Multi-Objective Parameter Estimation of Five-Parameter Solar Cell Array by Using Differential Search Algorithm

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ABSTRACT

Electric circuit modelling of PV cells and devices is an important task for determining the electrical characteristic of a PV system. Predicting the model parameters for measured or simulated data which lets identifying the model for both mathematical solution and simulation studies is key point. In this paper, a simple and efficient nature inspired search method based on Differential Search Algorithm (DSA) has been presented and used for estimating the PV cell parameters. By using the proposed DSA method, the cell parameters such as light generated current, diode reverse saturation current, diode ideality factor, series and shunt resistance values are determined for a given I-V characteristic for a PV device. Subsequently, the PV cell model is simulated for different operating conditions which are determined by cell temperature and solar radiation values and the results are presented..

Keywords: Solar power, PV cell, Parameter estimation, Optimization

1 INTRODUCTION

Since electricity plays a vital role in the economy and industrial activity of a country, electric power systems have extensively expanded in the past decades. Electricity is generated in stations, transmitted by high voltage transmission networks, and delivered to consumers. With the ever-growing energy demand, power systems become more complex and difficult to control because the systems are being operated under highly stressed conditions such as unscheduled power flows and higher losses [1]. In the recent years, despite the technological progress on science; the problem of lack of energy continues by being much more vital. As the quality and accuracy of mathematical and psychical models of electrical systems improve, renewable technologies become the focus of theoretical and practical studies. In particular, solar energy attracts much attention. The utilization of photovoltaic (PV) conversion energy is today an emerging technology, characterized by gradually declining costs and increasing acquaintance with the technology [2].

Equivalent modelling of PV devices is an important task for determining and designing optimal PV systems. In total, three different models are required to model the electrical power output of a PV system for given irradiance and ambient temperature. These include a thermal model for finding the PV cell temperature, a radiation model for finding the solar energy absorbed in the PV cells and an electrical model for calculating the electrical characteristics of the PV system for the calculated absorbed radiation and cell temperature. Over the years, electrical models for varied complexities and accuracies have been developed for PV system. These include analytical models based on PV cell physics, empirical models and a few models which combine these two approaches [3].

In recent studies, PV cells are modelled in two basic types which are one diode equivalent model and two diodes equivalent model. The quality and accuracy of a model increase as the number of parameters of the model increase but concerns of mathematical difficulties and simulation duration cause model parameters to be chosen fixed or neglected. There have been various studies on PV cell modelling and parameter estimation. Marion [4] determined the current and voltage curves by using interpolation technique while King [5] develops an experimental model for PV devices. Townsend [6] developed a PV model equivalent circuit model by using four parameters and which neglects and chooses the shunt resistance infinite. Due to the accuracy issues of four parameter model, Beckman [7] asserted a new model and mathematical solution which is called five parameter model in which the parameters can be defined as I_L, I_0, a, R_s, R_{sh} where shunt resistance is also processed despite causing nonlinearity. Later, new methods are developed for determining the solution set of parameters by using the I-V curve [8] and the five parameter model is improved [9].

For the purpose of using and simulating the equivalent electrical circuit model of PV cell, the parameters aforementioned must be estimated and determined. Due to nonlinearity of the model, it is not possible to find a definite solution set numerically. Thus, estimation and optimization methods are used to determine these parameters with the purpose of converging to measured or simulated parameters as soon as possible. There are different methods have been used to estimate the parameters in literature. In some studies nonlinear solver scripts are used to determine the parameters while solving the equations numerically by defining and fixing a parameter in some others [10-11] or solving the nonlinear equations iteratively with the minimum convergence error [12]. In various numerical and heuristic optimization techniques are used to estimate the model parameters for different characteristics of PV cells. Levenberg-Marquardt optimization technique and simplex search algorithm are used in literature recently [13-14]. Fuzzy optimization [15-17], neural network based methods [18-19] and heuristic methods [20] are used to determine the model parameters of a PV cell.

Recently, a population based method, differential search algorithm (DSA), which is a new and effective evolutionary algorithm for solving real-valued numerical optimization problems is presented by Pinar Civicioglu [21]. The DSA simulates the Brownian-like random-walk movement used by an organism to migrate. In this paper, a novel DSA-based approach is proposed for the purpose of solving the OPF problem. The main contribution of this paper is determining the parameters of five parameter PV cell model by using DS algorithm. The accuracy of the estimated parameters by using DS algorithm are compared to simulated base model and results are presented.

2 EQUILAVENT ELECTRICAL CIRCUIT MODEL OF PV CELL

The equivalent circuit shown in Figure 1 consists of a light generated current source, a p-n junction diode and two resistances. I–V relationship in the equivalent circuit of Figure 1 is expressed by Eq. (1). The characteristic of any PV device are included in the model by five model parameters (I_L, I_o, a, R_s, R_{sh}). The model that describes the electrical performance of a PV device represented by Figure 1 using Eq. (1) is called the five parameter model [3].

$$I = I_L - I_0\left(\exp\left(\frac{V+I.R_s}{a.V_T}\right)-1\right) - \frac{V+I.R_s}{R_{sh}} \qquad \left(V_T = \frac{k.T_c}{q}\right) \tag{1}$$

where q, k and T_c are elementary charge, Boltzmann's constant and cell temperature, respectively.

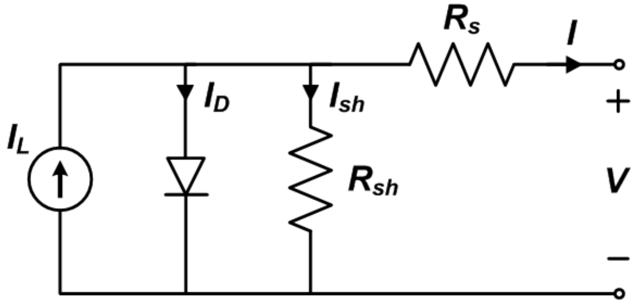

Figure 1: Equivalent circuit of a PV cell [22]

Eqs. (2) - (6) can be used to calculate the parameters in a desired operating condition which is dependent on cell temperature, solar radiation and band-gap energy of the PV material. Thus, the I-V and P-V characteristic of the PV cell can be predicted by using Eq. (1).

$$a = a_{ref}\left(\frac{T_c}{T_{ref}}\right) \tag{2}$$

$$I_L = \frac{S}{S_{ref}}(I_{L,ref} + (T_c - T_{ref}) \tag{3}$$

$$I_0 = I_{0,ref}\left(\frac{T_c}{T_{ref}}\right)^3 \exp\left(\left(NCS.\frac{T_{ref}}{a_{ref}}\right)\left(\left(\frac{E_{g,ref}}{T_{ref}}\right) - \left(\frac{E_g}{T_c}\right)\right)\right) \tag{4}$$

$$R_{sh} = R_{sh,ref}\left(\frac{S_{ref}}{S}\right) \tag{5}$$

$$R_s = R_{s,ref} \tag{6}$$

The notation of ref describes the parameters at standard test conditions (STC) where temperature and solar radiation are 25°C and 1000W/m^2 respectively in general. NCS and E_g represents the number of cells and band-gap energy, respectively. Eq. (7) can be used to calculate the band-gap energy for a current condition for different values of temperature where E_g = 1.43eV for GaAs type of material [8].

$$E_g = E_{g,ref}\left(1 - 0.0003174\left(\frac{T_c}{T_{ref}}\right)\right) \tag{7}$$

2.1 Objective Function for Parameter Estimation Problem

In order to achieve a valid solution set for the model parameters by using evolutionary methods, the objective function must be described in desired constraints and rules. The objective function namely fitness function is used to calculate and minimize the global error which leads the algorithm to a better solution set in the current space. The objective function, the normalized error function, is given in Eq. (8) below where m and e subscripts represent modelled and estimated values of variables, respectively.

$$ne = abs\left(\frac{I_{MP,m} - I_{MP,e}}{I_{MP,e}}\right) + abs\left(\frac{V_{MP,m} - V_{MP,e}}{V_{MP,e}}\right) + abs\left(\frac{I_{SC,m} - I_{SC,e}}{I_{SC,e}}\right) + abs\left(\frac{V_{OC,m} - V_{OC,e}}{V_{OC,e}}\right) \tag{8}$$

The assumed electrical model parameters assumed for five parameter model are as given in Table 1. The electrical characteristic of the model is given by Table 2. I-V and P-V curves for the assumed model parameters are given by Figure 2 and Figure 3, respectively.

Table 1 Electrical Model Parameters for Five-Parameter Model

Parameter	**Value**
$I_{L,ref}$	2.14 A
$I_{0,ref}$	2E-10 A
a_{ref}	1 V^{-1}
$R_{s,ref}$	53E-3 Ω
$R_{sh,ref}$	95E3 Ω

Table 2 Electrical Characteristics of the PV Cell

Characteristic	**Value**
Short circuit current (I_{sc})	3.14 A
Open circuit voltage (V_{oc})	19.29 V
MPP current (I_{MP})	2.83 A
MPP voltage (V_{MP})	12.57 V
Number of cells in series (NCS)	32-cells

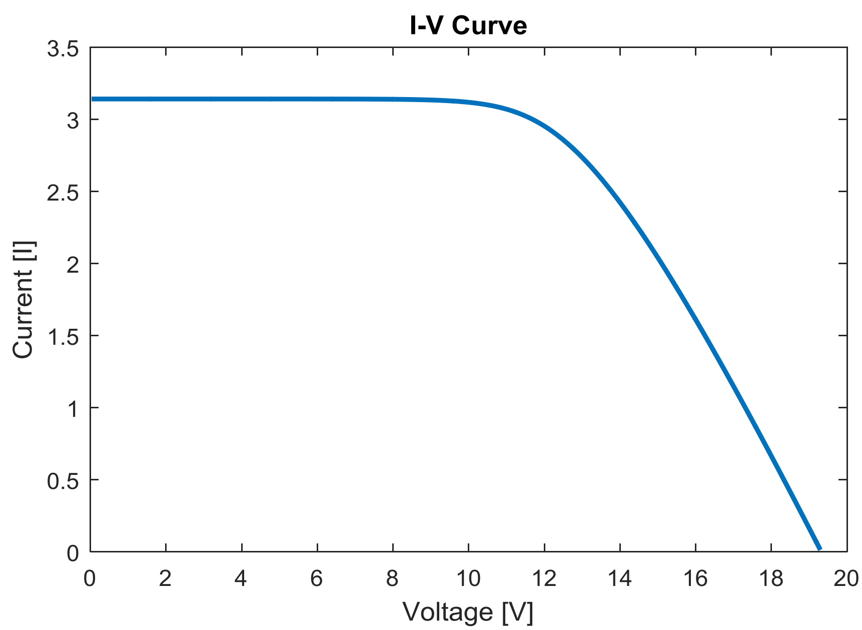

Figure 2: I-V curve for assumed parameters

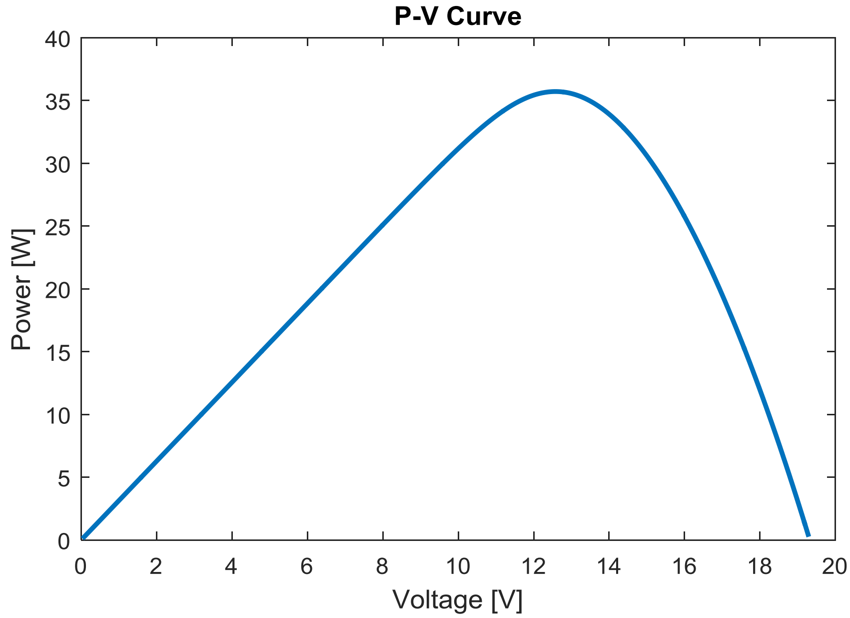

Figure 3: P-V curve for assumed parameters

3 DIFFERENTIAL SEARCH ALGORITHM (DS)

DS is a newly developed optimization algorithm which simulates the Brownian-like random-walk movement used by a living organism to migrate.

Quality and efficiency of the food sources in the nature such as meadows and lakes may vary because of the climatic changes during a year, decade or century. In order to find high quality food sources and overcome the famine, living organisms migrates seasonally through intervals. This behavior assures the organism move to a new environment where the food source is of a high quality and variation.

The migrating organisms form a super organism which comprises large number of individuals, and the superorganism starts to change its location by moving to areas containing high quality food sources. Movement of a super organism can be described by a Brownian-like random-walk model. The behavior of superorganisms has been modeled using a number of computational intelligence algorithms, such as PSO, cuckoo search, ant colony, and artificial bee colony. Many species of predatory living beings, before moving or migrating to a site, control the fertility of this one. In other words, if a superorganism desires to move to a new site that can meet its needs, this superorganism settles in this new site at least for a period of time. However, if a more fertile area is found, the superorganism continues its migration [21].

It is assumed, in DS algorithm, that a population made up of random solutions of the respective problem corresponds to an artificial-superorganism migrating. In DS algorithm, artificial-superorganism migrates to global minimum value of the problem. During this migration, the artificial-superorganism tests whether some randomly selected positions are suitable temporarily during the migration. If such a position tested is suitable to stop over for a temporary time during the migration, the members of the artificial-superorganism that made such discovery immediately settle at the discovered position and continue their migration from this position on [21].

The pseudo-code indicating the DS algorithm is given by Figure 4, where N is the population size, D is the dimension of the problem and G is the maximum number of generation.

N: *Size of the population*
D: *Dimension of the problem*
G: *Number of the maximum generation*

$Superorganism = initialize(\,), where\ Superorganism = [ArtificialOrganism_i]$
$y_i = Evaluate(ArtificialOrganism_i)$
$for\ \ cycle = 1{:}G\ do$
$\quad donor = \ SuperOrganism_{Random_{Shuffling(i)}}$
$\quad Scale = randg[2 \times rand_1] \times (rand_2 - rand_3)$
$\quad StopoverSite = SuperOrganism + Scale \times (donor - Superorganism)$
$\quad p_1 = 0.3 \times rand_4\ , p_2 = 0.3 \times rand_5$
$\quad if\ rand_6 < rand_7\ then$
$\qquad if\ rand_8 < p_1\ then$
$\qquad\ r = rand(N, D)$
$\qquad\quad for\ Counter1 = 1{:}N\ do$
$\qquad\qquad r(Counter1, :) = r(Counter1, :) < rand_9$
$\qquad\quad endfor$
$\qquad\ else$
$\qquad\ r = ones(N, D)$
$\qquad\quad for\ Counter2 = 1{:}N\ do$
$\qquad\qquad r(Counter2, randi(D)) = r\big(Counter2, randi(D)\big) < rand_{10}$
$\qquad\quad endfor$
$\qquad\ endif$
$\quad else$
$\qquad r = ones(N, D)$
$\qquad for\ Counter3 = 1{:}N\ do$
$\qquad\quad d = randi(D, 1, [p_2 \times rand \times D])$
$\qquad\quad for\ Counter4 = 1{:}size(d)$
$\qquad\qquad r\big(Counter3, d(Counter4)\big) = 0$
$\qquad\quad endfor$
$\qquad endfor$
$\quad endif$
$\quad individuals_{I,J} \leftarrow r_{I,J} > 0 \mid I \in i, J \in [1\ D]$
$\quad StopoverSite\big(individuals_{I,J}\big) \coloneqq Superorganism\big(individuals_{I,J}\big)$
$\quad if\ StopoverSite_{i,j} < low_{i,j}\ or\ StopoverSite_{i,j} > up_{i,j}\ then$
$\qquad StopoverSite_{i,j} \coloneqq rand \times (up_j - low_j) + low_j$
$\quad endif$
$\quad y_{StopoverSite;i} = Evaluate(StopoverSite_i)$
$\quad y_{Superorganism;i} \coloneqq \begin{Bmatrix} y_{StopoverSite;i} & if\ y_{StopoverSite;i} < y_{Superorganism;i} \\ y_{Superorganism;i} & else \end{Bmatrix}$
$\quad ArtificialOrganism_i \coloneqq \begin{Bmatrix} StopoverSite_i & if\ y_{StopoverSite;i} < y_{Superorganism;i} \\ ArtificialOrganism_i & else \end{Bmatrix}$
$endfor$

Figure 4: Pseudo-code of DS algorithm

As shown in the formulation above, the DS algorithm employs multiple random numbers in order to generate new artificial organisms and select artificial organisms randomly for the purpose of converging to global optimum. Primarily, there are 4 numbers; randg, rand1, rand2, rand3 randomly generated in each iteration which are used to generate new artificial organisms. Also, there are 6 randomly generated numbers; rand6, rand7, rand8 rand9, rand10 are used in the process of random selection. Thus, the processes aforementioned lead the algorithm to diverge from local minimum and search for possible global optimum meanwhile keeping the variables in constraints [23].

3.1 Implementation of DSA in Parameter Optimization

DSA is similar to those other population based heuristic methods which use randomly generated possible solution sets of pre-determined dimensions (D) in upper and lower constraints. In DSA, N number of artificial organisms composed of D components determined initially forms a super organism. The super organism represents the candidate solution sets consist of PV cell parameters such as I_L, I_0, a, R_s, R_{sh}. The fitness values of each solution set are calculated and determined by applying the objective function given by Eq. (8).

Stopover site, which contributes the migration motion of artificial organisms, is generated among an artificial organism and a randomly selected donor based on Brownian-like random walk model during the DSA process. It is worthwhile to note that stopover site is generated by using a scale factor which can be a pre-determined fixed value as well as a randomly generated number. This scale factor lets the current artificial organism move and change direction in its constrained D dimensional space based on the size and direction of donor. The stopover site is chosen and replaces the direction of current artificial organism with the condition of having a better fitness and also necessitated being in the upper and lower constraints aforementioned. Thus, a new migration motion in D dimensional space is formed spontaneously in each iteration by determining the best solution set which leads the super organism to the global optimal solution.

For the purpose of using the proposed DSA method for parameter estimation problem can be summarized as;

1. Load the system data and constraints.
2. Specify the DSA parameters such as number of individuals and maximum cycle.
3. Initialize a superorganism consisting a number of solution sets (individuals) for the first iteration.
5. Evaluate the fitness of the results, determine the best individual within the superorganism.
6. Generate new individuals depending on the best individual of the previous iteration
7. Increase cycle number by 1.
8. Evaluate the fitness value of newly produced superorganism.
9. Memorize the best global solution found so far.
10. Check if the maximum cycle met; stop the iteration process or jump to step 5.

4 RESULTS AND DISCUSSION

In order to estimate the parameters and optimize the system, the assumed five parameters given by Table 1 are searched in 5-dimensional space consisting of these variables by using DS algorithm. The fitness values for each iteration are calculated and new superorganisms are produced with the purpose of converging the global normalized error, given by Eq. (8), to zero.

In parameter estimation process, the upper and lower values of parameters are limited. Constraints and limit values of five parameter model are given by Table 3 below. If the parameter value violates the upper or lower limit, the upper or lower limit value is assigned as the new parameter value respectively.

Table 3 Upper and Lower Limits of Five Parameters

Parameter	Min.	Max.

$I_{L,ref}$	0.1 A	3 A
$I_{0,ref}$	0 A	E-12 A
a_{ref}	0 V^{-1}	1 V^{-1}
$R_{s,ref}$	0 Ω	1 Ω
$R_{sh,ref}$	70E3 Ω	120E3 Ω

By minimizing normalized error, PV cell parameters are intended to be found; I-V and P-V curves of the cell are generated.

4.1 Case 1

In this case, the parameter R_{sref} is searched by fixing the parameters I_L, I_0, a and R_{sh} at assumed values given by Table 1. It is seen that the algorithm achieves to minimum normalized error (ne), 0.0291 with the R_{sref} value of 0.057 Ω. The convergence chart of the DS algorithm for Case 1 is given by Figure 5.

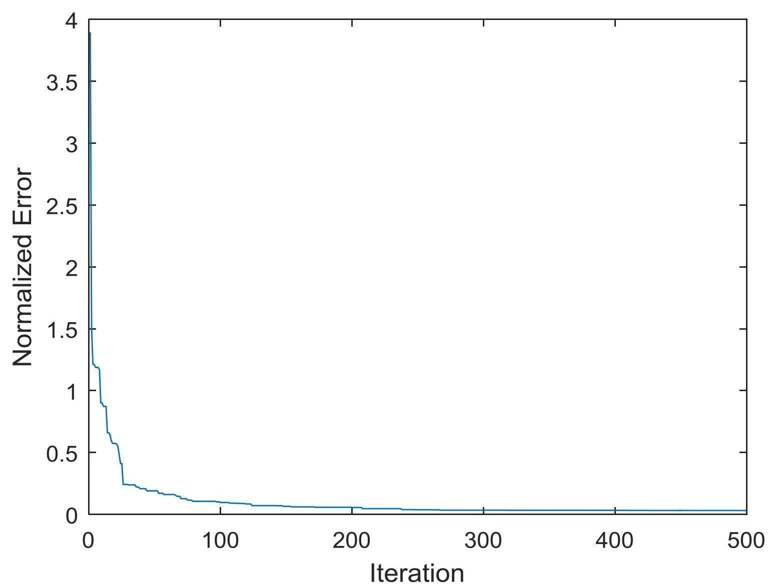

Figure 5: Convergence chart of normalized error for Case 1

4.2 Case 2

In this case, all five parameters are searched and converged by using the proposed DS method and the results are given in Table 4. The normalized error which is a multi-objective function consists of absolute difference ratios I_{sc}, V_{oc}, I_{mp} *and* V_{mp} converges to 0.1617 with the values for I_{Lref}, I_{0ref}, a_{ref}, R_{sref} and R_{shref} of 2.13, 2.9×10^{-10}, 0.97, 0.058, 94×10^{3} respectively which can be seen in detailed and given in Table 4. The value of normalized error is 3.32 initially and continues to decrease in the parameter optimization process by using DS method effectively. The convergence chart of the DS algorithm for Case 2 is given by Figure 6.

Table 4 Parameter Estimation for Five-Parameter Model

Parameter	Assumed	Estimated
$I_{L,ref}$	2.14 A	2.13 A
$I_{0,ref}$	2E-10 A	2.9E-10 A

a_{ref}	1 V^{-1}	0.97 V^{-1}
$R_{s,ref}$	53E-3 Ω	58E-3 Ω
$R_{sh,ref}$	95E3 Ω	94E3 Ω

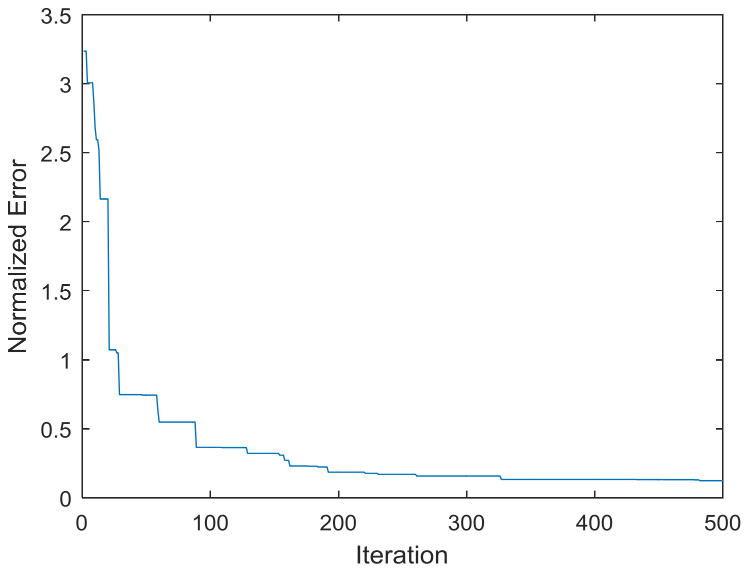

Figure 6: Convergence chart of normalized error for Case 2

The I-V and P-V curves for assumed and estimated parameter values of series connected PV cells are given by Figure 7 and Figure 8, respectively. It can be stated that the calculated V_{oc} value by using the estimated parameters is 18.43V while it is 19.29V in the assumed model. The power at maximum power point is 32.53W for estimated parameter while same variable is 35.57W in the assumed model.

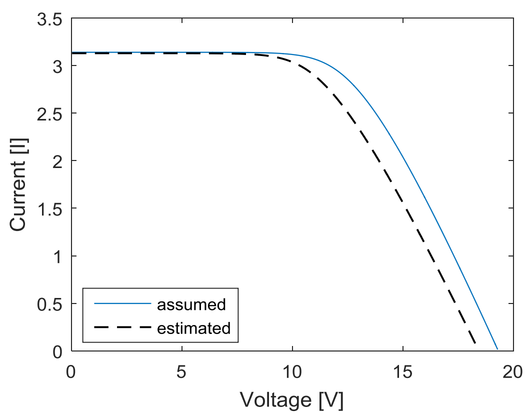

Figure 7: I-V curve of series PV cell for assumed and estimated parameters

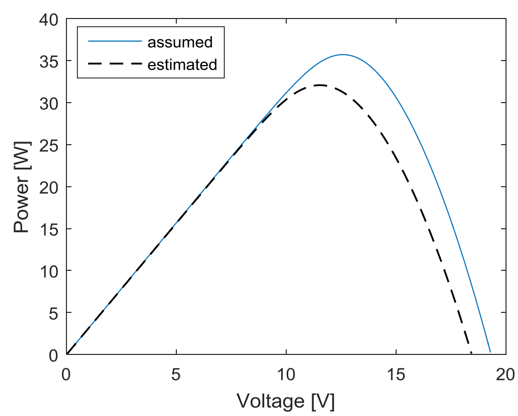

Figure 8: P-V curve of series PV cell for assumed and estimated parameters

5 CONCLUSION

In this paper a differential search based optimization method, DSA, is proposed and successfully applied to solve a multi objective function within the constraints regarding to PV cell modelling and parameter optimization. The results obtained by using the proposed DSA method, which are presented in detail, are compared with assumed model in paper and the efficiency of the DSA is demonstrated. Thus it is concluded that DSA provides a good solution performance, robustness and superiority and can effectively be used in large scaled, non-linear and non-convex problems of parameter estimation problems owing to its high solution quality and rapid convergence speed.

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