

A Comprehensive Review of Swarm Optimization Algorithms for MPPT Control of PV Systems under Partially Shaded Conditions

Deepthi Pilakkat, S. Kanthalakshmi, S. Navaneethan

Abstract—Nowadays many researchers have been investigating on different photovoltaic (PV) modeling methods, various configurations of arrays, numerous algorithms, converter topologies etc to improve the efficiency of solar system. Improving the efficiency of solar panel by utilizing the correct maximum power point tracking (MPPT) control has become more important for conceiving the solar power reasonably. For designing an efficient PV system, an appropriate literature review is necessary for all the researchers. In this paper, a compendious study of different Swarm Intelligence (SI) based MPPT algorithms for PV systems feasible under partially shaded conditions are presented. SI algorithms use motivation from the foraging nature of animals and insects. In the last few decades, SI has gained tremendous attention as it has been proven as an efficient control technique for global optimization problems.

Index Terms—Bio-Inspired optimization algorithms, Maximum Power point tracking (MPPT), Solar PV systems, Swarm Intelligence (SI) algorithms.

Review Paper

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I. INTRODUCTION

DUE to the cost reduction and governmental aids, the PV technology has grown rapidly in each year at a rate of 30% [1]. About 1.8×10^{11} MW power from sun is intercepted by the earth which is ever greater than any other form of energy consumption [2]. Due to the partial shading on the PV panel the efficiency of the system will decrease, increase the cost and complexity [3]. Since the efficiency of the photovoltaic (PV) panel is approximately 20 % -30 %, the maximum power point tracking (MPPT) controllers in PV systems are very important. The performance of the PV system can be enhanced in combination with MPPT by means of electronic power controllers [4].

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The efficiency of a PV system can be substantially increased beyond 95% by bringing the highest possible power out of a PV module. Numerous algorithms have been developed to track the maximum power point effectively. Most of the current MPPT algorithms vary in tracking speed, implementation expense, number of sensors used, implementation of hardware, ability to track true MPP during partial shading conditions (PSC) and other aspects. All the MPPT algorithms are essentially categorized under any of the two following: conventional and non-conventional MPPT algorithms.

The conventional MPPT techniques such as Perturb and Observe (P&O) [5]-[6], Incremental conductance (INC) [7]-[8], Fractional Open Circuit Voltage (FOV) [9], Short-Circuit Current Control (SCCC) [10] are the most widely used techniques due to its simplicity and ease of implementation. Other types of MPPT algorithms, including Artificial Intelligence (AI) [11], Fuzzy Logic (FL) [12]-[13], and Bio-Inspired (BI) [14] algorithms are also available in literature, which fall under the category of non-conventional MPPT algorithms. Biologically inspired algorithms have been used in recent years as the key techniques to get the best solutions to real engineering design optimization problems. They always offer an optimal solution for optimization problems while maintaining a perfect balance between the components. Most researchers have paid more attention to this field in the last few decades. The two most predominant and successful classes in bio-inspired algorithms are evolutionary algorithms and swarm intelligence based algorithms. These algorithms are derived from the study of the natural evolution of living things and their swarming behavior. Fig.1 shows the general classification of different MPPT algorithms used in for photovoltaic applications. Nature-inspired optimization algorithms are developed as powerful tools to solve the complicated problems. SI is a fairly new interdisciplinary research field, which has become popular these days [15]. It is possible to adapt and apply the characteristics and lifestyles of birds, animals and other living organisms to solve many real world problems. SI-based optimization algorithms have been developed to model animals' intelligent behavior. In these modeling systems, by sharing information, a group of organisms such as ants, bees, birds and fish communicate with each other and with their environment, resulting in the use of their environment and resources. Many SI based algorithms such as Artificial Bee Colony algorithms (ABC)[16], Particle Swarm Optimization (PSO) [17], Bat Algorithm (BA) [18]

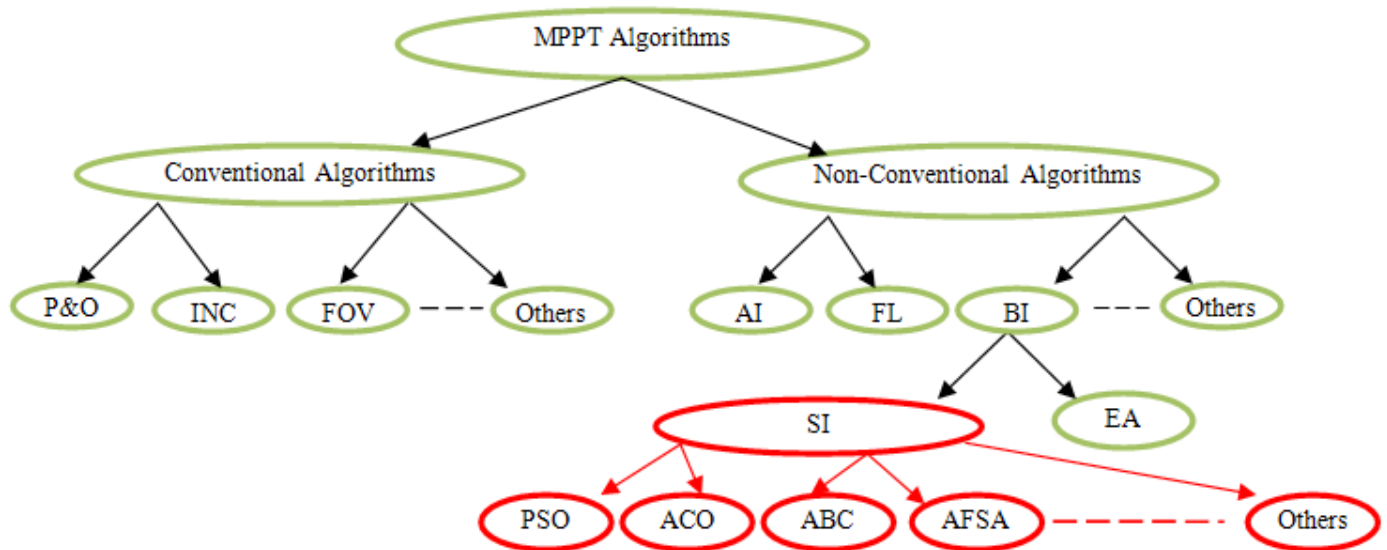


Fig. 1. Classification of MPPT algorithms used in PV system

etc. have been used for many real world optimization applications including MPPT tracking. Nevertheless, some difficulty remains, and new algorithms are still required for better optimization. While new algorithms, including chicken swarm optimization (CSO) [19], Krill herd algorithm (KHA) [20], Grey Wolf Optimization (GWO) [21] etc., are still imminent, the development of a better algorithm from nature's knowledge is an interesting research subject. This paper reviews the implementation of various MPPT algorithms (particularly on SI), which are influenced by nature and are used in partial shading conditions (PSC) for solar PV systems.

II. PV SYSTEMS UNDER PARTIAL SHADING CONDITION

A PV panel is the basic building block of a photovoltaic generation system (PGS). The PV panels consist of a large number of series or parallel solar cells to provide the necessary voltage and current. The change in temperature or irradiance will directly affect the output of PGS. When partial shading occurs, there exhibits multiple number of power peaks in power-voltage (P-V) curve. For better understanding of shading effects, Fig.2(a) shows a PV array with four modules connected in series (with bypass diodes connected in parallel with each module

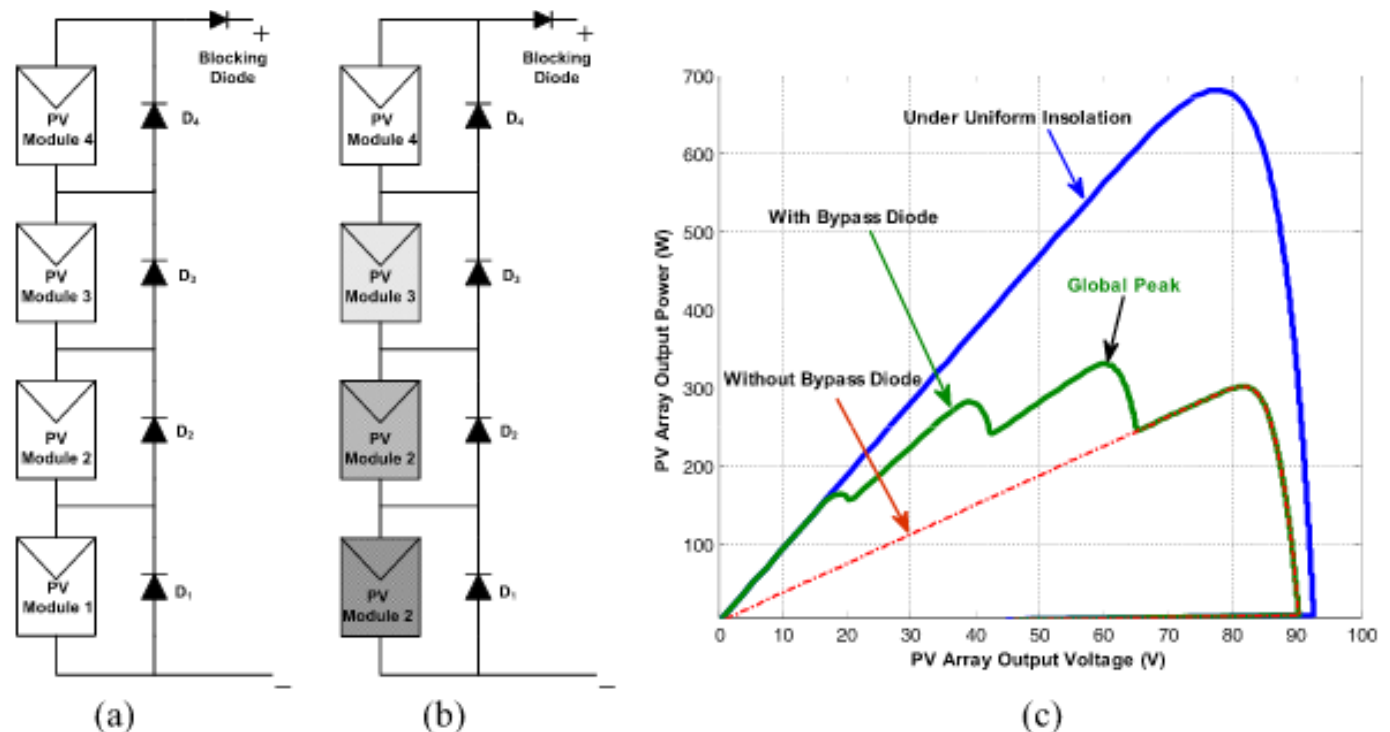


Fig. 2. Operation of solar PV array (a) under uniform insolation, (b) under shading condition, and (c) corresponding P-V curve [22]

and one blocking diode connected in series in the string) under uniform insolation condition. In Fig. 2(b) the PV modules are undergoing PSC and the corresponding P-V characteristics are shown in Fig. 2(c) with multiple power point (MPP) [22]. These complex P-V features would confuse local MPP (LMPP) monitoring, rather than global MPP (GMPP). To track GMPP, a global optimization algorithm is required, so that maximum power can be extracted from the PV panel.

III. MODELING OF A PV SYSTEM UNDER PARTIAL SHADING CONDITIONS

The general mathematical model in equation (1) gives the output power from a PV panel.

$$I_{PV} = N_p \cdot I_{ph} - N_p \cdot I_s \left[\exp \left\{ \frac{q(V_{PV} + I_{PV}R_s)}{N_s \cdot A \cdot k \cdot T_{op}} \right\} - 1 \right] \quad (1)$$

where, N_p and N_s represents parallel and series connected cells. I_{ph} denotes the photo current of the module, I_s represents saturation current, q is electron charge, k is Boltzman constant, A is ideality factor and T_{op} is module operating temperature in Kelvin. The equation (1) is no longer applicable in the case of PSC because dissimilar levels of irradiance are dispersed between the PV arrays as shown in figure number 2 (Fig. 2). The characterization of PV systems under PSC therefore requires a new mathematical model. Alajmi et al. undertook a comprehensive study in 2013 on various irradiation conditions for various PV module connections [23]. The authors derived a general numerical model for n series connected PV modules under partial shading conditions which is given in equation:

$$V_{PV} = \begin{cases} \sum \frac{AKT n_s^{us}}{q} \ln \left(\frac{I_{sc} \lambda^{un} - I_{PV}}{I_o} \right), & I_{PV} > I_{Nstep} \\ \vdots & \vdots \\ \sum \frac{AKT n_s^{us}}{q} \ln \left(\frac{I_{sc} \lambda^{un} - I_{PV}}{I_o} \right) + \frac{AKT n_s^{s1}}{q} \ln \left(\frac{I_{sc} \lambda^{s1} - I_{PV}}{I_o} \right), & I_{1step} < I_{PV} < I_{2step} \\ \sum \frac{AKT n_s^{us}}{q} \ln \left(\frac{I_{sc} \lambda^{un} - I_{PV}}{I_o} \right) + \frac{AKT n_s^{s1}}{q} \ln \left(\frac{I_{sc} \lambda^{s1} - I_{PV}}{I_o} \right) + \dots + \frac{AKT n_s^{sN}}{q} \ln \left(\frac{I_{sc} \lambda^{sN} - I_{PV}}{I_o} \right), & I_{PV} < I_{Nstep} \end{cases} \quad (2)$$

where n_s^{us} is the number of unshaded PV modules and λ^{un} is the unshaded radiation. n_s^{sN} is the number of partially shaded PV modules with the highest radiation level and λ^{sN} is the highest radiation level. N is the number of distributed radiation levels. I_{sc} is the short-circuit current of the unshaded PV modules. I_{1step} is the short-circuit current of the shaded PV module. I_{2step} is the short-circuit current of the shaded PV modules with the highest radiation level.

IV. SWARM INTELLIGENCE BASED MPPT ALGORITHM FOR PV SYSTEMS

The following sections address various SI-based MPPT optimization algorithms used in PV systems.

A. Particle Swarm Optimization Algorithm (PSO)

It is an optimization algorithm based on swarm intelligence developed by Eberhart and Kennedy in 1995 [24]. This algorithm is inspired from the swarm behavior of social animals like fishes and birds. In this, a large number of particles (agents) travel around in the search space in search for the best solution. Each particle in the problem space represents a potential solution vector P_i (Position). These particles adjust its velocity according to its own flying experience and experience of its companions. The velocity of each particle is represented by a velocity vector V_i . A fitness function ' f ' shall be calculated using P_i as a quality measurement input. Each particle retains the best fitness it has achieved so far and sets it to P_{best} as its individual best position. In addition, the best solution is taken as G_{best} between all particles that have been achieved so far in the swarm. All of this information is made available for all particles to converge to the best global solution [25].

For finding an optimal solution for a problem, PSO adjusts the personal best position (P_{best}) and global best position (G_{best}) using the following equations:

$$V_{i(j+1)} = \omega V_{i(j)} + C_1 r_1 (P_{best} - P_{i(j)}) + C_2 r_2 (G_{best} - P_{i(j)}) \quad (3)$$

$$P_{i(j+1)} = P_{i(j)} + V_{i(j+1)} \quad (4)$$

where P_i presents the position of particle and V_i is the velocity, ω is the inertia weight which is used to represent the impact of previous particle velocity on its current one. r_1 and r_2 are random variables uniformly distributed within $[0, 1]$. C_1 and C_2 are the coefficients of acceleration. The flowchart of conventional particle swarm optimization is shown in Fig. 3.

PSO has been widely extended for various applications such as complex and multi-dimensional optimization problems. The major advantages of PSO includes simple computation, reliable and robust, guaranteed global convergence, and simple application with less expensive controller. Recently, PSO algorithm has been considered as one of the promising algorithm for solution of global optimization problems.

i. Application of PSO in MPPT

Miyatake et al. revised the standard PSO approach in 2007 to be extended to regulate the MPPT [26]. The fitness function f often changes with regard to atmospheric or electric load variations in real-time applications. The algorithm must be restarted to track the real MPP in these instances. The particles are reinitialized if the above conditions change and the following two equations are used to identify them:

$$|v_{i+1}| < \Delta v \quad (5)$$

where v_{i+1} represents the velocity of the next particle and Δv represents change in velocity, and:

$$\frac{P_{i+1} - P_i}{P_i} < -\Delta P \quad (6)$$

where P_i is the power output of the solar panel.

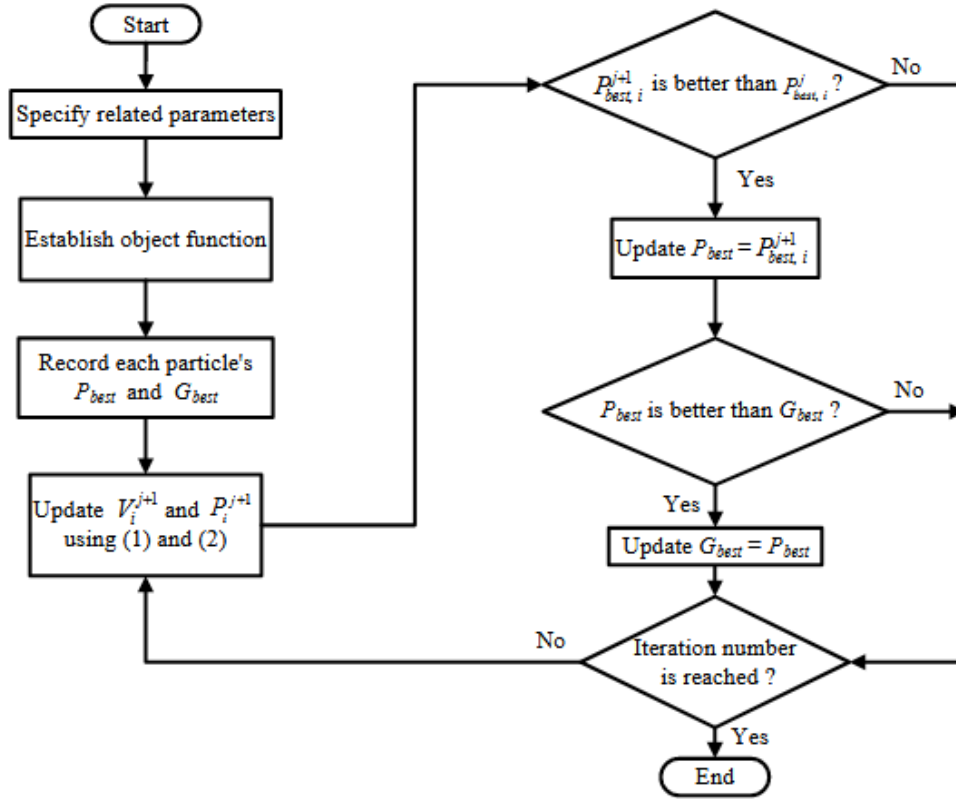


Fig. 3. Flowchart of conventional PSO algorithm [26]

The equations (5) and (6) correspond to agent's convergence detection and sudden change of insolation, respectively.

For practical application of PSO for MPPT controllers in PV system, the position of particle, P_i is considered as the duty cycle d_i . Thus, the velocity, acts as a perturbation in the current duty cycle and the equation changed as shown below.

$$d_{i(j+1)} = d_{i(j)} + V_{i(j+1)} \quad (7)$$

To reduce the difficulty in finding MPP, Phimmasone *et al.* in 2009 [27] modified the conventional PSO technique by adding a repulsive term to the PSO equation. This modification simplifies the PSO and enhances their response to monitor the MPP under different atmospheric conditions. It leads to greater productivity and lower costs. The enhanced PSO-MPPT algorithm by means of overall energy production is superior to traditional PSO-MPPT methods.

In 2012, Ishaque and Salam, successfully modified the conventional PSO algorithm by eliminating the random variables and introduced a new Deterministic PSO (DPSO) algorithm [28]. Moreover, only one parameter needs to be tuned in the proposed method; which is the inertia weight. For implementing the DPSO algorithm they used TMS320F240 DSP on the Dspace DS1104. The authors claim that the proposed method has good accuracy and better speed compared to the conventional hill climbing method.

In the same year, Liu *et al.* proposed a modified PSO algorithm for PV generation systems under partial shading conditions [29]. In conventional PSO method equation (3)

and (4) are used to update the particle, in which w , C_1 and C_2 are constants. In this paper, authors modified these constants as variables and updated equation (3) as shown below.

$$V_{i(j+1)} = w_j V_{i(j)} + C_{1(j)} r_1 (P_{best} - P_{i(j)}) + C_{2(j)} r_2 (G_{best} - P_{i(j)}) \quad (8)$$

To speed up the convergence the inertia weight, ω is set as maximum in the initial condition and is linearly decreased using equation (9):

$$w_j = w_{max} - \frac{k}{k_{max}} (w_{max} - w_{min}) \quad (9)$$

where, w_{max} and w_{min} are the maximum and minimum values of w , and k_{max} is the maximum allowed number of iterations.

The direction of particles will also be biased by modifying C_1 and C_2 . If $C_1 > C_2$, it will move towards the direction of p_{best} , whereas if, $C_1 < C_2$, it will move in the direction of g_{best} . In this paper, C_1 and C_2 are interpreted as linearly decreasing and linearly increasing functions, respectively with the help of the following equations:

$$C_{1(j)} = C_{1,max} - \frac{k}{k_{max}} (C_{1,max} - C_{1,min}) \quad (10)$$

$$C_{2(j)} = C_{2,min} + \frac{k}{k_{max}} (C_{2,max} - C_{2,min}) \quad (11)$$

In equation (10) and (11), $C_{1,min}$, $C_{1,max}$ and $C_{2,min}$, $C_{2,max}$ are the minimum and maximum values of C_1 and C_2 , respectively.

The authors claim the suggested approach has the following benefits. (1) Very high tracking efficiency of over 99.5%. (2) Easy to implement. (3) Guaranteed convergence in a reasonable time to the optimal solution. (4) Furthermore, only knowing the number of series cells is necessary for the proposed method; therefore, the system is independent.

A hybrid PSO algorithm which combines the conventional P&O and PSO algorithm is introduced by Lian et al. in 2014 [30]. The P&O algorithm first tracks the LMPP with the proposed method, and then the PSO actively seeks the GMPP in the second stage. This results in less search space in the second stage and quickly converges to GMPP. In 2016, Chaieb and Sakly introduced one of the other hybrid methods combining the Simplified Accelerated Particle Swarm Optimization (SAPSO) with the conventional Hill Climbing (HC) algorithm [31]. The author's aim was to develop an MPPT controller with high efficiency, quick response and less hardware and software requirements. For the validation of the proposed method under PSC it has been simulated and implemented for practical application. It shows that under PSC the HSAPSO system can track GMPP in the same exactness and efficiency with less hardware complexity and cost than the traditional PSO.

B. Artificial Bee Colony Algorithm (ABC)

ABC is a reasonably new swarm intelligence based algorithm for global optimization. It is introduced by Dervis Karaboga in the year 2005 [32], based on the foraging behavior of honey bees. The artificial bee colony consists of three fundamental groups. They are employed bees, onlooker bees and scout bees. Fifty percent of the bee colony comprised of employed bees and other fifty percent made up of onlooker bees. The food source selection, evaluation, memorization and exchange of information between the bees are the fundamental idea of artificial bee colony. Initially an employed bee goes to a food location to collect nectar and then it conveys the information about the location and quantity of the nectar to the employed bees with the help of waggle dance movements. The onlooker bees at the hive thus move towards the food location with the highest nectar and begin exploitation. The employed bee with abandoned food source will become a scout and go for searching of new locations.

i. Application of Artificial Bee Colony algorithm in MPPT

The flowchart of ABC algorithm used for MPPT in PV system under PSC is shown in Fig.4. Total size of the bee colony is equally divided as employed bees and onlooker bees. All employed bees are randomly chosen different duty cycles using equation (12) and then this duty cycle are updated with the help of equation (13) based on the output power quantity.

$$x_i = d_{min} + rand[0,1](d_{max} - d_{min}) \quad (12)$$

$$x_{i-new} = x_i + \phi_i [x_i - x_k] \quad (13)$$

where, ϕ_i is an arbitrary variable selected between [-1,1]. The duty cycle with maximum power is optimized by comparing the

probability factor associated with each duty cycle. The probability is calculated with the help of the following equation:

$$p_i = \frac{f_i}{\sum_{N=1}^{N_p} f_N} \quad (14)$$

where, f_i is the fitness factor of i^{th} location and is calculated by equation (15):

$$f_i = \begin{cases} \frac{1}{1 + Objval_i}; & \text{if } Objval \geq 0 \\ 1 + abs(Objval_i); & \text{Otherwise} \end{cases} \quad (15)$$

where, $Objval$ is the objective value at i^{th} location. The process will reinitialize whenever there are changes in solar irradiation. The following condition of inequality characterizes this change in insolation.

$$\left| \frac{P_{pv} - P_{pv_old}}{P_{pv_old}} \right| \geq \Delta P_{pv} \% \quad (16)$$

This condition makes sure that, even if the solar irradiance changes, ABC algorithm is always able to track the GMPP [33].

Several researchers have conducted MPPT control in PV systems based on this algorithm. In 2015, A soufyane Benyoucef *et. al* [34] proposed ABC algorithm to be used in MPPT in PV systems. The authors examined this algorithm under different partial shading conditions and compared it to the PSO algorithm. For each shading pattern they executed this algorithm 200 times and concluded from the result that the ABC algorithm is performing better, specifically in terms of the number of successful convergences.

In 2013, the artificial bee colony MPPT algorithm was used by Bilal for photovoltaic plants [35]. The ABC algorithm to minimize the objective function is used here. For MPPT problems it is important to trace the maximum point at which power is maximum. To this end he proposed a transformation of the y axis to minimize objective function. The transformed power value is determined by the equation:

$$P' = 250 - P \quad (17)$$

where P is the instantaneous value of power. The maximum output power for the selected panel is 200W. So a transformation value of 250 is chosen for an efficient and non-interfering transformation. This transformation results in a mirror image of the PV curve. The author also compared the results of the ABC algorithm with those obtained by P&O for different shading patterns. Finally he concluded that at high irradiance levels ABC algorithm gives better results compared to P&O.

ABC MPPT was studied by Babar and Craciunescu in 2014 for use with PV systems and compared with other algorithms such as P&O, Fuzzy Logic Controllers (FLC), and Genetic Algorithm (GA) etc [19]. They used objective function maximization for maximum power extraction with certain functional modifications. The power is chosen as the objective function for MPPT problems. They noticed that the ABC algorithm was

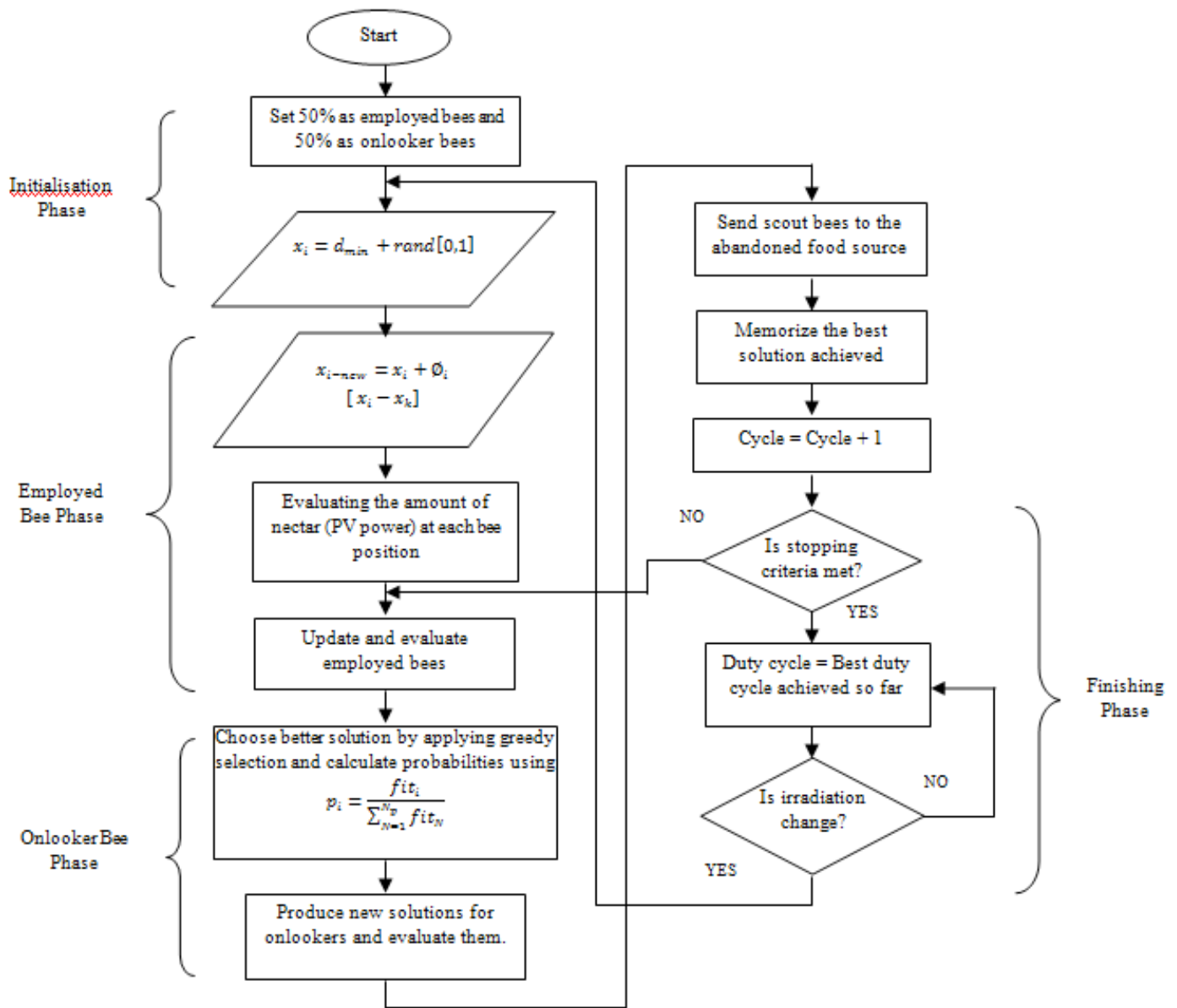


Fig. 4. Flowchart of ABC algorithm used for MPPT [36]

tracking MPP and extracting maximum power very quickly. These are; however, subject only to uniform insolation conditions.

The problem of MPPT under in-homogeneous insolation condition has been solved by Kinattungal Sundareswaran et. al in 2015 [37]. They developed an enhanced ABC algorithm in which the scout bee phase presented in the general ABC algorithm has been eliminated and included a new reinitiating search phase. In this phase, if the solar insolation changes (it will have an impact on change in the power output) the algorithm will get reinitiated. Any power output shift has been sensed and sampled in each 0.1s. They concluded that ABC has faster tracking characteristics and less oscillating power output. Based on the experimental validation of the developed approach, they conclude that the ABC algorithm shows better energy savings and revenue generation compared to other MPPT methods.

C. Ant Colony Optimization Algorithm (ACO)

Another prominent SI algorithm is ACO, proposed by Marco Dorigo in early nineties and effectively applied for several combinatorial optimization issues [38]. Later on, these algorithm has been used for many continuous optimization problems [39]-[40]. This is a probabilistic algorithm inspired by the social behavior of ants based on how they find an optimal path for searching of their food.

These ants randomly move along the search space to explore food source, while depositing pheromone on the ground in order to attract more members of the colony [41]. The quantity of pheromone on the moving path is directly proportional to the amount of food. Thus, the trail with largest amount of pheromone becomes the target path [42].

ACO_r is one of the main ACO based algorithm proposed by Socha and Dorigo in 2008 for continuous optimization problem [43]. Initially there are k arbitrary solution vectors are

chosen. The vectors $S_i(i=1,2..k)$ and its fitness function $f(s_i)$ in the archive are shown in Fig.5 [44]. The optimum solution is attained by updating all possible solutions in the archive until the stopping condition is met. The general procedure for generating solution for ACO_R based optimization problem includes the following three steps. They are initialization, generation of new solutions, and ranking and updating solution [45].

S_1	S_1^1	S_1^2	...	S_1^i	...	S_1^n	ω_1	$f(s_1)$
S_2	S_2^1	S_2^2	...	S_2^i	...	S_2^n	ω_2	$f(s_2)$
.
.
.
S_j	S_j^1	S_j^2	...	S_j^i	...	S_j^n	ω_j	$f(s_j)$
.
.
.
S_k	S_k^1	S_k^2	...	S_k^j	...	S_k^n	ω_k	$f(s_k)$
G^1	G^1	G^1	...	G^i	...	G^n		

Fig. 5. Solution generation process in ACOR [44]

Step 1: Initialization

In this step, initial values for all the parameters like, number of ants (N), size of archive (K), maximum number of iterations etc are selected. Then, k arbitrary solutions are generated and stored in the solution archive, with $k \geq N$, and further, based on the fitness value, all these solutions are ranked as: $f(s_1) \leq f(s_2) \leq \dots \leq f(s_k)$ [44].

Step 2: Generation of new solutions

For each dimension, new solutions are generated by sampling the probability density function which is represented by the following Gaussian kernel.

$$G_i(x) = \sum_{l=1}^k w_l g_l^i(x) = \sum_{l=1}^k w_l \frac{1}{\sigma_l^i \sqrt{2\pi}} \exp\left(-\frac{(x - \mu_l^i)^2}{2\sigma_l^{i^2}}\right) \quad (18)$$

where $G_i(x)$ is the Gaussian kernel for the i^{th} solution and $g_l^i(x)$ is the l^{th} sub-Gaussian function for the i^{th} solution. The mean, and standard deviation is calculated by the following equations, respectively:

$$\mu^i = (\mu_1^i, \dots, \mu_{l_1}^i, \dots, \mu_{k_1}^i) = (s_1^i, \dots, s_{l_1}^i, \dots, s_{k_1}^i) \quad (19)$$

$$\sigma_l^i = \xi \sum_{j=1}^k \frac{|s_j^i - s_l^i|}{K-1} \quad (20)$$

where ξ is the speed of convergence (as ξ increases, convergence time also increases) and S_j is the chosen solution.

Weight ω_l is given by the following equation:

$$w_l = \frac{1}{QK\sqrt{2\pi}} \exp\left(-\frac{(l-1)^2}{2Q^2k^2}\right), (w_k \leq \dots \leq w_1 \leq \dots \leq w_2 \leq w_1) \quad (21)$$

where Q is a parameter representing the importance of the best ranked solution. More discussion about the parameters of Q and

ξ can be found in paper[43]. The probability of choosing the Gaussian sub-function is based on the following equation (22):

$$p_l = \frac{w_l}{\sum_{r=1}^{r=k} w_r} \quad (22)$$

Step 3: Ranking and archive updating

The above process is repeated for every sample and generates M new solutions. Add the newly generated solutions to the original solutions and rank all these $M + K$ solutions. Then keep only the K best solutions in the archive. The whole procedure is repeated until the maximum iteration is reached or the termination conditions are satisfied.

i. Application of Ant Colony Optimization algorithm in MPPT

In order to apply ACO to find MPP in solar PV systems, ant's behavior in searching of food is mimicked by many researchers. The pheromone deposition at each location is considered as the output power at that location and the position of ant is considered as duty cycle. The following steps involved in the process of ACO for MPPT.

Step 1: In this step the number of ants and step size of ant's movement is fixed. Let the step size is labeled as ' ϑ_l ', which decreases exponentially as the iteration proceeds. ϑ_l for k^{th} iteration is given by,

$$\vartheta_l(k) = \vartheta_0 e^{-k} \quad (23)$$

where ϑ_0 is initial step size.

Step 2: Locate these ants at different positions in the solution space. The minimum and maximum duty ratio is considered to be 10% to 90%. Thus the equal distribution of ants between 10% to 90% of duty ratio will guarantee to track the GMPP. (In the traditional ACO, random distribution of ants is deployed).

Step 3: The power output of the PV system is calculated for each ant position. The amount of pheromone at each location shall be considered to be the power at that location.

Step 4: The ant with maximum pheromone will continue to stay at its current position, and all other ants will update its position using the following equation [46]:

$$d_i^{k+1} = d_i + \vartheta_l \bar{a} \quad \text{Subjected to} \\ d_{imin} \leq d_i^{(k+1)} \leq d_{imax} \quad (24)$$

where \bar{a} is a unit vector. Iteration is said to be done if all the ants complete their action.

Step 5: Repeat steps 3 and 4 until all the ants converge to MPP.

L.L Jiang *et al.* in 2013 proposed ACO for MPPT under partial shading conditions [47]. In this paper, the authors successfully analyzed the relationship between convergence speed and tracking accuracy. As the number of ants increases, possibility to converge at the accurate duty cycle also increases. But it will take more time to converge all ants into the MPP. Smaller number of ants will give speedy convergence; conversely, they can simply happen to trapped on one of the LMPP. The viability

of this projected scheme is confirmed with the irradiance of different shading patterns by simulation. The correlation between the dimension of the archive and the proportion of the derived power for all the cases is examined in the paper.

In 2016, Sundareswaran *et al.* used 5s PV configuration with two different non uniform irradiance profiles in order to analyze the performance of ACO MPPT [46]. They have compared the conventional P&O with ACO and found that P&O method is a smoothly varying one with low ripple content in the output power but failed to track GMPP, whereas ACO is a promising method for tracking GMPP under PSC. Thus the authors have proposed a new MPPT method called ACO-PO, which combines the global search ability of ACO in the formative stages and local search ability of P&O in the later stages. This method possessed good static and dynamic tracking characteristics with lower CPU usage. Experimental analysis is also presented to validate the novelty of the proposed algorithm.

S. Titri *et al.* in 2017 [48], proposed a modified ACO MPPT algorithm called ACO-NPU-MPPT. They included a modification in the Pheromone updating strategy so as to reduce the computational time with high accuracy, less oscillations and increased robustness. Various tests are conducted for differently varying weather conditions and for different partial shading conditions. Validation of this algorithm has been performed by comparing it with some conventional, soft computing and biological methods.

D. Artificial Fish Swarm Algorithm (AFSA)

In 2002, Li *et al* proposed a new evolutionary swarm-based algorithm called Artificial fish swarm algorithm (AFSA) [49]. This algorithm is motivated by the intelligent behavior of fish swarms such as foraging, collision behavior and communication between fish individuals so as to reach the global optimum.

Artificial fish (AF) is an imaginary creature of real fish, which is used for carrying out the analysis and justification of a problem, and can be realized by means of animal ecology theory. The solution space for an AF is mainly the environment where it lives and the states of other AFs. The current state and the states of the nearby fish determine the next behavior of an AF [50] while the receiver has no knowledge of the transmitter spreading sequence, only knows the length of spreading sequence. The presented estimation method by Artificial Fish Swarm Algorithm (AFSA). Unlike in PSO algorithm, each AF keeps the current position and the companion's position to obtain the global best position, whereas in PSO past experiences are noted.

As shown in Fig. 6, AF observes external perception with its visual awareness. Current state of AF is denoted by vector X . The visual is equal to the visual distance, and X_v is the future place in visual where the AF determines to shift towards. If X_v has an improved food quantity than the current location, AF moves from X to X_{next} . Or else, continues in the current position and selects another spot in its vision.

Food density in location X is considered as the fitness value in that position, and denoted as $f(X)$. The maximum length of each step is denoted as 'step'. The distance between two AFs

placed in X_i and X_j are determined by (Euclidean distance) [51].

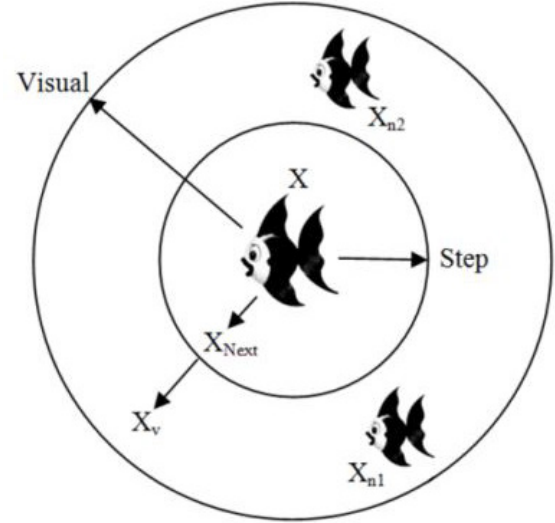


Fig. 6. Artificial Fish and the Environment [51]

This algorithm has been applied for many optimization problems and the different behaviors of fish are modeled mathematically as follows: [52]-[53].

(1) AF_Random Behavior:

The AF will move randomly in its area of vision. Let the current position be X_i . When it chooses another location, X_j , randomly it will move to that position. It is given by equation (25):

$$X_j = X_i + Visual \cdot rand() \quad (25)$$

where $rand()$ is the random number between $[-1,1]$.

(2) AF_Preying Behavior:

Let $F(X)$ is the quantity of food at each location (objective function). If $F(X_i) > F(X_j)$ in a minimization problem, it continues in the current direction using equation (26):

$$X_{i(t+1)} = X_{i(t)} + \frac{X_j - X_{i(t)}}{\|X_j - X_{i(t)}\|} \cdot Step \cdot rand() \quad (26)$$

Otherwise, again select another random state X_j and check whether it satisfies the condition. If it cannot satisfy after some limit number, it moves a step randomly using equation:

$$X_{i(t+1)} = X_{i(t)} + Visual * rand() \quad (27)$$

(3) AF_Swarming Behaviour:

AF searches its companion AF, denoted as X_c , in its neighborhood. If X_c has more food quantity than X_i , and the crowd factor of X_c is less than X_i , AF move towards X_c using the equation (28):

$$X_{i(t+1)} = X_{i(t)} + \frac{X_c - X_{i(t)}}{\|X_c - X_{i(t)}\|} * Step * rand() \quad (28)$$

Otherwise it will follow the preying behavior.

(4) AF_Following Behaviour:

An AF at position X_i find X_{max} with $F(X_{max})$ is the maximum value in the near fields, and position of X_{max} is not too crowded, then follows equation .

$$X_{i(t+1)} = X_{i(t)} + \frac{X_{max} - X_{i(t)}}{\|X_{max} - X_{i(t)}\|} * Step * rand() \quad (29)$$

(5) AF_LeapingBehaviour:

In order to avoid setting up on local minima, AF will leap out of the current state, if there is no big difference in the food concentration, after some iteration and is determined by equation (30):

$$If(F(X_i) - F(X_j)) < eps \quad (30)$$

The new location is given by

$$X_{(t+1)} = \alpha X_{(t)} + *Visual * rand \quad (31)$$

where α is a parameter which will allow the AF to have some other abnormal behavior, and eps is a constant.

(6) AF_BulletinBehaviour:

This behavior is used to memorize the food concentration at current location and the optimal AF's state. Each time the bulletin is updated and the optimal value is the final value of the bulletin. The algorithm will get terminated after completing the given number of iteration or a steady state of error range is achieved in the bulletin.

The process of AFSA is shown as follows:

- (a) Initialize the AFSA parameters: Population of AF, Iteration time, Step, Visual, Crowd factor (δ), try_number.
- (b) Randomly generate position of AF using equation .
- (c) Update the position of each AF using the four behaviors: Preying, Swarming, Following, Leaping, and Bulletin.
- (d) Evaluation and fitness value of each AF is calculated. If better food location is not found after try_number, AF moves randomly.
- (e) Repeat step c until termination criteria is satisfied.

i. Application of AFSA in MPPT

The position of AF is represented as the optimal duty ratio of the converter for MPPT control in PV systems. The objective function to be optimized is given as

$$\begin{aligned} & \text{Maximize } P_{pv}(d) \\ & \text{Subject to the constraint: } d_{min} \leq d \leq d_{max} \end{aligned}$$

where d is the duty cycle, d_{min} and d_{max} represents minimum and maximum duty cycle values.

Being attracted by the prospective of the AFSA, many improvements for the ordinary AFSA have been developed recently. M. Mao *et al.* [54] proposed a modified AFSA based MPPT for grid connected PV system in 2017. The authors introduced some characteristics of PSO algorithm to the ordinary AFSA in order to improve its performance.

Initially they introduced the speed parameter of particle to each of the artificial fishes. The equation for speed of particle is updated as follows:

$$V_{i(t+1)} = wV_{i(t)} + \frac{X_c - X_{i(t)}}{\|X_c - X_{i(t)}\|} * Step * rand() \quad (32)$$

Secondly, memory is introduced and this makes the AF to swim around its optimal position. Thus the updated speed equation is:

$$V_{i(t+1)} = \omega V_{i(t)} + \frac{X_{pbest} - X_{i(t)}}{\|X_{pbest} - X_{i(t)}\|} * step * rand() \quad (33)$$

Thirdly, the communication behavior is introduced and updated the equation as shown in equation (34):

$$V_{i(t+1)} = wV_{i(t)} + \frac{X_{gbest} - X_{i(t)}}{\|X_{gbest} - X_{i(t)}\|} * Step * rand() \quad (34)$$

where X_{gbest} is the global optimum position of AF.

In this paper, the objective function to be maximized is formulated as the P-I characteristics of the series connected panels as shown in equation (35):

$$fit = I * \sum_{k=1}^{n_s} PV_{prog}(I_k, Sun_k, T_k), ns \quad (35)$$

where, $PV_{prog}(I, Sun, T)$ is the characteristic function of output power versus current. I is the current, and Sun and T represent irradiance and temperature respectively.

In paper [56] to maximize the performance of photovoltaic devices, Maximum Power Point Tracking (MPPT) the authors implemented the AFSA for MPPT control of a single-stage PV grid-connected system. The optimal power output is extracted by tuning the parameters of AFSA by simulation. The authors considered three different schemes for obtaining the optimum values for iteration number and fish scale. It is also concluded that as the iteration count increases there is an improvement in output but the convergence time increases. Maximum power output with minimum time has been obtained in third scheme, by simultaneously changes the number of AF and number of iterations. The output is compared with traditional P&O MPPT control method. The authors proved the effectiveness and reliability of the proposed AFSA method with both simulation and experimental analysis.

The advantages of AFSA include high accuracy, flexibility, global search ability, fast convergence and fault tolerance. Whereas it has some disadvantages such as high time complexity, lack of stability among global and local search.

V. OTHER SI BASED ALGORITHMS

More over to the above discussed algorithms, some of the recently developed SI algorithms are reviewed in this paper based on the inspiration and advantages. Table 1 shows the comparison of newly introduced SI optimization algorithms used for MPPT control under PSC.

TABLE I.
COMPARISON OF DIFFERENT SI BASED ALGORITHMS USED IN SOLAR PV SYSTEMS UNDER PARTIAL SHADING CONDITIONS

SL NO	MPPT	Introduced by	Introduced on	Inspiration	Advantages
1	Ant Colony Optimization (ACO) [38] [55]	Marco Dorigo	1999	Foraging behavior of ant colony	Convergence does not depend upon the first location of the sample, low cost, easy control, robust to different shading conditions.
2	Particle Swarm Optimization (PSO) [24] [30]	Kennedy and Eberhart	1995	Bird Flock trying to reach an unknown destination	Simplicity of implementation, scalability in dimension, and good empirical performance.
3	Artificial fish Swarm Algorithm (AFSA) [56] [49]	Li Xiaole et al.	2002	Foraging, cluster and collision behavior and mutual assistance between fish swarm	Convergence does not depend upon the initial location of the artificial fish, flexible and fault tolerance.
4	Artificial Bee Colony (ABC) [32] [37] [57]	Dervis Karaboga	2005	Foraging behavior of honey bees	Convergence is independent of initial conditions, Simple, uses less control parameters
5	Cat Swarm Optimization (CSO) [58] [59]	Shu-Chuan Chuet al.	2007	Natural behavior of cats	System independent, High tracking accuracy and fast convergence, No oscillations around MPP, Efficient to track GMPP
6	Firefly Algorithm (FA) [60]	Xin She Yang	2007	Flashing patterns of the firefly	Automatic subdivision of the whole population into subgroups, multimodal optimization, high ergodicity and diversity in the solutions
7	Cuckoo Search Algorithm (CSA) [61]	Yang and Deb	2009	Breeding behavior of cuckoos	High efficiency, Fast convergence, efficient randomization, less tuning parameters required and Robust technique
8	Bat Algorithm (BA) [62]	Yang and Gandomi	2010	Echolocation behavior of Microbats	Simple and flexible, easy to implement quick convergence to GMPP
9	Grey Wolf Optimization (GWO) [63]	Mirjalili et al.	2014	Leadership hierarchy and hunting mechanism of Grey wolve	Robust, High efficiency, few parameters required for tuning, Transient and steady state oscillations are zero.
10	Chicken Swarm Optimization (CSO) [19]	XianbingMeng et al.	2014	The behaviors of the chicken swarm.	Robust, better convergence, high efficiency.
11	Spider Monkey Optimization algorithm (SMO) [64]	Jagdish Chand Bansal et al.	2014	Fission-fusion social behavior of spider monkeys	Fast and accurate convergence
12	Ant Lion Optimizer (ALO) [65]	SeyedaliMirjalili	2015	Hunting mechanism of ant-lions in nature	Tracking true power point under PSC.
13	Dragonfly Algorithm (DA) [66]	SeyedaliMirjalili	2015	Hunting and migration swarming behaviors of dragon flies	Good exploration and exploitation characteristic, fast tracking, less energy loss and system independent
14	Whale Optimization Algorithm (WOA) [67]	Mirjalili et al.	2016	Behaviors of humpback whale	High accuracy, Fast tracking

VI. CONCLUSION

As far as the photovoltaic system concerned, the maximum power point differs with respect to the atmospheric conditions. Consequently the MPPT control techniques also gained importance to crop maximum power from PV systems. During partial shading conditions the chances of falling into local power peaks is high because of the presence of multiple power peaks in the P-V curve. In such cases, the tracking of global power peak is essential. In this article, a comprehensive review of swarm intelligence optimization control algorithms to track global power for photovoltaic systems under partial shading condition is presented. The review presented the recently emerging optimization algorithms and its application in PV system for tracking

global maximum power point. The methods are compared in terms of their swarm intelligence and advantages.

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