A review of Artificial Intelligence Algorithms for Extracting Maximum Power from the PV system under Partially Shaded Condition

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Abstract: *The increase in energy demand and soaring prices of fossil fuels together with concerns about environmental issues have generated enormous interest in the utilization of renewable energy sources. In recent years, the solar energy is drawing more attention owing to its advantages such as zero green houses emission & pollution, low maintenance cost, absence of moving parts and freedom from environmental pollution. Due to the high initial cost of Photovoltaic (PV) power generation systems and their low energy conversion efficiency, a PV system is generally operated to extract maximum power from the PV source. The objective of maximum power point tracking (MPPT) is to extract maximum power generated by the PV systems under varying conditions of temperature and solar insolation. A major challenge in PV systems is to analyze the nonlinear current-voltage (I-V) characteristics so as to obtain a unique maximum power point on its power-voltage (P-V) characteristic curve. The process of MPPT is complicated due to the fact that the PV curves vary largely with solar insolation and temperature. Many researchers have proposed and implemented a variety of methods, both conventional and non-conventional, to solve MPPT problem. However, most of conventional tracking methods fail to work properly under partial shaded conditions. Partial shaded SPV modules produce several local maximum power points, making the tracking of Global Maximum Power Point (GMPP) difficult. Hence many researchers have tried to use artificial intelligence techniques such as Particle Swarm Optimization (PSO), Differential Evolution (DE), Ant Colony Optimization (ACO), Colony of Fire Flies (FF), Cuckoo Search (CS), Artificial Bee Colony (ABC) algorithm, Symbiotic Organism Search (SOS) algorithm and Fruitfly Optimization Algorithm (FOA) etc. This paper presents a review of artificial intelligence optimization techniques to address the Maximum Power Point Tracking of Solar Photovoltaic arrays under partial shaded conditions. The performances of these techniques are presented in respect of their tracking efficiency.*

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Keywords: *Global Maximum Power Point (GMPP),Particle Swarm Optimization (PSO) techniques, Differential Evolution (DE), Ant colony optimization (ACO), Colony of FireFlies (FF) ,Cuckoo Search (CS), Artificial Bee Colony algorithm (ABC), Symbiotic Organism Search (SOS) algorithm and Fruitfly Optimization Algorithm (FOA).*

I. Introduction

Electricity is an essential factor of economic development for all the countries. In recent years the share of renewable energy in electricity production is growing significantly all over the world. Among these solar energy plays a vital role in the production of power and commercial usages [1]. Global installed solar photovoltaic capacity has increased over the past four years from 14.7GW in 2008 in to 97.4 GW in 2012.

Most of this capacity was installed in the European Union countries around 68.8GW which accommodate 70% of the world solar power generation capacity [2].

In India, around 25,000 villages are located in remote and inaccessible areas where it is not possible to electrify through conventional power generation grid. Hence one has to opt for renewable energy sources [3] as rural electrification is very essential to improve socio-economic conditions.

Till date, India has established solar power generated installation capable of producing around 2208.36MW by the year of 2014. Among the Indian states, Gujarat has been the leader of solar power generation and contributes 2/3rd of the total photovoltaic power.

Though the majority of photovoltaic power generation comes from independent solar plants, nowadays, roof top photovoltaic power generation is gaining more attention due to the fact that urban India has large amount of empty rooftop spaces which avoids the usage of land and environmental concerns [4].

Generation of electricity from solar energy improves con-version of solar energy into electricity not only improves generation of electricity but also reduces pollution due to fossil fuels. while the output power of solar panel depends on factors like solar irradiance, temperature and the load impedance [5], the output power of PV system gets affected by shading from adjacent buildings, tress, overhanging vegetation, roof slope and roof aspect.

Solar shading is one of the biggest problems which affects the overall performance and efficiency of the solar panels. Shading can be classified as hard and soft shading. Hard shade occurs when a solid object or obstacle is placed in front of the array, blocking the sunlight in a clear and definable shape. Soft shade occurs when the overall intensity of the light is reduced, such as haze or smog in the atmosphere.

Soft shade will allow voltage to be generated, but less current will flow from the module. Hard shade cast on a portion of the area on a solar module will open the circuit, causing the voltage generated by the module to drop [6]. Shading of solar cells is a critical performance issue because: (a) the shaded cells can get reverse biased and consume power instead of generating power resulting in loss of total output power, (b) the power losses in the individual shaded cells would result in local heating and cause thermal stress on the surrounding cells resulting in hot spots and local defects which potentially result in the failure of the entire array [7], and (c) extreme cases of shading can generate reverse bias that might exceed solar cell breakdown voltage and damage the solar module [8].

The shading problem is rectified by connecting bypass diodes in parallel to the solar module. These diodes allow shaded cells to be bypassed, allowing the current from other modules in the string to flow continuously.

Without the bypass diodes, any shade on any cell in the string would cause the entire string to stop producing power. If the power output of shaded cells is reduced, the performance of unshaded cells also decline due to their electrical connection to the shaded ones.

Silvestre et al [9] maintained that when the current generated by an unshaded cell flows through a shaded cell, the shaded cell will have negative voltage and the power will be dissipated in this cell, causing a hot spot, and leading to cell damage.

Giraud et al [10] studied effect of partial shading, in which PV array is not illuminated uniformly and found that the difference in solar irradiance causes mismatch in generated power between the solar modules.

Generally solar panels can be connected in three ways to form PV array viz; (i) connecting the modules in series within the string and strings are connected in parallel to form an array (series-parallel), (ii) connecting the modules in parallel within the string and then combine the strings serially (parallel-series) and (iii) Total Cross Tied (TCT) or bridge linked interconnection [11].

The better performance is achieved by connecting the modules in the parallel then connecting with series, the choosing of too many modules in parallel connection leads to less robust configuration and also the parallel connection is not suitable for all operating conditions.

Karatepe [12] found that TCT interconnection of solar array produce nominal response to reduce the partial shading losses.

Kaushika and Gautam [13] proposed that, changing the interconnection schemes of the modules from Series-Parallel to TCT increases the power by more than 4% and the TCT configuration is considered as the best solution to mitigate the mismatch losses under partially shaded conditions.

Sheriff and Boutros [14] proposed a reconfiguration scheme for PV modules using transistors as switches between cells.

Nguyen and Lehman [15] implemented new reconfiguration technique in the PV arrays and proposed two reconfiguration algorithms based on the switching matrix. It reduces the number of sensors and switches used, but if the shaded area is too large it is not effective and also they did not proposed any mathematical formulation for the optimal reconfiguration of solar array.

Eldein et al [16] proposed a mathematical formulation for the optimal reconfiguration of photovoltaic arrays to minimize the partial shading losses. This paper formulates the reconfiguration problem as a mixed integer quadratic programming problem and finds the optimal solution using a branch and bound algorithm.

Patnaik et al [17] proposed the technique in which shaded modules are disconnected from the array during shading condition. Hence it requires more current sensors to measure the current flowing through bypass diode. Further it also requires separate switching circuits for connecting and disconnecting the PV module.

Maki and Valkealahti [18] investigated the effect of partial shading on long string, parallel strings and multi-string. These studies shows that short strings connected individually or in parallel are the best array configuration compared to long series string connection.

The losses due to partial shading are not proportional to the shaded area but also depend on the shading pattern, array configuration and the physical location of shaded modules in the array.

Velasco Quesada et al [19] proposed a electrical reconfiguration techniques which aims to distribute the effect of solar shading in which, electrical connections are changed dynamically according to the switching matrix there by increasing the current flowing in the string of the PV module during shading condition. Even though the power loss is reduced in this technique the cost and complexity increases.

Rani and Ilango et al [20] presented a technique in which modules are configured as array in the form of TCT connection based on the Su Do Ku puzzle pattern arrangement to distribute the shading effect over the entire array. In array reconfiguration techniques, the electrical connections of the modules are dynamically changed based on the shading conditions but in the Su Do Ku arrangement it remains fixed under all conditions. In this technique there is no need of separate voltage and current sensors, and also it does not require any control algorithm like reconfiguration technique. Power enhanced by this technique was around 26.12% higher than conventional TCT array configuration. The main drawback of this technique is difficult to make electrical connection between the PV modules arranged in Su Do Ku pattern.

II. Need of MPPT Algorithm for PV System

PV system is generally operated to extract maximum power due to high initial cost, power loss on system configuration, shading pattern and bypass diodes integrated in the PV modules. Maximum power point tracking (MPPT) is implemented in order to optimize the power generation of the PV system. MPPT is defined as the optimal point at which voltage and current are maximum in the PV system. The real challenge in the PV generation system is to choose a distinct maximum power point on its non linear power voltage (P-V) characteristic curve.

When atmospheric conditions fluctuate, the maximum power point of the PV system changes its position and its PV curve takes multiple peaks as shown in fig(1).

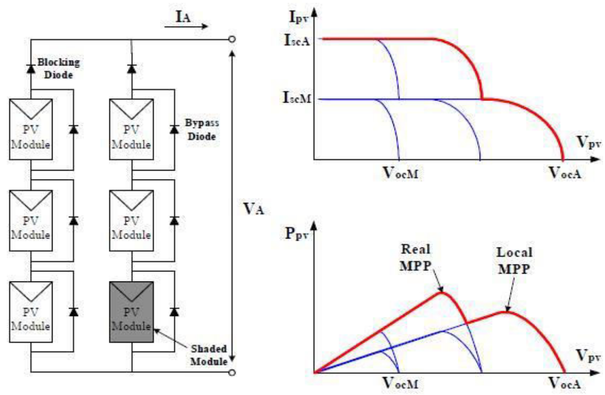

Fig.1. PV array characteristic curves under PSC

There are two neighborhood MPPs on the P-V curve during Partial Shading Condition (PSC), out of which only one is the genuine MPP. It is needed to converge into a global MPP for extracting maximum power from the PV system. The optimization algorithm selected for MPPT ought to ideally possess the properties of easy process steps, quicker convergence, and assure convergence to GMPP along with practiceableness of implementation in a very low cost digital controller. The tracking efficiency of MPPT is calculated by taking the ratio between averaged output power obtained under steady state and maximum available power of the PV array under certain shading pattern.

There are several optimization method available for tracking the MPP such as Perturb and Observe (P & O) [21], incremental conductance [22], hill climbing and short circuit current and open circuit voltage [23], load current & load voltage maximization technique, fuzzy control [24], neural network based schemes [25] to name a few.

III. Artificial Intelligence Algorithm:

In this paper a review of some biologically inspired optimization algorithms used for solving the problem of MPPT under partially shaded condition in PV system, such as Particle Swarm Optimization (PSO) techniques, Ant Colony Optimization (ACO), Differential Evolution (DE) algorithm, Fireflies (FF) algorithm, Cuckoo Search (CS) algorithm, Artificial Bee Colony (ABC) algorithm, Symbiotic Organism

Search (SOS) algorithm and Fruitfly Optimization Algorithm (FOA) are made.

A. Particle Swarm Optimization Technique

PSO is a stochastic, population-based artificial intelligence algorithm developed by Eberhart and Kennedy in 1995 [26]. It is a straightforward and feasible meta-heuristic methodology found from the conduct of bird flocks.

The number of particles form a swarm that flies all over the viable space to look for fruitful region in which optimal solution may exist.

The two vectors $Z_i=[z_i^1 z_i^2::::z_i^N\ ]$ and $V_i = [v_i^1 v_i^2:::::v_i^N\ ]$ are related to each particle (i) in the N-dimension search space.

During their search, individuals from the swarm associate with every others in a certain manner to upgrade their search experience. The particles take after the accomplishment of neighboring particles and attained to its own success. The most frequently used methodology is the gbest model where the entire population is considered as a single neighborhood throughout search experience. In every iteration, particles with finest solution impart its position co-ordinates (gbest) data with the rest of the swarm. Based on its own best search experience (gbest) and (pbest), the particles update its coordinates as per mathematical equation (1) and (2)

$$v_i^{k+1} = wv_i^k + c_1 rand_1\left(pbest_i^k - z_i^k\right) + c_2 rand_2\left(gbest_i^k - z_i^k\right) \quad (1)$$

$$z_i^{k+1} = z_i^k + v_i^{k+1} \quad (2)$$

where c_1 and c_2 are two positive acceleration constants, $rand_1$ and $rand_2$ are two randomly generated numbers with a range of [0; 1], w is the inertia weight.

In this case, it is a linearly decreasing function of the iteration index.

$$w(k) = w_{max} - \left(\frac{w_{max}-w_{min}}{iter_{max}}\right) * iter \quad (3)$$

Where $iter_{max}$ is the maximum number of iteration, $iter$ is the current iteration number, w_{max} is the initial weight and w_{min} is the final weight.

PSO algorithm implementation for MPPT process as follows [27],

Step 1: Examined number of modules interconnected, insolation pattern and temperature for each module.

Step 2: Initialize PSO parameters such as w_{max},w_{min}, c_1, c_2 and $iter_{max}$.

Step 3: Set initial population of N particles (design variables) with random positions and velocities.

Step 4: Compute objective value, current and power.

Step 5: Measure the fitness of each particle.

Step 6: Update personal best: Compare the fitness value of each particle with its pbest. If the present value is better than pbest, then set pbest value to the current value.

Step 7: Update global best: Compare the fitness value of each particle with gbest. If the present value is better than gbest, set gbest to the current particles value.

Step 8: Update velocities: Calculate velocities using v_i^{k+1} equation (1).

Step 9: Update positions: Calculate positions using z_i^{k+1} equation (2).

Step 10: Return to step4 until the current iteration reaches the maximum iteration number.

Step 11: Obtain the best value of current and corresponding power in the final iteration and calculate the corresponding duty cycle value.

Brunton, Rowley et al [28], proposed the Perturb and observe (P & O) method for tracking MPPT of the PV system. This control scheme needs external circuitry to repeatedly perturb the array voltage in addition to consequently measure the changing in the output power.

The P & O algorithm fails under rapidly changing environmental conditions, because it cannot discriminate the difference between changes in power due to environmental effects and changes in power due to the intrinsic perturbation of the algorithm thus produce high oscillation and the tracking speed is low. This problem is overcome by PSO which is effectively implemented in [29].

Particle swarm optimization is highly potential due to its simple construction, easy operation, and fast computation capability. In this case of slow variation in the solar insolation, a proper initialization of duty cycles in PSO is very critical. In this case, a change in the duty cycle from the previous one should be small to track the MPP this exits the steady-state oscillations which leads power loss. To address these issues modified particle swarm optimization is employed in [30]. In this, once the particles reaches MPPT, velocity of the particle is becomes zero, due to this the steady state oscillation is completely eliminated which increases the tracking speed and by with increasing the system efficiency.

B. Ant Colony Optimization Technique

The ant colony optimization (ACO) is a probabilistic algorithm used to determine the global optimal solution for all non linear problems.

This optimization technique is based on the performance of ants looking for a way between their province and a source of food [31].

Considering an N-dimensional search space where M is the number of colonies, N is the number of ants present in each colonies.

The transition probabilities of the ants are well-defined as follows

$$p_{ij} = \left(\tau_j^{\alpha}\, \eta_{ij}^{\beta} / \left(\sum_{j=1}^{m} \tau_j^{\alpha}\, \eta_{ij}^{\beta}\right)\right) \quad (4)$$

Where, $\eta_{ij}^{\beta} > 0$ elsewhere $p_{ij} = 0$

τ_j is the attraction strength in region j, η_{ij} refers to the difference between target function searched from the region i to j. The variables α and β are the influence factors.

Attraction strength can be calculated using

$$\tau_j\,(t+1) = \rho\tau(t) + \sum_{k=1}^{m} \Delta\tau_j^k$$

and (5)

$$\Delta\tau_j^k = Q/L_j^k$$

where L is the variation of target function, ρ is a constant [0; 1] and Q is the pheromone density released from ant colonies.

At first, every ant in the certain area starts moving randomly. Each area has its own particular fascinating quality to all ants. Because of distinction in fascinating quality, each ant builds transition from lower to higher strength area. Based on this, transition probability of each area is measured. In the next following cycles, ants travel towards a more attraction strength area. By sequential iteration ants travel towards the optimized point i.e MPP [32].

The ACO based optimization is implemented in [33] to solve the MPPT problem for PSC. In these, PV power is considered as target function and current in the PV string as control variable.

The control vector is defined by the mathematical equation as

$$s^t = [I_1^t, I_2^t \;\ldots\ldots\ldots.. I_N^t] \quad (6)$$

where s^t is the current vector at the t_{th} step, I_N^t is the current control value for N_{th} PV string at the t_{th} step.

The objective function of this optimization problem $f(s^t)$ is described as the summation of the power output from each PV sub-string by

$$f(s^t) = \sum_{j=1}^{N_{pp}} (I_j^t)(V_j^t) \quad (7)$$

Where I_j^t and V_j^t are the current control variable and the voltage control variable for j_{th} PV string at the t_{th} step respectively.

During the search process, the power of each current vector $f(s^t)$ is measured and evaluated at each stage. In every iteration the solution obtained is compared and updated with newly generated solutions. The process is repeated until the global MPP is obtained.

The ACO implemented in [34] has formulated to operate continuously and easily adjust to changing in environmental conditions. The major benefit is, it needs only one combination of voltage and current sensors that increases the system reliability and less cost. And also it increases the efficiency of the PV system, even though is not applied to the distributed MPPT controllers.

Besheer et al [34] used ant colony optimization algorithm to fine tuning of the input weighting for MPPT controller on standalone PV array. It exhibits best response in quick settling time and perfect tracking even under great variations in irradiance levels.

C. Differential Evolution

Differential Evolution algorithm is a stochastic, optimize based evolutionary algorithm. The problem is optimized by generating a population of the candidate based on the formula and assigning the candidate in the best fitness value. Initial population is produce randomly and then it is improved by following process such as selection, mutation, and crossover.

The Differential Evolution optimization process is conducted by means of the following operations in [35]:

(i) Initialization:

To start the optimization process, an initial population for the first generation P, initial parameter values X_{ij} must be selected randomly in uniform between lower L and higher H bound interval $[X_{iL}, X_{iH}]$,

$$P^G = X_{iL} + rand[0,1].(X_{iH} - X_{iL}) \quad (8)$$
$$i = 1,2 \ldots\ldots NP,\; G = 1,2 \ldots.\, G_{max},$$

where *NP* and *G* represents number of population and number of generation.

For each individuals vector consists of control variables D. $X_i^G = X_{ij}^G, j = 1,2 \ldots\ldots D$

(ii) Mutation:

Mutation is a process of creating a mutant vector V_i^G for each target vector X_i^G in the current population. For a given parameter vector X_i, G, three vectors $\left(X_{r1,G}, X_{r2,G}, X_{r3,G}\right)$ are randomly selected such that the indices $i, r_1, r_2, and\, r_3$ are distinct.

A donor vector $V_{i,G+1}$is created by adding the weighted difference between the two vectors to the third (base) vector as

$$V_{i,G+1} = X_{r1,G} + F.\left(X_{r2,G} - X_{r3,G}\right) \quad (9)$$

where F is a user-defined constant (also known as the mutation scaling factor), which is usually select from the range (0,1).

(iii) Crossover:

In the process of crossover, next generation mutated individual

$V_{i,G+1} = \left[V_{1i,G+1,}V_{2i,G+1,}V_{ji,G+1} \;\ldots\ldots V_{Di,G+1}\right]^t$ and the present individual

$X_{i,G} = \left[X_{1i,G,}V_{2i,G,}X_{ji,G} \;\ldots\ldots X_{Di,G+1}\right]^t$are mixed to the yield the trial vector

$$U_{i,G+1} = \left[U_{1i,G+1,}U_{2i,G+1,}U_{ji,G+1} \;\ldots\ldots U_{Di,G+1}\right]^t$$

$$U_{j,i,G+1} = \begin{cases} V_{i,j,G+1}, & if arandnumber \leq 0 \\ X_{j,i,G}, & otherwise \end{cases} \quad (10)$$
$$j = 1,2 \ldots\ldots D, G = 1,2 \ldots. N_p$$

where D is also the number of genes. CRε[0; 1] is the cross over factor and must be set by the user.

(iv) Evaluation and Selection:

The parent is substituted by its young within the next generation when the fitness of the later is better. Otherwise, the parent is retained. The first step is one-to-one competition (Local search). The next step selects the best individual in the population (Global search).

$$X_{i,G+1} = arg - max\left(f\left(X_{i,G}\right), f\left(U_{i,G+1}\right)\right)$$
$$(11)$$
$$X_{b,G+1} = arg - max\left(f\left(X_{i,G+1}\right)\right)$$

Where $i = 1,2, \ldots\ldots N_p$

In the process of MPPT problem, the PV equation is the fitness function and perturbation voltage V_{pv}, either current I_{pv} or duty cycle D are used as control variables.

$$P^G = x_i^G = d_i^G \;\vee\; I_{pvi} \;\vee\; V_{pvi} = \left[x_{1,}x_{2,}x_{3,} \ldots\ldots x_i\right] \quad (12)$$

To begin the optimization process, control parameters for initial population is considered. The first generation fitness function values P_0 are calculated by measuring the current and voltage of the PV array corresponding to each target vector. The output power P_{pv} is used as fitness function $f(X_{Gi})$, which is obtained by multiplying the measured voltage and current of the PV array. Next mutation process is carried out to generate mutation vector V_{Gi} by mutating with a target vector X_{Gi} for each generation G.

Next the algorithm enters in to the loop of crossover to generated a trial vectors U_{Gi}. In the selection process is compared with the fitness value of each target vector X_{Gi}corresponding trial vector U_{Gi}, to create new members of population for the next generation using equation (12). The process of mutation, crossover and selection will be repeated until the fittest value is obtained i.e global MPP.

Tajuddin et al [36] proposed the MPPT technique for static pre-determined PV curves. This technique is not practically applicable to real time PV system because the temperature and solar irradiance are continuously changing in phenomena.

Ishaque et al [37] proposed modified DE algorithm for MPPT problem. In this technique dynamic objective function is formulated which effectively satisfied the large rapid fluctuation of solar irradiance and also reduced the steady state oscillation once it reaches the exact MPPT. It is fast convergence and produced overall efficiency 99.6% during partial shaded condition.

Wang et al [38] proposed both static and dynamic PV curves and unified MPPT controller is designed by differential evaluation algorithm. This method is justified using three different modules.

D. Firefly Algorithm

Firefly algorithm was first introduced by yang [39]. It is a metaheuristic algorithm inspired by flashing behavior of fireflies to attract other files for mating purpose. The rhythmic flash, the rate of flashing and the amount of time from part of the signal system that brings both sexes together. For simplicity in describing firefly algorithm, the following three assumptions are made: 1) all fireflies are unisex so that one firefly will be attracted to other fireflies regardless of their sex; 2) the attractiveness between two fireflies is proportional to relative brightness and the less brighter one will move toward the more brighter one. If there is no brighter one in a firefly colony, each one will move randomly and 3) the brightness of a firefly is affected or determined by the landscape of the objective function.

For a maximization problem, the brightness can simply be proportional to the value of the objective function.

Consider p and q be two fireflies positioned at X_p and X_q, respectively. Let the distance between these two fireflies is denoted as r_{pq}. In a single dimensional space, we can write

$$r_{pq} = \|X_p - X_q\| \quad (13)$$

The degree of attractiveness β, is a function of distance between two fireflies and is given by

$$\beta(r) = \beta_0 \, e^{-\gamma(r_{pq})^n}, \quad n \geq 1 \quad (14)$$

In the above equation, γ is termed as absorption coefficient, used to controls the decrease of light intensity. The value of γ, is between 0 and 10. The symbol β_0 is initial attractiveness and is chosen as 1, such that the brightest firefly strongly determines the position of other fireflies in its neighborhood.

Assuming that the brightness of firefly p is less than that of q, the new position of firefly p is given by the following equation:

$$X_p^{t+1} = X_p^t + \beta(r)\left(X_p - X_q\right) + \alpha\left(rand - {}^1/_2\right) \quad (15)$$

Here, random movement factor α is constant in the range [0; 1] and *rand* is a random number uniformly distributed between *0* and *1* for each movement of firefly. A large amount of α makes the movement to explore the solution through the distant search space and the smaller α tends to facilitate local search.

The steps of FA algorithm toward MPPT are described below:

Step 1: Fix the constant parameters of the FA such as $\beta_0, \gamma, \alpha, n,$ and population size *N*. In this algorithm, consider the duty cycle d of the dc-dc converter as position of the firefly and power generated $P_{pv}$by the PV array as brightness of the firefly with respect to position of this firefly.

Step 2: In this step, the fireflies are permitted to search in a certain space region that is in between the minimum and maximum values of the duty ratio of the dc-dc converter[d_{min}: d_{min}]

Step 3: In this step, the duty ratio of the dc-dc converter is operated corresponding to the position of each firefly sequentially. The output power P_{pv} is measured with respect to each duty ratio. This step is repeated for position of all fireflies in the population.

Step 4: The firefly with maximum brightness retains in its same position and the remaining fireflies update their position based on equation (3).

Step 5: Stop the program if the dc-dc converter operates at the optimum duty cycle corresponding to GMPP, otherwise go to step (3).

Step 6: Reinitiate the FA if the solar insolation changes, which is detected by the digital controller by sensing the change in the power output.

Sundreswaran et al [40] reports that the FA-based tracking is superior, fast converging, reduced computational complexity, and tracking speed. The transients in power, voltage and current before reaching GMPP are very least when compared to P & O and PSO methods.

E. Cuckoo Search Algorithm

Cuckoo Search is an optimization algorithm developed on the parasitic reproduction strategy of cuckoo birds. Generally cuckoo birds behave as brood parasitism such that laying their eggs in other birds (host birds) nests [41].

Based on the behavior of cuckoos, the yang and deb [42] has developed three rules: (1) the cuckoos lays only one egg at a time and spot it in arbitrarily chosen nest. (2) the next generation is created by the highest quality eggs which is spot on the best nest. (3) the number of accessible nests is fixed.

The number of eggs laid by a cuckoo found by the host bird is consider as probability P_a, where $0 < P_a < 1$. If the cuckoos eggs are found, the host bird can abandon its nest or destroy cuckoos eggs. Either way a new nest will be generated with a probability of P_a for a fixed number of nests. Based on these three rules, the CS algorithm can be developed.

In cuckoo reproduction strategy, searching for a suitable host birds nest is an significant which proceeds in a random manner. In cuckoo algorithm searching of nest is described by Levy flight. Levy flight moves in random step where step sizes are calculated from Levy distribution according to a power law [43].

The behavior of levy flight is applied in the meta-heuristic search algorithm for the application of MPPT in PV system.

In CS based MPPT, suitable variables must be selected for the search. To begin, the specimens of PV voltages has to be taken V_i $(i = 1,2,3 \dots n)$. The total number of specimens and the step size are denoted by n and α respectively. The fitness function (J) is dependent on the PV voltage at MPP is $J = f(v)$.

Initially, the generated specimens are used to calculate the power which is set as the initial fitness value. The best sample is chosen based on the maximum power obtained by its corresponding specimens of PV voltage. Thereafter new voltage samples are generated based on the following equation.

$$V_i^{(t+1)} = V_i^t + \alpha \oplus Levy(\lambda) \qquad (16)$$

where $\alpha = \alpha_0 \left(V_{best} - V_i\right)$.

The levy distribution is presented as

$$S = \alpha_0 \left(V_{best} - V_i\right) \oplus Levy(\lambda) \approx K * \frac{u}{(|V|)^{1/\beta}} \left(V_{best} - V_i\right) \qquad (17)$$

where β= 1.5, k is the multiplying co efficient and u, v are determined from the normal distribution curves.

Jubaer Ahmed et al [44] described the implementation of CS algorithm for MPPT. To begin, all the constants and variables to be specific the voltage, current, power, number of specimens and the value of β are initialized. The initial power is calculated by using the present value of voltage and current. The new value of voltage and power are stored in the voltage V_i^t and fitness J_i^t arrays, respectively.

In addition, prior to the start of each iteration, a check out is conducted to determine whether the specimens have already attained convergence or not. If the specimen's posses converged to MPP, they will merge as a same value and so does the respective power. If the specimens does not meet converge, all the power values of the corresponding specimens are measured and stored in the J_i^t array.

By assessing the array, the specimen with highest power is picked as the best specimen. Thereafter, by ideals of Eq.(17) all other specimens are compelled to go towards this best value. The step sizes are calculated by performing the Lvy flight search. Accordingly, a new set of specimens are found and the corresponding powers are calculated. And then, if any specimen with lesser power is cut-off and a new specimen is generated. This iteration continues until all the specimens converge to the optimum point, i.e. MPP.

F. Artificial Bee Colony Algorithm

The artificial bee colony algorithm (ABC) is population based optimization algorithm constructed from the smart foraging behavior of honey bee swarm, developed by Karaboga in 2005 [45].

The colony has three groups of bees: employed bees, onlookers and scouts. It is expected that, the every food stuff has one employed bee. The number of foodstuffs nearby the hive is usually adequate to the number of employed bees in the colony. Employed bees go to their foodstuffs and return to hive and dances on this region. The employed bees food source has been deserted turns into a scout and begins to search for discovering another new foodstuff. Onlookers watch the dance movement of employed bees and select foodstuffs relying upon dances.

In the implementation of MPPT based ABC algorithm, the position of the foodstuff (Duty cycle) denotes the optimal solution to the MPPT problem and the amount of foodstuff are represents the corresponding quality (Power) of the associated solution.

The steps taken by the algorithm [46] is explained below:

step 1: At the starting the population is created within the range of upper and lower limit. The employed bees are permitted to move in the search space to attain the particular solution.

The initialization is done by the following equation,

$$x_{ij} = x_j^{min} + rand\ (0,1)\left(x_j^{max} - x_j^{min}\right) \qquad (18)$$

where $i = 1,2,3, \ldots .SN$ and $j = 1,2,3, \ldots .D$. SN is the population of the colony and D is the number of parameters to be optimized by the algorithm.

Step 2: After initialization each food source is allotted to the employed bee. The employed bee changes the position of the food sources based on the information of nearby food source. Once it reaches it analysis the quality of food source. The nearby food sources are found by the following equation

$$t_{ij} = x_{ij} + \Phi\left(x_{ij} - x_{kj}\right) \qquad (19)$$

In the above equation j is a random integer in the range of [1, D] while D and k=1, 2,3,….SN is a randomly chosen index that is different than i and Φ_{ij} is a randomly distributed number in the domain [-1, +1].

The fitness function for the nearby food source is calculated by the following equation,

$$fitness_i = \begin{cases} 1 = (1 + f_i) & if\ f_i \ > 0 \\ 1 = \left(1 + abs(f_i)\right) & if\ f_i \ > 0 \end{cases}$$

Step 3: If all the employed bees have completed their searches, then the information food source is shared to onlooker bees. The onlookers bees chooses one of their best sources depending on the dance of the employed bees. It is done by probabilistic selection scheme,

$$P_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \tag{20}$$

Step 4: The remaining food sources are abandoned and a new food source is searched by the scout bees and replaced with the abandoned sources.

Step 5: The above steps are repeated until the optimized solution (GMPPT) is reached.

G. Symbiotic Organism Search Algorithm

Symbiotic Organism Search (SOS) is a metaheuristic population based optimization algorithm proposed by Min-yuan cheng [47]. The word symbiosis means "living together" describes the two different organism depends on each other or mutually beneficial to fulfill the susceptance in the ecosystem under different environmental conditions. There are three different symbiotic relationships are naturally found in the ecosystem namely mutualism, commensalism and parasitism. Based on these relationship algorithm is formulated in three phase to find the optimal solution.

(i) Mutualism Phase:

In mutualism, both participating organism gets mutually benefits. For example, the relationship between starlings and buffalo. Starlings get ticks from buffalo's skin and the itching on buffalo's skin will be reduced.

In mutualism phase, X_i is an organism interact with randomly chosen organism X_j with aim of increases the benefits mutually to survive in the ecosystem. The new organism X_{inew} and X_{jnew} are calculated based on the following equation.

$$X_{inew} = X_i + rand(0,1) * (X_{best} - Mutual\_Vector * BF_1)$$

$$X_{jnew} = X_j + rand(0,1) * (X_{best} - Mutual\_Vector * BF_2)$$

$$Mutual\_Vector = \frac{X_i + X_j}{2}$$

Where,

BF_1 and BF_2 represents benefit factors which chosen either as 1 or 2 depends on level of benefits.

X_{best} represents the highest degree of adaptation.

The organisms are updated only if the new organism is fittest than previous organism.

(ii) Commensalism Phase:

In commensalism, is a cooperative relationship between two unique species in which one gets benefits and the other is unaffected. For example relationship between remora fish and sharks. The remora fish eats the left over foods of shark thus by remora fish gets benefits without affecting the shark. In this phase, an organism X_j is selected randomly interact with X_i in the ecosystem.

The organism X_i tries to get benefit and the X_j itself neither benefits nor affected from the interaction. Then the fittest organism is updated only if new fitness valve is better than previous value by the following equation,

$$X_{inew} = X_i + rand(-1,1) * (X_{best} - X_j)$$

(iii) Parasitism Phase:

In parasitism, a symbiotic relationship between two different species in which one get benefits and the other is effectively damage. The example is between the anopheles mosquito and human body. Anopheles injects plasmodium parasite into the human body which create fatal threats causing the body to eventually die. In this phase, parasite vector is created by duplicating the organism X_i and interact with randomly selected organism X_j in the ecosystem. If the parasite vector has better fitness value than the organism X_j, then it will destroy the organism X_j, otherwise parasite vector will never again have the capacity to live in the ecosystem. Thus each organism interacts randomly with other organism in the ecosystem randomly and the process is repeated till the termination criteria is met.

Prakash S et al [48], proposed SOS algorithm for tracking MPPT under partially shading condition for the PV system. The main advantage of this algorithm is that, it does not require any definite tuning parameters. So it show sign of best response in quick settling time and the tracking efficiency is comparatively higher than conventional algorithms.

H. FruitFly Optimization Algorithm

The Fruit fly Optimization Algorithm (FOA) is a new method for finding global optimization based on the food finding manners of the fruit fly.

The naturally fruit fly itself is better than other species in detecting and discernment, particularly in osphresis and vision. The Fruit fly Optimization Algorithm is another strategy for finding global optimization developed based on discovering of foodstuff manners of the fruit fly by Wen-Tsao Pan [49].

The actually fruit fly itself is superior to different species in distinguishing and insight, especially in osphresis and vision. The osphresis organs of fruit flies can discover a wide range of aromas skimming all around; it can even notice food source from 40 km away. At that point, after it draws near to the nourishment area, it can also utilize its delicate vision to discover food and the company's flocking area, and fly towards that bearing as well. The proposed fruitfly algorithm steps are described, as below:

Step 1: choose the initial position of a fruitfly randomly in the boundary.

$$InitX\_axis, InitY\_axis$$

Step 2: Random direction and distance of searching for food using the sense of smell of a fruit fly individual is calculated by the equation,

$$X_i = X\_axis + Random\_value$$

$$Y_i = Y\_axis + Random\_value$$

Step 3: As the location of food cannot be known, the distance ($Dist_i$) to the origin is estimated before the decision value of smell concentration (S) is calculated; this value is the reciprocal of distance.

$$Dist_i = \sqrt{X_i^2 + Y_i^2}$$

$$S_i = \frac{1}{Dist_i}$$

Step 4: Substitute smell concentration judgment value (S) into smell concentration judgment function (or called Fitness function) so as to find the smell concentration ($Smell_i$) of the individual location of the fruit fly.

$$smell_i = function(S_i)$$

Step 5: Find out the fruit fly with maximal smell concentration (finding the maximal value) among the fruit fly swarm.

$$[best\_smell; best\_index] = \max(smell)$$

Step 6: Keep the best smell concentration value and x, y coordinate, and at this moment, the fruit fly swarm will use vision to fly towards that location.

$$X\_axis = X(best\_index)$$

$$Y\_axis = Y(best\_index)$$

Step 7: Enter iterative optimization to repeat the implementation of steps 2–5, then judge if the smell concentration is superior to the previous iterative smell concentration, if so, implement step 6.

Prakash S et al [50], implement the fruit fly optimization algorithm for the application of tracking maximum power from the PV system under different environmental conditions. The FOA-based MPPT can handle partial shading conditions efficiently and it outperforms the conventional algorithm in terms of faster convergence to global point, tracking speed, reduced steady state oscillations, and higher tracking efficiency.

A comparison of technique explained in section III as applied to MPPT problem is presented in Table 1 for quick reference.

Table 1
Comparison Of Artificial Intelligence Algorithms

Method	Algorithm complexity	Hardware implementation	Convergence speed	Efficiency (η)
PSO [26,27, 28,29]	Easy	Easy	Slow	Low, 99.47%
ACO [31,32, 33,34]	Moderate	Moderate	Moderate	High, 99.60%
DE [35,36, 37,38]	Moderate	Moderate	Fast	High, 99.50%
FF [39,40]	Easy	Easy	Very Speed	Very high, 99.97%
CS [41,42, 43,44]	Moderate	Moderate	Speed	High, 99.96%
ABC [45,46]	Moderate	Moderate	Fast	High 99.65%
SOS [47,48]	Easy	Moderate	Very Fast	High 99.87%
FOA [49,50]	Easy	Easy	Very Fast	High 99.80%

IV. Conclusion

This paper reviews and describes the optimization procedure to find GMPP of partial shaded condition for eight different optimization techniques, with the objective of maximizing the power. Their advantages and disadvantages are compared based on published results.

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