EVOLUTIONARY OPTIMIZATION APPROACH FOR FINDING GPPP OF A PV ARRAY SYSTEM UNDER HETEROGENEOUS OPERATING CONDITION

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Abstract: *This research work investigates an evolutionary optimization approach for finding Global Peak Power Point (GPPP) of a Photovoltaic (PV) array system under Heterogeneous operating conditions. The presence of a by-pass diode introduces multiple peaks in the Power-Voltage (P-V) and multiple steps in Current-Voltage (I-V) characteristics of a PV array under Heterogeneous operating conditions. The Particle Swarm Optimization (PSO) and Bacterial Foraging Optimization (BFO) techniques have been incorporated to determine the effective GPPP under shadow conditions. The effects of cognitive coefficient of individual particles (C_1) and the social coefficient of all particles (C_2) play a major role in finding the optimum solution in the search space of PSO are also studied. The BFO algorithm has a large number of control parameters when compared to PSO and it shows significant improvements in terms of convergence speed and final accuracy towards reaching the GPPP. The mathematical model of proposed PV system have been developed and simulated in Matlab-simulink environment to track the GPPP. The simulated results of Incremental Conductance (INC) method, PSO and BFO are evaluated and compared for different shading patterns of the PV array system. From the obtained results, it is found that the BFO algorithm gives considerable improvements than INC and PSO algorithms.*

Key words: *Photovoltaic, Global Peak Power Point, Incremental Conductance, Particle Swarm Optimization algorithm and Bacterial Foraging Optimization algorithm.*

1. Introduction.

This research paper focuses the exploitation of green energy for promoting the PV system. The sun radiates more photons which are sufficient to generate electrical power for meeting the energy demands [1]. Solar energy has certain intermittent issues, not shining at night and also during daytime there may be cloudy or rainy weather and partial shadow effects which reduce the intensity of sunlight falling on the PV modules. The change in solar irradiation (G) and the effects of shadow over the PV panel are referred as Heterogeneous conditions. A major challenge in using a PV generation is to tackle its nonlinear I-V characteristics, which results in the necessity of detection of a unique Peak Power Point (PPP) on its P-V curve. A PV array system (3x3 PV modules) including bypass diodes and blocking diodes developed for this study is shown in Fig.1. It is important to consider the effects of bypass diodes and blocking diodes in a PV array under Heterogeneous operating condition. The resulting P-V characteristic curve becomes more complex and exhibits multiple peaks. The presence of multiple peaks reduces the effectiveness of the PV system and it is also important to identify the optimum PPP under different shading patterns [2].

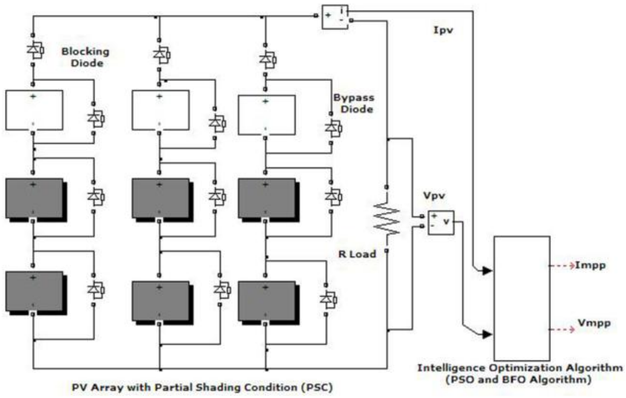

Fig.1 Block diagram of the proposed PV system.

This research paper aims to employ an evolutionary optimization algorithm for finding GPPP and to enhance performance of the PV array system under Heterogeneous operating conditions. The research paper is organized as follows: The section-2 discusses the non-linear characteristics of a PV array under shading patterns, section-3 illustrates the concept of PSO algorithm and parameter selection to optimize the location of GPPP in the P-V characteristic curve and the section-4 explains a global optimization BFO algorithm for achieving the optimum location of global maxima through multiples of local maxima under different shading conditions of a PV array by mimicking the foraging behavioral characteristics of Escherichia coli (E. coli) bacteria. The section-5 deals with comparison of results obtained from INC, PSO and BFO algorithms and discussion. The section-6 ends with the conclusion part of the research work findings.

2. P-V and I-V Characteristics of a PV Array under different Shading Patterns

The modeling of PV system has been comprehensively illustrated in earlier studies [3, 4] with the effects of bypass diodes and blocking diodes. The parameters of the PV module have been obtained from the manufacturer datasheet (MS24250) for this analysis purpose. The Matlab-simulink for shading pattern-1 is illustrated in Fig. 2. The calculated maximum power (P_{max}) is accounted as 2251.8W, 1512W, 1124.55W and 1015.75W under Homogenous & Heterogeneous conditions which are tabulated in Table- 1. The variation in the value of P_{max} is due to the loss of radiations caused by the effects of partial shadings and low solar irradiations over the PV panels.

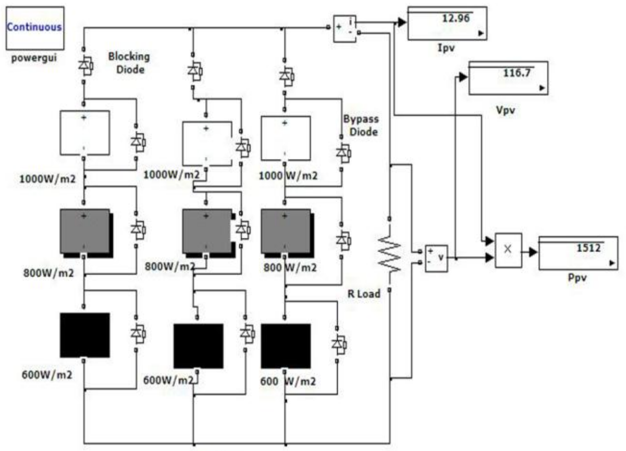

Fig.2 Matlab-simulink of PV array under shading pattern-1

Table 1 P_{max} of PV array under different shading patterns

Shading Pattern	Solar irradiation (W/m^2)			$P_{max.}$ (W)
1	1000	1000	1000	1512
	800	800	800	
	600	600	600	
2	1000	1000	1000	1124.55
	400	400	400	
	700	700	700	
3	1000	1000	1000	1015.75
	500	500	500	
	400	400	400	
Homogenous condition (STC)				2251.8

The consequence of by-pass diode and the non-linearity behavior of the PV array under Heterogeneous conditions are noticed as multiple steps in I-V & multiple peaks in a P-V characteristic curve which are plotted in Fig.3 and Fig.4 respectively. Moreover, the conventional methods struck by the Local Peak Point (LPP) and it fail to track the GPPP under Heterogeneous shading patterns. The next section illustrates the effective tracking of GPPP under shadings by employing evolutionary optimization techniques.

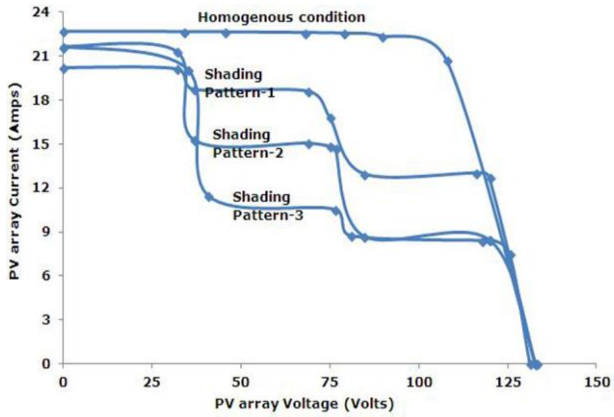

Fig.3 I-V characteristics of PV array under Homogenous and Heterogeneous condition

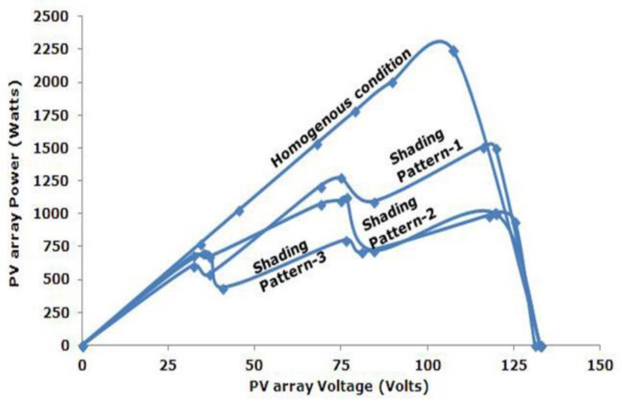

Fig.4 P-V characteristics of PV array under Homogenous and Heterogeneous conditions

3. Particle Swarm Optimization Algorithm

PSO is an effective meta-heuristic technique that can be implemented to optimization problems [5-9] having many local optimal points and it is adopted here to realize the GPPP under shadowed conditions of the PV array. The intelligence of Swarms with their movement towards the global solution starts from a random selection & it continues in a search space from previous iterations and also the accuracy of the solution is achieved by evaluating its fitness function. The particles keep track of its coordinates in the solution of search space are associated with the personal best (p_{best}) solution that has been achieved by that individual particles and the track of the best solution as compared with any other particles in the neighborhood of the search space is representing the global best (g_{best}) of that particle obtained which is illustrated in Fig.5.

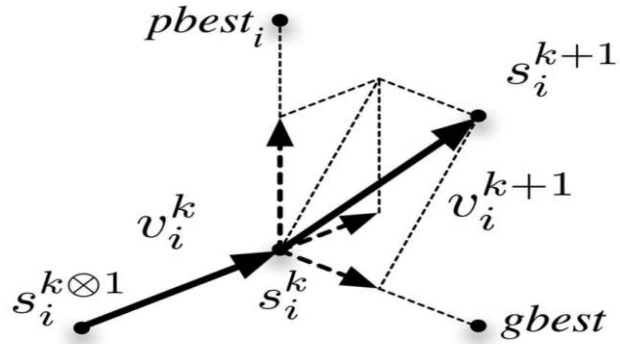

Fig.5 Particle movements in the search space of PSO.

At each time step, the particles move with velocity (v_i) from its position (S_i) towards their p_{best} locations and each particle ultimately progress to reach an optimal or close to an optimal global solution in the search space. The particle's position and their velocity in the search space are expressed in equation (1) and equation (2) respectively.

$$S_i^{k+1} = S_i^{k} + v_i^{k+1} \tag{1}$$

$$v_i^{k+1} = w.v_k + C_1 r_1 (p_{best,i} - S_i^{k}) + C_2 r_2 (g_{best} - S_i^{k}) \tag{2}$$

where, k - iteration number, w - inertia weight, C_1 - cognitive coefficient of individual particles, C_2 - social coefficient of all particles. The random variables (r_1 & r_2) are uniformly distributed (0-1) and it continues the stochastic movement within iterations. The range of velocity [0, v_{max}], helps the search space in closer to area of the global solution. The $p_{best,i}$ stores the best position of the i^{th} particle as expressed in equation (3) and g_{best} stores the best position of all the particles showing the GPPP location in the multiple peaks of the P-V curve. The occurrence of variations in the solar irradiations and amount of partial shading make power fluctuations in the PV system. In this study, the PV panel voltage has been fixed from 0 to V_{oc} and current from 0 to I_{sc} and it depends on the configuration of the PV array system.

$$P_{best,i} = S_i^k \text{ when } F(S_i^k) \geq F(S_i) \tag{3}$$

$$S_i^k = [S_1^k, S_2^k \ldots S_i^k \ldots S_{N-1}^k, S_N^k] \tag{4}$$

$$\left| \frac{F(S_{i+1}) - F(S_i)}{F(S_i)} \right| > \Delta P \tag{5}$$

The evaluation of the particles is carried out based on the PV panel output power and which is represented as a fitness evaluator (F) for the particles. The position of i^{th} particle location (S_i^k) at k^{th} iteration is expressed in equation (4), which shows the position of the number of particles (N) in the search space of the problem under the consideration.

A detailed procedure for implementing the PSO algorithm for finding GPPP is illustrated in Fig. 6. The problem has been formulated with the objective of two dimensions (2D) as a function of PV array voltage (V_{PV}) and PV array current (I_{PV}) which helps to track the peak power.

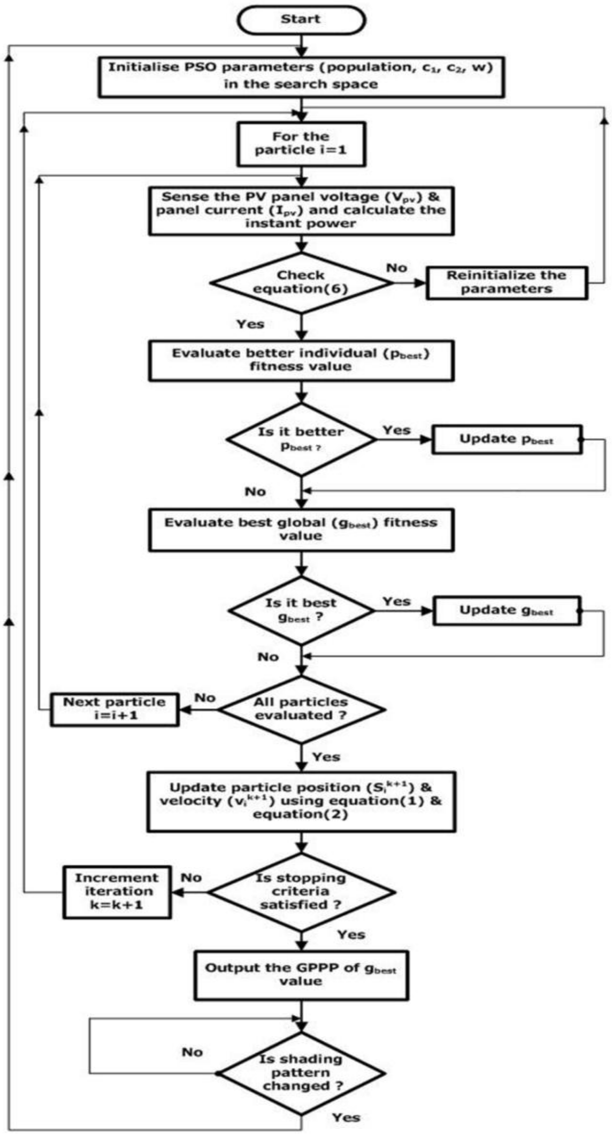

Fig.6 Flow chart for finding GPPP using PSO algorithm.

In this study, the number of particles is approximated as 100 and during the initialization phase, these particles can be placed in a fixed position or be placed in the space randomly. The peaks of the P-V curve occur nearly at multiples of 80% of the PV module open circuit voltage (V_{oc}) and the minimum displacement between successive peaks is also nearly 80% of V_{oc}. Therefore, the particles are initialized on fixed positions which cover the entire search space of the solution.

The cognitive coefficient of individual particles and the social coefficient of all particles play a major role in finding the optimum solution in the search space. The greater value of C_1 finds the better individuals and higher value of C_2 finds the best individuals among the all particles in the solution space which is referred as a global solution. The sum of C_1 and C_2 is accounted as the value of 4 [10-11]. In this research work, the effective value of finding GPPP is analysed for the different combination of C_1 and C_2 values and it is illustrated that the inappropriate design values of C_1 and C_2 leads the local maximum rather than the global one and it affects the convergence speed and accuracy also. The four different combinations of C_1 and C_2 values have been taken to study their effects in finding the GPPP in the search space under shading patterns of the PV array. The Matlab M-Files has been developed for finding the optimum GPPP location under different shading patterns of solar irradiation. The simulated performance curve for shading pattern-1 and shading pattern-2 for different values of C_1 and C_2 has been plotted in Fig.7 and Fig.8 respectively. The simulation responses illustrated that the best convergence reaches closer to the global solution for the values of C_1=0.1 and C_2=3.9 and for other values, the solutions are diverged from the global solutions where the GPPP is located. Inertia weight (w) is the other important parameter which influences the convergence of this algorithm [12] and also it helps to control the velocity of the particles moving towards the GPPP. The higher value of the inertia weight (w≥0.8) speeds up the convergence to the optimum solution whereas lower value narrows down the range of the search space. In this work the inertia weight is assumed as 0.9.

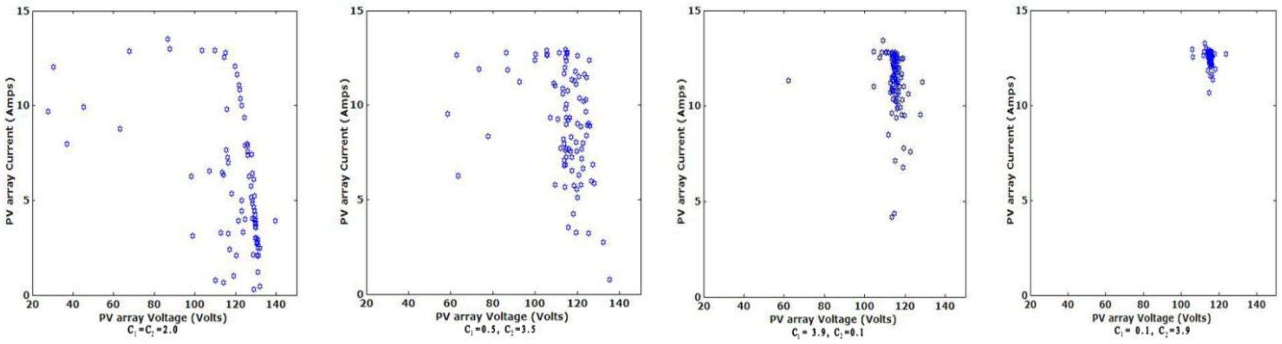

Fig.7 Performance curve for different values of C_1 and C_2 under shading pattern-1

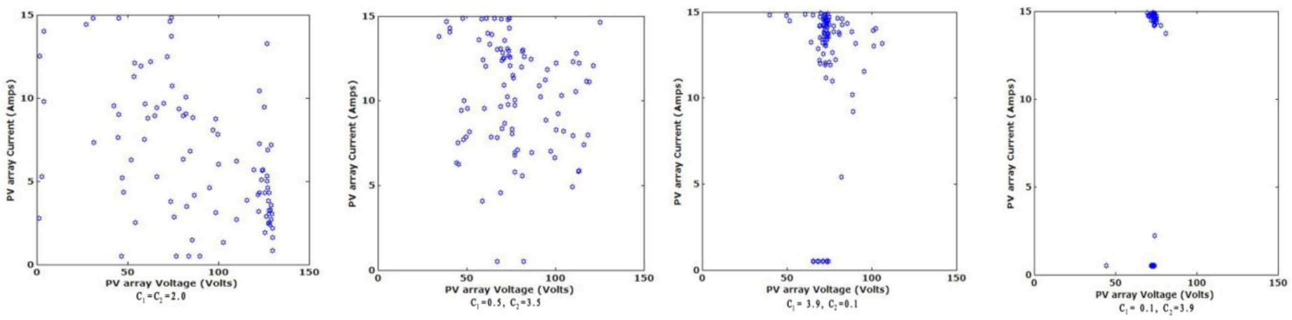

Fig.8 Performance curve for different values of C_1 and C_2 under shading pattern-2

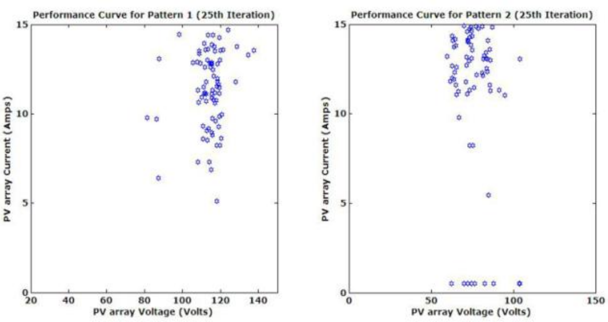

Fig. 9 Performance curves obtained by PSO at the end of 25th iteration

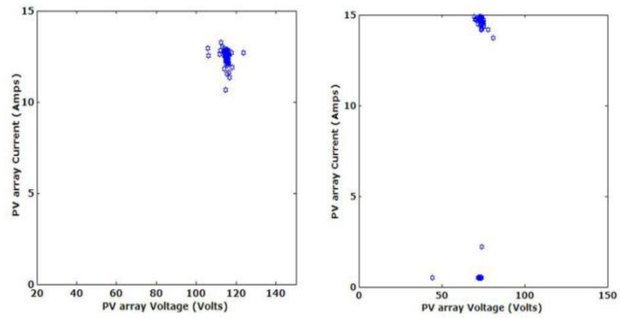

Fig. 10 Performance curves obtained by PSO at the end of convergence

The performance curve for shading pattern-1 and pattern-2 has been illustrated in Fig.9 and Fig.10 at the end of 25th iteration and during convergence respectively. The stochastic behavior of the Swarm intelligence is incorporated in finding the GPPP of the PV array system under three different shading conditions and the simulated results are tabulated in Table-2 which shows the peak power (P_{mp}) detected values. Moreover, the PSO algorithm is adaptive and it is initialized by sensing the changes in the operating levels of the PV array system and also it prevents the convergence of the problem at the local maxima location.

Table 2 Peak power detection using PSO algorithm

Shading pattern	**V_{mp} (Volts)**	**I_{mp} (Amps)**	**P_{mp} (Watts)**
1	115.2	12.8	1414.56
2	74.25	14.85	1102.61
3	117.7	8.41	989.86

4. Bacterial Foraging Optimization Algorithm

In this research work, a new evolutionary computation technique, BFO approach has been realized to achieve the GPPP from multiples of LPP under different shading conditions of a PV array system by mimicking the behavior of E. coli bacteria. An E. coli present in our intestines undergoes important stages such as Chemotaxis, Swarming, Reproduction, Elimination & Dispersal for its survival. A social and non-social foraging strategies are two categories, the former one uses its own energy and get help from other members in the population, but the later one follows its own energy and do not seek help from others in the same solution space. Here, the social foraging strategy is adopted to find the global solution among the local maxima. During the foraging process of Chemotaxis stage, when the bacteria are not finding a better solution, it will turn to a new direction (tumble action) and evaluate the new fitness value. If it is really improved, then it will continue to steps in the same direction (run process) until no significant improvement in fitness value has been found or reaches a predetermined threshold number of moving steps. Hence, an E. coli bacterium performs the tumble and /or run operation (movement of the bacteria) during its entire lifetime is expressed in equation (6) as below; represent the position of each member in the population of the S-bacteria at the jth chemotactic step.

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + c(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i).\Delta(i)}} \qquad (6)$$

where θi (j, k, l) represents the position of each member in the population of the ith bacterium at jth chemotactic step, kth reproduction step and lth elimination & dispersal step, c(i) is related to the step size in the arbitrary path specific by the tumble (run length unit) and a unit length vector in the random direction [-1, 1] is represented by Δ [13,14]. This movement of an E. coli is continued until a bacterium reaches the direction of the global solution region to explore its local and global search properties separately.

Computation of the fitness value for the ith bacterium, J (i,j,k,l) using equation (7) is illustrated below:

$$J(i,j,k,l) = J(i,j,k,l) + J_{cc}(\theta^i(j,k,l), p(j,k,l)) \qquad (7)$$

set J_{Last} = J (i,j,k,l) and to save this value because there is a possible to get a better results during the tumble.

$$J_{Last} = J(i,j,k,l) \qquad (8)$$

In Swarming stage, the group behavior has been observed that, each E. coli bacterium will signal other via attractants to Swarm together. A group of E. coli cells organize themselves in a traveling pathway helps them to comprehend into groups and, thus, move as concentric patterns of swarms with high bacterium density [15]. The signaling function between cells can be represented using the equation (9). The left side of the equation is the objective function which has been added with the actual objective function of the problem under study. ‘p’ represents the dimension of the search space (number of variables) which is to be optimized. In this research work, the different values of the panel voltage (V_{PV}) and panel current (I_{PV}) formulate the search space of the solution.

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{S} J_{cc}(\theta, \theta^i(j,k,l)) \qquad (9)$$

$$= \sum_{i=1}^{S}(-d_{att}\exp(-w_{att}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)) + \sum_{i=1}^{S}(h_{rep}\exp(-w_{rep}\sum_{m=1}^{p}(\theta_m - \theta_m^i)^2)) \qquad (10)$$

$w_{attractant}$ (w_{att}), $h_{attractant}$ (h_{att}), $w_{repellant}$ (w_{rep}) and $h_{repellant}$ (h_{rep}) are the different coefficients used in the evaluation process of BFO. After a certain number of complete swims, the better half of the population undergoes the reproduction and eliminating the rest of the population. In order to escape local optima, an elimination dispersion event is carried out where some bacteria are liquidated at random with a very small probability and the new replacements are initialized at arbitrary locations of the search space solutions. The health of bacterium ‘i’ can be computed by using the equation (11).

$$J^i_{health} = \sum_{j=1}^{N_c - 1} J(j,k,l) \qquad (11)$$

Furthermore, in reproduction the least healthy bacteria die and the other healthiest bacteria each split into two bacteria, which are placed in the same location. This makes the population of bacteria constant in the evolution process. Besides, in elimination and dispersal, any one bacterium is eliminated from the total set by dispersing it to an arbitrary position on the optimization field. Elimination and Dispersal help in reducing the behavior of stagnation i.e. being trapped in a premature solution point or local optima. After many generations, poor foraging strategies are either eliminated or shaped into good ones. A comprehensive procedure for finding GPPP under shadowed condition using BFO is illustrating in Fig.11. A function to be optimized is developed with following expression using Matlab M-File program.

$$J(i, j+1, k, l) = Live\_fn(P(V_{pv}, I_{pv})) \tag{12}$$

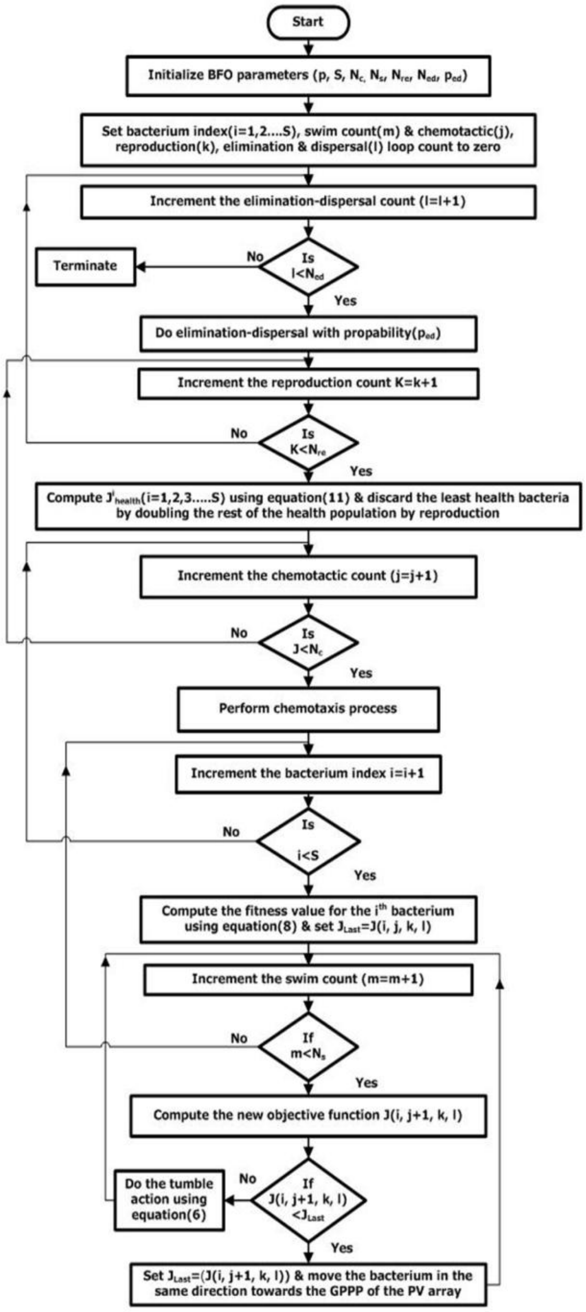

Fig.11 Flowchart representation of BFO algorithm for finding GPPP of PV array

The parameter settings of BFO algorithm has been tabulated in Table-3.

Table 3 Parameter settings of BFO algorithm

Parameters	Values
No. of bacterium(S)	100
Maximum number of steps(N_s)	3
Number of chemotactic steps(N_c)	1
Number of reproduction steps(N_{re})	4
Number of elimination and dispersal steps (N_{ed})	4
Length of swim (l)	1
Probability of elimination/dispersion (P_{ed})	0.1
The size of the step taken in the random direction specified by the tumble C(i)	0.1

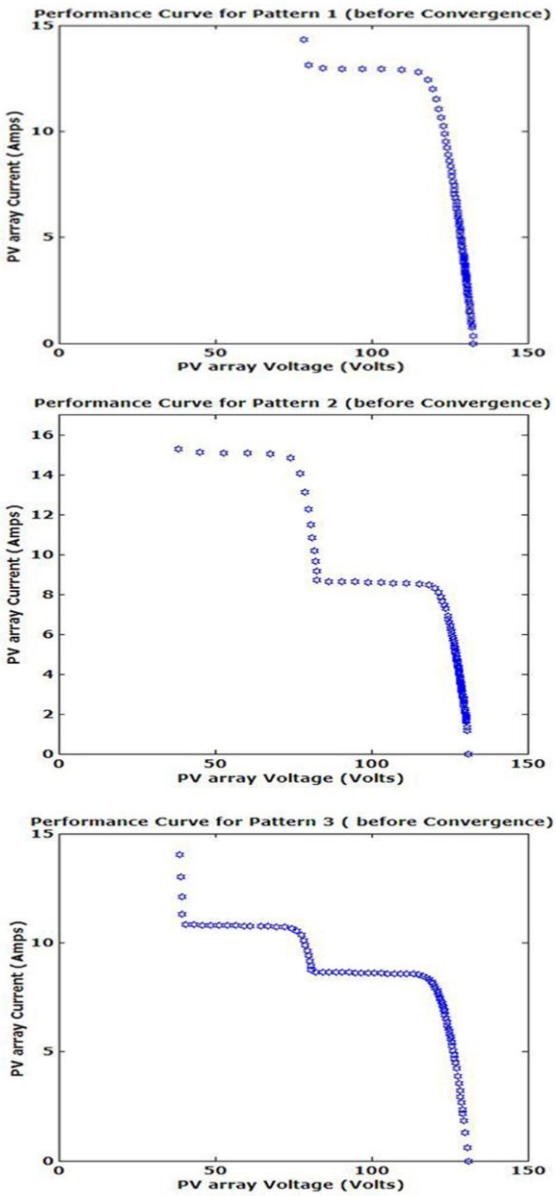

Fig.12 Performance curve of BFO under different shading patterns before convergence

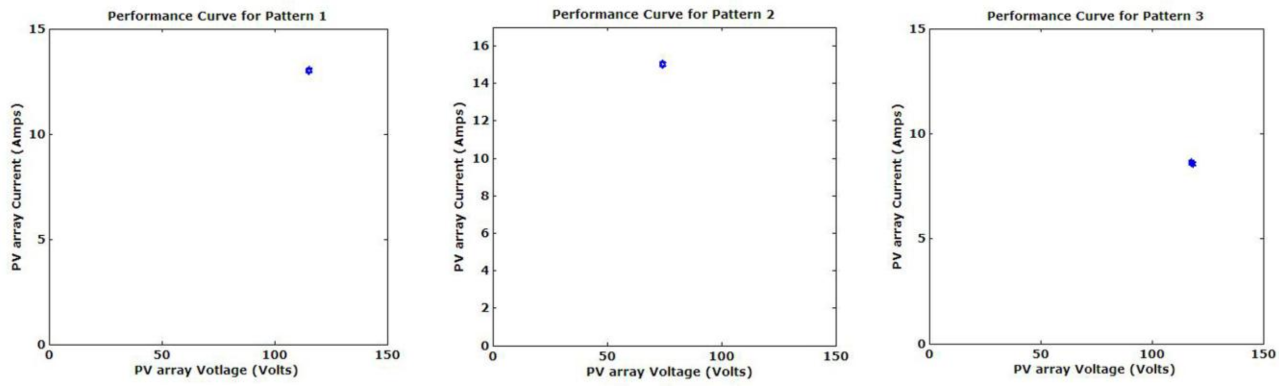

Fig.13 Performance curve of BFO under different shading patterns after convergence

Before and after convergence of the performance curves under the three shading patterns are illustrated in Fig.12 and Fig.13 respectively. The results obtained using BFO algorithm proves that the location of P_{mp} is very closer to the GPPP under all shading conditions with faster convergence speed and good accuracy without being struck with local maxima points.

5. Comparative Analysis of Results

This research work also compares the simulation results with conventional INC algorithm, which it fails to find the GPPP under the shadowed conditions. BFO has converged to the optimal solution to many problems where the most analytical methods fail to converge and also has its advantages such as less computational burden, global convergence, less computational time requirement. PSO and BFO methods are able to discriminate the global PPP from local PPP under shadowed conditions. The comparative results analysis has been taken for INC, PSO and BFO algorithms in finding the GPPP of PV array under different partial shading conditions and is tabulated in Table 4.

Table 4 Comparative analysis of results obtained from INC, PSO and BFO algorithms

Shading pattern	MPPT Tech.	V_{mp} (Volts)	I_{mp} (Amps)	P_{mp} (Watts)	P_{max} calculated
1	INC	110.25	12.4	1367.1	1512
	PSO	115.2	12.8	1414.6	
	BFO	115.30	13.06	1505.8	
2	INC	72.15	14.1	1017.3	1124.55
	PSO	74.25	14.85	1102.6	
	BFO	74.34	15.06	1119.6	
3	INC	114.5	8.05	921.73	1015.75
	PSO	117.7	8.41	989.86	
	BFO	117.83	8.61	1014.5	

The P_{mp} values obtained from these algorithms are also compared with the calculated P_{max} value and it is found that, BFO algorithm locates a global solution very close to the P_{max}. Moreover, the BFO algorithm has a large number of control parameters as compared to PSO algorithm, it shows significant improvements in terms of convergence speed and final accuracy towards reaching the GPPP during shading conditions. Table-5 illustrates the elapsed time taken for PSO and BFO for reaching the GPPP under different shading patterns. BFO shows significant improvement in searching the GPPP.

Table 5 Comparison of peak power and elapsed time for PSO and BFO algorithms

Shading Pattern	PSO		BFO	
	P_{mp} (Watts)	Elapsed time (sec)	P_{mp} (Watts)	Elapsed time (sec)
1	1414.6	2.557	1505.8	1.702
2	1102.6	2.62	1119.6	1.737
3	989.86	2.68	1014.5	1.792

6. Conclusion

This proposed work has been investigated an evolutionary optimization method for finding the GPPP of a PV array system under Heterogeneous operating conditions. The P-V and I-V characteristics of a PV array system under these conditions have been studied where it exhibits multiple peaks in the P-V curve. The computational intelligence of a PSO and BFO algorithms are described to identify the global operating point of a PV array system under shadow conditions. Moreover, the effects of cognitive coefficient of individual particles and the social coefficient of all particles values in PSO for finding an optimum solution in the search space are also evaluated. The PSO and BFO methods are showing their ability in distinguishing the global solution from local maxima under shadowed conditions. Also, the BFO algorithm locates a global solution very near to the maximum power than INC and PSO algorithms with better convergence speed & accuracy towards the finding of GPPP under shading conditions of a PV system.

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