from PV;

DC converter duty ratio (∂) in the MPPT approach is regarded as option variable, i.e., the posture;

To reduce the tracking time, the FSSO approach is custom-fitted by eliminating the occurrence of hunters.

The following steps are taken into account while implementing the FSSO technique.

Starting: Initially, FSs "N" numbers are placed at various locations. In the solution area, the duty ratio of the DC converter can be estimated for "i" iteration count by these points as follows:

$$\partial_i = \partial_{min} + \frac{(i-1)(\partial_{max} - \partial_{\min})}{N} \quad ; i = 1, 2, 3, \ldots\ldots N \tag{34}$$

Wellness evaluation: The DC converter employed is gradually running with each duty ratio in this progression (i.e., with each FS posture). Each food source feature shows instantaneous power yield PV (∂) for each "∂". This sequence is repeated for all "∂", whereas MPPT goal wellness function "$f(\partial)$" can be determined as

$$f(\partial) = \max\,(PV(\partial)) \tag{35}$$

- Declaration and categorization: The duty cycle at which the system yields maximum power is considered as hickory tree, while acorn trees are considered as the most excellent FS positions;
- Posture update: After the examination of occasional observing situation, the duty cycle is updated, and wellness is assessed from that point.

Important conditions followed in FSSA are as follows:

Occasional observing conditions: These conditions help FSSA to avoid being stuck in LMPP. The cyclic constant (O_C) and its base value ($O_{\min}$) for a single-dimensional space with "i and i_m" as the count of the present and maximum number of cycles allowed are

$$O_C^i = \left| x_{at}^i - x_{ht} \right| \tag{36}$$

$$O_{min} = 10e^{-6}/365^{i/i_m/25} \tag{37}$$

For investigating the superior search area, Levy distribution is employed. As a result, the OTFS duty cycle is relocated.

- Groove contemporized: Squirrels of hickory tree maintain their position. The squirrels on acorn tree, on the other hand, find a way to access the hickory tree. The arbitrarily chosen squirrel (ATFS) from normal trees chooses the hickory tree, while the leftover (NTFS-ATFS) is pressed to the acorn tree. The duty cycle is changed:

$$\partial_{at}^{i+1} = \partial_{at}^i + H_c h_d \left(\partial_{ht}^i - \partial_{at}^i \right) \tag{38}$$

$$\partial_{ot}^{i+1} = \partial_{ot}^{i} + H_c h_d \left(\partial_{ht}^{i} - \partial_{ot}^{i} \right) \tag{39}$$

$$\partial_{ot}^{i+1} = \partial_{ot}^{i} + H_c h_d \left(\partial_{at}^{i} - \partial_{ot}^{i} \right) \tag{40}$$

- Convergence Resolution: If the utmost number of iterations has been reached, the algorithm is terminated and gives the duty cycle at the point where the converter follows GMPP.
- Re-initialization: In rapidly changing environmental conditions, the duty ratio (FSs posture) is reinitialized to hunt new GMPP in accordance with Equation (41).

$$\frac{P_{pv}^{i+1} - P_{pv}^{i}}{P_{pv}^{i+1}} \geq \Delta P\ (\%) \tag{41}$$

The complete steps of FSSO algorithm in tracking GMPP are depicted in Figure 20.

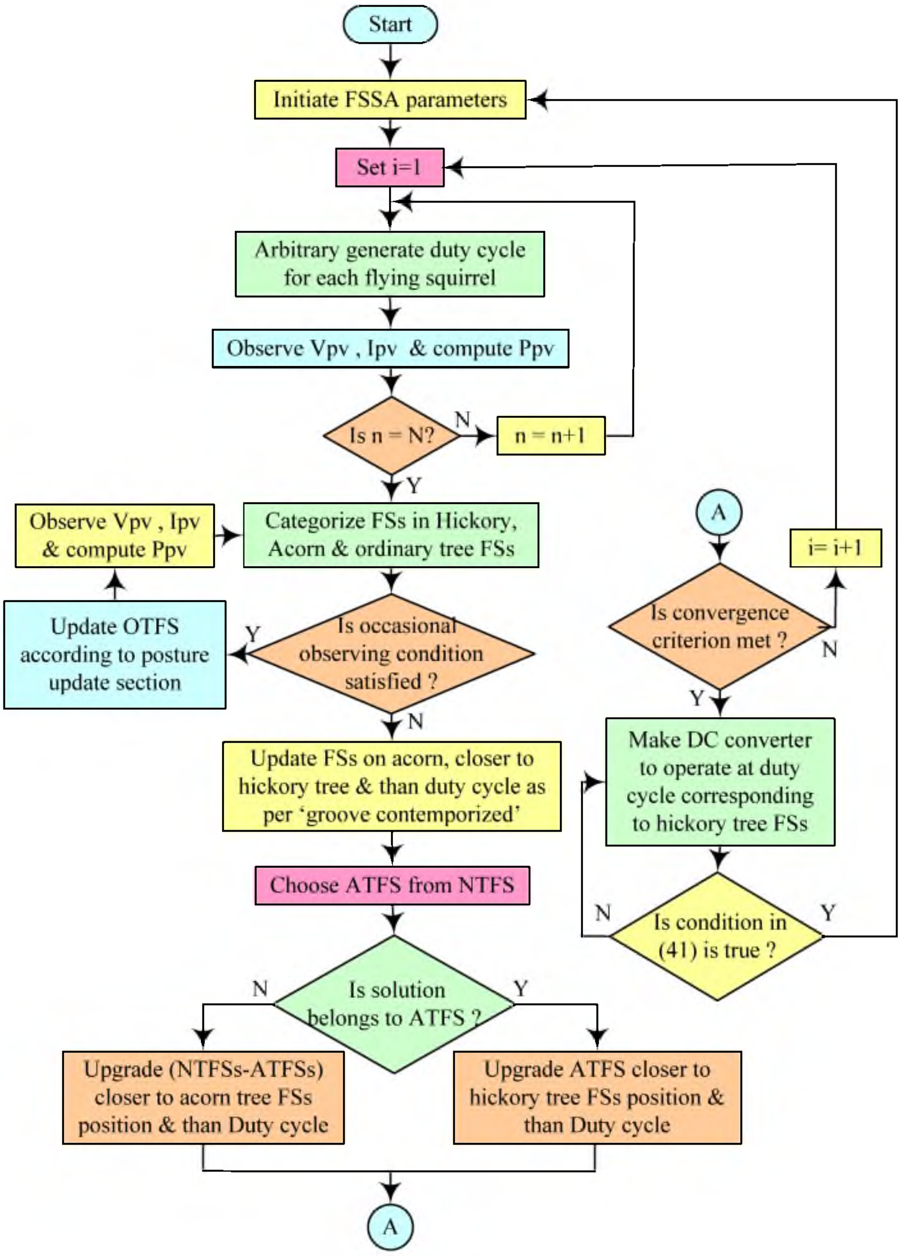


Figure 20. FSSO-based MPPT technique [89].

Table 5. Taxonomy on recent reported work on bio-inspired techniques to track GMPP.

Authors [Reference No.]	Optimization Techniques	Best Optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Saad W et al. [90]	Proposed FA, P&O	Proposed	200	1PV module	201.7 37.7	2.40, 8.02	1000 and 200	Non uniform	NA
Farzaneh J et al. [91]	MFA, P&O PSO, FA	MFA	200.143	4 PV module in series	397.52	9.41	1000–400	Non uniform	2.22
Nusaif AI et al. [92]	MFA, P&O PSO, FA	MFA	265.737	3 × 3	1264, 1206, 1582, 834	1.77, 31.08, 17.70, 27.91	1000–100	Non uniform	0.085–0.124
Abo-Khalil AG et al. [93]	OFA, FA P&O	OFA	NA	NA	48, 36.5, 29	0.418, 2.24, 34.88	NA	Non uniform	0.2–0.33
Shi J-Y [94]	INC-FA, P&O INC, FA	INC-FA	60	4 × 1	81.4	76.19	1000–100	Non uniform	0.98
Omar FA et al. [95]	Proposed FA P&O	Proposed FA	NA	3 PV module in series	100,150,200, 300,400,500	25.00, 2.04, 108.33, 100, 110.52, 170.27	NA	Non uniform	1.3
Chitra A et al. [96]	INC, FA, MFA	MFA	200.143	2 PV module in series	330, 255	6.24, 3.23	1000–600	Non uniform	0.0018–0.0064
Mosaad MI et al. [97]	CS, NN, INC	CS	59.9	1PV module	60.47, 48.24	2.68, 3.36	1000–800	uniform	NA
Shi J-Y et al. [98]	ICS, CS PSO, P&O	ICS	60	4 PV module in series	87.547	74.97	1000–200	Non uniform	0.88
Hidayat T et al. [99]	CSA, P&O	CSA	72	2 PV module in series	97, 107.92, 107.63, 114.94, 124.56, 74.53, 72.58	45.86, 70.75, 63.99, 77.89, 81.52, 5.40, 0.276	944–495	Non uniform	NA
Bilgin N et al. [100]	FFO, PSO, CSO, BOA	FFO	NA	3 PV module in series	531.46, 377.63	5.73, 4.26	1000–278	Non uniform	NA
Ibrahim A-W et al. [101]	CSA, MPSO, MP&O, ANN	CSA	250	4 PV module in series	699.6, 928.5, 534.7, 694.7	67.93, 29.40, 13.25, 4.215	1000–400	Non uniform	0.5–0.7
Bentata K et al. [102]	DCSA, CSA	DCSA	249	2 × 2, 4 PV module in series, 3 × 2, 6 PV module in series	989.29, 482.06, 797.3, 656.45	0.00, 13.31, 6.40, 16.09	1000–200	Non uniform	0.046- 0.085
Singh N et al. [103]	FSSO, P&O, PSO, GWO	FSSO	40	4 PV module in series, 2 × 2	61.66, 48.65, 79.75, 35.37	107.53, 85.68, 61.73, 3.23	900–100	Non uniform	0.3–1.8
Fares D et al. [104]	ISSA, SSA, PSO, GA	ISSA	135	3 PV module in series	227.83, 142.82, 98.79	0.065, 0.098, 0.050	900–100	Non uniform	0.2
Al-Shammaa A A et al. [105]	CS, PSO	CS	NA	4 PV module in series	293.57, 415.38, 578.96	0.00, 0.67, 0.52	1000–200	Non uniform	1.32, 1.29, 1.28
Watanabe R B et al. [106]	FF, P&O	FF	213.15	3 PV module in series	638.7, 553.1, 316.9	0.251, 31.87, 58.05	1000–300	Non uniform	0.18, 0.22, 0.21

Table 6. Pros and cons of recent work based on bio-inspired techniques.

Authors [Reference No.]	Pros	Cons
Saad W et al. [90]	• Zero oscillations around GMPP • High tracking efficiency	• Algorithm is not validated on hardware • Highly intricate to design
Farzaneh J et al. [91]	• Requires no periodic tuning • High accuracy	• Very high tracking time
Nusaif AI et al. [92]	• Varying population size is adapted in each iteration, resulting in improved tracking time and efficiency	• Oscillations around GMPP
Abo-Khalil AG et al. [93]	• High tracking efficiency • Able to process examine MPP	• Power oscillations around GMPP
Shi JY [94]	• High switching speed during shaded to unshaded conditions • No oscillations in steady state	• High tracking time • Computationally complex compared to other MPPT approaches
Omar FA et al. [95]	• High tracking efficiency • Less complex to implement	• High convergence time • Required sensors for its operation
Chitra A et al. [96]	• Very low tracking time	• Low tracking efficiency • Many parameters initializations are required
Mosaad MI et al. [97]	• Randomization process makes the algorithm more effective	• Required tuning of parameters
Shi J-Y et al. [98]	• Tracking ability is enhanced by introducing adaptive step concept • Random steps of CS are eliminated	• High computational complexity
Hidayat T et al. [99]	• Track MPP efficiently in different PSCs	• Levy flight affects the convergence level • Oscillations around GMPP
Bilgin N et al. [100]	• High tracking efficiency	• No record of tracking time in different PSCs • Large no of iterations are required
Ibrahim A-W et al. [101]	• Not dependent on initial location	• Low oscillations around GMPP
Bentata K et al. [102]	• Initial particles are independent • Requires smaller number of iterations which saves power	• Requires higher number of particles • Highly intricate to design
Singh N et al. [103]	• Predators are eliminated for modifying squirrel positions	• High tracking time • High computational cost
Fares D et al. [104]	• High tracking efficiency	• High execution intricacy • Oscillations around GMPP
Al-Shammaa A A et al. [105]	• Only two control parameters are required • No initial situations are assumed for working	• High tracking time • Oscillations in steady state.
Watanabe R B et al. [106]	• Low tracking time	• Power variations in steady state.

4.4. Other AI-Based MPPT

This section of the paper explains other artificial intelligence methods applied in the field of tracking maximum power from the PV array along with a report of the various latest research performed concerning it in Tables 7 and 8 respectively.

4.4.1. Fuzzy Logic Control

FLC converts its analog input to digital values. This technique examines the output power of PV array for every sample. If the change fraction is greater than zero, voltage is enhanced by FLC by adjusting the duty cycle and vice versa. As a result, the maximum power ratio is zero. FLC inputs error "e", and its change "∂e" with samples in time "k_i" can be computed as

$$e = \frac{P_{pv}(k) - P_{pv}(k-1)}{V_{pv}(k) - V_{pv}(k-1)} \quad (42)$$

$$\partial e = e(k) - e(k-1) \quad (43)$$

Figure 21 shows a block diagram of FLC control. The input variables are changed to linguistic variables by using different distinct membership functions. Thereafter, they are manipulated on the basis of the "if-then" rule by applying the required conduct of the scheme. Finally, they are converted to their numerical equivalent [107]. This approach shows fewer oscillations, fast response [108], and high tracking efficiency in contrast to conventional MPPT approaches. However, it suffers from high computational complexity.

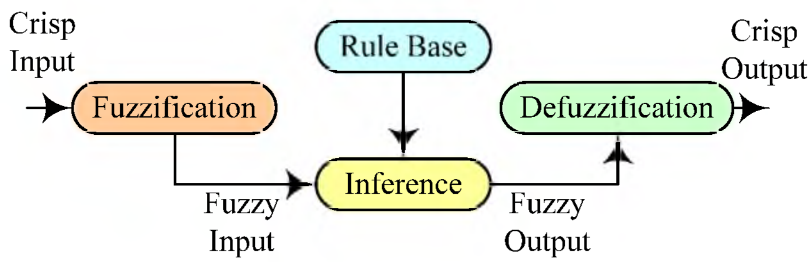


Figure 21. Block representation of FLC-based MPPT.

4.4.2. Artificial Neural Network

An ANN is a set of static learning models. For anticipating a precise output for each input, this approach simulates a biological neural system. Figure 22 shows the three-layered structure of ANN in which the neuron quantity in each layer varies depending on the situation.

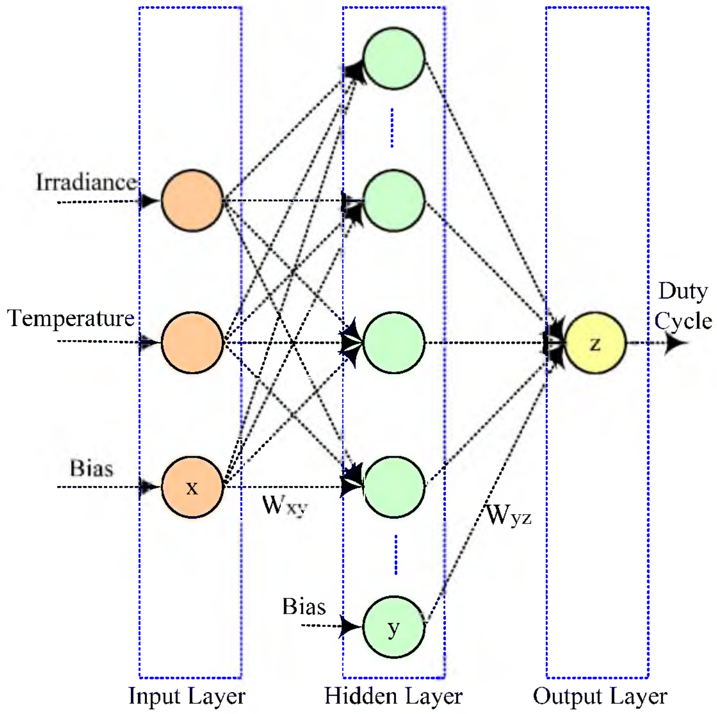


Figure 22. Three-layer structure of ANN [109].

These networks are used as an MPP system to predict the best possible values of power or voltage that can be produced at a given time. These values act as base values in deciding the converter's duty cycle. The PV module parameters and atmospheric parameters are included in the input variables and then processed by hidden layers in the network. The procreation algorithm is retroactive and grades in a mishap. Thereafter, utilizing neurons of center layer, it feeds back the output through the input neurons. The following Equation is used to calculate the presence of hidden neurons:

$$n_h = \frac{1}{2}(n_i + n_o) + \sqrt{n_t} \tag{44}$$

A complete experimental setup assists in data collection. The dataset is then obtained by feeding atmospheric conditions and array parameters into the ANN to find output V_m and P_m. This set is then transformed into an instructional one, which moves into the premeditated ANN, where it is taught how to perform. Moreover, the functions of input data serve as instruction data for the ANN model that was created. Then, the model learns how to execute on its own. The assessment datasets examine the performance of the constructed ANN after the instruction phase, and the errors are sent back to the ANN until all of the neurons' weights are changed correctly. MPPT using ANN is more accurate and shows less oscillation around MPP [109]. These algorithms suffer from the drawback of high computational complexity.

4.4.3. Evolutionary Computational Techniques

Evolutionary computation is an area of artificial intelligence and soft computing that studies a family of algorithms for global optimization inspired by biological evolution. GA and DE are ones amongst them used to track MPP.

GA is a computer model that is inspired by evolution and consists of chromosomes. These chromosomes include information on a potential solution to a problem. Each chromosome has its own set of characteristics. This algorithm is used in wide applications. In contrast to tracking MPP, it is able to boost the PV voltage, which represents the chromosomes and their fitness value that corresponds to PV power. The main idea is to make genetic changes to a population of people and discover the ideal ones corresponding to the fitness function. Figure 23 shows the flowchart of GA.

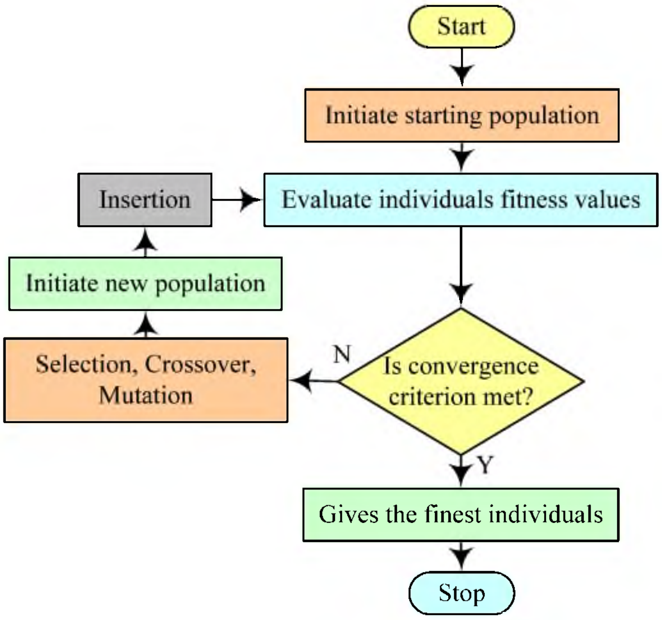


Figure 23. Flowchart of GA [110].

DE is another evolutionary computational algorithm applied to problems based on global optimization. It is applicable to track GMPP in PSCs due to its simpler execution and wide search freedom. The DC converter duty cycle is used as a target vector "∂_n" by this approach. Initially, the target vector with two dimensions is initialized as "∂_n" for each iteration and generation as the population. It chooses three random particles after one generation in order to reduce the execution time. Following that, the selected duty cycles are used to calculate the PV array's associated powers "P_n". "P_{best}" is picked as the maximum power in the set of "P_n", and "∂_{best}" is chosen as the corresponding "∂_n". The weight difference between any two target vectors is then used by a mutation factor (M) and forms the mutated particle by adding this difference to the remaining target vector. The mutated particle is also called the donor vector "DV_n". The mutation's way should be towards "P_{best}". Following mutation, donor and target vectors are combined by a crossover procedure to create trial vector "TV_n" and estimate the PV array's power.

Table 7. Taxonomy on recent reported work on other artificial intelligence techniques to track GMPP.

Authors [Reference No.]	Optimization Techniques	Best Optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Verma P et al. [111]	AFLC, FLC P&O	AFLC	360	3 PV module in series	521.5, 250.6, 198.1	7.30, 0.642, 4.26	900–100	Non uniform	0.1–0.19
Rahman MM et al. [112]	PSO-ANN PSO	PSO-ANN	60.53	4 PV module in series	135.9, 202.1	0.00, −0.04	900–400	Non uniform	0.22, 0.21
Farzaneh J [113]	Proposed P&O, PSO	Proposed	60	3 PV module in series	87.12, 116.74	46.00, 94.17	1000–300	Non uniform	0.15, 0.1
Manikandan PV [114]	Proposed P&O	Proposed	320	1 PV module	36.88, 37.2, 37.66	53.73, 50.12, 51.36	1200–400	Non uniform	NA
Al-Majidi SDet al. [115]	ANFIS FLC, P&O	ANFIS	185	5 PV module in series	924	0.2168	1000	Uniform	0.07
Aymen J et al. [116]	Neuro fuzzy Fuzzy	Neuro fuzzy	60	1PV module	50.262, 45.736, 40.856, 35.633, 30.156	0.001, −0.004, 0.0171, 0.0533, 0.0763	1000–600	Non uniform	NA
Farajdadian S [117]	AF-FA AF-PSO SF, PSO, P&O	AF-FA	220.7	NA	220.5, 175.1, 124.3	1.37, 20.26, 72.87	1000–600	Non uniform	NA
Eltamalya AM et al. [118]	GWO-FLC PSO	GWO-FLC	185.22	NA	54.6, 92.8	40.00, 20.51	1000–200	Non uniform	NA
Chen Y-T et al. [119]	Proposed fixed-step INC FLC-HC ASVSS	Proposed	60	NA	157.3,46.83	5.92, 2.51	1000 and 300	Non uniform	0.42, 0.52
Raj A et al. [120]	ANN-INC INC, P&O	ANN-INC	NA	NA	450	6.13	NA	Non uniform	NA
Abdellatif WSE et al. [121]	FB, P&O, INC	FB	305.226	NA	100.38, 80.17, 59.87	3.14, 3.13, 3.11	1000–600	Non uniform	NA
Mohammed SS et al. [122]	GA fuzzy Fuzzy ANFICS	GA fuzzy	60	1 PV module	44.17, 36.11, 41.68, 41.70, 24.07	0.546, 5.64, 0.506, 0.870, 11.22	791–481.1	Non uniform	NA
Tandel BG et al. [123]	GA, P&O	GA	200.143	16 PV module in series	1319.12	81.16	1000–250	Non uniform	NA
Karthika S et al. [124]	GA-tuned PI PI	GA-tuned PI	200	7×7	7020	56.69	1000 and 200	Non uniform	0.001
Dehghani M et al. [125]	PSO-GA PSO, GA INC, P&O	PSO-GA	1S	NA	98.85, 78.69, 58.64	9.67, 9.30, 9.23	1000–600	Non uniform	< 0.3
Bendary FM et al. [126]	ANFIS-GA ANFIS, NN, FLC	ANFIS-GA	40.9081	NA	40.90, 27.78, 19.28	15.24, 0.908, 1.10	1000–500	Non uniform	< 0.3
Firmanza AP et al. [127]	Proposed DE PSO	Proposed DE	100	2 PV module in series	170.5, 87.9, 152, 130.9	1.66, −0.34, 0.462, 0.383	1000–400	Non uniform	0.233- 0.371

Table 7. *Cont.*

Authors [Reference No.]	Optimization Techniques	Best Optimization Techniques	PV Module P_m (W)	PV System Size	GMPP (W)	Improved GMPP (%)	Irradiance (W/m^2)	Shading Patterns	Tracking Time (s)
Neethu M. et al. [128]	DE PSO	DE	215	4 PV module in series	663.8	81.41	900–600	Non uniform	366
Kamaruddina NI et al. [129]	DE, P&O	DE	125	3 × 3	489.3, 497.2	39.87, 56.40	1000–250	Non uniform	NA
Joisher M et al. [130]	Proposed, PSO, DE	Proposed	95	2 PV module in series	11, 20.33, 13.88	120.0, 18.40, 16.5	NA	Non uniform	1.0
Algarín C R et al. [131]	FLC P&O	FLC	65	1 PV module	11.7, 24.4, 37.7, 51.3, 64.9	0.00	1000–200	Non uniform	NA
Cheng P-C et AL. [132]	Asymmetrical FLC, Symmetrical FLC, P&O	Asymmetrical FLC	220	NA	44.12, 222.18	6.134, 04.53	1000 and 200	Non uniform	0.7, 5.6
Liu C-L et al. [133]	Asymmetrical FLC, Symmetrical FLC, P&O	Asymmetrical FLC	220	NA	222.69	7.63	1000	Uniform	0.91
Kececioglu O F et al. [134]	Proposed, AIC	Proposed	250	1 PV module	249.4, 244.2	0.605, 0.825,	1000–600	Non uniform	0.008
Hayder W et al. [135]	NN-P&O IPSO	NN-P&O	120	1 PV Module	90.2943, 55.2495, 73.076, 98.6604	0.00	1100–600	Uniform	0.2003, 0.0003, 0.7003, 0.0003
Hua C-C et al. [136]	Proposed, P&O+PSO, GA	Proposed	21.31	3 PV module in series	42.90, 37.38, 32.56, 26.73, 22.06	2.21, 0.402, 0.618, 0.074, 5.499	1000–300	Non uniform	12, 15, 16
Zhang P et al. [137]	Improved DE, DE, PSO	Improved DE	NA	4X3	644.57, 857.56	0.041, 0.282	800–350	Non uniform	0.019, 0.02
Bakkar M et al. [138]	DSM-based FLC, FLC	DSM-based FLC	80	1 PV module	80	122.2	700	Non uniform	NA
Batainesh K et al. [139]	Hybrid, FLC+P&O, FLC	Hybrid FLC+P&O	270	1 PV module	127.9, 57.9, 126.2, 46.1	4.40, 3.02, 18.16, 21.31	1000–100	Non uniform	NA
Guerra M I S et al. [140]	ANIFS, P&O, ANN, Fuzzy	ANN	245	NA	956.6, 1674, 2190, 1631	0.525, 0.600, 0.274, 0.803	548–303	Non uniform	NA

Table 8. Pros and cons of recent work based on other artificial intelligence techniques.

Authors [Reference No.]	Pros	Cons
Verma P et al. [111]	• Low shading losses • Low settling time	• Complicate to design
Rahman MM et al. [112]	• Improvement in tracking time • High tracking efficiency	• GMPP is not improved • Not tested on hardware setup
Farzaneh J [113]	• Highly accurate • Requires fewer numbers of training data, which eliminates tracking error	• Highly intricate to design
Manikandan PV [114]	• Enhanced optimal solution	• Low tracking efficiency • Oscillations around GMPP
Al-Majidi SD et al. [115]	• Drift problem is avoided • Low converging time	• Oscillations in steady state • High cost of implementation
Aymen J et al. [116]	• High reliability • Combines advantages of FLC flexibility and ANN learning capacity	• Computationally more complex • High cost of implementation
Farajdadian S [117]	• High accuracy in tracking GMPP • Lower percentage MPP error	• Power fluctuations • Highly complex to intricate
Eltamalya AM et al. [118]	• Re-initializing process enables searching agents to follow new GMPP	• Array size is not specified • No record of tracking time • Oscillations in output power
Chen Y-T et al. [119]	• High tracking capability • Low tracking time	• Array size is not specified • High cost of implementation
Raj A et al. [120]	• Low ripples in output power	• Low tracking efficiency
Abdellatif WSE et al. [121]	• Oscillations in steady state is reduced	• Size of PV array is not specified • Highly intricate to design
Mohammed SS et al. [122]	• High tracking efficiency • Highly accurate	• Computationally more complex
Tandel BG et al. [123]	• Highly accurate in detecting GMPP	• Requires large numbers of iterations
Karthika S et al. [124]	• Ability to track GMPP in vary short duration of time	• Tested in only single change in irradiance
Dehghani M et al. [125]	• Quick response time • High accuracy	• Not tested on hardware • Highly intricate to design
Bendary FM et al. [126]	• High tracking efficiency	• High cost of implementation
Firmanza AP et al. [127]	• High convergence speed due to mutation factor	• Algorithm loses GMPP tracking in some cases • Oscillations around GMPP
Neethu M. et al. [128]	• Low oscillations around GMPP	• High tuning time • High computational cost
Kamaruddina NI et al. [129]	• Able to track true GMPP • Required minimum control parameters	• More values of iterations required • Intricate to design
Joisher M et al. [130]	• Able to track true GMPP	• Power oscillations at output • Computationally more complex
Algarín C R et al. [131]	• Fewer oscillations in steady state • No power loss	• Computationally more complex • Generates error in measuring low powers

Table 8. *Cont.*

Authors [Reference No.]	Pros	Cons
Cheng P-C et al. [132]	• Increased tracking performance without increase in calculation burden	• High tracking time • Low accuracy
Liu C-L et al. [133]	• Improved tracking accuracy • Asymmetrical membership function improved the MPPT performance	• Oscillations around GMPP • High transient time • Computationally more complex
Kececioglu O F et al. [134]	• Oscillations in steady-state output are eliminated	• Computationally more complex
Hayder W et al. [135]	• Low transient time	• If irradiance remains constant for long, algorithm does not show better performance • Computationally more complex in design
Hua C-C et al. [136]	• No oscillations in steady state	• High tracking time • High computational cost
Zhang P et al. [137]	• Mutation factor is modified to limit the random search • Low tracking time	• Comparatively requires large numbers of iterations • Computationally complex
Bakkar M et al. [138]	• Highly accurate	• Issues in determining safe operating region • High cost of computation
Batainesh K et al. [139]	• Highly accurate • No trapping in LMPP	• Oscillations around GMPP • High cost of implementation
Guerra M I S et al. [140]	• Negligible oscillations around GMPP • Fast tracking response	• High cost of implementation • Computationally more complex

After having the deep analysis of all these MPPT techniques, a concluded comparative study has been depicted in Table 9 for better understanding as

Table 9. Comparative analysis of various MPPT.

Categorization	Technique	Execution Cost			Accuracy			Tracking Speed			Oscillations Around MPP				Computational Complexity			Analog/Digital	
		L	M	H	L	M	H	L	M	H	L	M	H	~Z	L	M	H	D	A/D
Conventional	P&O		●		●			●					●		●				●
	INC			●		●			●			●				●		●	
	FOCV	●			●					●			●		●				●
	FSCC	●			●					●		●				●			●
AI-Based Metaheuristic techniques	ACO	●				●				●				●	●			●	
	PSO		●			●			●			●				●			●
	ABC			●		●				●				●			●	●	
	GWO		●				●		●					●	●			●	
	SSA		●				●		●					●	●			●	
	FFA		●				●		●					●	●			●	
	CS			●			●			●				●		●		●	
	FSSO			●			●			●				●		●		●	
Other AI	FLC		●				●			●				●			●	●	
	ANN			●			●		●					●			●	●	
	GA			●			●		●					●			●	●	
	DE		●				●		●					●		●		●	

L, low; M, medium; H, high; ~Z, nearly zero; D, digital; A/D, analog/digital.

5. Research Gap and Findings

There are total 16 techniques reported in this paper. In 23 papers conventional MPPT techniques, 42 papers swarm intelligence MPPT techniques, 21 papers bio-inspired, and in 35 papers other AI-based techniques are discussed. Therefore, a total of 121 papers were mainly studied, which are focused on these MPPT techniques. The remaining 23 out of 144 papers were used in other important sections. The classification of papers focusing on different techniques can be seen in Figure 24.

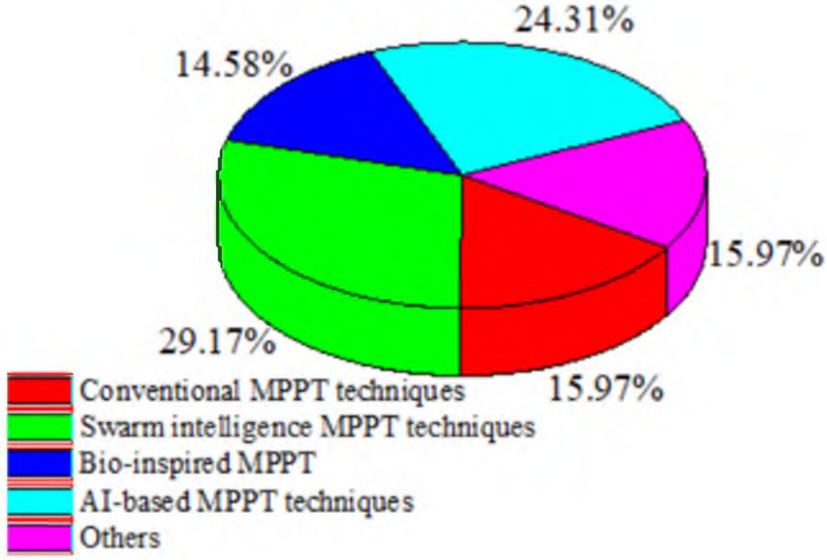


Figure 24. Papers focused on different MPPT techniques.

The authors are mainly classified concerning conventional MPPT techniques, meta-heuristic AI techniques, and other AI-based techniques. Further, conventional MPPT techniques are classified as perturb and observe, incremental conductance, fractional open-circuit voltage, and fractional short-circuit current; particle swarm optimization, artificial bee colony, grey wolf optimization, and salp swarm algorithm fall under swarm intelligence MPPT techniques; and firefly MPPT algorithm, cuckoo search, and flying squirrel search optimization techniques are classified as bio-inspired techniques [141–144]. While swarm intelligence and bio-inspired techniques are metaheuristic AI techniques, other AI-based MPPT techniques are fuzzy logic control, artificial neural network, and evolutionary computational techniques (genetic algorithm and differential evolution).

After conducting a thorough analysis of metaheuristic MPPT approaches based on conventional and AI techniques in this paper, one can easily find the following gaps in this area:

- Despite the fact that conventional techniques are simpler and work better in unshaded spaces, they have the downside of slow response. In their findings, oscillations around GMPP are observed;
- Even though these methods are frequently modified, power loss still occurs while monitoring open-circuit voltage or short-circuit current. Additionally, these methods need a large number of sensors to function, but those numbers can be decreased;
- In PSCs, AI approaches are effective, but they have the disadvantage of having high computational complexity;
- These methods require a great deal of time to track GMPP because of the large number of iterations. Despite the fact that many of these are only tested on virtual platforms, real-world validation is still crucial;
- Most of the reported work ignores the effect of load variation, which is crucial for building any PV system.

6. Challenges and Future Work

This paper comprehensively elaborates many recently reported works to track GMPP in PSCs in detail along with their pros and cons. Presently, over eighty MPPT optimization techniques have been published, and more than four new techniques are published each year. This article covers the recent findings in each MPPT technique in a tabular form. Because there are so many optimization strategies in the literature, picking one becomes quite challenging. Avoiding local MPP and local hotspots of PV array is critical for any optimization strategy. Moreover, when these algorithms are built, there is a requirement to manage energy. Research on efficient MPPT techniques can be rationalized in the future by considering many other critical factors such as local hotspots, array reconfigurations, and cell materials, which contribute to producing maximum power during PSCs. With the aid of smartphones, an MPPT application can also be set to work at any time via the Internet.

7. Conclusions

Solar PV systems are regarded as the most capable energy source in renewable power-generation systems due to the copious availability of sunlight. However, unpredictable weather makes their working efficiency low. Thus, MPPT techniques are used to yield maximum power from these systems in any weather conditions. Much research has been done till now in this field, but selecting an appropriate technique for specific circumstances has always been difficult. For the mentioned reason, this study reassesses the art of various MPPT optimization strategies developed by various researchers so far in a different manner. Conventional and AI-based MPPT techniques are elaborated separately with simplified flowcharts in respective sections with the aim to understand their basic principles in detail for new learners. Following the appropriate evaluation of each study, a tabular summary was created on important attributes of PV systems under PSCs, such as array size, % improvement in GMPP, level of irradiance, and tracking time, forming novel datasheets. In this paper, the reported taxonomy of MPPT techniques can help new learners, researchers, amd professional engineers to interpret the performance of each MPPT approach under different climatic scenarios. After careful analysis, it is easy to conclude that traditional techniques are less complex and work well in unshaded environmental conditions. However, they have the disadvantage of slow response. AI techniques perform well in PSCs with negligible oscillations in a steady state, with high accuracy and high tracking efficiency, but they suffer from high computational complexity. With the tabulated pros and cons of each reviewed article, new learners can easily find the research gaps that still exist in this field. With the help of the comparison table based on important parameters, while incorporating any MPPT in PV system, one can select most appropriate MPPT approach in a specific application. Furthermore, this analysis reveals that AI-based MPP controllers are the best option to deal with PSCs. As a result, a large research area has opened up for new researchers. To summarize, this review paper will be a useful resource for researchers or industrialists to utilize in choosing the most appropriate MPPT method for a certain objective.

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Abbreviations

MPPT	Maximum power point tracking	PV	Photovoltaic
PSCs	Partial shading conditions	RES	Renewable energy sources
P–V	Power–voltage	GMPP	Global maximum power point
P&O	Perturb and observe	INC	Incremental conductance
HC	Hill climbing	BI	Bio-inspired
SI	Swarm intelligence	AI	Artificial intelligence
ANN	Artificial neural networks	FLC	Fuzzy logic control
ECI	Evolutionary computational intelligence	I–V	Current–voltage
MPP	Maximum power point	LMPP	Local maximum power points
DC	Direct current	CS	Cuckoo search
FOCV	Fractional open-circuit voltage	FSCC	Fractional short-circuit current
ACO	Ant colony optimization	ACO-P&O	Ant colony optimization–perturb and observe
SP-INC	Self-predictive incremental conductance	SPC	Semi pilot cell
PC	Pilot cell	CSAM	Current Sensorless Method with Auto-modulation
VSS	Variable step size	PSO	Particle swarm optimization
ABC	Artificial Bee Colony	GWO	Grey wolf optimization
SSA	Salp swarm algorithm	APSO	Accelerated PSO
LIPSO	Lagrange interpolation PSO	TS	Takagi–Sugeno
VCPSO	Variable coefficients PSO	CFPSO	Constriction factor-based PSO
OD-PSO	Overall distribution PSO	P&O-PSO	Perturb and observe-PSO
EGWO	Enhanced GWO	GWO-GSO	GWO–golden-section optimization
GWO-P&O	GWO–Perturb and observe	GOA	Grasshopper optimization algorithm
BOA	Bat algorithm	SSPSO	Series salp PSO
FA	Firefly elgorithm	ISSA	Improved salp swarm algorithm
DE	Differential Evolution	WOA	Whale optimization algorithm
SSO	Salp swarm optimization	ISSA	Improved salp swarm algorithm
SSPO	Hybrid salp swarm–perturb and observe	ABC-P&O	Artificial bee colony–perturb and observe
GMPPT	Global maximum power point tracking	MABC	Modified artificial bee colony
AIC	Angle of incremental conductance	IPSO	Improved particle swarm optimization
OGWO	Opposition-based learning GWO	DFO	Dragonfly optimization
TSA-PSO	Tunicate swarm algorithm with PSO	IABC	Improved artificial bee colony
SPF-P&O	Surface-sased polynomial fitting P&O	HGWO	Hybrid grey wolf optimization
DSM	Dynamic safty margin	ICPSO	Incremental conductance-based PSO
FSSO	Flying squirrel search optimization	BS	Best solution

Nomenclature

I_{pv}	PV output current
I_{ph}	Photocurrent
I_{sh}	Shunt current
I_D	Diode current
I_0	Diode reverses saturation current
q	Electron charge
N_{cs}	Number of cells in series
$\dot{K}$	Boltzmann constant
T	Temperature
V_{pv}	PV output voltage
R_{se}	Series resistance
R_{sh}	Shunt resistance
P_{max}	Maximum power
V_{oc}	Open-circuit voltage
I_{sc}	Short-circuit current
ΔP	Change in power
ΔV	Change in voltage
Δi	Change in current
V_{mpp}	Voltage at maximum power point
b	Proportionality constant
I_{mpp}	Current at maximum power point
d	Constant current factor
P_m	Maximum power
$\hat{G}_i(x)$	Gaussian kernel solution
$\hat{g}_k^i$	Sub-Gaussian function
μ_k^i	Mean value
$\tilde{\alpha}_k^i$	Standard deviation
w_k	Weight factor
ϕ	Best optimal operating solution
$\in$	Convergence rate
$p_{p,best}$	Individual best position
$p_{g,best}$	Swarm optimum position
Y_n	nth particle position
v_n	nth particle velocity
ω	Inertia burden
$\alpha_1 \& \alpha_2$	Social and cognitive acceleration coefficients
$\mu_1 \& \mu_2$	Arbitrary variables that are uniformly distributed between zero and one in terms of their assessments
ft	Target function
$Y_{max,i} \& Y_{min,i}$	Nth-dimension maximum and minimum values.
Y_j	Arbitrarily selected food source
$\alpha_{i,k}$	Arbitrary number between
$\vec{X}_P$	Prey vector
$\vec{X}_{P_{GW}}$	Position vector of grey wolf
$\vec{A} \& \vec{B}$	Coefficient vectors
$\vec{r}_1 \& \vec{r}_2$	Random variables
$X_{m,n}^{new}$	$X_{m,n}$-rationalized candidate solution
P_n	Position of food source

$X_n^+ \& X_n^-$	Decemberision variables maximum and minimum value
μ_0	Initial call
$x_{i,y} \& x_{j,y}$	i^{th} and j^{th} fireflies spatial coordinate "y" components
L	Step length
γ	Variance
$\partial_{max} \& \partial_{min}$	Maximum and minimum duty cycle
$X_{at} \& X_{ht}$	Squirrels' posture address at hickory and acorn trees
H_C	Hovering constant (~1.90)
h_d	Hovering distance
P_{pv}	PV output power
V_m	Maximum voltage
n_h	Hidden neuron numbers
n_i	Injected input neurons numbers
n_o	Output neurons numbers
n_t	Instruction samples numbers

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