Parameter Extraction of Solar Photovoltaic Module Using Adaptive Genetic Algorithm Approach

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***Abstract*- Recently many research on modelling of current verses voltage (I-V) characteristics of Photovoltaic (PV) module have been carried out. Lack of information about the precise values of model parameters militate against the accurate modelling. In addition, the non-linear nature of I-V curve, require an efficient method to determine the model parameter values with precision leading to accurate modelling. This paper proposes an Adaptive Genetic Algorithm (AGA) approach for parameter extraction and modelling of I-V characteristics. Measured field operating data of FVGENERGY 50P (FVG 50P) polycrystalline solar module installed at Malam Aminu Kano International Airport, Kano was used for the algorithm. Results revealed low root mean square Error (RMSE) and mean absolute error (MAE) values of 1.8784×10^{-4} and 0.0102%; 1.3480×10^{-4} and 0.02420% and; 1.4176×10^{-4} and 0.04596% for clear sunny, cloudy and harmattan weather conditions respectively. These results confirm the accuracy of AGA and can be relied upon for PV module parameter extraction and modeling of I-V characteristic.**

Keywords—Photovoltaic, genetic algorithm, Parameter Extraction, photovoltaic module characteristics, modelling

I. INTRODUCTION

Utilization of PV energy for power generation has increased in recent years, due to improvement in solar panel efficiency. This has remarkably boosted the applications based on photovoltaic usage. PV power generation has now been considered as an alternative to a conventional source of power supply particularly in rural areas. The direct and derived advantages of photovoltaic energy include; diversification of energy supply, acceleration of rural electrification in the developing countries, low emission of greenhouse gases, reclamation of degraded land, and increase of regional/national energy independence [1,2]. Optimizing PV system performance to maximize the cost-effectiveness is dependent on accurate parameter extraction and modelling of photovoltaic (PV) current-voltage (I-V) characteristics.

Accurate parameter extraction and modelling of I-V characteristics of PV cell/module is of primary concern because it allows the designer to optimize the system performance and to maximize the cost-effectiveness of the system. The solar cell parameters are the light current I_{ph}, diode reverse current I_o, series resistance R_S, shunt resistance R_p and diode ideality factor n. PV modules are nonlinear and very complex but still very popular components in power generation, they are easy to install and operate. In recent times. It is important to model the PV module to accurately determine the I-V characteristic which describes the behaviour of the module equivalent electrical circuit at different operating conditions. Extracting the parameter of the PV module for predicting the behaviour of the module is very essential for purpose of design and simulations. The PV module consists of several PV cells connected in series, and parallel connection. PV cells are modelled using a single diode or double diode, although the double-diode circuit provides better modelling of the loss in the depletion region caused by the recombination of carriers, the single-diode model still offers a good compromise between the model accuracy and simplicity [3].

In literature, the most commonly methods used for PV parameter extraction and I-V characteristics determination are empirical and artificial intelligence. The empirical methods include; new five-parameter model [4], least squares algorithm [5], Lambert W-function [6-8], Analytical methods [9,10], Chebyshev polynomials [11]. Symbolic algebra [12]. On the other hand, artificial intelligence (AI) or heuristic methods follow a non-technologically specific approach where the model's equation is optimally fitted on a set of measurements, usually the I-V curve. Among the AI methods are; PSO [13,14], bacterial foraging algorithm (BFA) [15], GA [16], improved adaptive differential evolution algorithm [17], Artificial Immune system (AIS) [18], modified artificial bee colony algorithm [19], firefly algorithm (FA) [20], bird mating optimizer [21], pattern search [22], harmony search [23], tunicate swarm algorithm [24], tree growth-based optimization algorithm [25]. Some researchers combined two methods to form hybrid methods, among which are; hybrid differential evolution with whale optimization algorithm [26], hybrid nelder-Mead and modified particle swarm optimization [27], hybrid differential evolution/electromagnetism-like algorithm [28], levenberg–marquardt algorithm combined with simulated annealing [29]. Researchers have used GA for PV cell/module parameter extraction however, there is need to continuously improve the accuracy of the models. These has led to the modification and development of adaptive genetic algorithm by selecting the best crossover and mutation rates over the parameter range using adaptive means.

This paper proposed the application of Adaptive Genetic Algorithm (AGA) for solar PV module parameter extraction and accurate modelling of I-V characteristics to improve on the accuracy and consistency of the result. It is carried out based on measured field data of FVG 50P polycrystalline PV module installed at Mallam Aminu Kano International Airport, Kano.

II. METHODOLOGY

A. Problem formulation

Modelling of Solar cells is done basically to describe the I-V characteristics of the equivalent electrical circuit. Several models have been developed previously to describe solar cells behaviors, single-diode model (SDM) and double diode model (DDM) are used in practice. Moreover, module model (MM) is also used to describe the behavior of a PV module.

B. Single diode model

PV cells can be modeled as a current source in parallel with a diode. The PV cell behaves like a diode when the cells are not exposed to light, in this condition no voltage or current is produced. However, if it is connected to an external supply, it generates current I_o called diode saturation current or dark current. As the intensity of incident light increases, a current is generated by the PV cell [30]. The equivalent electrical circuit of the single diode model has five parameters to be extracted (I_{ph}, I_o, R_S, R_{sh} and n).

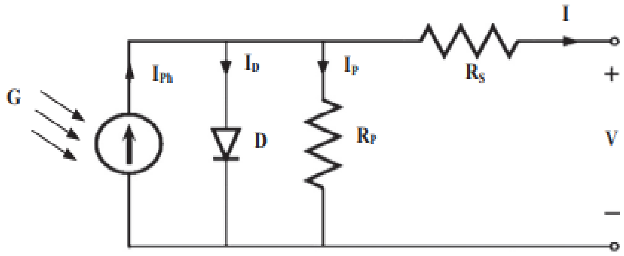

Fig. 1. Equivalent circuit of a single diode P cell

Using Kirchhoff's Current Law (KVL), the terminal current of the cell is given by Equation (1) and the diode current is given in Equation (2)

$$I = I_{ph} - I_D - \frac{V + IR_S}{R_p} \qquad (1)$$

$$I_D = I_o\left\{\exp\frac{q(V + IR_S)}{nkT} - 1\right\} \qquad (2)$$

I_{ph} is the light-generated current which is directly proportional to the light falling on the cell i.e solar irradiance G, linearly related to cell temperature T, and depends on the materials used and fabrication processes. I_D is the diode current, I_o is the diode saturation current, R_s and R_p are series and shunt resistance respectively, I and V are the terminal current and voltage respectively, n is the diode ideality factor, q is the elementary charge of value $1.6\text{x}10^{-19}$ Coulombs and k is a Boltzmann's constant of value $1.38\text{x}10^{-23}$ J/K.

Substituting Equation 2 into Equation 1 we obtained Equation 3 which is the single diode model equation.

$$I = I_{ph} - I_o\left\{\exp\frac{q(V + IR_S)}{nkT} - 1\right\} - \frac{V + IR_S}{R_p} \qquad (3)$$

C. Module Model

A solar module is a combination of series and parallel solar cells; series strings are connected in parallel to each other. Practical solar modules are composed of various PV cells connected in series or parallel. Equation 4 is the mathematical expression of the terminal equation related to the currents and voltages of a PV module with N_p parallel strings and N_s series cells [22, 23].

$$I = I_{phN_p} - I_{oN_p}\left\{\exp\frac{q\left(\frac{V}{N_s}+\frac{R_S}{N_p}\right)}{kTn} - 1\right\} - \frac{\frac{V}{N_s}+\frac{IR_S}{N_p}}{R_p} \qquad (4)$$

N_s= number of series cells =36, N_s=1

D. Optimization Process

This paper realized MM from SDM equation. To realize the objective function, the I - V relationship given in Equations (4) can be rewritten in homogeneous form:

$$f(I,V,x) = 0 \qquad (5)$$

$$x = I_{ph}, I_o, R_S, R_p, \text{n} \qquad (6)$$

$$f(I,V,x) = I - I_{ph} - I_o\left\{\exp\frac{q\left(\frac{V}{N_s}+\frac{R_S}{N_p}\right)}{kTn} - 1\right\} - \frac{\frac{V}{N_p}+\frac{IR_S}{N_p}}{R_p} \qquad (7)$$

V and I are the experimental terminal voltage and current points, f is the vector of parameter to be extracted. The purpose of the optimization process is to determine the optimal parameters by minimizing the fitness function. A small value of fitness function indicates a small error between the simulated current (I_s) and measured current (I_m). The value of f is calculated for each pair of the experimental data. We use the root mean square error (RMSE) as a criterion to quantify the difference between the model results and the experimental data.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i(V,I,x))^2} \qquad (8)$$

N is the number of experimental data.

The objective function is minimized with respect to the parameters range given in Table 4. The model parameters are successively adjusted by AGA until a termination criterion is met. The smaller the objective function value the better the solution vice versa. Whenever an experimental data is used, no information about the values of the model parameters. Therefore, any reduction in the value of objective function is significant because it brings about an improvement in the knowledge of the real values of model parameters.

Table 1: Upper and lower range of PV module parameters.

Parameter	Lower	Upper
Light current (I_{ph}):	0	3.5
Diode reverse sat. current (I_o)	0	50
Diode ideality factor (n)	1	2
Series resistance(R_S)	0	2
Shunt resistance (R_p)	0	2000

E. Genetic Algorithm

Genetic algorithm is a computational model that imitates natural evolution in design and implementation. It belongs to a class of evolutionary algorithm, which is based on survival of the fittest. They are global in their search which is the major difference from the conventional search methods. GA used pseudo-probabilistic rules and not deterministic ones to solve a fitness function that does not contain derivatives. Each possible solution is a code of the decision vector, considering the upper and lower constraints. The initial population generation is formed by randomly generating population members (possible solutions). The generations are produced through successive iterations, and members of each generation are evaluated and then calculate the fitness function, with the member possessing the least error being selected. GA varies the crossover and mutation rate when the solution does not improve over certain number of epochs. GA has been widely used in recent times for optimization and prediction purposes in science and engineering applications. Detailed description of GA can be found in the literature [31, 32].

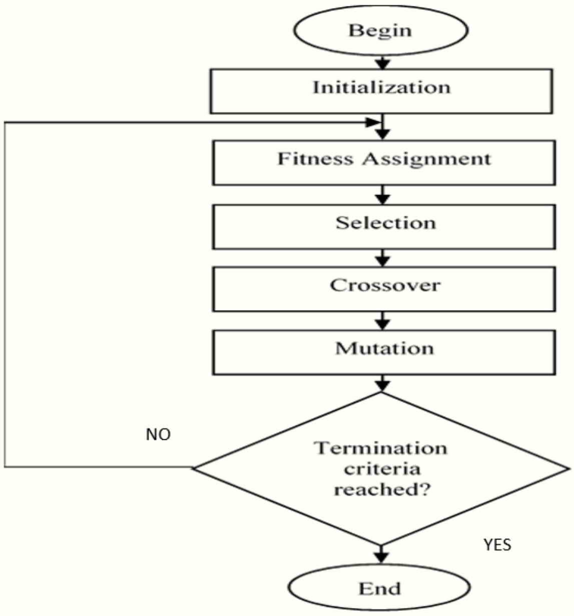

Fig. 2. Genetic Algorithm flow chart

Steps of AGA algorithm used in this paper are as follows:

Step 1: Initialization

Initial GA parameters are; Maximum Number of Generation (NG_{max} = 300), Population Size (N_p = 100), Crossover Probability (P_c = 0.3 - 0.8), Mutation Probability (P_m = 0.01 – 0.1).

PV parameter range as in Tables 1.

Step 2: Generate initial population

Step 3: Evaluate according to Equation (7)

Step 4: Selection

Step 5: Crossover

Step 6: Mutation

Step 7: If number of Iteration < 300 go back to step 3, if not go to step 8

Step 8: If solution does not improve adapt P_c and P_m

Step 9: Output PV parameters, fitness error and PV characteristics

Step 10: Stop

III. RESULTS AND DISCUSSION

Data for this research work was obtained from experimental testbed installed at Mallam Aminu Kano International Airport Kano, Nigeria. The testbed consists of the following sub-systems; FVG 50P solar module, temperature sensor, pyranometer, multichannel data logger, digital voltmeter, digital ammeter, and variable resistive load. A single PV module FVG 50P with a nominal output power of 50W at standard test conditions was used for this experiment. Resistive load was varied at a constant solar irradiance (G) and cell temperature (T), current and voltage for each varied load is measured. Measurements were carried out at (G=998W/m^2 T=36.9°C) during clear sunny weather condition, (G=620W/m^2 T=30.9°C) during cloudy weather condition and (G= 202W/m^2 T=22.3°C) during harmattan weather condition.

GA is coded and implemented in MATLAB environment to extract the PV module parameters using single diode models. Table 2 summarizes the PV module parameters extracted for measurements under clear sunny, cloudy and harmattan weather conditions respectively with their corresponding RMSE.
Extracted PV parameters were used to create simulated I-V data. I-V characteristics plot of measured and simulated values is presented in Fig 4 to 6 with their corresponding fitness function plots as shown in Fig 7 to 9. I-V characteristics and low RMSE values of 1.8784 x10^{-4}, 1.3480 x10^{-4}and 1.4176 x10^{-4} under clear sunny, cloudy and harmattan weather conditions respectively, revealed good agreement between the experimental data and the model results which proves the efficient performance of AGA. The fitness function represents the best objective function value at each iteration.

`Fig. 3. Expiremental test bed

Table 2. PV parameter for clear sunny, cloudy and harmattan weather conditions

Weather Condition	$I_{ph}(A)$	I_o(μA)	n	$R_S(\Omega)$	$R_p(\Omega)$	RMSE
Clear Sunny	2.6040	7.115	1.6734	1.3583	993.2975	1.8784 x10^{-4}
Cloudy	1.6090	0.117	1.3670	1.2723	1318.4123	1.3480 x10^{-4}
Harmattan	0.8960	0.237	1.3730	0.9635	598.9980	1.4176 x10^{-4}

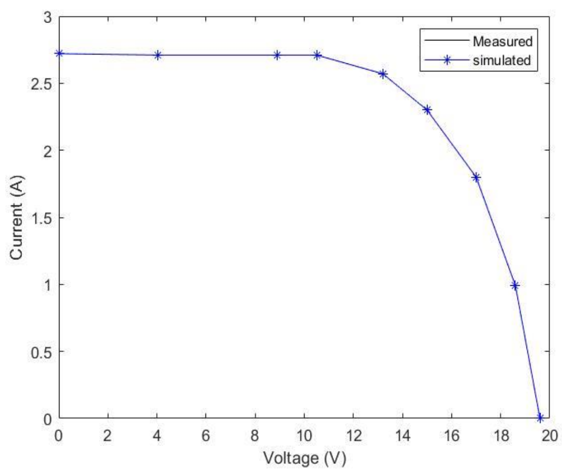

Fig. 4. I-V characteristics plot under clear sunny weather condition

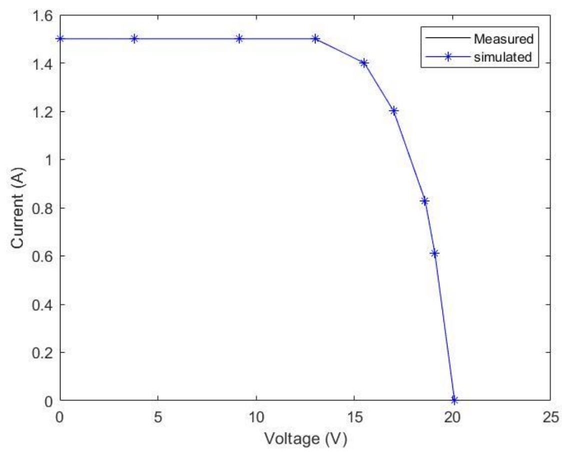

Fig. 5. I-V characteristics plot under cloudy weather condition

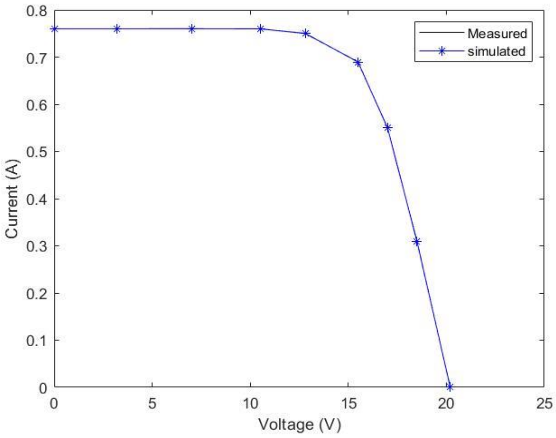

Fig. 6. I-V characteristics plot under harmattan weather condition

The accuracy of the model was further determined by analyzing how close is the simulated current "I_s" is to the measured current "I_m". Mean absolute error formula is presented in equation 9. Error analysis results presented in Table 3 to 5 revealed the high accuracy of the PV module parameter extraction process with law MAE values of 0.0102%, 0.02420% and 0.04596% for clear sunny, cloudy and harmattan climatic seasons respectively.

$$\text{Relative error (RE)} = \frac{I_m - I_s}{I_m} \tag{9}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|RE| \tag{10}$$

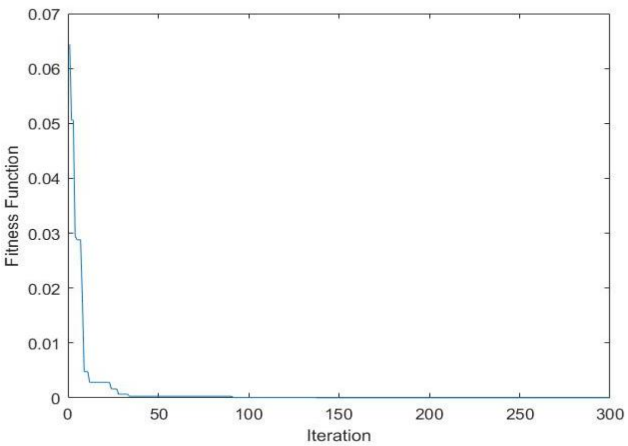

Fig. 7. Fitness function under clear sunny weather condition

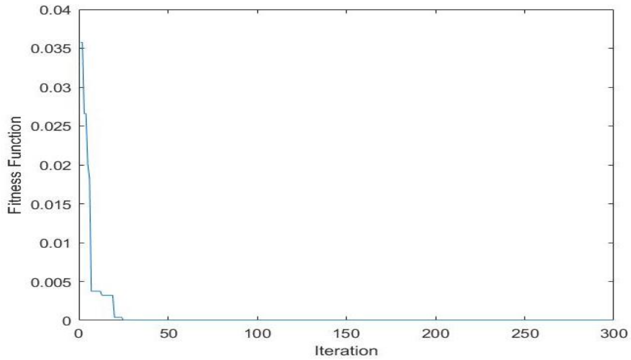

Fig. 8. Fitness function under cloudy weather condition

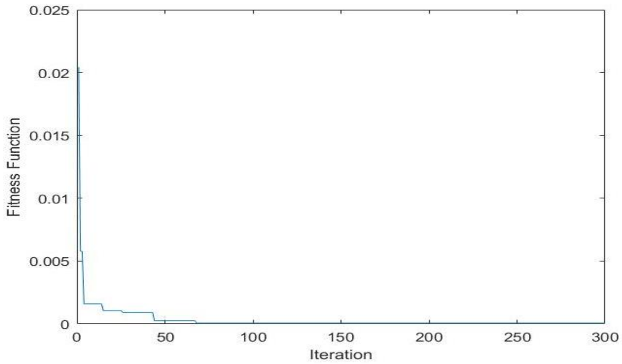

Fig. 9. Fitness function under harmattan weather condition

Table 3. Error analysis under clear sunny weather condition

S/N	V (V)	I_m (A)	I_s (A)	RE
1	4.02	2.7100	2.7096	0.01476
2	8.9	2.7100	2.7105	-0.01845
3	10.5	2.7100	2.7099	0.00369
4	13.2	2.5700	2.5702	-0.00778
5	15	2.3000	2.3000	0
6	17	1.8000	1.8003	-0.01666
7	18.6	0.9900	0.9899	0.010101
MAE				0.000102

Table 4. Error analysis under cloudy weather condition

S/N	V (V)	I_m (A)	I_s (A)	RE
1	3.8	1.5	1.5004	-0.02666
2	9.12	1.5	1.4999	0.006666
3	13	1.5	1.4996	0.026666
4	15.5	1.4	1.4001	-0.007142
5	17	1.2	1.1996	0.033333
6	18.6	0.83	0.8303	-0.036144
7	19.1	0.61	0.6102	-0.032786
MAE				0.000242

Table 5. Error analysis under harmattan weather condition

S/N	V (V)	I_m (A)	I_s (A)	RE
1	3.2	0.76	0.76	0
2	7	0.76	0.7596	-0.052632
3	10.5	0.76	0.7603	0.0394736
4	12.8	0.75	0.7499	-0.013333
5	15.49	0.69	0.6901	-0.014492
6	17	0.55	0.5504	0.0727272
7	18.5	0.31	0.3096	0.1290322
MAE				0.0004595

IV. Conclusion

The following conclusion can be drawn from this paper:

i. PV module parameter extraction base on single diode model was carried out using AGA.
ii. Accurate I–V characteristic of a real system (FVG 50P PV module) was determined by extracting the unknown parameters.
iii. The statistical analysis revealed the robustness of the AGA technique in parameter extraction problems for different operating conditions based on low RMSE and MAE values of (1.8784 x 10^{-4}, 0.0102%), (1.3480 x 10^{-4}, 0.02420%) and (1.4176 x 10^{-4}, 0.04596%) for clear sunny, cloudy and harmattan weather conditions respectively.
iv. Based on the discussion of results, it can be concluded that AGA is an effective and robust technique for accurate PV module parameter extraction and modelling of I-V characteristics.

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