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Optimisation of Solar Photovoltaic (PV) Parameters Using Meta-Heuristics

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Abstract. This paper presents a critical analysis of the meta-heuristic techniques used in various researches on the optimisation of photovoltaic (PV) parameters, which involves the use of different algorithms in order to extract and improve these parameters from the Single Diode Model (SDM), Double Diode Model (DDM) and Three Diode Model (TDM) respectively. The modelling parameters such as the photon current, saturation current, the series and parallel resistances are investigated to understand the optimum value. It will also equate the results of datasheet values from PV manufactures with experiment values obtained from PV module measurements. The meta-heuristics techniques to be considered include Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Harmony Search (HS), Flower Pollination Algorithm (FPA), Simulated Annealing (SA), Teaching Learning Based Optimisation (TLBO), and other different hybrid solutions to optimize the convergence speed. Root Mean Square Error (RMSE) is used as a performance indicator of each meta-heuristic technique. These optimisation techniques are utilised in extracting the parameters of a 5W polycrystalline panel at Standard testing conditions. The results presented in this paper compared the performances of the mentioned meta-heuristics on the single, double and triple diode models respectively.

Keywords: Double Diode Model, Genetic Algorithms, Single Diode model, Parameter Extraction, Photovoltaic cell models, Three Diode Model.

1. Introduction

There exist global concerns regarding the utilisation of non-renewable energy sources such as fossil fuels. These concerns have to do with the immediate combustion of fossil fuel in generation. This combustion has led to serious environmental impacts such as climate change which is a worldwide concern. This motivates to investigate alternative sources of energy including renewables such as Solar Photovoltaic (PV), wind energy etc. Solar PV has shown the superior potential for the replacement of petroleum derivatives to meet the energy demand in many countries worldwide, as it has no moving parts and has little negative impact on the environment. However, due to the high cost of the modules and intermittent availability of solar energy, it is necessary to develop an accurate model of the PV system, especially the modules (Ishaque, Salam, and Taheri 2011).

The efficiency and maximum power point of the solar PV vary with temperature and irradiation. It is crucial to give the right values of PV parameters for the modelling and simulation of PV systems. The module parameters of the solar PV are extracted from manufacturers datasheet under standard testing conditions (Khanna et al. 2015). The traditional methods for predicting parameters of photovoltaic cells are the Analytical and Numerical methods that have been discussed in details in (Jordehi 2016).

The analytical method, depends upon key PV parameters such as the open circuit voltage (V_{oc}), short-circuit current (I_{sc}), voltage and current values at maximum Power Point (MPP), and the gradient of the current-voltage curve. The analytical approach makes the calculation of the photovoltaic parameters easier and faster. The accuracy of this approach lies primarily in the points chosen on the current-voltage curve (I-V). On the other hand, the numerical method depends upon the usage of iterative algorithms. However, it is a highly computational and expensive process as all points on the I-V curve must fit. The precision of the numerical method depends upon the values of the parameters extracted, fitting algorithm and cost function (Vanish, Swamy, and Marsaline Beno 2016).

The mathematical model of PV modules demonstrates the non-linear current-voltage (I-V) characteristics and different models have been developed to further analyse and understand their behaviours under varying operating conditions [2]. Amongst all the proposed models, SDM and DDM are the most common and mainly used for PV modelling [3]. The SDM is said to be the most popular amongst the other models due to its satisfactory performance and simplicity. It possesses five unknown parameters and is also referred to as the five-parameter model. The DDM is a more complex model and has seven unknown parameters. Moreover, there is a less known model called the Three Diode Model (TDM), which is more complex and requires higher computation power [4].

Modelling a PV module involves estimating the non-linear I-V curves. Precise modelling of PV modules is important for evaluating and forecasting the performance of the PV system. The existing literature on PV modelling have focused on the electrical circuit characteristics of the module when it is exposed to environmental variations which include changes to temperature and Irradiation (Mughal, Ma, and Xiao 2017). To determine the parameters for the various PV circuit models, several computational methods based on both analytical and conventional methods have been discussed in literature. Such methods include the Lambert-W function (Gao et al. 2016), iterative method (Nassar-Eddine et al. 2016), analytical extraction method (Batzelis and Papathanassiou 2016) and metaheuristic computational approaches(Humada et al. 2016). The applicability of explicit formulas was analysed to determine the suitability of such methods for parameter identification (Piazza et al. 2017).

Several authors have addressed metaheuristic computational methods for parameter estimation. Harmony search based algorithm was utilised by (Askarzadeh and Rezazadeh 2012) who investigated parameter identification for SDM and DDM respectively. Repaired adaptive differential evolution (R_{cr}-IJADE) is proposed by (Gong and Cai 2013) who applied this method for parameter extraction of a single diode model. A hybrid GA-PSO algorithm was presented for extracting single diode model parameters (Saravanan and A. Panneerselvam 2013). Memetic algorithm is proposed for optimal determination of the parameter values for a single diode equivalent solar cell model (Yoon and Geem 2015). PSO is used to extract and estimate the solar cell parameters for a three diode model in (Khanna et al. 2015). Fireworks algorithm (FWA) is used in (Sudhakar Babu et al. 2016) to extract the parameter for a two diode PV model.

Optimisation algorithms including Nonlinear Programming algorithms, simulated annealing and genetic algorithm were previously used to extract PV parameters through the minimisation of objective functions (Awadallah and Venkatesh 2015). Evolutionary Algorithms (EAs) have also been utilised to produce effective results in the solution of optimisation problems as the traditional methods of solving non-linear problems are quite tasking. Hence, EAs can be conveniently used for PV parameter extraction [5]. EAs are also referred to as Metaheuristics. The main issue with metaheuristics is the convergence of solutions as premature convergence can easily fall on a local optimum and choose it as a local solution [3].

From the above studies, it can be concluded that most of the studies have focused predominantly on optimisation of PV parameters of SDM and DDM models. Only a few attentions were paid attention for the modelling and parameter optimisation of the TDM model due to its modelling complexity compared with other PV models.

Therefore, the main aim of this paper is to conduct a comprehensive study of comparison between these three PV models for parameter extraction. A careful comparison using Meta-heuristic techniques to extract PV parameters is performed. A comparative study will be conducted with information acquired from photovoltaic manufacturers datasheets to explore the precision and competences of the proposed used meta-heuristic techniques for both internal and external performances. These techniques have shown effectiveness in estimating PV parameters for real time applications.

The rest of the paper is organised as follows: in Section 2, development of different PV models along with proposing a GA model for optimisation of the PV parameters are presented. In Section 3, key findings are analysed and discussed followed by the conclusion and future work in the final section.

2. Methodology

2.1 Modelling theory of the PV

The modelling and simulation of photovoltaic systems remain important for understanding the characteristics, effectiveness and performance of such systems [3]. The SDM, DDM and TDM equivalent circuit models were discussed in various literatures that provides a background for understanding the nonlinear characteristics (current-voltage (I-V) and power-voltage (P-V)) of the photovoltaic system.

2.1.1 PV single diode Model (SDM)

The electrical circuit of a photovoltaic cell is made up of a source of current coupled in parallel with a single diode and two resistances namely the shunt and series resistances (R_{sh} and R_{sr}) respectively as shown in Figure 1. The single diode model is the most common photovoltaic model because of its minimalism and accuracy. But, at low irradiation levels and varying temperatures, the exactness of the single diode model drops closely to the value of the open circuit Voltage (V_{oc}). This model is also known as the five parameters model which is made up of the photon current (I_{ph}), diode saturation current (I_0), series resistance (R_{sr}), shunt resistance (R_{sh}), and diode ideality factor (n) which can be extracted from this model [3]. The output current of the PV cell can be expressed as;

$$I = I_{ph} - I_0\left[\exp\left(\frac{q(V+R_{Sr}*I)}{n*K*T}\right)-1\right]-\frac{(V+R_{Sr}*I)}{R_{Sh}} \quad (1)$$

The output current of the PV module is defined by;

$$I = I_{PV} * N_P - I_0 * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{Sr}}{N_P}*I\right)}{n*K*T}\right)-1\right]-\frac{\left(\frac{V*N_P}{N_S}+R_{S}r*I\right)}{R_{SH}} \quad (2)$$

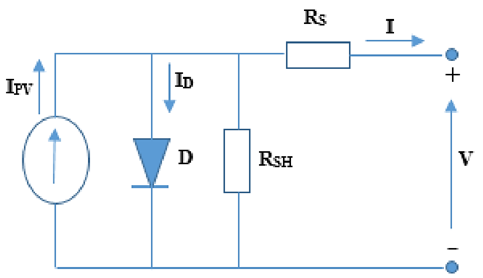

Fig 1. The equivalent circuit of the single diode model.

2.1.2 PV Double Diode Model (DDM)

When an extra diode is added to the single diode model, it leads to a new model known as DDM which improves the precision of the PV system. The extra diode accounts for the recombination current losses at the depletion region. The DDM is known as the seven parameters model consisting of the reverse saturation currents of two diodes (I_{d1} and I_{d2}), diode ideality factors: diffusion (α_1) *and* recombination (α_2), I_{PV}, Rs_r, R_h . The equivalent circuit of the double diode model is as shown in figure 2

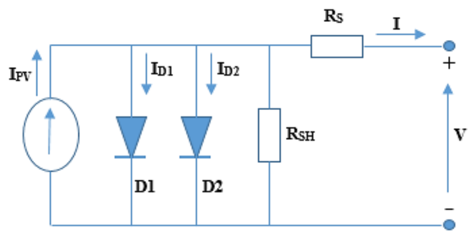

Fig 2. The equivalent circuit of double diode model.

The output current of the PV cell and module are defined by;

$$I = I_{PV} - I_{d1}\left[\exp\left(\frac{q(V+R_{Sr}*I)}{n_1*K*T}\right) - 1\right] - I_{d2}\left[\exp\left(\frac{q(V+R_{Sr}*I)}{n_2*K*T}\right) - 1\right] - \frac{(V+R_{Sr}*I)}{R_{Sh}} \tag{3}$$

the terms $\boldsymbol{n_1}$ and $\boldsymbol{n_2}$ represent the diffusion and recombination ideality factors of both diodes while I_{d1} and I_{d2} are currents of both diodes respectively.

$$I = I_{PV} * N_P - I_{d1} * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{Sr}}{N_P}*I\right)}{n_1*K*T}\right) - 1\right] - I_{d2} * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{Sr}}{N_P}*I\right)}{n_2*K*T}\right) - 1\right] - \frac{\left(\frac{V*N_P}{N_S}+R_{Sr}*I\right)}{R_{Sh}} \tag{4}$$

The I_{PV}, I_{d1}, I_{d2}, R_{Sr}, R_{Sh}, n_1 and n_2 parameters are extracted from the I-V curve.

2.1.3 Photovoltaic Three Diode Model (TDM)

The addition of a third diode to the double diode model yields the three-diode model which denotes the criticality of the nonlinearities of photovoltaic cells in the event of leakage current occurring at the grain boundary and surface of photovoltaic cells [8,9]. (Nishioka et al. 2007)This model provides a better accuracy for parameter estimation and analysis [17]. The parameters of this circuit consist of eight parameters that vary and one parameter that is fixed. The variable parameters are *r* for recombination ratio, I_{d1}, I_{d2}, I_{d3} are the recombination current parameters for the first, second and third diodes respectively, R_P represents series resistance connected to the third diode, R_{Sr1}, R_{Sr2}, R_{SH}. The shunt resistance R_{sh} is set as a fixed parameter [25]. The TD model is depicted in Fig. 3. and the output current of the photovoltaic cell and the module are defined by [26];

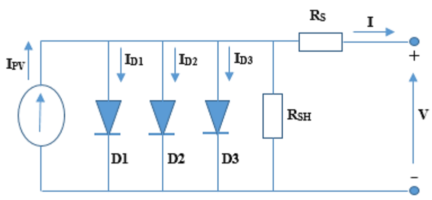

Fig 3. The equivalent circuit for the three-diode model.

Consequently, the mathematical expression for TDM is as shown in equation 5.

$$I = I_{PV} - I_{d1}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_1*K*T}\right)-1\right] - I_{d2}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_2*K*T}\right)-1\right] - I_{03}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_3*K*T}\right)-1\right] - \frac{(V+R_{S}*I)}{R_{SH}} \quad (5)$$

A photovoltaic module using the assembly of a triple diode model can be expressed as

$$I = I_{PV} * N_P - I_{d1} * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{S}r}{N_P}*I\right)}{n_1*K*T}\right)-1\right] - I_{02} * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{S}r}{N_P}*I\right)}{n_2*K*T}\right)-1\right] - I_{d3} * N_P\left[\exp\left(\frac{q\left(\frac{V}{N_S}+\frac{R_{S}r}{N_P}*I\right)}{n_3*K*T}\right)-1\right] - \frac{\left(\frac{V*N_P}{N_S}+R_{S}r*I\right)}{R_{SH}} \quad (6)$$

Parameters of I_{PV}, I_{d1}, I_{d2}, I_{d3}, R_{Sr}, R_{Sh}, n_1, n_2 and n_3 are extracted from the I-V curve of the measured experimental data.

It can be observed that the output currents of the SD, DD and TD models are nonlinear transcendental and implicit functions. Though, in actual conditions, the nonlinear transcendental solution for all parameters of I_{PV}, I_{d1}, I_{d2}, I_{d3}, n_1, n_2, n_3, R_{Sr}, and R_{Sh} are varied with the irradiation and temperature (Han, Wang, and Chen 2014). There is no defined explicit analytical solutions of the current (*I*) and voltage (*V*) and as such the numerical curve fitting and optimization algorithm methods are necessary to find out the solution for I-V (El-Naggar et al. 2012). The key objective of the optimization process is to search the global ideal parameters of the photovoltaic that agrees with the experimental I-V and P-V data (Ulaganathan and Devaraj 2016). In order to routinely alter the alteration between the measured and model data, the error function that defines the three models is given as (Oliva, Cuevas, and Pajares 2014):

For SDM,

$$f_{SDM}(V,I,x) = I - I_{PV} + I_d\left[\exp\left(\frac{q(V+R_{S}r*I)}{n*K*T}\right)-1\right] + \frac{(V+R_{S}r*I)}{R_{SH}} \quad (7)$$

For DDM,

$$f_{DDM}(V,I,x) = I - I_{PV} + I_{d1}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_1*K*T}\right)-1\right] + I_{02}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_2*K*T}\right)-1\right] + \frac{(V+R_{S}r*I)}{R_{SH}} \quad (8)$$

For TDM,

$$f_{TDM}(V,I,x) = I - I_{PV} + I_{d1}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_1*K*T}\right)-1\right] + I_{d2}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_2*K*T}\right)-1\right] + I_{d3}\left[\exp\left(\frac{q(V+R_{S}r*I)}{n_3*K*T}\right)-1\right] + \frac{(V+R_{S}r*I)}{R_{SH}} \quad (9)$$

2.2 Development of Meta-heuristic Algorithms

There exist various meta-heuristic optimisation techniques which include Genetic Algorithm (GA), Particle Swarm Optimisation (PSO), Flower Pollination Algorithm (FPA). The optimisation algorithm used in this work is Genetic Algorithm due to its capability for solving large scale parameters (Mohamed 2017). Genetic Algorithm is an evolutionary algorithm inspired by the theory of natural evolution and selection proposed by Charles Darwin [21]. GA technique is a parameter estimation method that deals both with constrained and unconstrained optimisation problems in engineering applications (Ismail, Moghavvemi, and Mahlia 2013). The unknown parameters of the photovoltaic cell are individuals of the population and are estimated using non-discrete evolution methods. At each stage of the model, individuals are arbitrarily chosen from the current populace to be utilised as parents for creating the next generation of children (Naomi T. Agbu (Coventry University) 2017). The three significant operators utilised in genetic algorithm at each populace level to form the next generation are improved by the three common operators of GA described as:

- Selection
- Crossover
- Mutation

The flowchart for Genetic algorithm is as shown in figure 4 below.

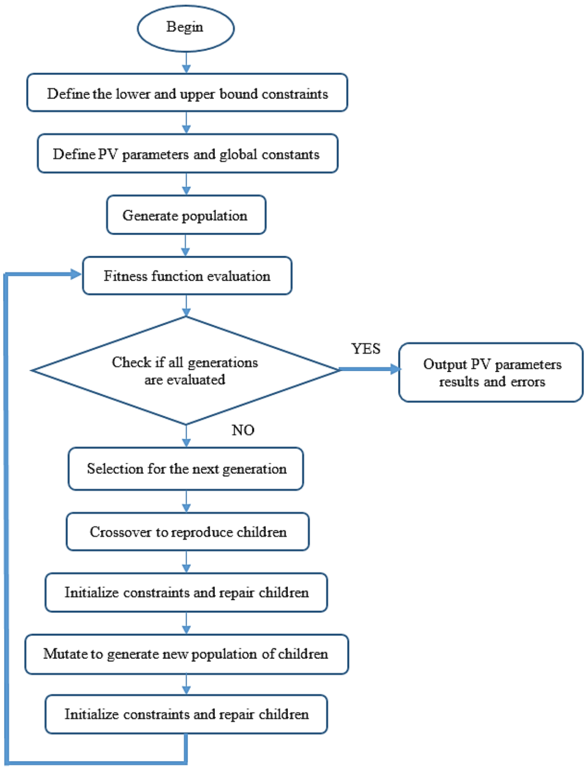

Fig 4. Genetic Algorithm (GA) Steps flowchart (Naomi T. Agbu (Coventry University) 2017)

The proposed algorithm starts with identifying all lower and upper bound constraints related to the three PV models including SDM, DDM and MDM models. All PV parameters and other global constraints will then be clearly defined. A chromosome structure will be designed to accomodate all the PV model parameters that need optimisation. A number of these individual chromosomes, forming a population of these individuals will be generated. Each chromosome will then be evaluated using a fitness function (i.e. objective function), which is represented here as a convergence speed. The fitness values should be calculated to be used in the natural selection process. If the last generation test and evaluation condition is reached out, outputs of the PV parameters and errors are obtained. Otherwise, individuals of chromosomes are scaled according to their fitness values before the selection process is conducted.

Selection is an important process for the GA where the best solutions, in terms of fitness values, are selected as parents. There are various selection approaches and most popular ones are tournament selection and roulette-wheel selection. The selected parent solutions are then used in the reproduction process called crossover where parents are recombined to form the next generation (i.e. offspring). Crossover lets the offspring to inherit characteristics from its parent solutions and hence strong genes are transferred to next generations in the evolutionary process. Next mutation is applied to the newly generated offspring where some genes of the offspring are randomly altered using a mutation probability. For real valued genes, as in our study, this can be done by selecting a random value from the range of possible values. Mutation is essential for GA as it helps to preserve the diversity in the population and helps avoid falling in local minima or maxima. The generated offspring then replaces the weaker or older solutions in the population. In order to preserve the best individuals in the population the concept of elitism is used. Elitism lets some of the best or elite members pass on to the next generation.

3. Results and Discussions

The simulations are carried out using Genetic Algorithm (GA), Teaching Learning Based Optimisation (TLBO), Generalized Oppositional Teaching Learning Based Optimization (GOTLBO), Flower Pollination Algorithm (FPA), Harmony Search (HS), Cuckoo Search, Simulated Annealing (SA), Conventional Particle Swarm Optimisation (CPSO), Particle Search (PS), Hybrid Particle Swarm Optimisation and Simulated Annealing (HPSOSA), which is a combination of both PSO and SA, and finally Improved Artificial Bee Colony (IABC).

The meta-heuristics models are coded using MATLAB considering the mathematical expression of the dissimilar model types as can be seen in the analysis of problem segment. The ideality factors of the various photovoltaic models are $n_1 = 1$, $n_2 = 2$ and $n_3 = 3$ for the SD, DD and TD respectively. The reproduction of these variable models concur with the works of (Soon, Low, and Goh 2014) and (Sarkar 2016).

The simulated results at STC for the double diode and triple diode can be seen in figure 5 and 6 that the voltage drop for the I-V and P-V features when contrasted with the SDM. The features of the modules demonstrate that the three-diode model accounted for the most loss as it compensates the leakage currents and grain boundaries through the peripheries.

Unlike the DD model that performs and gives more practical I-V characteristics that exhibits current recombination losses even at lesser irradiation values. Hypothetically, the three-diode model can be proposed to be more precise and accurate, however it faces difficulties at lower irradiation levels.

The intricacy of the three diode model for validation is generally approximated, however it can be utilised as the electrical circuit model solution to reproduce the long term routine of photovoltaic cell technology because, it not only accounts for the losses of the leakage current but also accounts for the external surface areas that often deteriorates over time.

More mechanisms for deciding the exact value for the ideality factor of the third diode needs to be carried out for STC. The I-V and P-V curve at STC for the three photovoltaic modules representing the electrical equivalent SD, DD and TD models are given in figure 5 and 6 respectively.

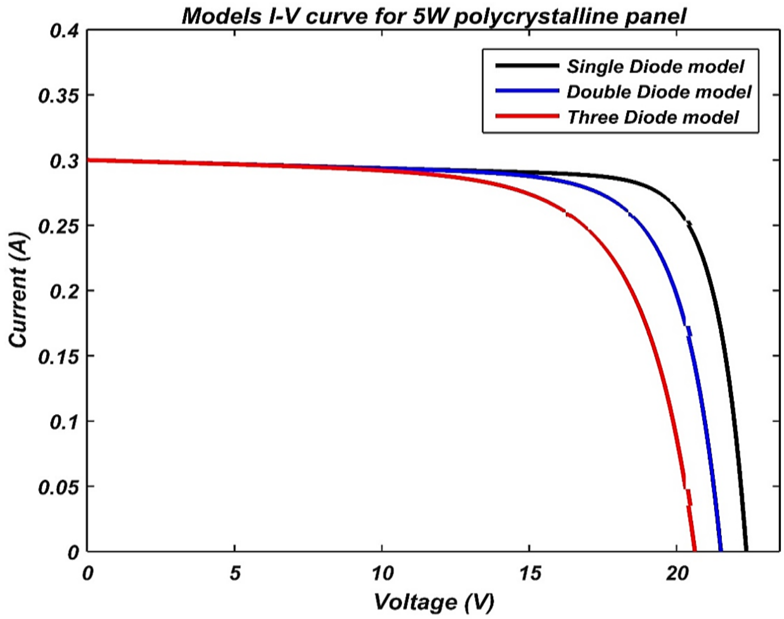

Fig 5. I-V curve for the SDM, DDM and TDM of the 5W polycrystalline Panel at STC.

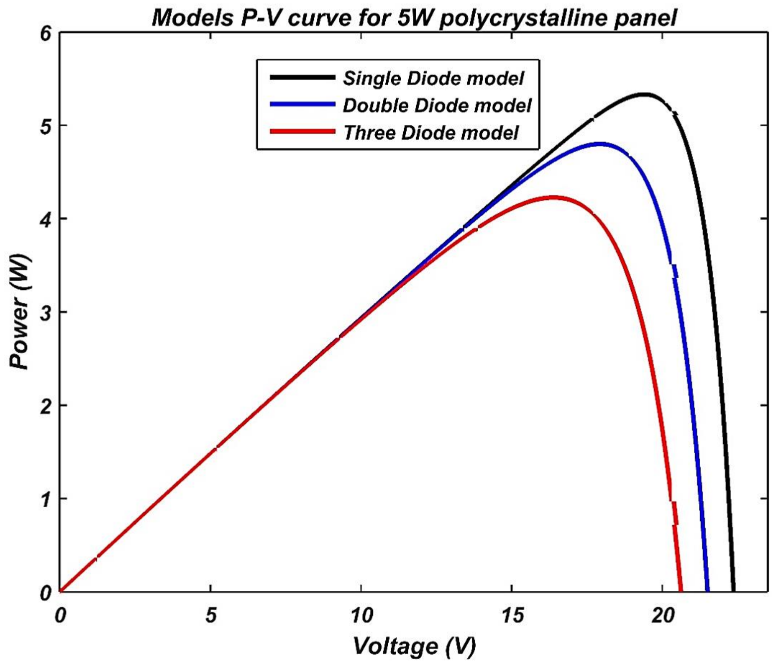

Fig 6. P-V curve for the SDM, DDM and TDM of the 5W polycrystalline Panel at STC.

Furthermore, other optimisation algorithms are compared against genetic algorithm and their performance are presented in Tables 1-3 respectively.

Table 1. Comparison of different algorithms for parameter extraction of SDM using experimental indoor readings

5W polycrystalline panel, Irradiance = 901.2 (W/m^2), Temperature = 20°C					
Parameters	I_{PV}	I_0	R_S	R_{SH}	n
GA	0.1291	4.144e-05	1.5611	1480.69	3.71
TLBO	0.1248	1.352e-11	0.0121	1613.62	4.53
GOTLBO	0.1258	1.857e-10	0.0085	847.33	5.13
HS	0.1282	2.803e-05	0.0013	1988.22	3.05
FPA	0.1231	1.054e-09	0.02423	1992.82	5.67
SA	0.1228	4.342e-05	2.20905	730.22	5.01

Table 2. Comparison of different algorithm for parameter extraction of the DDM using experimental indoor readings

5W polycrystalline panel, Irradiance = 901.2 (W/m^2), Temperature = 20°C							
Parameters	I_{PV}	I_{01}	R_S	R_{SH}	n_1	I_{02}	n_2
GA	0.1241	2.073e-05	0.0089	1987.70	12.56	9.28e-06	9. 11
TLBO	0.1228	4.762e-05	0.0127	1774.04	47.97	3.31e-15	3.31
GOTLBO	0.1232	2.123e-06	0.0157	1340.83	29.56	2.75e-14	3.52
HS	0.1247	4.821e-05	0.0118	1975.20	14.16	2.82e-05	6.02
FPA	0.1237	1.912e-06	0.0101	1908.81	43.51	3.91e-08	7.03
SA	0.1222	2.833e-05	0.0695	1368.97	25.14	2.79e-05	10.96

Table 3. Comparison of different algorithm for parameter extraction of the DDM using experimental indoor readings

5W polycrystalline panel, Irradiance = 901.2 (W/m^2), Temperature = 20°C									
Parameters	I_{PV}	I_{01}	R_S	R_{SH}	n_1	I_{02}	n_2	I_{03}	n_3
GA	0.1244	9.797e-06	0.0234	1843.62	49.95	6.781e-06	10.66	1.653e-06	48.59
TLBO	0.1219	1.146e-05	0.0013	1594.23	21.13	2.337e-16	3.05	1.706e-07	15.87
GOTLBO	0.1224	1.922e-16	0.0093	1344.21	23.03	1.692e-06	17.23	3.438e-06	34.28
HS	0.1287	4.915e-05	0.0725	1340.95	14.08	3.308e-05	24.07	3.166e-05	19.29
FPA	0.1281	4.558e-05	0.0021	1515.47	37.37	1.382e-05	48.77	1.324e-07	37.07
SA	0.1228	2.406e-05	0.0041	607.19	29.82	5.023e-05	35.72	1.456e-05	12.77

Tables 1-3 detail the optimal photovoltaic cell parameters evaluated by the various optimisation algorithms as solutions for the Single diode, double diode and three diode models respectively. The three Tables above show the successful ideal parameters estimation method for the algorithms and proposed methods for the three PV models and as such the quality of the estimated parameters.

The performance of the designed algorithms was evaluated using Root Mean Square Error (RMSE) criterion. The evaluation results are as shown in Table 4 reveal that GOTLBO , SA and TLBO produced the best parameter optimization methods for the SDM, DDM and TDM respectively

Table 4. Comparison of Meta-heuristics algorithms using the RMSE Criterion

Algorithms	SDM	DDM	TDM
GA	0.0051	0.2524	0.4292
TLBO	0.0033	0.2230	0.0994
GOTLBO	0.0027	0.2101	0.1440
HS	0.0109	0.3794	0.2153
FPA	0.0058	0.1944	0.1515
SA	0.0072	0.1583	0.1887

4. Conclusion

Different meta-heuristics algorithms have been used for extraction and estimation of PV parameters. These parameters were analysed based on the simulated values from datasheet information and experimental values. The parameters extracted were the photon current, saturation current, the series and parallel resistances. The PV models used to form the objective function were the single diode, double diode, and three diode models respectively. The algorithms were used to optimise these models using the minimisation type in order to reach the global minimum solutions with a faster convergence speed. The accuracy was determined from the Root Mean Square Error (RMSE) retrieved from the case studies used in this paper and GOTLBO, SA, and TLBO produced the best results for the authors respectively. The reason behind some algorithms performed poorly is attributed to the number of variables and control parameters assigned to the PV models and algorithms respectively. However, there was limited research available for the Three Diode Model in literature. This could be as a result of its complexity and need for higher computational strength. This delimitation of the Three Diode Model presents further research problems that researchers could further investigate.

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