A COMPREHENSIVE OVERVIEW OF SOFT COMPUTING BASED MPPT TECHNIQUES FOR PARTIAL SHADING CONDITIONS IN PV SYSTEMS

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Keywords	Abstract
Photovoltaic System, Maximum Power Point Tracking, Soft Computing Technique.	Nowadays, solar or photovoltaic energy is the most commonly used renewable energy resources in the world. Despite its advantages such as freely available, low maintenance cost, pollution-free, inexhaustible, and reliable, its low conversion efficiency is a major drawback. To increase the efficiency of the photovoltaic system, all photovoltaic modules in the array must be operated at maximum power point. Therefore, maximum power point tracking technique is used for predicting and tracking the maximum power point. In the literature, maximum power point tracking techniques are generally classified as soft computing and conventional. Soft computing techniques are more preferred from both of them, because they can accurately track maximum power point of photovoltaic systems. In this study, an extensive review of soft computing based maximum power point tracking techniques under partial shading conditions until today is presented. The techniques are compared from the point of photovoltaic array dependency, sensors required, tracking efficiency, tracking speed, algorithm complexity, and oscillation around maximum power point.

PV SİSTEMLERDE KISMİ GÖLGELENME KOŞULLARINDA ESNEK HESAPLAMA TABANLI MAKSİMUM GÜÇ NOKTASI İZLEME TEKNİKLERİNİN KARŞILAŞTIRILMASI

Anahtar Kelimeler	Öz
Fotovoltaik Sistem, Maksimum Güç Noktası Takibi, Esnek Hesaplama Teknikleri.	Günümüzde güneş ya da fotovoltaik enerji yenilenebilir enerji kaynakları arasında yaygın olarak kullanılmaktadır. Güneş enerjisi, maliyetsiz, atmosfer dostu, işletme ve bakım maliyetinin az olması ve evrensel olarak her yerde bulunması gibi avantajlarına rağmen, düşük enerji verimliliği en büyük dezavantajıdır. Fotovoltaik sistemlerin verimliliğini arttırabilmek için fotovoltaik dizideki modüller maksimum güç noktalarında çalıştırılmalıdır. Bu nedenle, maksimum güç noktasını tahmin etmek ve izlemek için maksimum güç noktası izleme teknikleri kullanılır. Literatürde, maksimum güç noktası izleme teknikleri genellikle esnek hesaplama ve klasik teknikler olmak üzere sınıflandırılır. Ancak, maksimum güç noktasını doğru bir şekilde takip edebildikleri için esnek hesaplama teknikleri tercih edilmektedir. Bu çalışmada, geçmişten günümüze kadar kısmi gölgeleme koşullarında esnek hesaplama tabanlı maksimum güç noktası izleme tekniklerinin kapsamlı bir derlemesi sunulmuştur. Teknikler, fotovoltaik dizi bağımlılığı, gereken sensörler, takip verimliliği, takip hızı, algoritma karmaşıklığı ve maksimum güç noktası etrafında salınım durumları açısından karşılaştırılmıştır.

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1. Introduction

As the human population is increasing with each passing day in the world, the energy demand is also increasing. Despite this, the conventional energy resources such as coal and petroleum decreases drastically. Moreover, greenhouse emission increases due to usage of conventional energy sources. For these reasons, interest in the solar or photovoltaic (PV) energy between the renewable energy resources increases by degrees because of its advantages such as cleanliness, free of cost, inexhaustible, and less maintenance cost (Ngan and Tan, 2011; Eltawil and Zhao, 2013; Bendib et al., 2015; Saravanan and Babu, 2016; Dileep and Singh, 2017; Bingöl and Özkaya, 2018). Despite advantages, PV systems have many disadvantages such as the low conversion efficiency, the variation of maximum power under changing environmental conditions, nonlinear characteristic, and low conversion efficiency (Ngan and Tan, 2011; Eltawil and Zhao, 2013; Bouilouta et al., 2013; Enany et al., 2016). Due to these disadvantages, PV system must be run at maximum power point (MPP) to achieve maximum efficiency in operation. In order to enhance the performance of the PV system, maximum power point tracking (MPPT) can be mostly used in PV systems (Liu et al., 2016; Dileep and Singh, 2017). MPPT is used to predict and track the MPP of the PV system and then to force to run at the MPP under all environmental conditions (Saravanan and Babu, 2016; Amir et al., 2016).

The MPP changes with changing of the solar irradiation and temperature (Bouilouta et al., 2013; Dileep and Singh, 2017). Under partial shading conditions (PSCs), the PV modules in the PV array don't get uniform solar irradiation, so there is multiple local and one global peak point on power-voltage (P-V) characteristic of array due to using bypass diodes connected to the each PV module. In the present case, MPPT of the PV array is a complex and challenging task (Ji et al., 2011; Bouilouta et al., 2013; Liu et al., 2015; Seyedmahmoudian et al., 2016).

Many research about MPPT methods have been presented in the literature and they can be generally categorized as soft computing and conventional techniques (Ram and Rajasekar, 2017). The most used conventional techniques are perturb and observe (P&O), hill climbing (HC), fractional open circuit voltage (FOCV), incremental conductance (INC), and fractional short circuit current (FSCC) (Eltawil and Zhao, 2013; Bhatnagar and Nema, 2013; Reisi et al., 2013). While the conventional MPPT techniques are good for tracking the MPP under uniform solar irradiation, these techniques fail to track the MPP under PSCs. Moreover, the conventional techniques show high steady state oscillations, poor convergence, and slow tracking speed under PSCs to track the MPP. Due to the disadvantages of the conventional MPPT techniques, soft computing (SC) based MPPT techniques have been given in the literature. Soft computing methods are highly suitable for PSCs due to their robustness, flexibility, and reliability (Ahmed and Salam, 2015; Belhachat and Larbes, 2015).

In this paper, soft computing based MPPT techniques in the literature till date are presented on the contrary to most of the reviews about MPPT techniques. The working principle and structures of all techniques are explained in detail. Moreover, a comprehensive analysis is presented for all techniques according to following criteria: PV array dependency, tracking efficiency, tracking speed, sensors required, algorithm complexity, and oscillation around maximum power point. The information collected and edited in this study will be useful for future research in this area.

The paper is structured as follows: the effect of partial shading on PV system is explained in Section 2. In Section 3, MPPT techniques under partial shading and a general classification of SC based MPPT techniques are presented. Section 4 discusses the SC based MPPT techniques for some criteria.

2. Effect of Partial Shading on PV Characteristics

One of the most important factors that cause negative effect on a PV array is PSCs. Partial shading (PS) can be defined as non-uniform distribution of solar irradiation for all modules in a PV array. Various factors such as tree and building shadow, movement of the clouds, dust on a PV module can causes PS. Under uniform conditions, all modules in a PV array have same electrical characteristics. However, when PSCs occurs, electrical characteristics of the shaded modules are different from the unshaded modules. The shaded PV module generates the less current than the unshaded PV module. In this case, the shaded module carry negative voltage and the power will be delivered. Therefore, the heat of the module increases and this may damage the module, which is called 'hot spot'. In order to prevent the hot spot effects, bypass diodes are connected in parallel to the PV modules. Although the bypass diodes prevent the hot spot problem, multi peak points in the P-V characteristic of the array are occurred (Bidram et al., 2012; Moballegh and Jiang, 2014; Malathy and Ramaprabha, 2017; Bana and Saini, 2017). To explain the effects of PSCs on the PV array, a 3×1 series connected PV array is shown in Figure 1. P-V and I-V characteristics of PV array are given in Figure 2 (a) and (b). When P-V characteristic are analyzed, there is one global MPP under uniform condition. Although, there is one MPP without bypass diode, three peak point have been occurred with bypass diode. According to I-V characteristics, the current of the PS with bypass diode is same with the uniform condition because bypass diodes provide an alternate current path.
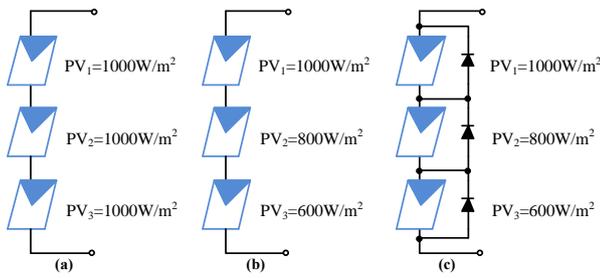
Figure 1. 3×1 series connected PV array under (a) uniform solar irradiation, (b) PS without bypass diode, and (c) PS with bypass diode
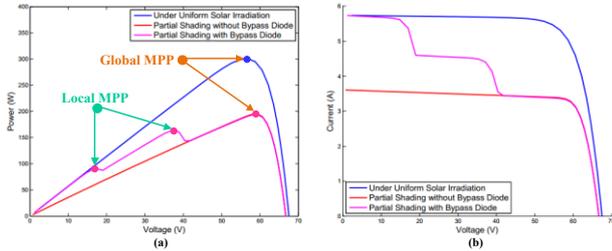

Figure 2. (a) P-V and (b) I-V characteristics of PV array

3. Maximum Power Point Tracking Techniques under PSCs

A general block diagram of MPPT based PV system is given in Figure 3. The extracting maximum power is done by adjusting the duty cycle of DC-DC converter. From the sensed parameters, which can be measured temperature (T), solar irradiance (G), PV voltage (V_{PV}) and current (I_{PV}), the MPPT algorithm generates the optimum duty cycle so as to obtain maximum power from PV system (Salam et al, 2013; Ishaque and Salam, 2013).
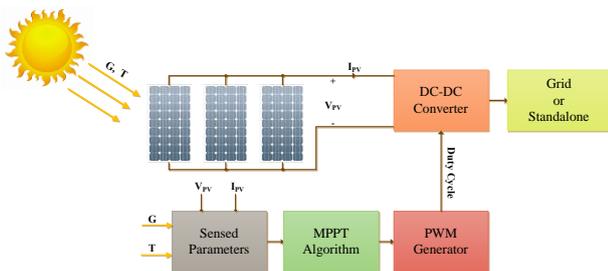

Figure 3. A general block diagram of MPPT based PV system

Generally, MPPT algorithms can be categorized as soft computing and conventional techniques in the literature. The conventional techniques are HC, P&O, FOCV, FSCC, and INC. The most important drawback of conventional techniques is that they cannot track global MPP under PSCs. Due to this reason, SC based MPPT techniques have been presented in the literature. SC techniques are highly suitable for PSCs due to their robustness, flexibility, and reliability. Classifying of the SC based MPPT techniques are demonstrated in Figure 4 (Salam et al, 2013; Ishaque and Salam, 2013; Jordehi, 2016).
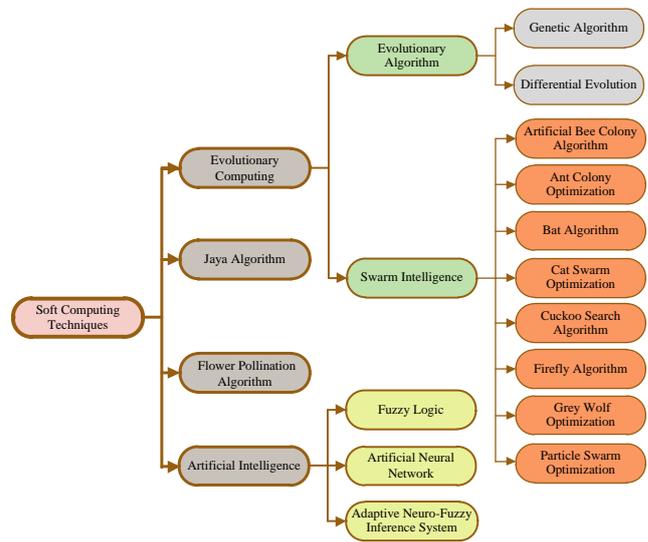

Figure 4. Classifying of the SC based MPPT techniques

3.1 Artificial Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm proposed by Karaboga is based on the foraging behavior of honey bees (Karaboga, 2005). In ABC, artificial bee's colony composes of three types of bees: employed bees used to search the food and to share this information with the colony, unemployed or onlooker bees which try to find a food source by watching the employed bees, and scout bees searching a new food source randomly. They communicate and coordinate to each other to obtain optimal solution in a short time (Karaboga, 2010; Sundareswaran et al., 2015; Soufyane Benyoucef et al., 2015; Mohapatra et al., 2017). In the algorithm, location of a food source and the quantity of nectar denote a solution of the optimization problem and the fitness value of the related solution, respectively. The algorithm starts with a parameter initialization and it generates an arbitrarily initial population (P) of SN solutions, which is the population size. Each solution x_i is n-dimensional vector. For initialization process, Equation (1) is used.

$$x_{i,j} = x_{min,i} + rand[0,1](x_{max,i} - x_{min,i}), \; i = 1, \dots, SN, \;\; j = 1, \dots, n \tag{1}$$

Here, n is the number of optimization parameters, $x_{max,i}$ and $x_{min,i}$ are the upper and lower bound of the $x_{i,j}$, respectively. The employed bees evaluate the new food sources and they are used the Equation (2) for generating a candidate food position (v_i) from the old value (x_i) in memory.

$$v_{i,j} = x_{i,j} + \varphi_{i,j}(x_{i,j} - x_{k,j}) \tag{2}$$

In Equation (2), x_k is an arbitrarily selected food source, $\varphi_{i,j}$ is a random number between [-1, 1], $k=1, \dots, SN$ and it must be different from i. The onlooker bees select food source of employed bee calculated on the basis of probability connected to the food source as below:

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$$p_i = \frac{f(x_i)}{\sum_{n=1}^{SN} f(x_i)}, \qquad i = 1, 2, \ldots, SN \qquad (3)$$

where $f(x_i)$ is the fitness function of x_i. Performance of old and new candidate source position are compared. When the new food source is equal or better than the old one, the old one is replaced with a new one. On the other hand, the old one is preserved in the memory. If a position can't be improved during the specified number of cycles, it is assumed that the food source is given up. In this case, the scout bees find out a new food source with x_i using Equation (1) (Karaboga and Basturk, 2007; Karaboga, 2009; Sawant et al., 2016).

Sundareswaran et al. (2015) have carried out simulation and experimental study for two different PV array configurations under PSCs. Both the results of experimental and simulation demonstrate that the ABC algorithm is far superior to particle swam optimization (PSO) and enhanced P&O with regard to confirmed convergence to global optimum with minimum time and oscillations are reduced. In another study, the proposed ABC algorithm have been compared to PSO under PSC. The proposed algorithm has better tracking performance and convergence, but slow convergence speed compared to PSO (Soufyane Benyoucef et al., 2015).

3.2. Ant Colony Optimization

The Ant Colony Optimization (ACO) presented by Dorigo and Gambardella is inspired by foraging behavior of the ants (Dorigo and Gambardella, 1997; Jiang and Maskell, 2014). Each ant in population is allured to other ant with its attractive force. Depending on the attractive force, the ants migrate from the lower strength zone to the higher strength zone. After each iteration, attractive force is calculated and ants move to the optimum solution [5]. Firstly, K random solutions whose size is greater than number of ants in population (N) are generated and stored in the solution archive. The solutions are ranked by their fitness value $f(s_j)$ and it is given in Equation (4) (Jiang and Maskell, 2014; Das et al., 2017).

$$f(s_1) \leq f(s_2) \leq \ldots \leq f(s_K) \qquad (4)$$

Gaussian distribution function given in Equation (5) is used for determining the positions of ants.

$$G_j(x) = \sum_{l=1}^{K} w_l g_l^j(x) = \sum_{l=1}^{K} w_l \frac{1}{\sigma_l^j \sqrt{2\pi}} e^{\left[-\frac{\left(x-\mu_l^j\right)^2}{2\left(\sigma_l^j\right)^2}\right]} \qquad (5)$$

Here, $G_j(x)$ is the Gaussian kernel for j^{th} dimension of the solution, σ_l^j and μ_l^j are j^{th} dimensional standard deviation and mean value and w_l is the weightage factor. They are respectively calculated by Equations (6-8).

$$\sigma_l^j = \varepsilon \sum_{i=1}^{K} \frac{\left|s_i^j - s_i^j\right|}{K-1} \qquad (6)$$

$$\mu^j = \left\{\mu_1^j, \ldots, \mu_l^j, \ldots, \mu_K^j\right\} = \left\{s_1^j, \ldots, s_l^j, \ldots, s_K^j\right\} \qquad (7)$$

$$w_l = \frac{1}{QK\sqrt{2\pi}} e^{\left[-\frac{(l-1)^2}{2Q^2K^2}\right]}, \ w_K \leq \cdots \leq w_l \leq \cdots \leq w_2 \leq w_1) \qquad (8)$$

where ε is the convergence speed, Q is the parameter of best optimal operating solution. The probability value of Gaussian function is given as follows:

$$P_l = \frac{w_l}{\sum_{t=1}^{K} w_t} \qquad (9)$$

The iteration process is repeated until new optimal solution is produced [37].

Jiang and Maskell (2014) have proposed a uniform implementation scheme where there is a single central MPPT. The efficiency of the ACO based MPPT is confirmed with simulations and experimental setup under uniform and PSCs. In another study, the authors have compared the ACO to constant voltage tracking (CVT), PSO, and P&O under different PSCs (Jiang and Maskell, 2013).

3.3. Adaptive Neuro-Fuzzy Inference System

Adaptive Neuro-Fuzzy Inference System (ANFIS) architecture is an integration of fuzzy logic and neural network algorithm. The general structure of the ANFIS for 2 inputs (x and y) is shown in Figure 5. The functions of each layer are described below. In the structure, there are 5 layer and each layer consists of several nodes (Jiang, 1993; Abu-Rub et al., 2012). The functioning of the ANFIS is as follows:

Layer 1: It is the fuzzification layer. Each node i is an adaptive node given by:

$$O_{1,i} = \mu_{A_i}(x), \qquad i = 1 \text{ and } 2 \qquad (10)$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \qquad i = 3 \text{ and } 4 \qquad (11)$$

where A_i and B_i are the linguistic labels characterized by μ_{A_i} and μ_{B_i}, respectively.

Layer 2: The nodes in the layer are fixed nodes and labeled as Π. Each node calculates the firing strengths of each rule by cross multiplying all incoming rules. Firing strength is represented as w_i.

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_{i-2}}(y), \qquad i = 1 \text{ and } 2 \qquad (12)$$

Layer 3: The nodes are also fixed nodes labeled as N. In this node, the ratio of the each firing strength of ith rule to the sum of firing strength of all rules are calculated as:

$$O_{3,i} = \frac{w_i}{\sum w_i} = \bar{w}_i, \qquad i = 1 \text{ and } 2 \qquad (13)$$

Layer 4: Every node i is an adaptive node with a node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i(\alpha_i + \beta_i x + \gamma_i y), \qquad i = 1 \text{ and } 2 \qquad (14)$$

where α, β, and γ are the constant parameters.

Layer 5: The final output is the weighted average of outputs of all rule.

$$O_{5,i} = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} \overline{w}_i f_i}{\sum_{i=1}^{2} \overline{w}_i} \qquad (15)$$
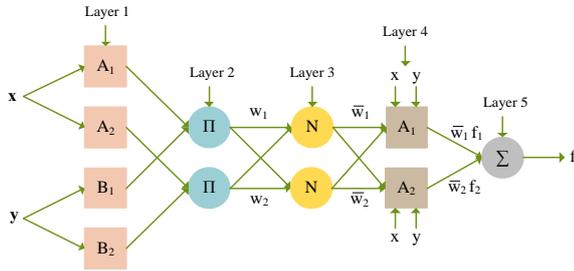

Figure 5. The general structure of the ANFIS

Abu-Rub et al. (2012) have presented an ANFIS-based MPPT controller under fast varying weather condition. The simulation results demonstrates that the maximum power is obtained with proposed MPPT method under rapidly changing environmental conditions. In another study, TCT configured PV array have been used under PSCs for different PSCs. The results indicate that ANFIS-based MPPT method can effectively track MPP (Belhachat, F., & Larbes, C., 2017).

3.4. Artificial Neural Network

The Artificial Neural Network is inspired by biological nervous systems such as the brain. It composes of connectors and neurons and similar with brain neuron structure. The architecture of a multilayer feed forward network consists of an input layer in which input data groups are introduced to the network, hidden layer which receives the data from input layer, processes it, and then transmits it to the output layer, and an output layer which processes the data received from the hidden layer and creates the output. Information is generally stored as a set of connection weights. Training is the process of changing the connection weights using a methodology that is appropriate to the learning process. A network uses a learning method, which is a process defining the relation between the system inputs and outputs, and one of the most usual learning methods is the back propagation algorithm (Kalogirou, 2001). In (Rizzo and Scelba, 2015), the duty cycle of the DC-DC converter is adjusted according to the error between the desired and measured PV voltages. As a result, numerical simulations have confirmed the validity of the ANN based MPPT. Syafaruddin et al. (2009) have been presented a novel MPPT system using ANN and FL under PSCs. ANN is used for specifying the MPP voltage under PSCs and the MPP voltage is used as reference voltage in fuzzy logic. The results show that much more power can be obtained with the proposed system and efficiency can be increased.

3.5. Bat Algorithm

Bat Algorithm inspired by the behavior of bats while searching for food is proposed by Xin-She Yang. The main concept behind the BA is constructed using three simple and basic ideas (Yang and Gandomi, 2012; Gandomi and Yang, 2014; Kaced et al., 2017):
1. To feel the distance, all bats use echolocation and they can detect to distance of prey, background obstacles, and difference in the available prey or food in the search path.
2. Each bat flies arbitrarily with velocity v_i at position x_i with a fixed frequency f_{min}, loudness A_0, and changing wavelength λ for searching the prey. They adjust their wavelength or frequency and can adjust the pulse emission rate $r_i \epsilon [0, 1]$ based on the proximity of the prey.
3. Loudness of the bats changes A_0 to a minimum fixed value A_{min} as reducing with decreased distance of the food. BA starts its search using a random initial population. The process of updating the position and velocity of bats at time step t is as follows:

$$f_i = f_{min} + (f_{max} - f_{min})\beta \qquad (16)$$

$$v_i^t = v_i^{t-1} + (x_i^{t-1} - x')f_i \qquad (17)$$

$$x_i^t = x_i^{t-1} + v_i^t \qquad (18)$$

where β is defined for uniform distribution as a vector and selected between [0, 1]. x' is the current global best location, f_{min} and f_{max} are the minimum and maximum frequency of the ith bat, and β is a random value between [0, 1]. In algorithm, a random number β is generated and if this valued is greater than r_i, a new solution around the bat x_i is produced and it is calculated with Equation (19).

$$x_{new} = x_{old} + \varepsilon A^t \qquad (19)$$

Here, ε is a random number between [-1, 1] and A^t is the average loudness of all bats at t^{th} time step. Moreover, the loudness and rate parameter are renewed as follows:

$$A_i^{t+1} = \alpha A_i^t \qquad (20)$$

$$r_i^{t+1} = r_i^0(1 - e^{\gamma t}) \qquad (21)$$

where α and γ represent the constant values. If a bat finds its prey, the loudness value decreases. Loudness and pulse emission rate are inversely proportional to each other.

In a study, bat algorithm based MPPT method is proposed under PSCs. To affirm the efficiency of the BAT, experimental and simulation studies have been implemented under PSCs. The results demonstrate that the efficiency of the method is improved (Kaced et al., 2017).

3.6. Cat Swarm Optimization

Cat Swarm Optimization (CSO) suggested by Chu and Tsai is based on the living habits and foraging of cats. In

algorithm, each cat in the swarm has its own position which represents the solution set, velocity for each dimension, and a fitness value. Moreover, a flag is used to determine the mode of the cat. In CSO, the behavior of cats into two modes: seeking mode (SM), in which cats always remain alert and move very slowly, and tracing mode (TM) in which the cats chase the prey when feeling it. All cats in the population are arbitrarily divided down the middle groups at each iteration. One of them is carried by SM, while the other is carried by TM. The ratio between two groups is controlled by the mixture ratio (MR) (Chu and Tsai, 2007; Panda et al., 2011; Guo et al., 2016; Guo et al., 2017).

Seeking mode (SM)

A cat moves slowly and spend most of time to rest, but it is always alert in seeking mode. This mode has four main parameters; seeking range of the selected dimension (SRD) specifying the change of value for the chosen dimension, seeking memory pool (SMP) demonstrating the count of a cat copy, counts of dimension to change (CDC) symbolized the number of dimensions to be mutated, and self-position consideration (SPC) determining whether it is one of the candidate points to be moved to where it is currently located. This mode consists of four steps. These are;
1. Create SMP copies of the ith cat and store them in SMP.
2. Perform a mutation operator to X_{kd}. Here, $k \epsilon$ [1, SMP], $d \epsilon$ [1, D], and D is the dimensions number.
3) Assess the fitness value of all mutated copies in SMP and find the copy (X_{best}).
4) If X_i is worse than X_{best} in terms of fitness value, replace X_i with X_{best}.

Tracing mode (TM)

In TM, cats desire to trace targets and foods and they move rapidly toward a new position during chasing process. This mode can be defined as follows:
1. Calculate the velocity using the Equation (22).

$$V_{i,d} = w \times V_{i,d} + r_1 \times c_1 \times (X_{best,d} - X_{i,d}) \qquad (22)$$

where X_{best} represents the best position among all cats, c_1 is an acceleration constant, w is the inertia weight, and r_1 is the random number between [0, 1].
2. Check the velocities whether or not they are in the maximum velocity range. If the new velocity exceeds the maximum value, it sets equal to this limit.
3. Calculate the position using Equation (23).

$$X_{i,d} = X_{i,d} + V_{i,d} \qquad (23)$$

Guo et al. (2017) have proposed a modified cat swarm optimization based MPPT method. The validity of the algorithm is confirmed with various simulation and experiments under different PSCs. According to results, the algorithm is system independent, high performance with regard to tracking accuracy and convergence speed,

has high ability to find global MPP, and removes the power oscillation around MPP.

3.7. Cuckoo Search Algorithm

Cuckoo Search (CS) based on the brood parasitism of some cuckoo birds is developed by Yang and Deb (Yang and Deb, 2009). There are three types of brood parasitism: intraspecific brood parasitism, cooperative breeding, and nest takeover. When a host bird discover the eggs in its nest, it may either throw these eggs or build a new nest in another place. Cuckoo search model has three rules (Yang, 2013; Ahmed and Salam, 2014; Rezk et al., 2017):
1. Only one egg is produced by a cuckoo bird at a time.
2. The best nest will be transported to future generations.
3. Host nests have been considered fixed. Moreover, eggs thrown by a cuckoo are explored with a probability between [0, 1] by the host bird.

In CS algorithm, Lévy flights is a random walk of cuckoo birds used for generating new eggs and is specified by the power law as follows:

$$y = l^{-\lambda}, \qquad (1 < \lambda < 3) \qquad (24)$$

where λ is the variance and l is the flight length. To generate new solution, the Lévy flight is practiced using the Equation (25).

$$x_i^{(t+1)} = x_i^t + \alpha \oplus L\acute{e}vy\,(\lambda) \qquad (25)$$

Here, x_i^t is the sample, α is the step size, t and i are the number of iteration and sample, respectively. The value of α is the step size used in most cases as:

$$\alpha = \alpha_0(x_j^{(t)} - x_i^{(t)}) \qquad (26)$$

where α_0 is the initial step size, $x_j^{(t)}$ and $x_i^{(t)}$ are the two samples.

CS algorithm is similar to the GA and PSO methods. Due to using Lévy flights for step size, CS has a faster convergence and more efficient random [9].

In (Ahmed and Salam, 2014), the algorithm have been compared with PSO and P&O algorithms under PSCs. According to simulation results, CS has better performance than P&O and PSO according to transient behavior, steady state, and convergence speed. Furthermore, CS is shown to be tracking ability of MPP under PSCs. In another study, the performance of the PSO and CS have been evaluated against INR based tracker under three different PS scenarios. The results show that PSO and CS based MPPT methods have stability and high accuracy to achieve MPP for all shading scenarios (Rezk et al., 2017).

3.8. Differential Evolution Algorithm

Differential Evolution (DE) is evolutionary based algorithm proposed by Price and Storn. DE is based on the mutation so that the operating point is closer to the optimum value in the search space. DE has three fundamental process: selection, crossover, and mutation. The algorithm begins with initialization process and the population is arbitrarily initialized with the initial parameters. For each individual in population, fitness function is calculated and the operating point is moved to the best solution according to fitness function values (Storn and Price, 1997; Taheri et al., 2010; Tajuddin et al., 2012; Tajuddin et al., 2013).

In (Taheri et al., 2010), the DE algorithm is compared with the P&O under both uniform and PSCs. The simulation results demonstrates that it can track MPP faster and more accurate than P&O. Tajuddin et al. (2012) have evaluated the DE based MPPT method with regard to tracking capability for non-uniform or rapidly changing solar irradiation. The simulation results show that it has fast and accurate convergence under test conditions. In another study, a modified DE algorithm is proposed for providing fast and accurate convergence to global MPP under PSCs. The performance of the algorithm has been assessed using simulation under changing of solar irradiation. According to simulation results, modified DE based MPPT algorithm is better than HC from the point of convergence speed and accuracy (Tajuddin et al., 2013).

3.9. Firefly Algorithm

The Firefly Algorithm (FA) proposed by Yang is inspired by fireflies flashing behaviors. The behaviors of fireflies is that they communicate, search for prey, and find mates. In order to simplify the algorithm, three assumptions are considered (Yang, 2010; Yetayew et al., 2016; Dhivya and Kumar, 2017; Teshome et al., 2017):
1. There is no gender in fireflies and every firefly is attracted to other fireflies without considering their gender.
2. The attractiveness of a firefly is directly proportional to the brightness of the firefly. For example, the less bright firefly will move towards the brighter firefly. Moreover, when the distance between fireflies increases, attractiveness and brightness decrease.
3. The brightness of a firefly is specified by the objective function.

The two main functions in FFA are the formulation of attractiveness and the change in light intensity. The distance between two fireflies is expressed as the Euclidean distance given in Equation (27).

$$r_{ij} = \|x_i - x_j\| = \sqrt{\sum_{k=1}^{D}(x_{i,k} - x_{j,k})^2} \tag{27}$$

Here, D denotes the dimension, $x_{i,k}$ is the kth dimension of the ith firefly, $x_{j,k}$ is the kth dimension of the jth firefly, r_{ij} is

the distance between i^{th} and j^{th} fireflies. The attractiveness β of a firefly is defined as:

$$\beta(r_{ij}) = \beta_0 e^{-\gamma r^2 ij} \tag{28}$$

where β_0 is the attractiveness at $r=0$. The movement of the ith firefly can be expressed as:

$$x_i = x_i + \beta_0 e^{-\gamma r^2 ij}(x_j - x_i) + \alpha(rand - 0.5) \tag{29}$$

where α is a random movement factor between [0, 1].

In a study, the authors proposed a FA based MPPT method for sepic converter. Also, efficiency and performance of the FA are compared to P&O and PSO in simulation under PSCs. According to results, the FA tracks the global MPP faster than the others. It also reduces convergence and increases the efficiency of the converter (Dhivya and Kumar, 2017). In (Yetayew et al., 2016), the performance comparison of firefly and incremental conductance algorithms are presented under PSCs. The experimental results show that firefly algorithm has accurate tracking capability, fast dynamic response for PS, and low oscillation by comparison with incremental conductance algorithm.

3.10. Fuzzy Logic Control

Fuzzy logic control (FLC) is based on the principles of fuzzy set theory developed by Zadeh in 1965 (Ross, 2009). In binary logic, a variable is either 'completely true' or 'completely false'. However, in FLC, a variable can take a value between 0 and 1. The most important advantage of the FLC is that there is no need for precise mathematical modeling and the decision is based on estimated values. The general structure of FLC is shown in Figure 6.

Fuzzification: Each element of input data is converted into suitable linguistic values so that can be compared to the rules in the rule base. There are different membership functions such as, Gaussian, triangular, and trapezoidal.

Fuzzy inference process: It combines membership functions with the control rules to derive the fuzzy output.

Defuzzification: It uses different methods such as center of gravity, center of area, and center of sums method in order to convert the linguistic variables to numerical values. Gravity center and field center methods are often used in defuzzification methods (Das et al., 2017).
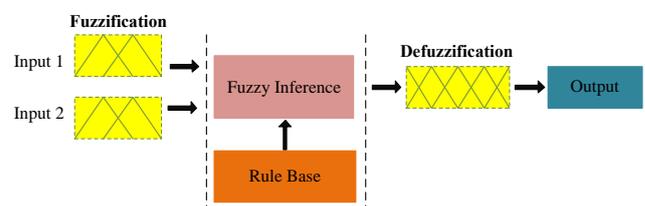

Figure 6. The general structure of FLC

3.11. Flower Pollination Algorithm

Flower Pollination Algorithm (FPA) proposed by Xie Yang is based on the pollination processes of the flower in the nature. The main process of this algorithm is the reproduction by pollination based on the transfer of pollen from flower to another. There is two type transfer: biotic pollination done by animals that visit the flowers called pollinators and abiotic pollination like by wind, gravity or water. The FPA algorithm is developed with the following rules (Yang et al., 2013; Yang et al., 2014; Ram et al., 2017; Ram and Rajasekar, 2017):
1. Cross pollination and biotic can be regarded as a global pollination process where flower pollen gametes are realized by pollinators carrying pollen move to comply with Levy flights.
2. Self-pollination and abiotic are used for local pollination, where the transfer of pollens between same species.
3. The flower constant can be developed by pollinators.
4. The exchange between local and global pollination can be checked by switch probability p which is between [0, 1].

The above rules are transformed to appropriate update equations. Therefore, for global pollination step and flower constant can be presented by Equation (30).

$$x_i^{t+1} = x_i^t + \gamma L(\lambda)(g_{best} - x_i^t) \qquad (30)$$

Here, x_i^t is the pollen, g_{best} is the current best solution, γ is the scaling factor which controls the step size, and $L(\lambda)$ is the Lévy flights-based step size. Insects can fly over long distances with Lévy distribution given in Equation (31).

$$L(\lambda) = \frac{\lambda \Gamma(\lambda) sin(\frac{\pi}{2})}{\pi} \frac{1}{S^{1+\lambda}}, \qquad S \gg S_0 > 0 \qquad (31)$$

Here, $\Gamma(\lambda)$ is the gamma which is valid for large steps $(S \gg S_0 > 0)$. Then, in order to model the local pollination, Equation (32) is used.

$$x_i^{t+1} = x_i^t + \varepsilon(x_j^t - x_k^t) \qquad (32)$$

Here, x_i^t and x_j^t are the pollens from different flowers of the same plant species and ε represents the local search in uniform distribution between [0, 1].

In (Shaiek et al., 2013), the performance of the FPA is evaluated for ten different shading conditions and its tracking performance is compared to PSO. It is found that FPA is capable of extracting the maximum power and has fast convergence speed. In (Subha and Himavathi, 2017), comprehensive performance evaluation of the FPA based MPPT method have been carried out under three shading pattern using simulation and hardware. According to results, the superiority of the FPA is proved when compared with P&O and PSO according to efficiency and convergence time. Moreover, it is more robust than the others and has quick convergence with zero steady-state oscillations.

3.12. Genetic Algorithm

Genetic Algorithm is an evolutionary computation introduced by Holland in 1975 through by the principles of natural evolution. The purpose of the algorithm is to create best species from its predecessors. In algorithm, a chromosome consisting of a fixed gene population represents a candidate solution. It has three fundamental operator: selection, crossover, and mutation. In selection process, a chromosome is randomly selected from the current generation for inclusion in the next generation to their fitness value. In crossover, two chromosomes are combined in order to produce a new chromosome. The mutation operator is used to provide genetic diversity (Mirjalili et al., 2014; Smida and Sakly, 2015). Smida and Sakly, (2015) have implemented, evaluated, and compared P&O, INC, and the GA methods under PSCs. Among these algorithms, GA has extracted the global MPP and tracks the global MPP when PSCs occurred.

3.13. Grey Wolf Optimization

Grey wolf optimization (GWO) is inspired by social hierarchy and hunting behavior of grey wolves. They live a strict social dominant hierarchy (Mohanty et al., 2016). There are four types of grey wolves: alpha (α) wolves which are the leader and decision maker, beta (β) and delta (δ) wolves which assist the α in decision making, and omega (ω) wolves which are the bottom of the pyramid and should submit to all the other dominant wolves. The main steps of grey wolf hunting are as follows:
a) Catching, monitoring and approaching the prey.
b) Seeking, surrounding, and disturbing the prey.
c) Attacking the prey.

During hunting, grey wolves surrounds the prey and the surrounding behavior can be modeled with Equation (33) and (34).

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_p}(t) - \overrightarrow{X_p}(t) \right| \qquad (33)$$

$$\vec{X}(t + 1) = \left| \overrightarrow{X_p}(t) - \vec{A}.\vec{D} \right| \qquad (34)$$

Here, X and X_p is the position vector of grey wolf and prey, respectively, t is the number of iteration, A, C, and D are the coefficient vectors. A and C are calculated using Equation (35) and (36).

$$\vec{A} = 2.\vec{a}.\overrightarrow{r_1} - \vec{a} \qquad (35)$$

$$\vec{C} = 2.\overrightarrow{r_2} \qquad (36)$$

Here, a decreases linearly from 2 to 0 and r_1 and r_2 is the random vectors between [0, 1] (Mohanty et al., 2016; Rao, 2016; Mohanty et al., 2017).

In (Mohanty et al., 2017), GWO based MPPT method have been proposed. The proposed algorithm are compared with improved PSO (IPSO) and P&O under PSCs. According to experimental and simulation results, GWO is

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better than IPSO and P&O with respect to tracking speed and tracking accuracy. Also, it has zero steady-state oscillations and high power efficiency.

3.14. Jaya Algorithm

Jaya algorithm presented by Rao is based on the principle of avoiding worst solutions (Huang et al., 2017). First, the worst solution is find and then, all solutions are removed from it. After, worst solution is updated from the worst solution. Thus, all solutions at the next iteration are better than previous worst solution. In the algorithm, fitness function is $P=f(V)$ and the solution is calculated as:

$$V_{i,j}^{k+1} = V_{i,j}^k + rand_1 \times (V_{i,best}^k - |V_{i,j}^k|) - rand_2 \times (V_{i,worst}^k - |V_{i,j}^k|), k = 1, \dots, n, \ i = 1, \dots, m, \ j = 1, \dots, p \quad (37)$$

where $V_{i,j}^k$, $V_{i,best}^k$, and $V_{i,worst}^k$ respectively represent the value of the ith variable of the jth solution, the value of variable i for the best solution, and the value of variable i for the worst solution during the kth iteration. $k, n, j,$ and p represents the number of iterations, maximum number of iterations, number of solutions, and maximum number of solutions. Moreover, $rand_1$ and $rand_2$ are the random numbers between [0, 1]. The next iterative updating is done with Equation (38) (Kennedy and Eberhart, 1995; Kumar et al., 2017).

$$V_{i,j}^{k+1} = \begin{cases} V_{i,j}^k, \ if \ f(V_{i,j}^k) > f(V_{i,j}^{k+1}) \\ V_{i,j}^{k+1}, \ otherwise \end{cases} \quad (38)$$

Kumar et al. (2017) have proposed Jaya based MPPT method and simulated it under various PSCs. According to results, the proposed method requires less iterations to converge to the GMPP and shows higher dynamical tracking efficiency than PSO methods.

3.15. Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) presented by Kennedy and Eberhart is inspired by the natural behavior of the fish flocks and birds (Ishaque et al., 2011; Badis et al., 2016). In the algorithm, a particle represents the each individual in the swarm and each particle has a velocity and position vector. These particles follow the same behavior: Each particle adjusts its position to best position of the swarm whose value is the most closest to the target. The algorithm initializes with a group of random solutions and tries to find the best value by updating each iteration. Each particle keeps its current and previous positions in the memory and determines the best position until that iteration which is called the personal best value (p_{best}). In addition, the best position of the whole particles by controlling the p_{best} values of the particles is determined and it is called global best position (g_{best}). After finding these values, velocity and position of the particles are updated as follows:

$$v_i^{k+1} = w. v_i^k + c_1 r_1 (p_{besti}^k - x_i^k) + c_2 r_2 (g_{besti}^k - x_i^k) \quad (39)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (40)$$

where k is the number of iterations, i represents the optimization vector variable, v_i^k and x_i^k are respectively the velocity and position of particle i of the kth iteration, c_1 is the cognitive coefficient of the individual particles, c_2 is the social coefficient of all particles, r_1 and r_2 are the random variables between [0, 1], and w is the inertia weight factor (Ishaque et al., 2012; Jumpasri et al., 2014). Ishaque et al. (2011) have compared to PSO with GA based MPPT under same PSCs. PSO based MPPT is more efficient than GA. Also, it is swiftly tracked the MPP than GA. In (Jumpasri et al., 2014), a modified PSO has been proposed. It has low tracking speed, and ability to track the MPP for the extreme environmental condition when compared to HC method. In another study, a comparative study between the HC and PSO based MPPT techniques has been presented. According to simulation and experimental results, PSO based technique can find global MPP more efficiently than HC. Moreover, PSO can reduce the steady state oscillation (Rajasekar et al., 2014). Babu et al. (2015) have presented a modified PSO technique for MPPT. According to simulation and experimental results, modified PSO has good tracking speed, almost zero steady state oscillations, and ability to track MPP under PSCs.

4. Discussion

In the literature, different MPPT techniques have been presented so as to track the MPP. Each technique has advantages and disadvantages. In this article, a comprehensive comparison between SC based MPPT techniques has been done on the following parameters: PV array dependency, sensors required, tracking efficiency, tracking speed, algorithm complexity, and oscillation around MPP. In Table 1, comprehensive analysis of SC based MPPT techniques is given. However, this analysis may not be a final conclusion because the studies for each technique have nor carried out under same conditions. Therefore, it is not possible to compare the methods on a common platform. Consequently, the authors have tried to do their best to provide a realistic comparison.

4.1. PV Array Dependency

An ideal MPPT technique should be array independent. In other words, it can track the MPP for all type of cell technologies, PV array size, and all configurations. While ANN, ANFIS, and FLC techniques are array dependent, other soft computing techniques are array independent.

4.2. Sensors Required

The sensors used in MPPT can be voltage, current, temperature, and solar irradiation. Generally, voltage and current sensors are used, but the ideal situation is to use only one sensor when the system consists of large size PV array with separate MPPT.

4.3. Tracking Speed

Tracking speed of the MPPT techniques can be defined as the speed of them to achieve the MPP. Under PSCs, global MPP changes and the MPPT technique must adapt and track the global MPP as quickly as possible. As a result, tracking speed is a crucial factor for MPPT under PSCs.

4.4. Algorithm Complexity

Basically, it is difficult to evaluate the MPPT methods according to algorithm complexity. SC based MPPT techniques are more complex than conventional techniques. Among the SC based techniques, there is no criteria to rank the complexities. However, in this paper, an evaluation and ranking are done according to algorithm parameters, number of steps and calculations, and complexity of structure.

4.5. Tracking Efficiency

Tracking efficiency can be determined as the tracking accuracy of the MPPT. It is calculated by Equation (43).

$$\eta = \frac{Tracked\ power}{V_{mpp}I_{mpp}} \tag{43}$$

5. Conclusion

In this paper, 15 SC based MPPT techniques used for PV system have been reviewed and presented. SC techniques are preferred due to the tracking ability under PSCs. Mathematical equations and flowchart of the each SC based MPPT technique are given in detail. Also, research articles about MPPT techniques, mentioned in the article, are carefully analyzed and listed in every subsections. These techniques are extensively compared with each other with regard to photovoltaic array dependency, sensors required, tracking efficiency, tracking speed, algorithm complexity, oscillation around maximum power point, and implementation.

Table 1. Comprehensive analysis of SC based MPPT techniques

MPPT Techniques	PV array dependency	Sensors	Tracking speed	Efficiency	Oscillation around MPP	Algorithm complexity
Artificial Bee Colony Algorithm	No	V, I	Fast	High	No	Complex
Ant Colony Optimization	No	V, I	Fast	High	No	Complex
Adaptive Neuro-Fuzzy Inference System	Yes	V, I, T, G	Fast	Low	No	Complex
Artificial Neural Networks	Yes	V, I, G	Fast	Low	No	Complex
Bat Algorithm	No	V, I	Fast	High	No	Complex
Cat Swarm Optimization	No	V, I	Fast	High	No	Medium
Cuckoo Search Algorithm	No	V, I	Very Fast	High	No	Medium
Differential Evolution Algorithm	No	V, I	Medium	High	No	Medium
Firefly Algorithm	No	V, I	Very Fast	High	No	Medium
Fuzzy Logic Control	Yes	V, I	Medium	Low	No	Medium
Flower Pollination Algorithm	No	V, I	Very Fast	High	No	Medium
Genetic Algorithm	No	V, I	Medium	High	No	Complex
Grey Wolf Optimization	No	V, I	Very Fast	High	No	Medium
Jaya Algorithm	No	V, I	Very Fast	High	No	Medium
Particle Swarm Optimization Algorithm	No	V, I	Fast	High	No	Medium

Conflict of Interest

No conflict of interest was declared by the authors.

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