Parameter Extraction of PV Cell Single Diode Model Using Animal Migration Optimization

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Abstract – *Photovoltaic cell model is designed to induce nonlinear current versus voltage (I-V) curves. Due to its nonlinearity, the model parameters cannot be obtained using standard measurement tools. Consequently, the optimization procedure usually carried out to accomplish this aim. In this paper, the Animal Migration Optimization (AMO) algorithm has been proposed to extract the unknown parameters of photovoltaic cell single diode model. The ability of AMO is generating quick, reliable and consistent results is put in test. Standard measurement data from the R.T.C France silicon cell is taken as a test bench. The efficiency of the proposed algorithm is finally highlighted by comparing its performance with four other algorithms including NM-MPSO, DA, OBWOA and iJAYA in terms of RMSE and MAE.*

Keywords: *Animal Migration Optimization (AMO), Parameter Extraction, PV Cell, Single Diode Model (SDM)*

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I. Introduction

Sun is the renewable source of energy in form of radiant light and produce heat to convert the heat energy to electricity. It is not limited source of energy and it is free to use as it is costless [1]. Nowadays, solar energy becomes much important source of energy compared to other energy such as fossil fuel. Fossil fuel is limited and can cause a lot of pollution to be occurred due to the harmful substances produce when burning it. There are several technologies that use solar energy such as photovoltaic, solar heating, molten salt power plants and artificial photosynthesis.

Photovoltaic (PV) cell or module normally being modeled based on the characteristic of the current versus voltage (I-V). This involved with the formulation of mathematical model or circuit model [2]. The PV I-V curve poses nonlinear characteristics. There are several circuit model that being used to describe the nonlinear I-V curve known as single diode model (SDM), double diode model (DDM) and three diode model (TDM) [3]. Among this, the most popular model was single diode equivalent circuit model due to less numbers of parameters and computational effort but produced accurate results. The key parameters in SDM to predict the performances of the solar cells which are generated photocurrent, shunt resistor, series resistance, diode ideality factor and diode saturation current [2]-[4]. An accurately determination of these parameters will reflect the simulation performance results.

The methods can be utilized to extract parameter from PV cell are analytical methods [4] and optimization methods [2]. Analytical methods use the transcendental mathematical equation to get the parameters of PV model. It was ease of implementation in application and less computational effort. Unfortunately, it limited to standard conditions only. When these conditions are change, it become less effective [5]. This drawback can be overcome by using the optimization method. In optimization method, normally, the curve fitting technique is applied. Whereby, all points and data that being measured are put into account for optimization. Thus, this optimization method is widely used due to its accuracy and less data interference.

Generally, the optimization approach can be grouped into two, namely, deterministic heuristic and metaheuristic algorithm [3, 4]. Deterministic algorithm is good in achieving converge results and expert in mathematical calculation. However, it final result always depend on its initial values [7]. This will cause the algorithm to generate the unwanted solution values. On the other hand, metaheuristic algorithms, often nature-inspired with multiple interacting agents, does not affected by initial value and normally more robust [6].

Hamid et all. [2] proposed a combination of modified Particle Swarm Optimization (PSO) and Nelder-Mead (NM) to determine the parameters of PV cell SDM, DDM and PV module. Exploiting NM as local search agent, the proposed algorithm not only show better performance compared to the original PSO but also suppresses other algorithms such as Bird Mating Optimizer (BMO) and Artificial Bee Swarm Optimization algorithm (ABSO). Oliva, D has applied two variants of Whale Optimization algorithm (WOA) to estimate PV cell model parameters known as Opposition-Based WOA (OBWOA) [8] and Chaotic WOA (CWOA) [9]. Both algorithms performance is excellent when compared with BMO and Simplified Teaching-Learning Based Optimization (STLBO). Moreover, Aydin et all. [3] had compared the performance of Sine-Cosine algorithm (SCA) with WOA in extracting the PV cell models and PV module parameters. As a result, the performance of WOA is much better than SCA in term of convergence speed and accuracy. Other metaheuristic algorithms which being used to estimate the PV cell model parameters are Dragonfly Algorithm (DA) [6], JAYA algorithm [10], Adaptive Differential Evolution algorithm [11], [12], Brent's algorithm [13], Ant Lion Optimizer [14], Artificial Bee Colony algorithm [15] and hybrid Trust-Region Reflective algorithm [16].

Whilst many metaheuristic algorithms are already being proposed to obtain SDM parameters, numerous algorithms are still being published in the literature, trying to observe their efficiency in optimizing the problem. This is due to the fact that there isNo Free Lunch theorem for optimization [17]. This theorem states a single algorithm cannot solve all optimization problems and their performance are varied depending on the type and how complex the problem is. Apart from that, another key factor is the need to obtain correct parameters in short time.

In this paper, an optimization algorithm known as Animal Migration Optimization (AMO) is proposed to estimate the SDM parameters. The capability of solving optimization with less parameters tuning are the key factor why this algorithm is chosen. As the authors acknowledgment, there is no literature being published regarding the performance of AMO in optimizing the SDM parameters. The nearest reported performance is in extracting the DDM parameters reported in [18]. The performance of this algorithm is tested by extracting the parameters of measurement data of 57 mm diameter commercial (R.T.C. France) silicon solar cell. The data is taken from the system with temperature of 33 °C and irradiance of 1000 W/m^2. The rest of this paper is arranged as followed. Section II is preamble part. In this part, all related theories are being explained in detail. In Section III, the obtained results are being elaborate including the comparison with existing results from literature. Finally, in Section IV, the overall conclusion is drawn.

II. Preamble

In this part, a PV cell single diode equivalent model is briefly explained. Then, the objective function used by the selected algorithm is defined. Lastly, general flow of AMO algorithm is elaborated.

A. Single Diode Model (SDM)

The SDM equivalent circuit with series and shunt resistances is shown in Fig. 1.

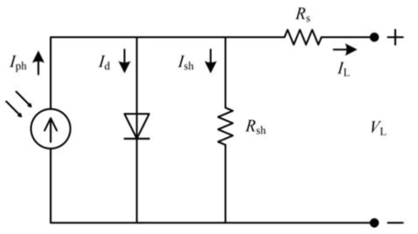

Fig. 1. Single Diode Model (SDM) [19].

Based on this circuit, by applying Kirchhoff's current law, the output current I_L can be written as:

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

where I_{ph} is photo-generated current, I_d is diode current and I_{sh} is shunt resistor current. Replacing the diode current, I_d with the Shockley equation for diode and substituting the current of shunt resistor with equation (2), the output current can be rewrite as in equation (3).

$$I_{sh} = \left(\frac{V_L + I_L R_S}{R_{Sh}}\right) \tag{2}$$

$$I_L = I_{ph} - I_O\left[\exp\left(\frac{V_L + I_L R_S}{aV_t}\right) - 1\right] - \left(\frac{V_L + I_L R_S}{R_{Sh}}\right) \tag{3}$$

Where the output voltage of the system is representing by V_L and the thermal voltage is referred as V_t . The V_t can be obtained as follow:

$$V_t = \left(\frac{kT}{q}\right) \tag{4}$$

where k stand for Boltzmann constant and q is electron charge with the value of 1.380650×10^{-23} J/K and 1.602176×10^{-19} C respectively. The temperature T must be in unit of Kelvin as it refers to the ideal factor of the diode.

Equation (3) show that there are five important elements in PV SDM need to be optimized which are the shunt resistance (R_{sh}), series resistance (R_S), photocurrent (I_{ph}), diode saturation current (I_o) and diode ideality constant (a).

B. Performance Indicators

The exact extracted value must coincide with unknown parameters of PV model. Calculated data should be suitable for measured data, particularly using the chosen model. Therefore, the difference between observed current and expected currents may be used to represent the degree of agreement. It can be compared by measuring each measurement's static errors to test the results ' reliability.

The main objective of this paper is to estimate the value of parameters based on the SDM by comparing and contrasting with measured experiment results. Due to that, the Root mean square error (RMSE) is chosen as the algorithm objective or fitness function. The equation is given as

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{N}}\sum \mathrm{f}(\mathrm{V},\mathrm{I},\mathrm{x})^2} \tag{5}$$

where $x = \{I_{ph}, I_o, R_s, R_{sh}, a\}$ and N is total measurement data point. To get the PV cell's best parameter vector, RMSE's value must be minimized as much as possible to make the model more efficient.

Additionally, for further verifying the accuracy of the extraction process of proposed algorithm, the mean absolute error (MAE) is selected as second key performance indicator. MAE is calculated using the following formulas:

$$\mathrm{MAE} = \frac{1}{N}\sum |I_m - I_c| \tag{6}$$

where N is measurement number, I_m and I_c is measurement and calculation currents, correspondingly

C. Animal Migration Optimization (AMO)

Animal Migration Optimization (AMO) is developed by Li et al [20] in 2014 is based on the animals behavior during migration. The purpose of migration may be different between each animal but their aim is similar, to discover a better life location. There are two mains steps introduced in this algorithm to mimic the process. The first one is the animal migration step and second, is the population updating step.

During animal migration step, each animal changes their position based on their nearest neighbors using the following formula:

$$X_i^{G+1} = X_i^{G} + \delta(X_{neighbor}^{G} - X_i^{G}) \tag{7}$$

where G is the generation counter, $X_i^G$is current animal on that generation, $X_{neighbor}^G$is the current neighbor of the animal X_i^G, and δ is the Gaussian distribution.

In the population updating step, some animal may leave the group either by joining other group or naturally death. Assuming the total number of populations, NP is fixed, the same number of animals may join the group, based on the probability Pa. The formula for this step is given as:

$$\begin{aligned} X_i^{G+1} = X_{r_1}^{G} &+ rand(X_{best}^{G} - X_i^{G}) \\ &+ rand(X_{r_2}^{G} - X_i^{G}) \end{aligned} \tag{8}$$

where $r_1, r_2, i \in [1 \ldots Np]$, and $r_1 \neq r_2 \neq i$ $rand$ is random number between 0 and 1, and X_{best}^G refer to the best of individual globally. The main steps of AMO is illustrated as flowchart in Fig. 2:

III. Results and Analysis

In this part, the performance of AMO in extracting SDM parameters was evaluated. The measurement data is based on experimental data setup of 57 mm diameter commercial (R.T.C. France) silicon solar cell taken at irradiance of 1000 W/m^2 and temperature of 33 °C [2]. The AMO parameters setting is directly adopted form [20]. The parameters setup for SDM parameters extraction using AMO is shown in Table I. There are five parameters need to be extracted. Before continuing with the optimization process, the boundary of each parameters needs to be identified to acknowledge the algorithm their search space area. Standard boundary which being adopted by many papers in the literature are taken [2], [6], [8]–[10] and being listed in Table II. The AMO algorithm has being simulated using Matlab for 30 runs for stability and reliability analysis.

TABLE I
PARAMETERS SETUP FOR ALGORITHM

Item	AMO	NM-MPSO [2]	DA [6]	IJAYA [10]	OBWOA [8]
No. of particles	70	70	70	20	150
No. of iterations	5000	5000	5000	50000	10000

TABLE II
UPPER AND LOWER BOUNDRY FOR PV PARAMATERS

Parameter	$I_{ph}(A)$	$I_o(\mu A)$	$R_s(\Omega)$	$R_{sh}(\Omega)$	a
Lower	0	0	0	0	1
Upper	1	1	0.5	100	2

The best objective of each runs is tabulated in Fig. 3. With reference to this graph, the best and the worst objective values are 9.938×10^{-4} and 9.8604×10^{-4} respectively with a mean value of 9.878×10^{-4}. Analyzing this graph, we can observe that the results produced by the AMO are persistence and consistence. This proved by looking at the small value of variance and standard deviation as being stated in Table III.

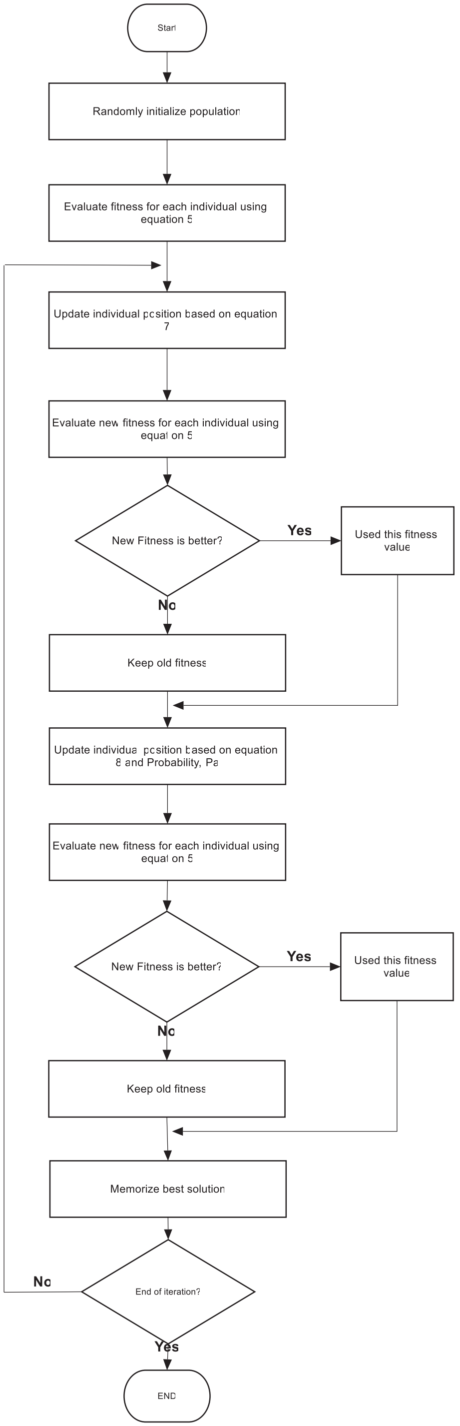

Fig. 2. AMO flowchart.

TABLE III
MEAN, STANDARD DEVIATION AND VARIANCE ANALYSIS VALUES

Animal Migration Optimization (AMO)	
Mean	9.7228×10^{-7}
Standard Deviation	2.0767×10^{-6}
Variance	4.3127×10^{-12}

The convergence speed can be expressed in the iteration times to achieve the optimum value. Fig. 4 shows the convergence process of the highest objective value. As can be seen, the AMO algorithm's convergence rate is very fast. The AMO reaches its lower value after 15 iterations and almost reaches its global optimum after 35 iterations

The characteristics I–V and P-V are reconstructed to analyze the consistency of the parameters found. These curves are shown in Fig. 5 and Fig. 6, respectively. It can be clearly seen from the observation of these graphs that the I-V and P-V characteristic obtained by the described model are well in line with the measured results. The equivalent values of voltage and current found compared with data from reference [2] at max power point demonstrated the reliability of the results obtained.

Table IV displays optimum parameters for the single diode model obtained based on the RMSE. The results are compared to Nelder-Mead-Modified Particle Swarm Optimization algorithm (NM-MPSO) [2], Opposition-Based Whale Optimization algorithm (OBWOA) [8], Dragonfly algorithm (DA) [6] and Improved JAYA algorithm (IJAYA) [10]. It is found that AMO only outperforms DA in terms of lower RMSE but is close to other algorithms.

For further accuracy verification, the value of MAE for all algorithms is calculated and positioned at the last row in Table IV. Perceiving these values, MAE of AMO is the second lowest after NM-PSO. This indicating the extracted values using this algorithm have highest accuracy compared to DA, IJAYA and OBWOA.

IV. Conclusion

This paper investigates the performance of AMO in determining the parameters of PV cell SDM. The algorithm was tested 30 times and the results showed accuracy by taking the standard deviation and variance values into account. Convergence speed is also fast as it can get nearly global optimum value only after 35 iterations.

Further verification is achieved by contrasting the results of the RMSE and MAE with the state-of-the-art algorithm. These findings are contrasted with the NM-, OBSHO, DA and IJAYA algorithms. From the observation, AMO outperforms the DA and closes with other algorithms in term of RMSE and outperforms other algorithm except NM-PSO in term of MAE. These show that the AMO has a strong ability to extract the parameters of the PV model. Although the convergence speed is fast and the final result is almost constant in every run, the reliability of the algorithm can be improved by improving the efficiency of the exploitation process. This can be achieved by adding a mutation operator or a combination with another algorithm.

TABLE IV
STATISTICAL RESULTS OF RMSE AND MAE OF DIFFERENT ALGORITHMS FOR SDM

Parameter	AMO	NM-MPSO [2]	DA [6]
$I_{ph}(A)$	0.7608	0.76078	0.777232
$I_o(\mu A)$	0.3239	0.32306	0.13031
$R_s(\Omega)$	0.03637	0.03638	0.0000
$R_{sh}(\Omega)$	53.7969	53.7222	8.2333
a	1.4815	1.48120	1.9979
RMSE $(\times 10^{-4})$	9.8604	**9.8602**	248.68
MAE $(\times 10^{-4})$	6.96	**6.808**	219.38

Parameter	IJAYA [10]	OBWOA [8]
$I_{ph}(A)$	0.7608	0.76077
$I_o(\mu A)$	0.3228	0.3232
$R_s(\Omega)$	0.0364	0.0363
$R_{sh}(\Omega)$	53.7595	53.6836
a	1.4811	1.5208
RMSE $(\times 10^{-4})$	9.8603	**9.8602**
MAE $(\times 10^{-4})$	8.275	8.269

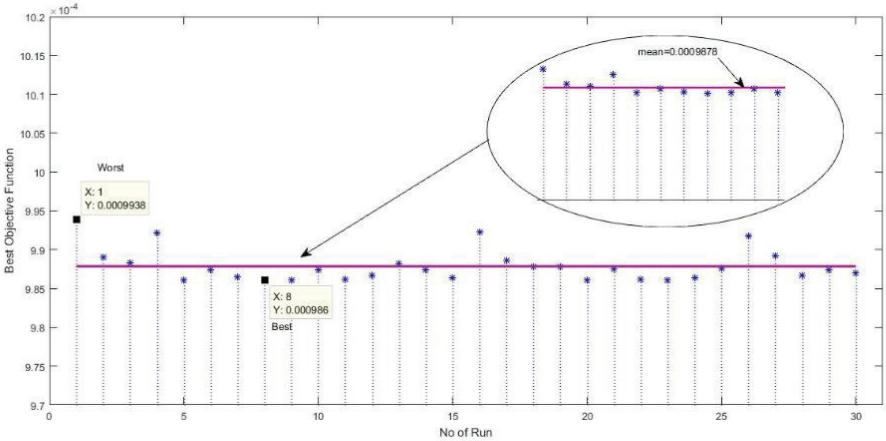

Fig. 3. The best objective value distributions for 30 trial runs.

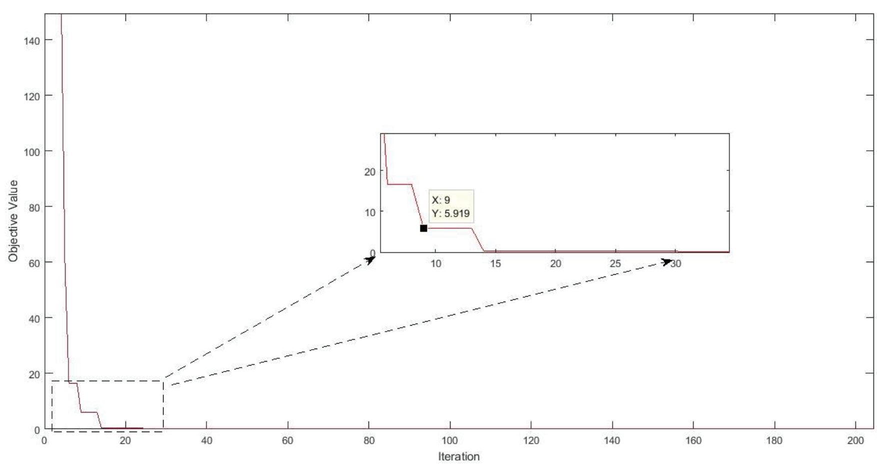

Fig. 4. The best objective value convergence curve.

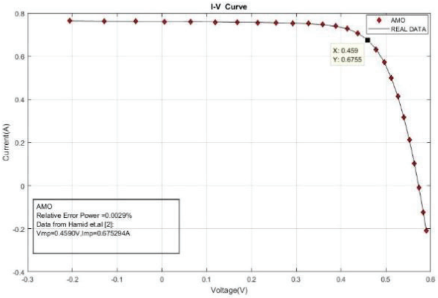

Fig. 5. I-V characteristic curve.

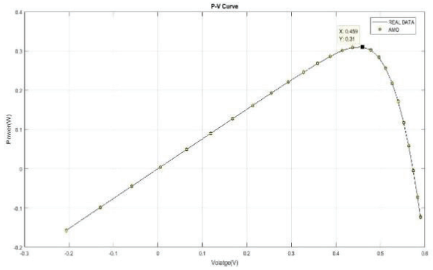

Fig. 6. P-V characteristic curve.

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