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8-Parameter Extraction in Photovoltaic Cell Using Firefly Optimization Technique

Adedayo M. Farayola, Yanxia Sun, Ahmed Ali
Department of Electrical and Electronic Engineering Sciences, University of Johannesburg, South Africa
Email: lordfaraday@yahoo.com, ysun@uj.ac.za, aali@uj.ac.za

***Abstract*— Photovoltaic (PV) cell modeling is an important study done to improve solar cell performance before fabrication. Different techniques have been implemented for the extraction of solar cell parameters to generate a high PV power. However, most of these techniques are considered less accurate and suffer some limitations that reduce their effectiveness. In this paper, five different techniques were compared under different cell temperature levels to determine the technique that yields the best results. Findings show that firefly algorithm exhibited the best performance and can be recommended for the extraction of solar cell parameters in PV cells.**

Keywords—Cultural algorithm, Fminsearch, Firefly algorithm, Genetic algorithm, PSO, PV cells and swarm intelligence.

I. Introduction

Over the last few decades, the demand for renewable energy such as solar energy has been growing due to the economy-friendly and the environmentally-friendly attributes with photovoltaic cells. Photovoltaic cells are often used to convert solar energy into electrical energy. Determining the parameters of PV cells at different working conditions is of high significance, as these parameters are used to generate the current-to-voltage (I-V) output curve, P-V (power-to-voltage) output curve and the maximum power point (MPP) of the photovoltaic cells. A PV cell is developed using either 1-diode or 2-diodes or more than two diodes. Examples of 1-diode cells are the four-parameter model comprising of four unknown parameters (I_{ph}, I_s, R_s, and A), the five-parameter model (I_{ph}, I_s, R_s, R_p and A), and the modified five-parameter model with two additional parameters (m and n) referred to as the seven-parameter model. I_{ph} represents the photon current, I_s is the diode saturation current, R_s is the series resistance, R_p is the parallel resistance, A is the ideality factor, (m and n) are the exponential constant for I_{ph} and A respectively. Example of a two-diode cell is the 8-parameter model comprising of eight unknown parameters. Both 4-parameter models and the 5-parameter models are considered simple but less accurate compared to the eight-parameter models that consider the current losses in PV cells due to recombination [1, 2].

Equation (1) presents the mathematical equation for an 8-parameter model with the assumption that the saturated current I_{s2} at the second diode D_2 is negligible.

$$I = I_{ph} - I_{s1}\left[e^{\frac{V+IR_s}{N_1V_t}} - 1\right] - I_{s2}\left[e^{\frac{V+IR_s}{N_2V_t}} - 1\right] - \left[\frac{V+IR_s}{R_p}\right] \tag{1}$$

This mathemeatical equation above is used to compute the amount of current (I) and voltage (V) produced in a PV cell, where photon current I_{ph}, saturated current at diode D_1 as I_{s1}, series resistance R_s, parallel resistance R_p and the quality factor ec are the first five-unknown cell parameters. The other three-unknown parameters (TIPH1, EG, and TXIS1) known as the temperature dependence characteristics are computed using equations (2)-(5),

$$I_{ph}(T) = I_{ph} \times \left(1 + TIPH1 \times \left(T - T_{measured}\right)\right) \tag{2}$$

$$I_{s1}(T) = I_{s1} \bullet \left(\frac{T}{T_{measured}}\right)^{\frac{TXIS1}{N1}} \bullet \exp\left(\frac{E_g \times \left(\frac{T}{T_{measured}} - 1\right)}{N_1 \times V_t}\right) \tag{3}$$

$$R_s(T) = R_s \times \left(\frac{T}{T_{measured}}\right)^{TRS1} \tag{4}$$

$$R_p(T) = R_p \times \left(\frac{T}{T_{measure}}\right)^{TRP1} \tag{5}$$

where TIPH1 is the first-order temperature coefficient for I_{ph} and TXIS1 is the exponential temperature for I_{s1}. TRS1 and TRP1 represent the exponential temperature for R_s and R_p respectively. $R_s(T)$ and $R_p(T)$ are the series and parallel resistance at the solar cell temperature (T) respectively and $T_{measure}$ represents the measured cell temperature.

The three popular methods used to extract solar cell parameters include analytical methods, fitting-algorithm methods and the optimization methods [3]. Analytical methods comprise of approximate analytical methods defined using simple functions and the exact analytical methods expressed using complex functions like Lambert $w-$functions. The analytical methods use the I-V output curve properties. That is, axis intercepts and the gradient at specific points are used to evaluate some of the unknown cell parameters. Despite the simplicity, precision with analytical methods still depend on the accuracy with the measured I-V data, inaccuracies initiated by numerical variation and the basic principles introduced for parameter extraction. The fitting-algorithm methods depend on the type of fitting algorithm used, the stated error function and the initial values of the parameters to be fitted. Optimization methods are the most recent approach introduced to extract and optimize the solar cells parameters with improved performances [4].

Optimization methods can be categorized into two: heuristic and metaheuristic optimization techniques [5]. Heuristic technique are the local search techniques commonly used to solve problems that require approximate solutions while metaheuristic techniques are used to solve problems with global solutions [6]. A good example of a heuristic technique is the Nelder-Mead technique that applies fminsearch method for optimization. Examples of metaheuristics are the genetic algorithm (GA), particle swarm optimization (PSO) and the cultural algorithm (CA).

Despite the robustness with metaheuristic techniques in solving optimization problems, these techniques are often designed for specific problems and show flaws when used for non-compliant optimization tasks. Some known flaws with optimization techniques include slow convergence, getting trapped at local optimum, poor exploitation and weak exploration [7]. In this paper, work will be done using five different optimization techniques to optimize and extract the 8-unknown parameters in a 2-diode cell model and their results compared to determine the most effective optimization technique that can be suggested for the extraction of solar cell parameters.

The layout of this paper is described as follows. Section II introduces the considered optimization techniques in the form of literature review. Section III and IV gives the experimental setup and results respectively while section V will be the summary.

II. OPTIMIZATION TECHNIQUES

The techniques considered in this work are discussed below.

1. Nelder-Mead Algorithm (Fminsearch): This is an example of heuristic-search technique commonly used to search for the local minima (acceptable solution) in an unconstrained multifunction using derivative-free approach. Basically, heuristic algorithms tend to solve optimization problems faster and more efficient than tradition methods such as golden-search method and quadratic-approximation method. However, heuristic algorithms often exhibit a lower accuracy, low precision, and low optimality. Heuristic-search methods are most often employed when approximate solutions are satisfactory and accurate (global) solutions are computationally expensive [8].

2. Genetic Algorithm (GA): GA is a direct random-search type of metaheuristic technique modelled using natural (Darwinian) evolution or selection process to search for the global solution in an optimization problem. Conventional GA works by creating a set of random initial population, then sequence of new population is introduced using individuals from the present population [9, 2]. To generate this new population, GA performs the follow steps:

- Determining the raw fitness scores in every member of the present population by evaluating its fitness value.
- Converting the raw fitness scores to a more suitable form through scaling as expectation values.
- Selection of members (parents) from their expectation value results.
- Selection of members with lower fitness values as elite individuals for the new population.
- Reproduction of offspring from parents using random changes in parents (mutation) or using crossover operators.
- Substituting the present population with the offspring to produce subsequent generation.
- The algorithm halts when the stopping condition is met.

3. Particle Swarm Optimization (PSO): PSO is another example of metaheuristic optimization technique proposed by J. Kennedy and R. Eberhart in 1995. PSO is inspired by the swarm behaviour of insects or bird flocks. PSO looks similar to genetic algorithm as both techniques are classified as population-based optimization techniques [10, 6]. In PSO, collection of individuals (particles) migrate in steps to a region with an initial velocity V_i^k. At each step, the algorithm evaluates the objective function for each particle using equations (6) and (7) respectively,

$$V_i^{k+1} = w \bullet V_i^k + c_1 r_1 \bullet (P_i^k - X_i^k) + c_2 r_2 \bullet (P_g^k - X_i^k) \tag{6}$$

$$X_i^{k+1} = X_i^k + P_i^k \tag{7}$$

where $k = 1,2,3,...,n$ is the swarm size, V_i^{k+1} is the particle velocity, X_i^{k+1} is the current position of a particle, P_i^k is the local best position, P_g^k represents the global best position, coefficients $(r_1 \text{ and } r_2)$ are random numbers between 0 and 1. w is the inertia and coefficients $(c_1 \text{ and } c_2)$ represent the learning factors. PSO procedure is given below:

- Creation of initial population (swarms) with an initial velocity.
- Objective function computation at each particle location in order to determine the best fitness value and the best location.
- Updating the velocity to obtain the particles' individual best location and the best location of their neighbours.
- Stop the iteration process when the stopping criterion condition is met.

4. Cultural Algorithm (CA): CA is an evolutionary algorithm proposed by R. G. Reynolds in 1991, inspired by the human-culture evolution development [11]. CA is a development to the traditional genetic algorithm and comprises of two fundamental mechanisms (population space and belief space). The population space incorporates the use of evolutionary operators likes mutation and crossover for its evaluation and reproduction. The belief space extracts collected information (knowledge) from nominated individuals in the population using five different knowledges (normative, situational, historical, domain and topographic) [12].

The normative knowledge ensures that selected individuals are maintained within a suitable variable-range to improve the evolutionary process. Situational knowledge provides number of cases as examples for the analysis of individuals. Topographic knowledge keeps track of the best individual cell in the search space region. Domain knowledge uses information about the problem dominion to monitor the search space. Historical or temporal knowledge supervises the search activity and captures vital incidents in the search. The collected information is then used to monitor the evolution process and to prevent the algorithm from getting trapped at local optimal solutions (premature convergence) [13]. The procedure for CA is illustrated below:

- Evaluation of individuals in the population space using performance function obj ().
- Determining individuals permitted to update the belief space using an acceptance function accept ().
- Knowledge from the selected individuals is used to modify the belief using function update ().
- Selection of individuals for the next generation by employing the influence () function on individuals in the belief space.
- Repeat step 1 to step 4 until a termination criterion is met.

5. **Firefly Optimization:** This is another swarm-intelligence algorithm suggested by X. Yang in 2008 based on the communal behavior of fireflies and their flashing-light patterns [14]. Fireflies use their flashing-light beams for attraction, security and prey hunting. To model a working firefly algorithm, three assumptions are considered [15, 16].

i. Fireflies are unisex and attract regardless of their sex
ii. The rate of attraction with fireflies depends on their brightness level. That is, brighter fireflies are attracted by the less bright fireflies and the level of brightness is inversely proportional to the firefly's distances apart.
iii. The intensity of firefly is computed from the cost (objective) function.

The expression of light intensity and the change in attraction with fireflies plays a major role in developing the firefly algorithm. The light attractive coefficient (β) in firefly is computed using equation (8),

$$\beta = \begin{cases} \beta_0 e^{-\gamma r_{ab}^2} & \text{when } \beta_{min} = 0 \\ \beta_{min} + \left(\beta_0 - \beta_{min}\right) e^{-\gamma r_{ab}^2} & \text{when } \beta_{min} \neq 0 \end{cases} \tag{8}$$

where β_0 is the light attractive coefficient when the distance apart r_{ab} between two fireflies is zero, β_{min} is the attractiveness when $r_{ab} = \infty$. γ is the light absorption coefficient. r_{ab} is the cartesian (Euclidean) distance between two fireflies (X_a and X_b) and is mathematically expressed as

$$r_{ab} = \left\| x_a - x_b \right\| = \sqrt{\sum_{k=1}^{d} \left(x_{a,k} - x_{b,k} \right)^2} \tag{9}$$

where $k = 1,2,3,...,D$, d is the problem element, variables $(x_{a,k} \text{ and } x_{b,k})$ are the $k-\text{th}$ dimension for fireflies x_a and x_b respectively.

III. SIMULATION MODEL

To validate the high performance with the proposed firefly algorithm, a comparison experiment was conducted using five different optimization techniques comprising of fminsearch (FM), genetic algorithm (GA), particle swarm optimization (PSO), cultural algorithm (CA) and the proposed firefly (FF) algorithm. The experiment aims at extracting some optimized variables (parameters) that can successfully minimize the objective function value $\left[lse = lse_{init} + (data\_diff' \times data\_diff) \right]$, where lse_{init} is the initial least square error set at zero, data_diff is the data difference (error) between the predicted current-to-voltage $I-V$ samples and the actual $I-V$ samples. These samples contain 2 × m dataset dimension, where m denotes 30 samples of I-V data separately collected at 0 °C, 25 °C, 70 °C, and 85°C respectively, while data_diff' is the error using m × 2 dimension.

The cell characteristics comprising of five-unknown parameters $\left(I_s, I_{ph}, e_c, R_s, \text{ and } R_p \right)$ as variables were searched within a search space comprising of two boundaries referred to as the lower boundary $L_{B1} = \left[1e-9,\ 1,\ 1,\ 1e-5,\ 5 \right]$ and the upper boundary $U_{B1} = \left[1e-6,\ 4,\ 2,\ 0.01,\ 20 \right]$ constraints. Similarly, the same minimization function (lse) was introduced to determine the temperature-dependenc characteristics cmprising of the remaining three-unknown parameters $\left(TIPH1, E_g, TXIS1 \right)$ within the search space $L_{B2} = \left[1e-6,\ 0,\ 0 \right]$ and $U_{B2} = \left[1,\ 4,\ 10 \right]$ respectively. Due to the random-search solution patterns with metaheuristic techniques, the considered optimization techniques were run four different times for each generation (iteration) number, and the best fitness results were recorded as case studies. The iteration numbers used as stopping criteria were 5, 10, 20 and 50 generations. The recorded optimized-parameters using least square error (lse) fitness functions for the five cell parameters and the three temperature-dependence parameters for each algorithm were then used to fit the predicted I-V output curves to the measured I-V output curves at different temperature levels (0 °C, 25 °C, 70 °C, and 85°C).

Table 1 presents the genetic algorithm parameters that were introduced to optimize the cell characteristics and the temperature-dependence characteristics.

Table 1. GA parameters

parameters	For 5-param evaluation	For 3-param evaluation
Population size	50	50
Scaling function	Rank	Rank
Selection function	Stochastic	Stochastic
Elite count	0.25	0.25
Crossover fraction	0.80	0.80
Mutation rate	Constraint dependent	Constraint dependent
Function tolerance	1e-6	1e-6
Constraint tolerance	1e-3	1e-3

Table 2 presents the used PSO parameters for the optimization problems. nPop is the population size, w is the inertia weight, w_{damp} is the damping ratio, while C_1 and C_2 represent the personal learning co-efficient and the global learning coefficient respectively.

Table 2. PSO parameters

Parameters	5-param	3-param
nPop	100	100
w	1	1
w_{damp}	0.99	0.99
C_1	1.50	1.50
C_2	2.0	2.0

Table 3 displays the cultural algorithm parameters that were used to extract the unknown cell characteristics and the unknown temperature-dependence characteristics. From the table, the acceptance ratio is represented as pAccept while the number of accepted individuals as nAccept.

Table 3. Cultural algorithm parameters

Parameters	5-param	3-param
Population size (npop)	50	50
pAccept	0.35	0.35
nAccept	18	18
alpha	0.30	0.30
Beta	0.50	0.50

Table 4 displays the firefly algorithm (FA) parameters used to extract the unknown cell characteristics and the temperature-dependence characteristics. From the table, the light absorption coefficient is represented as γ, the attraction coefficient base value as β, mutation coefficient as α, and mutation coefficient damping ratio as α_{damp}.

Table 4. Firefly algorithm parameters

Parameters	5-param	3-param
Population size (npop)	25	25
γ	1	1
β	2	2
α	0.2	0.2
α_{damp}	0.98	0.98

Table 5 presents the Nelder-Mead (fminsearch) parameters.

Table 5.Nelder-Mead Fminsearch parameters

Parameters	5-param	3-param
Max. function evaluations	1000	600
Maximum_tolerance	1e-4	1e-4
Function_tolerance	1e-4	1e-4

IV. EXPERIMENTAL RESULTS

Figures 1 - 3 present the graphical best-cost results using the considered optimization techniques (fminsearch (FF), genetic algorithm (GA), particle swarm optimization (PSO), cultural algorithm (CA), and the proposed firefly (FF) algorithm) to extract the 8-unknown parameters in solar cells using 5 iteration, 20 iteration and 50 iteration stopping criterion respectively. Each Figure comprises of two subplot Figures, where the left hand side (LHS) subplot Figure represents the cell characteristic optimization results while the right hand side (RHS) subplot Figure represents the temperature-dependence best-cost results for five different optimization techniques under different temperature levels.

For Figure 1, using 5 iteration number, the fast convergence, improved exploration and exploitation using firefly algorithm for the optimization of cell parameters and temperature-dependence parameters can be easily seen from the LHS and RHS subplot Figures.

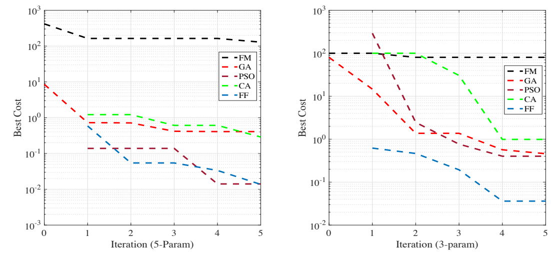

Figure 1. Optimization results using 5 iteration

Similarly for Figures 2 and 3, using 20 iteration and 50 iteration respectively, the improved performance with firefly (FF) algorithm can be seen. FF achieved the best results while fminsearch exhibited the worst performance results.

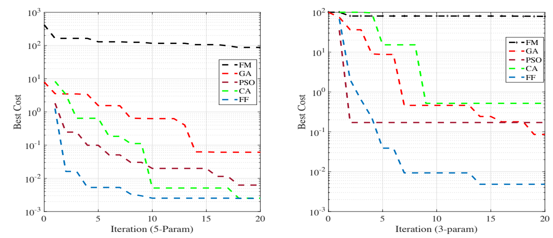

Figure 2. optimization results using 20 iteration

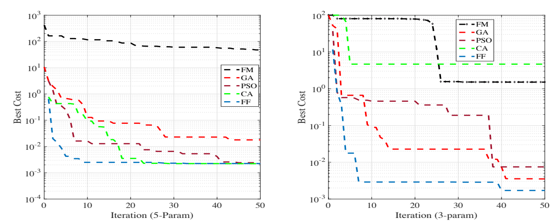

Figure 3. optimization results using 50 iteration

Figures 4 display the I−V output curves (measured and predicted) using optimization techniques at different temperature levels (0 °C, 25 °C, 70 °C, and 85°C). Each Figure comprises of four subplot Figures for 5 iteration, 10 iteration, 20 iteration, and 50 iteration stopping criterion respectively.

From Figure 4, the poor convergence with fminsearch algorithm can be seen in all the four subplot Figure cases. That is, the measured I−V output curves were not close to the fminsearch-predicted I−V output curves in all the cases.

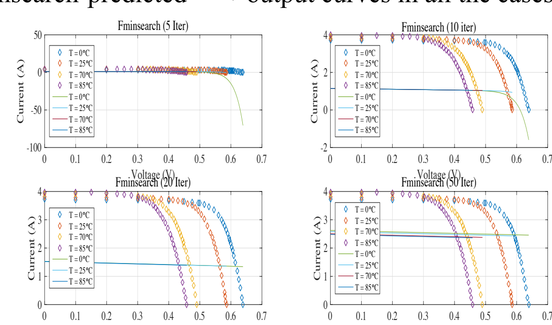

Figure 4. Fminsearch convergence

For Figures 5 - 8, the convergence performance improved as the generation number was increased from 5 iter to 50 iter. That is, better results were obtained using GA technique.

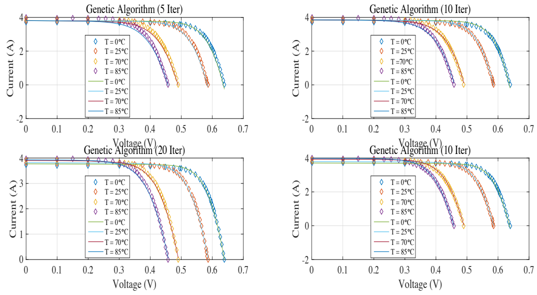

Figure 5. Genetic algorithm convergence

Figure 6 presents the I−V output curve results using PSO technique. From the graphs, PSO exhibited a better performance than fminsearch as the measured I−V output curves and the predicted I−V output were more fitting than that of fminsearch algorithm.

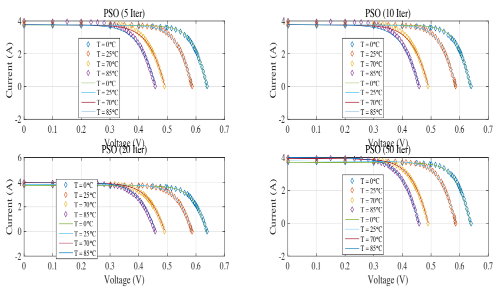

Figure 6. PSO convergence

Figure 7 presents the I−V output curve results using cultural algorithm. From the graphical results, CA exhibited a better performance than fminsearch technique but lower than that of GA and PSO techniques.

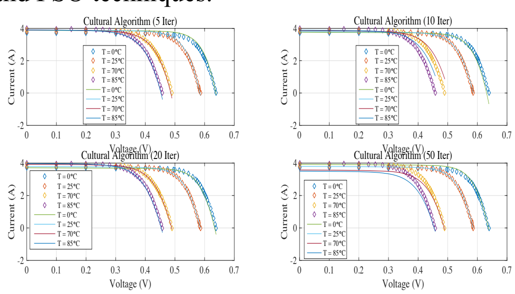

Figure 7. Cultural algorithm convergence

Figure 8 presents the I−V output curve results using firefly algorithm. The fast convergence, improved exploration and exploitation can be observed with firefly (FF) algorithm as the measured I−V output curves best-fit with the firefly-predicted I−V output curves in all cases.

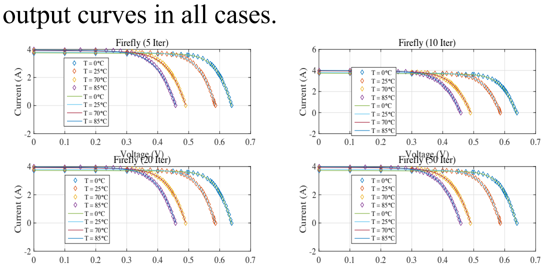

Figure 8. Firefly convergence

Table 6 presents the tabulated results recorded when temperature level T is 70 °C and using 5 iteration stopping criterion, where V represents the actual voltage in volts, I is the actual current in amps. From the tabulated results, firefly exhibited the best performance with a root mean square error (RMSE) value of 0.044 while fminsearch exhibited the worst performance with a RMSE value of 1.976.

Table 6. I-V output results at T = 70 °C and iter = 5 generation

Meas.	V	I	FM	GA	PSO	CA	FF
1	0	3.930	1.082	3.805	3.775	3.899	3.914
2	0.1	3.920	1.061	3.799	3.767	3.890	3.903
3	0.2	3.910	1.040	3.786	3.755	3.876	3.886
4	0.3	3.850	1.019	3.711	3.698	3.809	3.813
5	0.317	3.820	1.016	3.675	3.670	3.777	3.778
6	0.33	3.790	1.013	3.636	3.639	3.743	3.742
7	0.342	3.750	1.010	3.589	3.602	3.701	3.698
8	0.355	3.690	1.008	3.523	3.549	3.643	3.636
9	0.368	3.620	1.005	3.436	3.478	3.564	3.555
10	0.38	3.520	1.002	3.331	3.391	3.470	3.456
11	0.392	3.390	1.000	3.197	3.277	3.346	3.330
12	0.401	3.270	0.998	3.074	3.170	3.230	3.213
13	0.409	3.150	0.996	2.944	3.056	3.107	3.089
14	0.416	3.030	0.995	2.813	2.939	2.979	2.963
15	0.422	2.910	0.993	2.687	2.825	2.855	2.841
16	0.427	2.790	0.992	2.570	2.719	2.738	2.727
17	0.431	2.670	0.991	2.469	2.625	2.635	2.628
18	0.436	2.550	0.990	2.333	2.498	2.494	2.494
19	0.44	2.420	0.989	2.215	2.387	2.371	2.378
20	0.444	2.300	0.988	2.090	2.267	2.237	2.252
21	0.447	2.180	0.987	1.990	2.172	2.129	2.152
22	0.45	2.060	0.987	1.885	2.070	2.015	2.047
23	0.455	1.900	0.985	1.700	1.889	1.809	1.859
24	0.46	1.660	0.984	1.500	1.691	1.582	1.655
25	0.465	1.450	0.983	1.285	1.476	1.332	1.434
26	0.47	1.210	0.981	1.054	1.242	1.057	1.194
27	0.475	0.909	0.980	0.808	0.989	0.756	0.935
28	0.48	0.666	0.978	0.545	0.716	0.427	0.657
29	0.485	0.364	0.977	0.265	0.422	0.067	0.358
30	0.49	0.000	0.975	0.032	0.106	0.325	0.038
RMSE	-	-	**1.976**	**0.172**	**0.101**	**0.112**	**0.044**

Table 7 presents the tabulated results when temperature T is 70 °C and using 20 iteration. From the tabulated results, firefly exhibited the best performance with a RMSE value of 0.014 while fminsearch exhibited the worst performance with a RMSE value of 1.651.

Table 7. I-V output results at T = 70 °C and iter = 20 generation

Meas.	V	I	FM	GA	PSO	CA	FF
1	0	3.930	1.522	3.902	3.959	3.926	3.923
2	0.1	3.920	1.494	3.896	3.949	3.917	3.915
3	0.2	3.910	1.465	3.886	3.934	3.904	3.902
4	0.3	3.850	1.437	3.825	3.870	3.842	3.840
5	0.317	3.820	1.432	3.792	3.838	3.811	3.809
6	0.33	3.790	1.428	3.757	3.805	3.778	3.776
7	0.342	3.750	1.425	3.713	3.764	3.737	3.736
8	0.355	3.690	1.421	3.650	3.706	3.678	3.678
9	0.368	3.620	1.418	3.565	3.628	3.598	3.600
10	0.38	3.520	1.414	3.462	3.533	3.500	3.505
11	0.392	3.390	1.411	3.328	3.410	3.373	3.381
12	0.401	3.270	1.408	3.202	3.295	3.252	3.264
13	0.409	3.150	1.406	3.070	3.173	3.125	3.140
14	0.416	3.030	1.404	2.937	3.048	2.994	3.014
15	0.422	2.910	1.402	2.807	2.926	2.866	2.890
16	0.427	2.790	1.401	2.688	2.813	2.747	2.775

17	0.431	2.670	1.400	2.584	2.715	2.643	2.674
18	0.436	2.550	1.398	2.445	2.580	2.502	2.538
19	0.44	2.420	1.397	2.324	2.463	2.379	2.418
20	0.444	2.300	1.396	2.196	2.338	2.247	2.290
21	0.447	2.180	1.395	2.094	2.237	2.141	2.188
22	0.45	2.060	1.394	1.987	2.131	2.030	2.080
23	0.455	1.900	1.393	1.799	1.942	1.831	1.887
24	0.46	1.660	1.391	1.596	1.737	1.616	1.678
25	0.465	1.450	1.390	1.380	1.514	1.382	1.451
26	0.47	1.210	1.389	1.148	1.273	1.130	1.205
27	0.475	0.909	1.387	0.902	1.013	0.859	0.940
28	0.48	0.666	1.386	0.641	0.733	0.567	0.655
29	0.485	0.364	1.384	0.365	0.433	0.256	0.350
30	0.49	0.000	1.383	0.074	0.112	0.077	0.024
RMSE	**-**	**-**	**1.651**	**0.068**	**0.048**	**0.047**	**0.014**

Table 8 presents the tabulated results recorded when temperature T is 70 °C and using 50 iteration. From the table, firefly exhibited the best performance with a RMSE value of 0.012 while fminsearch exhibited the worst performance with a RMSE value of 1.146.

Table 8. I-V output results at T = 70 °C and iter = 50 generation

Meas.	V	I	FM	GA	PSO	CA	FF
1	0	3.930	2.506	3.933	3.948	3.577	3.935
2	0.1	3.920	2.480	3.928	3.939	3.567	3.925
3	0.2	3.910	2.454	3.920	3.925	3.552	3.911
4	0.3	3.850	2.428	3.874	3.863	3.495	3.849
5	0.317	3.820	2.423	3.848	3.832	3.466	3.818
6	0.33	3.790	2.420	3.818	3.800	3.436	3.785
7	0.342	3.750	2.417	3.781	3.759	3.399	3.745
8	0.355	3.690	2.413	3.726	3.701	3.345	3.687
9	0.368	3.620	2.410	3.650	3.623	3.273	3.609
10	0.38	3.520	2.407	3.554	3.527	3.185	3.514
11	0.392	3.390	2.403	3.427	3.402	3.070	3.389
12	0.401	3.270	2.401	3.305	3.285	2.962	3.272
13	0.409	3.150	2.399	3.175	3.160	2.846	3.147
14	0.416	3.030	2.397	3.041	3.032	2.727	3.019
15	0.422	2.910	2.396	2.909	2.907	2.611	2.895
16	0.427	2.790	2.394	2.787	2.791	2.503	2.778
17	0.431	2.670	2.393	2.681	2.690	2.408	2.677
18	0.436	2.550	2.392	2.537	2.552	2.279	2.539
19	0.44	2.420	2.391	2.411	2.432	2.166	2.419
20	0.444	2.300	2.390	2.277	2.303	2.045	2.289
21	0.447	2.180	2.389	2.170	2.200	1.948	2.186
22	0.45	2.060	2.388	2.058	2.091	1.846	2.077
23	0.455	1.900	2.387	1.859	1.897	1.663	1.883
24	0.46	1.660	2.386	1.645	1.687	1.464	1.671
25	0.465	1.450	2.384	1.415	1.459	1.248	1.442
26	0.47	1.210	2.383	1.169	1.212	1.013	1.194
27	0.475	0.909	2.382	0.906	0.946	0.760	0.927
28	0.48	0.666	2.380	0.627	0.661	0.488	0.641
29	0.485	0.364	2.379	0.332	0.356	0.196	0.333
30	0.49	0.000	2.378	0.021	0.030	0.117	0.005
RMSE	**-**	**-**	**1.146**	**0.025**	**0.015**	**0.284**	**0.012**

V. CONCLUSIONS

This paper presents the novelty using firefly algorithm for the optimization and extraction of unknown cell parameters and unknown temperature-dependence parameters in solar cells under different cell temperatures. Five different techniques comprising of fminsearch, genetic algorithm, particle swarm optimization, cultural algorithm and the proposed firefly algorithm were compared using 5 iteration, 20 iteration, and 50 iteration stopping criterion respectively. Obtained results confirm the improved performance and the fast convergence with firefly algorithm. Findings suggest that firefly algorithm can be recommended for solar cell parameter modelling as the predicted I-V output curves using firefly optimization technique best-fit with the measured I-V output curves in all the cases considered in this work.

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