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Solar PV modelling and Parameter Extraction using Artificial Immune system

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Abstract

In this paper, a meta-heuristics algorithm Artificial Immune System (AIS) is used for solar PV parameter estimation. Solar PV Double diode model parameter estimation is carried out by applying the new method. Estimated parameter values are substituted in developed MATLAB model and characteristics are obtained. For performance analysis, the results obtained using AIS are compared with Genetic algorithm (GA) and Particle Swarm Optimization (PSO). For further validation of the proposed method, error graphs are plotted for two panels using AIS, GA and PSO. The results confirm that the proposed method employing AIS outperforms GA and PSO in terms of convergence characteristics and absolute error.

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Keywords: Artificial Immune System (AIS), Double Diode Solar PV Model, Parameter Extraction, Genetic Algorithm (GA), Particle Swarm Optimization (PSO)

1. Introduction

Modelling of accurate I-V characteristics of the solar cell is challenging as it is non-linear in nature. For accurate modelling of non-linear I-V characteristics, each point on the I-V curve has to be matched exactly with the experimental values. Therefore an efficient method is essential to determine the model parameter values with precision. Among the different modelling methods proposed over the years to map the non-linear I-V characteristics, the most important ones are: single diode model [1, 2] and double diode model [3, 4]. With the use of just an additional diode to the single diode model, the accuracy obtained is remarkable.

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In literature, a lot of methods exist for solar PV parameter estimation: the most common approaches are: 1.analytical method [5-11] and 2. Evolutionary algorithm [12-16]. In analytical method, a set of transcendental equations are solved for parameter extraction of solar cell. An improved Lambert-W function for PV parameter identification is proposed in [5]. A built-in function is constructed using MATLAB and multi-variable version of the Newton–Raphson algorithm for curve fitting is applied [6].Comparison of parameters obtained via analytical method with experimental data is provided in [7]. A modified non-linear least error squares estimation based on Newton's method has been presented in [8]. Similar works based on analytical method can also be seen in [9-11]. However, the major shortcomings of these methods are dependency on initial value, complex mathematical computations and derivative dependent. In recent years, Meta heuristics algorithms have been employed and found to be suitable for panel parameter identification; as they are derivative free and they search for global optimum value with random initial guess. In literature, derivative free meta-heuristic optimization techniques like GA [12], PSO [13], SA [14], ABO [15] and BMO [16] have been used for parameter identification. All the aforementioned methods use Mean Square Error (MSE) as the objective function for parameter extraction. However, application of above objective function involves complex computation, requires more computational time, large error between actual and obtained values. In order to overcome these drawbacks, a new objective function is formulated and it is based on the fact that derivative of power with respect to voltage at maximum power point is equal to zero. In author's previous work, parameter estimation applying the above formulation was found to be successful [17]. Here, in this paper, the same formulation has been extended for double diode PV parameter estimation and tested. The problem of finding PV model parameter is framed as an objective function and solution is sought through Artificial Immune System (AIS).

2. Problem Formulation

The proper definition of the objective function is very important for accurate extraction of parameter values which ensures that the model behaves exactly the same as the PV panel. The following section discusses about the formulation of objective function.

The value of the DC power can be obtained using the following equation

$$P = VI$$

Differentiating the above equation with respect to voltage on both sides, we get

$$\frac{dP}{dV} = V\frac{dI}{dV} + I$$

It can be inferred that, the derivative of power with respect to voltage is equal to zero at Maximum Power Point (MPP). Applying MPP condition to the above equation we get,

$$\frac{dP}{dV} = V\frac{dI}{dV} + I = 0$$

The objective function is given by,

$$\min\left(\left.\frac{dP}{dV}\right|_{mp}\right) = \left|\frac{dI}{dV}\right|_{(V_{mp},I_{mp})} + \frac{I_{mp}}{V_{mp}}$$

dI/dV can be obtained by differentiating the basic current equation of double diode model with respect to voltage and is shown below

$$\left|\frac{dI}{dV}\right|_{(V_{mp},I_{mp})} = \frac{I_{o1}\,\Gamma\exp\{\Gamma(V_{mp}+I_{mp}R_s)\} + I_{o2}\,\Gamma\exp\{\Gamma(V_{mp}+I_{mp}R_s)\} - G_p}{1 + I_{o1}\,\Gamma R_s\exp\{\Gamma(V_{mp}+I_{mp}R_s)\} + I_{o2}\,\Gamma R_s\exp\{\Gamma(V_{mp}+I_{mp}R_s)\} - G_p R_s} \tag{1}$$

Where, $G_p = 1/R_p$ and $\Gamma = 1/aV_t$

In the above equation, the values of $I_{01}, I_{02,} V_{mp,} I_{mp}$ depends on values such as $G, T, V_{oc}, I_{sc}, R_s, R_p$ and a.

However, the values of $I_{01}, I_{02}, R_s, R_p, a_1$ *and* a_2 are unknown. Hence, these values are identified through steps of AIS.

3. Artificial Immune System and solar PV parameter extraction

AIS algorithm replicates the defence system of human body against pathogens [18].The natural immune system guards the body against dangerous organisms called antigens. Lymphocytes are a class of white blood cells which serves the protection of human body by producing corresponding antibody which is powerful enough to destroy the ill effects of antigen. In recent years, researchers are showing keen interest in AIS due to its powerful information processing capabilities [19]. The important processes involved in AIS are clonal selection, immune memory, affinity maturation, and receptor editing. The following are the steps involved in AIS implementation for Solar PV parameter estimation:

Step 1: Initialization of parameters
Step 2: Generation of initial population of antibodies
Step 3: Calculation of fitness value
All the randomly generated antibodies are allowed to interact with the antigen and the fitness value which is based on affinity is evaluated using Eq. (2). The best antibody is found out by measuring its affinity towards the antigen. The antibody with the highest affinity towards the antigen gives least fitness value.

$$Affinity = \frac{1}{\min\left(\left.\frac{dP}{dV}\right|_{mp}\right)} \tag{2}$$

Step 4: Regeneration of memory system
The antibodies with the highest affinity towards antigen, i.e. the 'healthy' antibodies possessing the ability to annihilate the antigen are added to the memory cells. A good set of model parameter values are conserved so that the objective function gets minimized after each iteration.
Step 5: Calculation of selection probability based on density probability and fitness probability
The selection of healthy antibodies is done taking into account the density probability and fitness probability. The fitness probability of an antibody is the proportion of its fitness to the sum of fitness of all the antibodies. Fitness probability can be written as:

$$p_f = \frac{f(x_i)}{\sum_{j=1}^{s} f(x_i)} \tag{3}$$

The density probability indicates the proportion of antibodies with same affinity to the total number of antibodies which can be expressed as

$P_d = 1/S(1 - t/S)$ for antibody with highest density

$P_d = 1/S(1 + (t^2/S^2 - St))$ for other S-t antibodies

The selection probability is calculated based on fitness probability and density probability which can be obtained by

$$p = \alpha p_f + (1-\alpha) p_d$$

Where $0 < \alpha < 1$

The antibodies with higher selection probability are selected for the next generation.

Step 6: Crossover and mutation

In crossover process, certain numbers of bits of selected antibodies are swapped to produce new set of antibodies. For better efficiency, multi-point crossover is performed and the crossover rate is chosen as 0.8.

Step 7: Termination

If a termination criterion is reached stop and print the results; otherwise go to step 3.

4. Results and Discussion

In order to estimate the performance of the proposed method solar PV parameter extraction method simulations and analysis were carried out for the results taken with GA and PSO methods. To validate the results taken using AIS method comparisons are made in terms of parameter set values, convergence characteristics and absolute error. Further, PV parameter extraction has been extended for different PV panels like SP70, SM55, S36 and KC200GT panels. For simulations the steps involved in all the three optimizations techniques i.e. GA, PSO and AIS have been coded in MATLAB. To analyse the performance of the proposed method parameters extracted via GA, PSO and AIS are simulated under similar working conditions i.e., with same population size, maximum number of iterations and parameter limits.

After several runs the best parameter set values that closely mimics the IV characteristics of the panel is identified. All the simulations are carried out under similar conditions. From Table 1, it is understood that AIS identifies optimal parameter set that strictly matches with the experimental data. To confirm the accuracy of the proposed method, obtained values were substituted in MATLAB/Simulink model to plot the I-V characteristics. The simulated I-V characteristics for different methods along with experimental data for SM55 panel are shown in Fig. 1. From the figure, it is obvious that the I-V plot obtained using AIS method is exactly matching with expected characteristics.

To show the superiority of the proposed method the convergence characteristics of all the three methods are plotted and it is presented is Fig. 2. A closer observation of the curve shows that AIS method reaches optimum value of 3.41e-5 in 8 iterations, whereas the other two methods take longer time to converge. Further, this behaviour stems from selection probability of AIS which helps in converging to the best solution. Moreover the convergence characteristics behaviour is reflected in the I-V characteristics i.e. AIS converges to minimum value which exactly matches with the experimental data. However, the other two methods are trapped in local minimum hence deviating from the actual experimental value.

Table 1. Comparison of model parameters of AIS with GA and PSO for four different panels

Irradiation W/m^2	Parameters	S36			SM55			SP70			KC200GT		
		GA	PSO	AIS	GA	PSO	AIS	GA	PSO	AIS	GA	PSO	AIS
1000	I_{01}	4.73E-09	7.54E-08	4.85E-09	1.68E-08	4.56E-08	2.35E-08	5.82E-10	1.59E-04	1.01E-08	2.15E-08	2.71E-08	1.11E-08
	I_{02}	8.67E-11	2.06E-10	9.33E-11	2.96E-10	2.23E-10	1.12E-10	6.07E-12	9.13E-07	1.87E-10	4.13E-10	4.13E-10	1.87E-10
	R_s	0.469	0.727	0.678	0.445	0.354	0.54741	0.486	0.450	0.502	0.303	0.2235	0.303
	R_p	351.90	319.26	200	200	319.86	410.55	200	416.07	264.90	343.10	298.77	343.10
	a_1	1.2	1.2	1.2	1.41	1.47	1.2	1.2	1.42	1.2	1.2	1.21	1.2
	a_2	1	1	1	1	1	1	1	1	1	1	1	1

4.1 Correctness of solution

To further validate the accuracy of the proposed method employing AIS algorithm, absolute error between the simulated and experimental values is calculated for two different panels namely Kyocera KC200GT and Shell SM55. Absolute error is computed using the following equation:

$$\text{Absolute error} = \left\lfloor I_{experimental} - I_{simulation} \right\rfloor \quad (4)$$

Absolute error curves are plotted for GA, PSO and AIS methods for 1000 W/m^2 irradiation and it is shown in Fig. 3. GA method is found to have the highest error in constant as well as linear region. Considerable amount of error persists with PSO method. AIS method outperforms the remaining two methods with lowest error which is almost negligible for the cases studied.

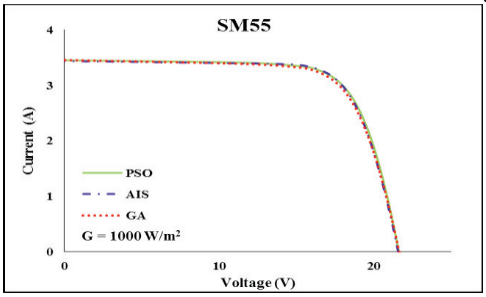


Fig. 1. Simulated I-V Curves for Different Optimisation Techniques

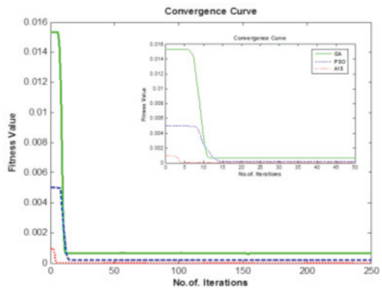
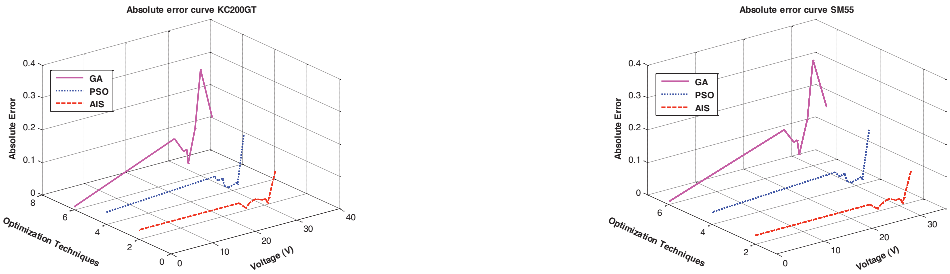


Fig. 2. Convergence Characteristics for all methods



(a) **Kyocera KC200GT** **(b)** **Shell SM55**

Fig. 3. Absolute Error Graphs for Kyocera KC200GT and Shell SM55 panels

5. Conclusion

In this paper, a new objective function based on derivative of power with respect to voltage at maximum power point is proposed. AIS algorithm is used to solve the above formulation to deduce seven model parameters namely $I_{01,} I_{02,} I_{pv}$, R_s , R_p , a_1 and a_2 . The results obtained demonstrate that the proposed formulation employing AIS is superior to GA and PSO method for different PV modules. Furthermore, the proposed formulation with AIS can be extended for parameter extraction of panels with different make/models.

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