# Bacterial Foraging Optimization Approach to Parameter Extraction of a Photovoltaic Module

**Article** *in* IEEE Transactions on Sustainable Energy · August 2017

DOI: 10.1109/TSTE.2017.2736060



**2 authors:**

Bidyadhar Subudhi
National Institute of Technology Rourkela



Raseswari Pradhan
Veer Surendra Sai University of Technology

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



# Bacterial Foraging Optimization Approach to Parameter Extraction of a Photovoltaic Module

Bidyadhar Subudhi, *Senior Member, IEEE* and Raseswari Pradhan

*Abstract*-This paper presents a new parameter extraction method for photovoltaic (PV) modules exploiting Bacterial Foraging Optimization (BFO) technique. In a PV system, validation of the model of a PV module with correctly chosen parameters is essential. An efficient parameter extraction method is required to estimate the parameters of PV module. Although, a number of parameter extraction methods are available in literature but there is a need to explore parameter extraction methods that could extract globally optimized parameters in changing weather conditions. One of the recent evolutionary computing approaches called BFO exhibits global optimization performance. Therefore, we employ BFO for extraction of parameters of a PV module. The proposed BFO based parameter extraction method has been tested for different types of PV modules at different test conditions. Analyzing both the simulation and experimental results obtained using BFO; it is found that the module parameters are more accurate compared to that of Newton-Raphson, Particle Swarm Optimization and Enhanced Simulated Annealing methods.

***Index Terms-* PV module parameters, parameter extraction, PSO, Newton-Raphson method, BFO.**

## NOMENCLATURE

| | | | |
|---|---|---|---|
| $I_{sc}$ | Short-circuit current | $I_{sh}$ | Current through $R_{sh}$ |
| $V_{oc}$ | Open-circuit voltage | $n_s$ | Number of series cells in the PV module |
| $I_{mpp}$ | MPP current | $k_b$ | Boltzmann's constant |
| $V_{mpp}$ | MPP voltage | $e$ | Charge of an electron |
| $P_{mpp}$ | MPP power | $V_t$ | Thermal voltage |
| $R_s$ | Series resistance | $G$ | Actual Solar irradiance |
| $R_{sh}$ | Shunt resistance | $G_{STC}$ | Solar irradiance at STC |
| $a$ | Diode-ideality factor | $T$ | Actual cell temperature |
| $I_{ph}$ | Photo-generated current | $T_{STC}$ | Cell temperature at STC |
| $I_0$ | Dark-saturation current | $V$ | Output voltage |
| $I_d$ | Current through diode *D* | $I$ | Output voltage |
| *STC* | Standard testing condition (1000 watts/m$^2$, 25 $^0$C) | | |

## I. INTRODUCTION

Recently, demand of PV energy has increased many fold as it is a promising renewable energy source. For efficient utilization of the available PV energy, the PV system should operate at its maximum power point (MPP). Therefore, an efficient maximum power point tracker (MPPT) is necessary. Since, MPPT is an essential component of a PV system, a lot of research is being pursued in this area and several MPPT techniques [1] have been proposed and implemented. To test any MPPT technique before its physical implementation, there is a necessity of verification through computer simulations. Hence, an accurate mathematical model of the PV module is essential for computer simulation analysis.

Mathematical models of a PV module such as two-diode and single-diode models are available in literature [2]. Although behavior of a two-diode model closely matches with that of the physical PV module but the model is very complex and its mathematical analysis is difficult. In view of these disadvantages, a single-diode model is popularly used [2]. An ideal single-diode model is assumed to be lossless and does not have $R_s$ and $R_{sh}$. Although this is simple but does not represent an accurate structure of a PV module. To improve the accuracy, both the resistances $R_s$ and $R_{sh}$ have been considered in the PV module as shown in Fig.1 [3]. This model is represented by five parameters i.e. $I_{ph}$, $I_0$, $R_s$, $R_{sh}$ and $a$ . It is known as single-diode-five-parameter model.

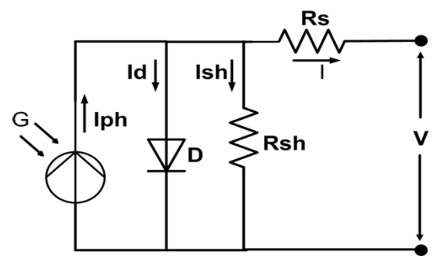



Fig.1. Single-diode-five parameter Electrical model of a PV module

Usually, the manufacturers' data-sheet of a PV module provides only a few information on PV module namely $I_{sc}$, $V_{oc}$, $I_{mpp}$ and $V_{mpp}$ at STC. Hence, all the parameters $R_s$, $R_{sh}$, $a$, $I_0$ and $I_{ph}$ of the model (Fig.1) are unknown. As these parameters need to be evaluated using a parameter extraction algorithm to design the mathematical model of a PV module. An analytical method has been reported in [4] in which the mathematical model of a PV module is represented by an empirical relationship between voltage $V$ and current $I$. This empirical relation between $V$ and $I$ can be determined by measuring $V$ and $I$ at different loads. The empirical relation between $V$ and $I$ is determined at the STC, hence although this analytical method performs efficiently at the STC but is found to be unsuitable using a single-diode-five-parameter model for wide range of varied weather conditions [3, 5]. In another method [3], parameters of a PV module namely, $R_s$, $R_{sh}$, $a$, $I_0$ and $I_{ph}$ are determined iteratively by varying each of these parameters in five dependent loops until the maximum power of the PV module matches with the power at the MPP. This method is simple and accurate but consumes a lot of time as it involves with five loops and a number of equations. It is also not reliable for other weather conditions other than the STC

B.Subudhi is working as Professor in the Department of Electrical Engineering, National Institute of Technology, Rourkela, India-769008.
R. Pradhan is working as Assistant Prof. in the Department of Electrical Engineering, VSSUT Burla. E-mail: bidyadhar@nitrkl.ac.in, rase1512@gmail.com

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



because the maximum power at the STC is only known from manufacturer's data-sheet. In parameter extraction approach [6], the above five loop problem has been simplified to a single loop problem by assuming the parameter $a$ as constant and $I_{ph}$ and $I_0$ with equations that are dependent on $R_s$, $R_{sh}$ and $a$. In this method, $R_{sh}$ is calculated by increasing $R_s$ until the maximum PV power becomes equal to the MPP power. This method is suitable to solve parameter extraction problem accurately at the STC but may fail at other weather conditions, because it assumes values of $R_s$, $R_{sh}$ and $a$ which are independent of weather conditions. Newton-Raphson method (NRM) is one of the best root-finding methods because of its accuracy. Hence, NRM has been applied in [3,7] for parameter extraction problem of PV module. But, five independent equations are required to find the values of $R_s$, $R_{sh}$, $a$, $I_0$ and $I_{ph}$. Hence, the computation of the Jacobian matrix used in the NRM algorithm is very complex, because the Jacobian matrix consists of twenty-five numbers of double-derivative terms. The Jacobian matrix has been further simplified in [7] for finding $R_s$, $R_{sh}$ and $a$. Here, $I_{ph}$ and $I_0$ are calculated solving two pre-defined equations that are dependent on $R_s$, $R_{sh}$ and $a$. To further simplify the above problem, the parameter $a$ is evaluated iteratively ($1 \le a \le 2$) and $R_s$ and $R_{sh}$ are solved by using the NRM until PV power matches with power at the MPP. But, in all these NRM methods [3, 7], singularity problem i.e. division by zero (due to existence of zero value of second derivative term at some voltages and currents) may arise if initial conditions of the parameters ($R_s$, $R_{sh}$, $a$, $I_0$ and $I_{ph}$) are chosen improperly. Also, these NRM methods are silent about the boundary limits of the parameters $R_s$, $R_{sh}$ and $a$. A lot of assumptions are taken in [3,7] in order simplify the five-parameter extraction problem which results in low value of $R_s$ and high value of $R_{sh}$ denoting the ideal conditions of PV module. Hence, there lies incorrectness on the validity of the parameters extracted by these NRMs. To resolve these issues, metaheuristics methods such as evolutionary computational algorithms can be used because these evolutionary algorithms are capable of accurate optimization in solution even where traditional mathematics fails.

Since the fitness function for the parameter extraction problem is a multi-modal optimization problem, evolutionary algorithms are suitable compared to the classical optimization techniques. A number of parameter extraction problems. But it is found that for the above problem, employing Genetic Algorithm (GA) has number of demerits such as low convergence speed and degradation of highly interactive fitness functions. Simulated Annealing (SA) method also employed for the PV module parameter extraction problem [8]. But it is seen in SA that there is trade-off between the cooling schedule and initial temperature. Due to these shortcomings of both SA and GA, Particle Swarm Optimization (PSO) has been employed for PV module parameter extraction problem, which has been found to provide improved solutions e.g. accurate module parameters [9]. But if the number iterations are increased, better results can be obtained with PSO compared to GA. To accurately model the PV module, an improved modeling approach using Differential Evolution (DE) method is discussed in [10]. Such approach enables the computation of model parameters at changing insolation and temperature point using the information given in the datasheet. But to determine the control parameters for employing DE algorithm it is quite challenging. Therefore, an improved adaptive DE (IADE) based optimization technique is proposed in [11] which uses a simple structure based on the feedback of fitness value in the evolutionary process. In [12], a two diode model of a PV cell consisting of seven parameters is used for parameter extraction using a penalty based DE at different environmental conditions. An improved DE with adaptive mutation per iteration algorithm (DEAM) has been proposed in [13] to find the parameters of a module. This extraction scheme employs the electromagnetism concept for adjustment of scaling factor in mutation and crossover rate to achieve improved performance of the DE and obtained parameters are found to be in close agreement with experimental data. A different variant of optimization approach called Flower Pollination Algorithm (FPA) has been applied in [14] to extract the PV module parameters which provides good results of parameter extraction at low irradiance levels.

In [15], a good review on different parameter extraction methods applied to determine optimal parameters of a PV model has been pursued. It is observed PSO approach is very effective for PV module parameter extraction problem. In [16-18], performances of five such evolutionary computational approaches i.e. GA, memetic algorithms, PSO, ant-colony systems and shuffled frog leaping have been compared. It has been demonstrated in [18], that PSO performs better than that of other four algorithms in terms of success rate and solution quality.

The proposed BFO method exploits advantages like accuracy of solution, consistency of solution and speed of convergence which outperforms other evolutionary techniques like SA, GA and PSO.

The PSO based parameter extraction method which is presented in [9] considers inverse barrier constraints for $R_s$, $R_{sh}$ and $a$. It obtains optimized values of parameters $R_s$, $R_{sh}$ and $a$ at any temperature condition. This method neither depends upon the initial condition nor on the gradient information. Since it depends only on the value of the objective function, it makes the algorithm computationally inexpensive, simple to implement and has low CPU and memory requirements. However, some experimental results show that although the global search ability of PSO is quite good but the local search ability around the optima is very poor [18]. This results in premature convergence in problems where multiple optima exist and hence, the performance is degraded.

Recently, another biologically inspired global optimization technique called BFO has been employed in many problems [18-19]. Use of BFO algorithm has following advantages:

(a) It is based on natural selection that tends to eliminate solutions with poor foraging strategies,

(b) Elimination of premature convergence

(c) Faster convergence speed than that of PSO and

(d) Better final accuracy than that of PSO [18].

Further, an Enhanced Simulated Annealing approach has been suggested in [20].Therefore, in this paper, first, the BFO algorithm has been chosen for optimal determination of parameters ($R_s$, $R_{sh}$ and $a$) at both variable temperatures and

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



solar irradiances. Subsequently its performances have been compared with that of PSO and ESA.

The paper is organized as follows. In section I, the parameter extraction problem of a PV module is presented in brief. In section II, the proposed BFO based parameter extraction method is described. The results and discussion are provided in section III followed by the concluding remarks in section IV.

## II. Problem Formulation

### *A. Modeling of a PV Module*

The output current of a single-diode five-parameter model (Fig.1) is given by [3]

$$I = I_{ph} - I_d - I_{sh} \tag{1}$$

$I_d$ denotes the diode current which can be expressed as

$$I_d = I_0\left[\exp\left(\frac{V+IR_s}{n_s V_t}\right)-1\right] \tag{2}$$

where $V_t$ is the thermal voltage and can be calculated as

$$V_t = \frac{ak_bT}{e} \tag{3}$$

$k_b$ denotes the Boltzmann's constant ($1.38\times10^{-23}$ J/K), $T$ is the PV module temperature (K) and $e$ is the charge of one electron. Similarly, $I_{sh}$ is the leakage current through $R_{sh}$ and is given by

$$I_{sh} = \frac{V+IR_s}{R_{sh}} \tag{4}$$

Using expressions for $I_d$ and $I_{sh}$ from (2) and (4) respectively in (1), the output current of single-diode-five-parameter model can be obtained as

$$I = I_{ph} - I_0\left[\exp\left(\frac{V+IR_s}{n_s V_t}\right)-1\right] - \frac{V+IR_s}{R_{sh}} \tag{5}$$

At solar irradiance $G$ and temperature $T$, the output current of PV module becomes

$$I = I_{ph}(G,T) - I_0(G,T)\left[\exp\left(\frac{V+IR_s(G,T)}{n_s V_t(G,T)}\right)-1\right] - \frac{V+IR_s(G,T)}{R_{sh}(G,T)} \tag{6}$$

The open-circuit voltage, short-circuit current at any solar irradiance $G$ and temperature $T$ are given by [3]

$$V_{oc}(G,T) = R_{sh}(G,T)\left[\begin{array}{l} I_{ph}(G,T) - \\ I_0(G,T)\left\{\exp\left(\frac{V+IR_s(G,T)}{n_s V_t(G,T)}\right)-1\right\}\end{array}\right] \tag{7}$$

$$I_{sc}(G,T) = \left(\begin{array}{l} I_{ph}(G,T) \\ -I_0(G,T)\left(\exp\left(\frac{V+IR_s(G,T)}{n_s V_t(G,T)}\right)-1\right)\end{array}\right) \times\left(\frac{R_{sh}(G,T)}{R_s(G,T)+R_{sh}(G,T)}\right) \tag{8}$$

Similarly, at the MPP under any solar irradiance $G$ and temperature $T$, PV current can be calculated as

$$\begin{aligned} I_{mpp}(G,T) &= I_{ph}(G,T) \\ &-I_0(G,T)\exp\left(\frac{V_{mpp}(G,T)+I_{mpp}(G,T)R_s(G,T)}{n_s V_t(G,T)}\right) \\ &-\frac{V_{mpp}(G,T)+I_{mpp}(G,T)R_s(G,T)}{R_{sh}(G,T)}\end{aligned} \tag{9}$$

Power at the MPP at any $G$ and $T$ can be calculated as

$$P_{mpp}(G,T) = V_{mpp}(G,T)\times I_{mpp}(G,T) \tag{10}$$

### *B. Temperature and Solar irradiance Effects on PV module Parameters*

At a given solar irradiance $G$ and temperature $T$, reference value of the short-circuit current $I_{sc}(G,T)$, open-circuit voltage $V_{oc}(G,T)$ and power at MPP $P_{mpp}(G,T)$ can be calculated as [6], [9]

$$I_{sc}^{*}(G,T) = \frac{G}{G_{STC}}\left[I_{sc}(STC)+K_I\left(T-T_{STC}\right)\right] \tag{11}$$

$$V_{oc}^{*}(G,T) = \left[V_{oc}(STC)+K_V\left(T-T_{STC}\right)\right] \tag{12}$$

$$P_{mpp}^{*}(G,T) = \frac{G}{G_{STC}}\left[P_{mpp}(STC)+K_P\left(T-T_{STC}\right)\right] \tag{13}$$

where $I_{sc}^{*}$(STC), $V_{oc}^{*}$(STC) and $P_{mpp}^{*}$(STC) are the reference values of the short-circuit current, open-circuit voltage and MPP power at STC respectively. $G_{STC}$ and $T_{STC}$ are the solar irradiance (=1000 watts/m$^2$) and temperature (=298 K) at STC respectively. $K_I$, $K_V$ and $K_P$ are the temperature coefficients at short-circuit current, open-circuit voltage and MPP respectively. All of the above six parameters ($I_{sc}^{*}$(STC), $V_{oc}^{*}$(STC), $P_{mpp}^{*}$(STC), $K_I$, $K_V$ and $K_P$) are provided by the manufacturer.

### *C. Formulation of the Parameter Extraction Problem*

The values of PV module parameters $I_{ph}$, $I_0$, $R_s$, $R_{sh}$ and $a$ are dependent on $G$ and $T$. At any $G$ and $T$, the dark-saturation and photo-generated currents can be calculated as follows.

$$I_o(G,T) = \frac{I_{sc}(G,T)+K_I\left(T-T_{STC}\right)}{\exp\left(\frac{V_{oc}(G,T)+K_V\left(T-T_{STC}\right)}{n_s V_t(G,T)}\right)-1} \tag{14}$$

$$I_{ph}(G,T) = \frac{G}{G_{STC}}\left\{\begin{array}{l} I_{sc}\left[\frac{R_s(G,T)+R_{sh}(G,T)}{R_{sh}(G,T)}\right] \\ +K_I\left(T-T_{STC}\right)\end{array}\right\} \tag{15}$$

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



Further, for any $G$ and $T$, the values of $I_{sc}$, $V_{oc}$ and $P_{mpp}$ can be calculated from the PV module model given by (7), (8) and (10). $I_{sc}$, $V_{oc}$ and $P_{mpp}$ can be represented in terms of $R_s$, $R_{sh}$ and $a$. The reference values of short-circuit current ($I_{sc}^*$), open-circuit voltage ($V_{oc}^*$) and MPP power ($P_{mpp}^*$) can be calculated analytically using (11), (12) and (13) respectively. Difference between $[I_{sc}, V_{oc}, P_{mpp}]^T$ and $[I_{sc}^*, V_{oc}^*, P_{mpp}^*]^T$ are the short-circuit current error, open-circuit voltage error and MPP power error respectively. The short-circuit current error ($E_{sc}$), open-circuit voltage error ($E_{oc}$) and MPP power error ($E_{mpp}$) need to be minimized by employing BFO algorithm formulating a suitable fitness function as shown in Fig.2.

## III. Proposed BFO Based Parameter Extraction Method

### A. BFO Algorithm

Survival of species in any natural evolutionary process depends upon their fitness criteria, which relies upon their food searching (foraging) and motile behavior. BFO rests on a simple principle of the foraging (food searching) behavior of *E. Coli* bacterium in human intestine. There are mainly four stages in a BFO optimized process such as chemotactic, swarming, reproduction and elimination and dispersal. In chemotactic stage, a bacterium can move in a predefined direction or change their direction of motion. In swarming, each bacterium provides a signal to other bacterium to move together. In reproduction, the healthiest bacterium split into two and less healthy bacterium die. In elimination and dispersal phase, a sudden unforeseen event occurs, that may drastically alter the smooth process of evolution and cause the elimination of the set of bacteria and disperse them to a new environment. This unknown event may place a newer set of bacteria nearer to the food location.

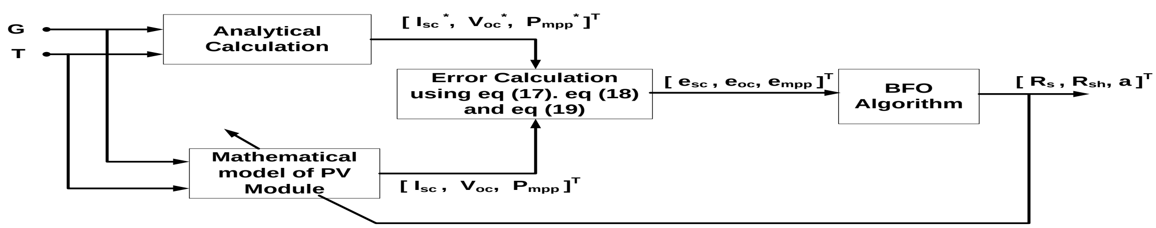



Fig.2. BFO based Parameter Extraction Method

### B. BFO Algorithm for Parameter Extraction Problem

In section A, it has been discussed that the parameter extraction of a PV module is basically an optimization problem where the errors need to be minimized (Fig.2). This minimization problem is to be accomplished by using the BFO that is described in this section. The fitness function is then solved using BFO algorithm (shown in Fig.3) to evaluate the unknown parameters ($R_s$, $R_{sh}$ and $a$).

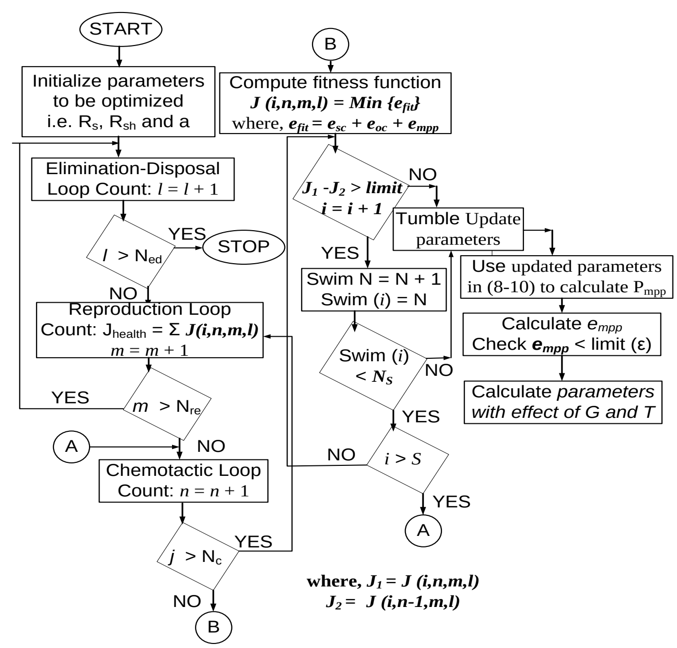



Fig. 3 Proposed BFO-Parameter Extraction Algorithm

In this BFO-Parameter Extraction algorithm, the following terms have been used.

$i$ = sample count
$l$ = elimination-dispersal loop count
$m$ = reproduction-dispersal loop count
$n$ = chemo tactic loop count
$S$ = total number of samples
$p$= number of parameters to be optimized
$N_s$ = swimming length
$N_c$ = number of chemotactic iterations
$N_{re}$ = maximum number of reproduction steps
$N_{ed}$ = maximum number of elimination and dispersal events
$P_{ed}$ = probability of elimination and dispersal events
$J(i,n,m,l)$ = fitness function
$J_{health}$ = factor representing health/ fitness/ suitability of each sample of parameters $R_s$, $R_{sh}$ and $a$
$C(i)$ = size of the step taken in the random direction specified by each run or tumble
$d_{attract}$, $\omega_{attract}$, $\omega_{repellant}$, $h_{repellant}$ = arbitrarily chosen weighing factors

For effective and accurate evaluation of the parameters, upper and lower limit constraints are also considered for each parameter. The fitness function and parameter constraints are defined as follows.

#### (a) Fitness Function

The fitness function for this parameter extraction problem can be defined as

$$\min_{R_s, R_{sh}, a, G, T} e_{fit} = e_{sc} + e_{oc} + e_{mpp} \quad (16)$$

where $e_{sc}$, $e_{oc}$ and $e_{mpp}$ are the absolute percentage of short-circuit current error, open-circuit voltage error and MPP power error respectively.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



$$e_{sc} = \left| \frac{I_{sc}(G,T) - I_{sc}^{*}(G,T)}{I_{sc}^{*}(G,T)} \right| \times 100 \quad (17)$$

$$e_{oc} = \left| \frac{V_{oc}(G,T) - V_{oc}^{*}(G,T)}{V_{oc}^{*}(G,T)} \right| \times 100 \quad (18)$$

$$e_{mpp} = \left| \frac{P_{mpp}(G,T) - P_{mpp}^{*}(G,T)}{P_{mpp}^{*}(G,T)} \right| \times 100 \quad (19)$$

*(b) Parameter Constraints*

The fitness function shown in (16) can be solved to extract of the parameters ($R_s$, $R_{sh}$ and $a$). For this, the inequality constraints for the parameters ($R_s$, $R_{sh}$ and $a$) are considered as follows.

$$\begin{cases} R_{s,\min} \le R_s \le R_{s,\max} \\ R_{sh,\min} \le R_{sh} \le R_{sh,\max} \\ a_{\min} \le a \le a_{\max} \end{cases} \quad (20)$$

*(c) Update unknown parameter*

Parameters are updated using the following equation.

$$x^i(n+1,m,l) = x^i(n,m,l) + u \times C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

where, $\Delta(i)$ is a random vector between [-1, 1].

## IV. Results And Discussion

The efficacy of the proposed BFO based parameter extraction method is tested using four PV modules (Shell SQ85, Shell SP70, SSI-M6-205 and Shell ST40). These four PV models are verified for some defined test conditions i.e.; solar irradiances $G$ (1000 watts/m$^2$, 800 watts/m$^2$, 600 watts/m$^2$, 400 watts/m$^2$and 200 watts/m$^2$) and temperatures $T$ (-25$^0$C, 0$^0$C, 25$^0$C, 50$^0$C and 75$^0$C).

### A. Simulation Results

For each test condition, the BFO algorithm was implemented using MATLAB and individual set of parameters ($R_s$, $R_{sh}$ and $a$) were evaluated. For this BFO approach to evaluate $R_s$, $R_{sh}$ and $a$, a set of 200 numbers of populations error of MPP power was calculated using (19).In the simulation of the proposed BFO-Parameter Extraction algorithm, we have considered the following parameters for BFO.

$$\begin{cases} S = 200, p = 3, N_c = 5, N_{re} = 10, \\ N_{ed} = 10, P_{ed} = 0.1, C(i) = 0.001, d_{attract} = 0.05, \\ \omega_{attract} = 0.3, h_{repellant} = 0.05, \omega_{repellant} = 0.05 \end{cases}$$

For ease in simulation and parameters evaluation all the three parameters ($R_s$, $R_{sh}$ and a) were considered to be bounded with the inequality constraints as defined in eq (19) and Table I.

TABLE I. INEQUALITY CONSTRAINTS FOR UNKNOWN PARAMETERS OF PV MODULES

| Parameters | PV Modules | | | |
|---|---|---|---|---|
| | Shell SQ85 | Shell SP70 | SSI-M6-205 | Shell ST40 |
| $a_{min}$ | 0.8 | 0.8 | 0.8 | 0.8 |
| $a_{max}$ | 2 | 2 | 2 | 2 |
| $R_{s,min}$ | 0.01 | 0.01 | 0.01 | 0.01 |
| $R_{s,max}$ | 2.0 | 2.0 | 2.0 | 2.0 |
| $R_{sh,min}$ | 140 | 140 | 100 | 140 |
| $R_{sh,max}$ | 300 | 300 | 600 | 300 |

Fig.4 shows the 3D-plot of fitness function and number of populations at different temperatures. This 3D-plot looks like a hilly curve and the global minimum of fitness function for each temperature is the deepest point in this curve. From this figure, it is clear that, for each temperature, the one among the populations that gives this deepest point is the fittest one. This fittest set of parameters ($R_s$, $R_{sh}$ and $a$) were recorded. Using this procedure, the parameters ($R_s$, $R_{sh}$ and $a$) were determined for all the test conditions ($G$ (1000 watts/m$^2$, 800 watts/m$^2$, 600 watts/m$^2$, 400 watts/m$^2$and 200 watts/m$^2$) and temperatures $T$ (-25$^0$C, 0$^0$C, 25$^0$C, 50$^0$C and 75$^0$C)).

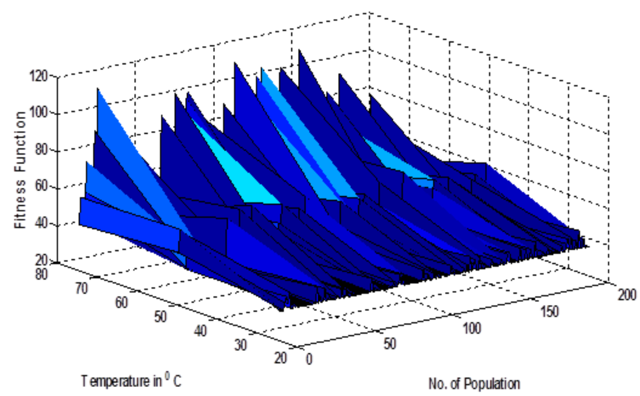



Fig.4. Comparison of Fitness Function of Shell SP70 PV Model for different populations at temperature variations

The efficacy of the proposed BFO parameter extraction scheme is verified by comparing its performance with three other existing parameter extraction methods proposed in [6,7,9]. The absolute percentage fitness functions calculated by (19) at STC of all the above four parameter extraction methods are compared in Table II. From this comparison, it is confirmed that BFO approach to parameter extraction yields lesser fitness function at STC considering the given mono-crystalline PV module i.e. Shell SQ85 (0.000134%), poly-crystalline PV module i.e. Shell SP70 (0.0016%) or thin-film PV module i.e. ST40 (0.000507%) compared to that of NRM, iterative and PSO parameter extraction methods.

TABLE II. COMPARISON OF ABSOLUTE % FITNESS FUNCTION AT STC

| Method | Shell SQ85 | Shell SP70 | SSI-M6-205 | Shell ST40 |
|---|---|---|---|---|
| NRM [7] | 0.0044 | 0.0354 | 0.0473 | 0.0133 |
| Comprehensive [6] | 0.0047 | 0.0085 | 0.0324 | 0.0234 |
| PSO [9] | 0.003 | 0.004 | 0.013 | 0.012 |
| Proposed BFO | 0.000134 | 0.0016 | 0.0018 | 0.000507 |

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



Fig.5 and Table III show the extracted parameters of Shell SP70 at different test conditions i.e. temperatures -25$^0$C to 75$^0$C. Analyzing the information provided by Fig.4 and Table III, it is found that like NRM and PSO parameter extraction methods, the BFO parameter extraction method converges to extracted parameters at test conditions other than that of STC also. But average fitness function ($e_{fit}$) at all test conditions for BFO is much less which is around 0.029% as compared to 0.18% for NRM and 0.073% for PSO.

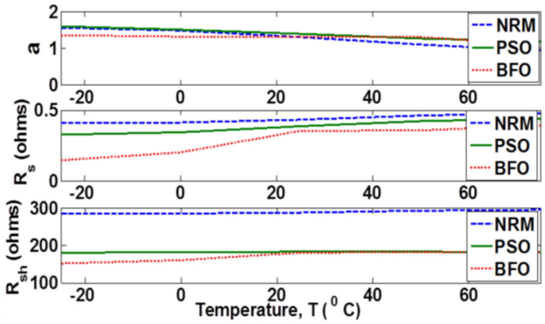



Fig.5. Comparison of Extracted Parameters of Shell SP70 PV Model using NRM, PSO and BFO Methods at -25$^0$C to 75$^0$C

TABLE III. EXTRACTED PARAMETERS OF SHELL SP70 PV MODULE USING DIFFERENT METHODS

| T ($^0$C) | NRM [7] | | | |
|---|---|---|---|---|
| | a | $R_s$ (ohms) | $R_{sh}$ (ohms) | $e_{fit}$ (%) |
| -25 | 1.5557 | 0.4082 | 285.2283 | 0.2365 |
| 0 | 1.4821 | 0.4113 | 285.2514 | 0.1363 |
| 25 | 1.3112 | 0.4309 | 287.538 | 0.0354 |
| 50 | 1.107 | 0.4625 | 292.55 | 0.1366 |
| 75 | 0.9422 | 0.4787 | 295.675 | 0.3371 |
| T ($^0$C) | PSO [9] | | | |
| | a | $R_s$ (ohms) | $R_{sh}$ (ohms) | $e_{fit}$ (%) |
| -25 | 1.6006 | 0.3264 | 181.108 | 0.193 |
| 0 | 1.5146 | 0.3435 | 182.2525 | 0.03 |
| 25 | 1.3894 | 0.3855 | 183.031 | 0.004 |
| 50 | 1.2717 | 0.4211 | 182.8944 | 0.064 |
| 75 | 1.1903 | 0.4403 | 182.2962 | 0. 38 |
| T ($^0$C) | Proposed BFO | | | |
| | a | $R_s$ (ohms) | $R_{sh}$ (ohms) | $e_{fit}$ (%) |
| -25 | 1.3558 | 0.1456 | 151.4257 | 0.055 |
| 0 | 1.3133 | 0.2013 | 160.891 | 0.02 |
| 25 | 1.3039 | 0.3521 | 180.3798 | 0.0016 |
| 50 | 1.3025 | 0.3554 | 181.3502 | 0.0045 |
| 75 | 1.1018 | 0.3939 | 182.1808 | 0.065 |

The calculated values of $R_s$, $R_{sh}$ and $a$ for all the tested PV modules using proposed BFO method are shown in Fig.6. From the obtained values of parameters (Fig.5), it is clear that the proposed BFO method successfully converges to extracted parameters for all the PV modules studied with various test conditions.

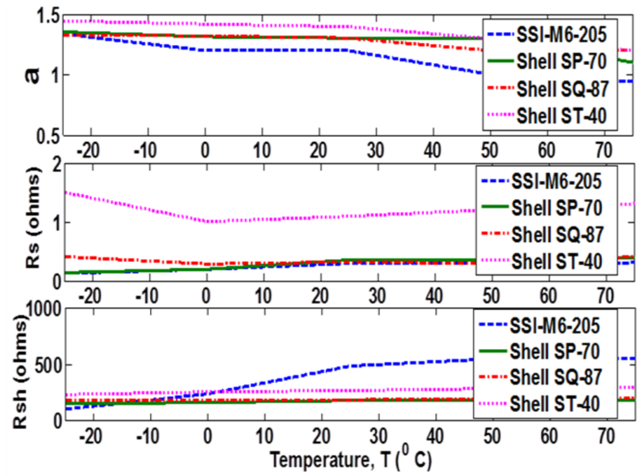



Fig.6. Comparison of Extracted Parameters of different PV Models using proposed BFO method at -25$^0$C to 75$^0$C

Fig.7 shows error versus temperature curves using BFO parameter extraction method of different PV modules. From this figure, it is clear that BFO method converges to extract PV module parameters for all types of PV modules i.e. mono-crystalline, poly-crystalline and thin-film. Also, BFO converges to an average of less than 0.1% of $e_{fit}$ for all PV modules at all temperatures. Similarly, BFO method converges to the extracted parameters of Shell SP70 PV module with an average $e_{fit}$ of around 0.005% (Table IV). Hence, the proposed BFO based parameter extraction method performs parameter extraction efficiently at changing solar irradiances also.

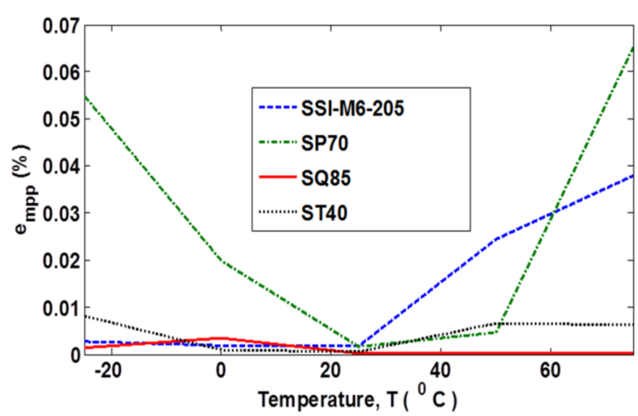



Fig.7. Comparison of Extracted Parameters of Shell SP70 PV Model using different Methods at -25$^0$C to 75$^0$C

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/TSTE.2017.2736060, IEEE Transactions on Sustainable Energy



TABLE IV EXTRACTED PARAMETERS OF SHELL SP70 PV MODULE AT DIFFERENT SOLAR RADIATIONS

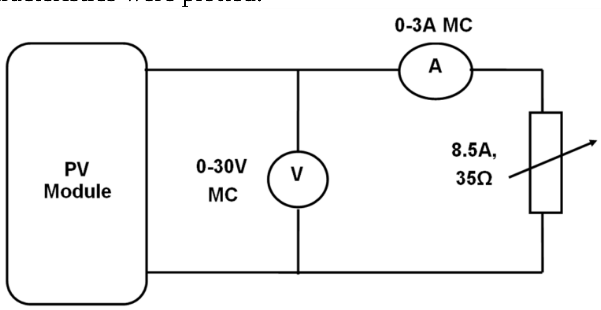
| G (watts/m$^2$) | a | $R_s$ (ohms) | $R_{sh}$ (ohms) | $e_{fit}$ (%) |
|---|---|---|---|---|
| 1000 | 1.3039 | 0.3521 | 180.3798 | 0.0016 |
| 800 | 1.0001 | 0.3424 | 116.8352 | 0.002 |
| 600 | 1.5931 | 0.3542 | 176.5206 | 0.005 |
| 400 | 1.2402 | 0.2027 | 416.9232 | 0.01 |

### *B. Experimental Results*

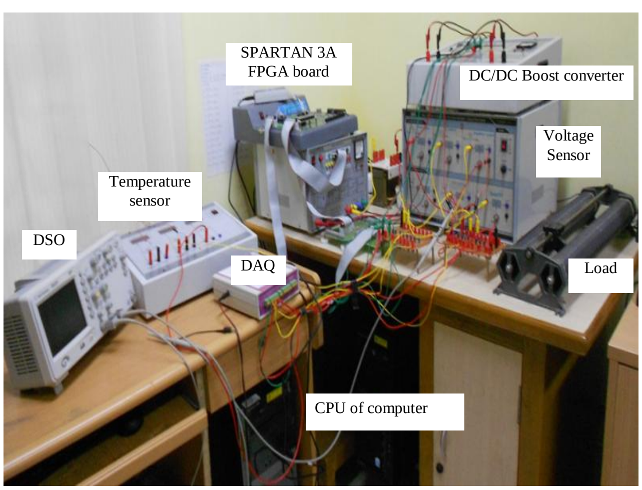
For experimental validation of the proposed BFO method, an experiment was conducted on a mono-crystalline PV module whose data-sheet parameters are as follows.

$$\begin{cases} V_{oc} = 21.7 \quad volts \\ I_{sc} = 1.85 \quad amps \\ P_{mpp} = 30 \quad watts \end{cases} \tag{21}$$

The circuit diagram and photo of experimental set-up for the above experiment are shown in Fig.8 (a) and (b) respectively. In this set-up, a rheostat of 8.5A and 35Ω rating was connected across the PV module. For measuring the voltage and current of the PV module, a 0-30V moving coil (MC) voltmeter and a 0-3A MC ammeter were used. Changing the load, the voltage and current of the PV module were measured and recorded. Power of the PV module was then calculated by multiplying the recorded voltage and current. Using the recorded values of voltage, current and power, I-V and P-V characteristics were plotted.




(a)




(b)

Fig.8. (a) Circuit of Experimental set-up and (b) Photograph of the experimental set-up.

Fig.9 shows the comparison between the experimentally obtained and the BFO simulated P-V characteristics. It can be seen from this figure that the simulated P-V characteristic using BFO extracted parameters more closely matches with the experimentally obtained P-V characteristic compared to that of PSO simulated P-V characteristics.

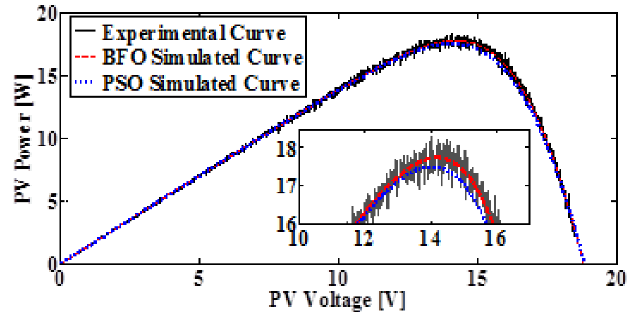
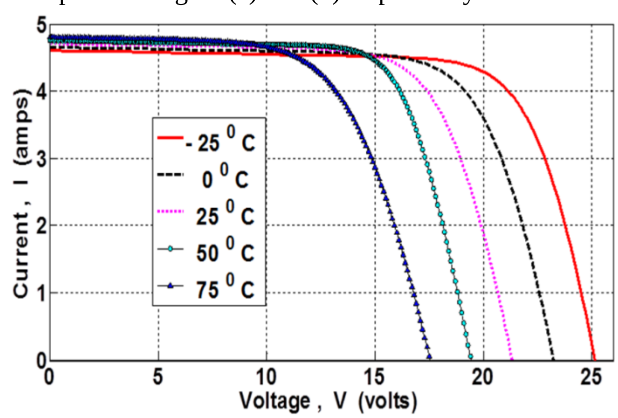



Fig.9. Comparison of P-V characteristics using Extracted Parameters of PM648 PV Model using proposed BFO Method with that of experimentally obtained curve at 658 watts/m$^2$ and 23$^0$C

### *C. Robustness and Convergence Analysis*

I-V and P-V characteristics of Shell SP70 PV module using parameters extracted by BFO method at different temperatures are compared in Fig.10 (a) and (b) respectively.




(a)

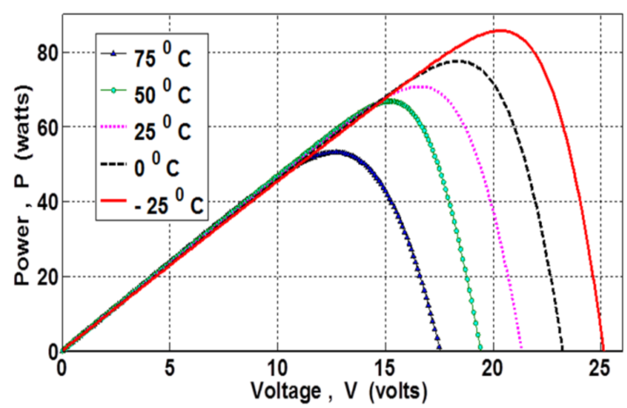
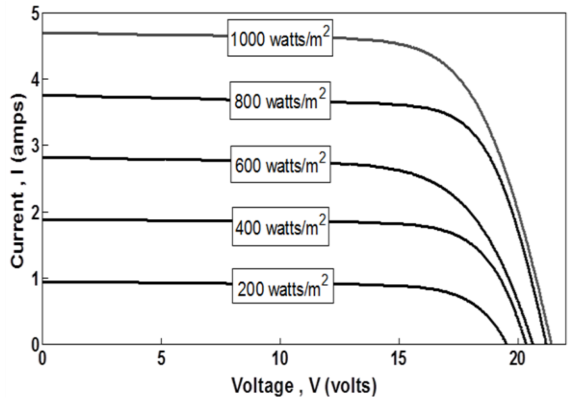
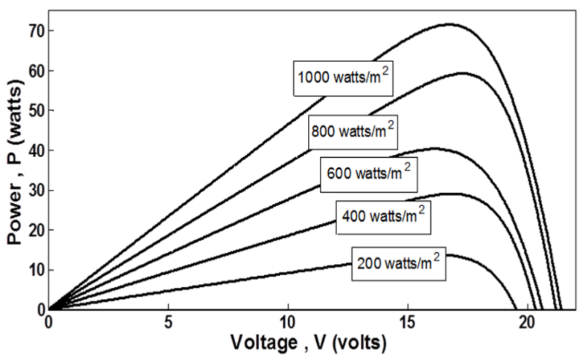



Fig.10. (a) Comparison of I-V characteristics using Extracted Parameters of Shell SP70 PV Model using proposed BFO Method at -25$^0$C to 75$^0$C and (b) Comparison of P-V characteristics using Extracted Parameters of Shell SP70 PV Model using proposed BFO Method at -25$^0$C to 75$^0$C

Similarly, Fig.11 (a) and (b) show I-V and P-V characteristics of Shell SP70 PV module using parameters extracted by BFO method (Table IV) at different solar irradiances respectively.




(a)




(b)

Fig.11. (a) Comparison of I-V characteristics using Extracted Parameters of Shell SP70 PV Model using proposed BFO Method at 200 watts/m$^2$ to 1000 watts/m$^2$ and (b) Comparison of P-V characteristics using Extracted Parameters of Shell SP70 PV Model using proposed BFO Method at 200 watts/m$^2$ to 1000 watts/m$^2$

Fig.12 further verifies the efficacy of the BFO parameter extraction method i.e. the BFO simulated P-V characteristics match with that of the experimentally obtained P-V characteristics in partially shaded condition.

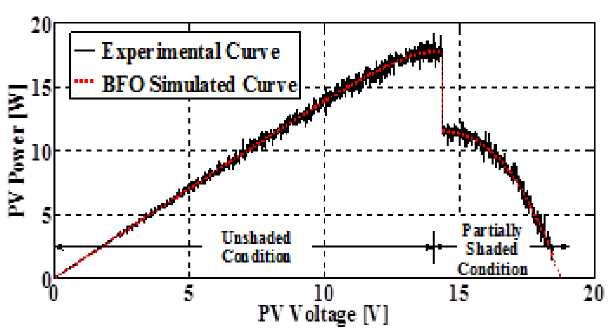



Fig.12. Comparison of P-V characteristics using Extracted Parameters of PM648 PV Model using proposed BFO Method at Unshaded condition and partially shaded condition

Again, the BFO simulated curve is compared with that of the Enhanced Simulated Annealing (ESA) [20] curve as shown in Fig.13. From this figure it can be seen that BFO simulated curve is better than that of ESA.

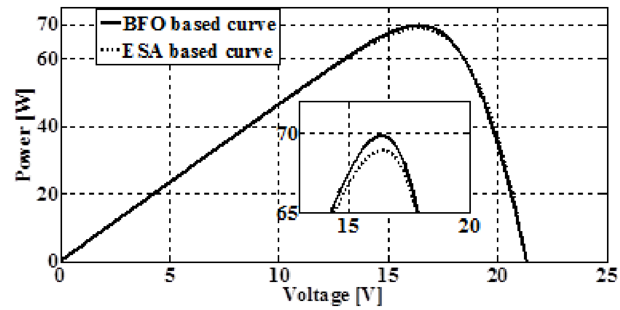



Fig.13. Comparison of P-V characteristics using Extracted Parameters of SP70 PV Model using proposed BFO Method and ESA method at STC

The speed of convergence of BFO algorithm as compared to other methods such as NRM, PSO and ESA has been tabulated in Table V for two different PV modules namely, Shell SP70 and SSI-M6-205. Further, in order to verify the robustness of the proposed estimation scheme, we considered the estimation performance with change in solar irrdiances from 200 watts/m$^2$ to 1000 watts/m$^2$. From Table V, it can be anlaysed that the convergence time in case of BFO algorithm is lesser than that of PSO and ESA algorithms both for Shell SP70 and SSI-M6-205 PV modules.

TABLE V. CONVERGENCE ANALYSIS OF DIFFERENT ALGORITHMS FOR PARAMETER EXTRACTION OF SHELL SP70 AND SSI-M6-205 PV MODULES

| Technique | SP70 PV Model | | SSI-M6-205 PV Model | |
|---|---|---|---|---|
| | 200 watts/m$^2$ | 1000 watts/m$^2$ | 200 watts/m$^2$ | 1000 watts/m$^2$ |
| BFO Simulated | 0.0345s | 0.0444s | 0.0513s | 0.06092s |
| PSO Simulated | 0.567s | 0.581s | 0.1048s | 0.1193s |
| ESA Simulated | 0.2513s | 0.3532s | 0.0812s | 0.1778s |

In Table VI, the percentage of average deviation of the output power is indicated from the actual power profile obtained through experimental setup. From this table, it can be seen that the percentage deviation of BFO, ESA and PSO simulated peak power from that of average experimentally obtained peak power is found to be 0.08%, 1.406% and 1.42% respectively. This proves that BFO simulated curve is more close to the experimental curve than that of ESA and PSO. Same experimental verification has been done taking SSi-M6-205 PV module and the results are shown in table V. These results also prove that BFO simulated curve is more close to the experimental curve than that of ESA and PSO.

TABLE VI. PERCENTAGE OF AVERAGE DEVIATION OF THE SIMULATED OUTPUT POWER FROM THE ACTUAL POWER AT 658 WATTS/M$^2$ AND 23$^0$C

| Technique | PM648 PV Model | | SSI-M6-205 PV Model | |
|---|---|---|---|---|
| | Power (W) | %age deviation | Power (W) | %age deviation |
| Average Experimental (W) | 17.781 | --- | 123.4 | --- |
| BFO Simulated | 17.767 | 0.08 | 124.15 | 0.61 |
| PSO Simulated | 17.528 | 1.42 | 124.87 | 1.19 |
| ESA Simulated | 17.531 | 1.406 | 123.95 | 0.45 |

## V. CONCLUSIONS

In this paper, a new parameter extraction method exploiting Bacterial Foraging Optimization technique has been proposed for estimating unknown parameters of PV modules considering a single diode model. This PV module parameter extraction scheme provides robustness in parameter determination for a wide range of weather conditions such as varied temperature and solar irradiance levels. The approach is applicable for extracting parameters of different types PV modules i.e. mono-crystalline, poly-crystalline and thin-film modules. Parameters obtained through this method are found to be more accurate compared to many other approaches such as PSO and ESA. In future paper we will be extending the application of this parameter extraction scheme to double diode models of PV module.

## REFERENCES


[1]. B.Subudhi and R. Pradhan, “A Comparative Study of Maximum Power Point Tracking Techniques for Photovoltaic System”, IEEE Transactions on Sustainable Energy, vol.4, no.1, pp.89-98, 2013.

[2]. A.N. Celik and N. Acikgoz, “Experimental Verification of the Operating Current of Mono-Crystalline Photovoltaic Modules Using Four- and Five- Parameter Models”, Applied Energy, vol. 84, no.1, pp. 1-15, 2007.

[3]. B.Subudhi and R. Pradhan, “A Comparative Study on Parameter Estimation Methods”, International Journal on Renewable Energy Technology (Inderscience), vol.3, no.3, pp.295-315, 2012.

[4]. W. Xiao, M.G.J. Lind, W.G. Dunford and A. Capel, “Real-time identification of optimal operating points in photovoltaic power systems”, IEEE Trans. on Industrial Electronics, vol. 53, no.4, pp. 1017-1026, 2006.

[5]. M. Chegaar, Z. Ouennoughi and F. Guechi, “Extracting dc parameters of solar cells under illumination”, Vacuum, vol.75, no.1, pp.367-372, 2004.

[6]. M.G. Villalva, J.R. Gazoli, E.R. Filho, “Comprehensive Approach to Modeling and Simulation of Photovoltaic Arrays”, IEEE Trans. on Power Electronics, vol.24, no.5, pp.1198-1208, 2009.

[7]. Sera, R. Teodorescu, P. Rodriguez, “PV Panel Model Based on Datasheet Values”, IEEE Conference on Industrial Electronics, pp.2392-2396, Vigo, Spain, 4-7, June 2007.

[8]. Asif S, Solar cell modeling and parameter optimization using simulated annealing, Jou. of Propulsion Power, vol.24, pp.1018–1022, 2008.

[9]. J.J. Soon and K-S Low, “Photovoltaic Model Identification Using Particle Swarm Optimization With Inverse Barrier Constraint”, IEEE Trans. on Power Electro, vol.27, no.9, pp.3975-3983, 2012.

[10]. K.Ishaque, and Z.Salam. "An improved modeling method to determine the model parameters of PV modules using differential evolution," Solar Energy, vol.85, no. 9, pp.2349-2359, 2011.

[11]. Jiang, Lian Lian, Douglas L. Maskell, and Jagdish C. Patra. "Parameter estimation of solar cells and modules using an improved adaptive differential evolution algorithm." Applied Energy, vol.112, pp.185-193, 2013.

[12]. K.Ishaque, Z.Salam, S.Mekhilef, and A.Shamsudin, “Parameter extraction of solar photovoltaic modules using penalty-based differential evolution”, Applied Energy, vol.99, pp.297-308,2012.

[13]. Dhiaa Halboot Muhsen, Abu Bakar Ghazali, Tamer Khatib, Issa Ahmed Abed, Extraction of photovoltaic module model’s parameters using an improved hybrid differential evolution/electromagnetism-like algorithm, Solar Energy, vol.119, pp. 286–297,2015

[14]. D.F. Alam, D.A. Yousri, M.B. Eteiba, Flower Pollination Algorithm based solar PV parameter estimation, Energy Conversion and Management, vol.101,pp. 410–422,2015

[15]. Vun Jack Chin, Zainal Salam, Kashif Ishaque, Cell modelling and model parameters estimation techniques for photovoltaic simulator application: A review, Applied Energy, vol.154,pp.500–519,2015

[16]. H. Ketabchi and B. Ataie-Ashtiani, "Evolutionary algorithms for the optimal management of coastal groundwater: a comparative study toward future challenges, "Journal of Hydrology, vol. 520, no. 1, pp. 193-213, 2015.

[17]. R. J. Rao, “A simple and new optimization algorithm for solving constrained and unconstrained optimization problems”, International Journal of Industrial Engineering Computations, vol. 7, no. 1, pp. 19-34, 2016.

[18]. S.J.Nanda, and G. Panda, “A survey on nature inspired metaheuristic algorithms for partitional clustering” Swarm and Evolutionary computation, vol. 16, no. 1, pp.1-18, 2014.

[19]. P.K. Ray and B. Subudhi "BFO Optimized RLS algorithm for Harmonics Estimation", Applied Soft Computing, vol.12, no.8, pp.1965-1977, 2012.

[20]. Z. Li, Q. Tang, and L. Zhang, “Minimizing energy consumption and cycle time in two-sided robotic assembly line systems using restarted simulated annealing algorithm”, Journal of Cleaner Production, vol. 135, no. 1, pp.508-522, 2016.


**Bidyadhar Subudhi**(M’94–SM’08) received Bachelor Degree in Electrical Engineering from National Institute of Technology (NIT),Rourkela, India, Master of Technology in Control & Instrumentation from Indian Institute of Technology, Delhi in 1988 and 1994 respectively and PhD degree in Control System Engineering from Univ. of Sheffield in 2003.

Currently he is a professor in the Department of Electrical Engineering at NIT Rourkela and coordinator, centre of excellence on renewable energy systems. He is a Fellow IET. His research interests include system and control theory, Control of PV Power System and Active Power Filtering

**Raseswari Pradhan** received Bachelor, Master Degree and PhD degree all in Electrical Engineering from Indira Gandhi Institute of Technology Sarang, Jadavpur University Kolkata, National Institute of Technology Rourkela, India respectively in 2002, 2008 and 2014. Currently she is an Assistant Professor in the Department of Electrical Engineering, Veer Surendra Sai University of Technology, Burla, India. Her research interests include control of Photovoltaic Power System and Microgrid.