Some new GWO variants for PV systems modelling

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ABSTRACT--*Single Diode Model (SDM) is a popularly model used for the modelling of PV cells where five parameters are to be determined. This work accurately determines the five parameters of the SDM using meta-heuristic algorithm. Three equations have been considered for parameter extraction. The parameters of three widely used panels (KC200GT multi-crystal, MSX-60 poly-crystalline, and CS6K-280 M mono-crystalline) are extracted. The summation of the square of errors is used to define the error function. The Grey Wolf optimization (GWO) and its variants are being used. The values of the parameters and the error for all the three panels are compared for each algorithm. The results obtained are very promising and the error in the results is very less with EGWO proving out to be the best.*

Keywords-- *Single double model (SDM); Grey wolf optimizer (GWO); parameter estimation*.

I. INTRODUCTION

For the past few years, the world has experienced a lot of issues related to the conventional methods for producing electricity. The major reasons for these issues are high pollution, depletion of natural resources and hazards. As a result, the world is constantly working on producing electricity through renewable energy. Out of these the solar energy is the fastest developing area due to its unlimited availableness, no pollution, zero noise and low maintenance. A photovoltaic cell (PV) is the one which is receiving the most attention for the generation of power [1-2]. Unfortunately, the efficiency of the cells is very low and the initial installation costs are very high. The working of the PV cells is completely dependent on the availability of solar irradiance. Further, in the harsh physical conditions the panels experience accelerated degradation [3]. Therefore, a lot of research is required in the field of PV cells to increase its efficiency.

Nowadays, there has been large amount of research done in the mathematical modelling and parameter extraction of the PV cells. The accurate parameters not only give the real view of the mathematical model but also is directly dependent on the efficiency of the cells. The knowledge of the parameters of the PV cells helps to operate the solar PV plant at its full capacity and maximum efficiency [4]. The accurate values of the parameters are also required for the quality control of the PV cells when they are manufactured in the industries. The manufacturer does not provide the information related to parameters in the datasheet [5].

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For the mathematical modelling of the PV cells it is most desirable to have a model that follows the I-V characteristic of the ideal cell as closely as possible under operating conditions. The most popular method of achieving this is to model the equations and the circuit that contains both the linear and non-linear components. Most of the times it is required to simulate the results of the PV cells in a simulator. Many models have been proposed over the years for the modelling the PV cells [6]. The SDM is the widely accepted model and produces highly accurate result for the parameters when used for various types of PV cells and panels at different physical and climatic environments. The calculation of the parameters with the help of this model is quite simple in terms of computation as there are only 5 parameters. The 5 parameters being photovoltaic current I_{ph}, ideality factor a, saturation current I_0, series component which appears as resistance and is generated due the path and everything that comes in the way of the current R_s, parallel resistance component R_p. The five parameters calculated helps to form the I-V characteristic of the cell [7-8].

There are primarily two approaches of estimating solar cell parameters one is analytical approach and the other is numerical approach. The curve between I and V is highly non-linear. The analytical methods require the values of voltage and current at each point [9]. Also, the relation between I and V forms an implicit function of I, so the analytical methods cannot be used for obtaining the solutions [10] as the results obtained would be very poor. The second method is the numerical method. It is an optimization problem and it continuously optimizes the results so as to reduce error between estimated I-V curve and the actual datasheet. Numerical based methods can be further divided into two parts those are – deterministic and heuristic methods. The deterministic methods provide good results still possess some limitations. Their requirement is that the objective function should have convexity, continuity and differentiability. These are completely based on the initial guess taken. A wrong initial guess spoils the whole results. Hence, to solve all the above-mentioned limitations, metaheuristic algorithms are preferred. These are based on algorithms which continuously monitors the results until they are optimized and the curve fitting to the ideal one is obtained. The algorithms are generally nature-based algorithms and have proved to give effectiveness in the result. The main advantage of the metaheuristic approach is that the objective function does not require the continuity and differentiability [11-14].

Metaheuristic algorithms are widely popular among the researchers. Many nature-based metaheuristic algorithms are emerging recently, either they are newly developed or the existing ones are modified. With the use of new algorithms, there is always a scope of obtaining better results. According to no-free lunch theory there may some algorithm which gives good results in one set of problem but fails to crack the other. Hence, the use of the new algorithm would always be appreciated. New models of PV cells such as double diode model (DDM), modified double diode model (MDDM) and three diode model (TDM) have been developed and may be used to obtain better results for parameter extraction.

The rest of the paper has been organized in the following way; in Section 2 the problem statement is defined, in Section 3 the methodologies used for the parameter extraction is explained, in Section 3 the results obtained from the runs is discussed and analyzed, in Section 5 the conclusion of the paper is written.

II. PROBLEM STATEMENT

The basic equation for the modelling of the PV cells used is Shockley's equation of diodes. According to the equation-

$$I = I_0\left[exp\left(\frac{q(V+IR_S)}{aKT}\right) - 1\right] \tag{1}$$

where, I_0 is reverse saturation current, a is the ideality factor of the diode, R_s is the series resistance connected in the circuit, K is the Boltzmann constant (1.3806503×10^{-23} J/K), T is the PV cell temperature in Kelvin (K) and q is the electronic charge (1.60217646×10^{-19}C).

Fig. 1 depicts the network model of the SDM. It comprises of a current source expressing the photovoltaic current (I_{pv}), a series resistance $R_{s,}$ a diode D, a parallel resistance R_p. Applying Kirchhoff's Current Law for the calculation of the load current (I),

$$I = I_{ph} - I_D \;\; - \frac{V+IR_S}{R_p} \tag{2}$$

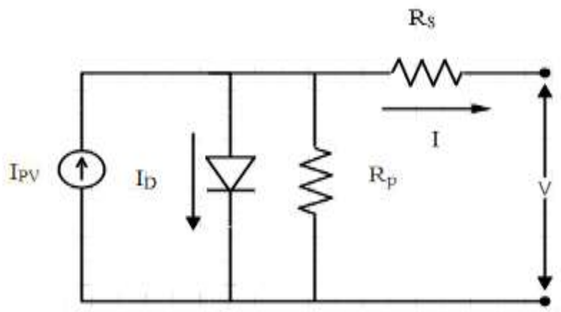

Figure 1: Mathematical model of SDM [1]

Substituting the value of I_D from equation (1) in equation (2) then it becomes

$$I = I_{ph} - I_0\left[exp\left(\frac{q(V+IR_S)}{aKT}\right) - 1\right] - \frac{V+IR_S}{R_p} \tag{3}$$

In order to develop the constraints using the known data from the manufacturer's specification sheet, different conditions were imposed on equation (3)-

1. Open circuit condition, $V = Voc, I = 0$, then equation (3) becomes

$$I_{ph} = I_0\left[exp\left(\frac{qV_{oc}}{aKT}\right) - 1\right] - \frac{V_{oc}}{R_p} \tag{4}$$

2. Short circuit condition, $V = 0, I = Isc$, then equation (3) can be modelled as

$$I_{sc} = I_{ph} - I_0\left[exp\left(\frac{q(IR_S)}{aKT}\right) - 1\right] - \frac{IR_s}{R_p} \tag{5}$$

3. Maximum Power Point (MPP) condition, $V = Vmp, I = Imp$, then equation (3) can be derived as

$$I_{mp} = I_{ph} - I_0\left[exp\left(\frac{q(V_{mp}+I_{mp}R_S)}{aKT}\right) - 1\right] - \frac{V_{mp}+I_{mp}R_S}{R_p} \tag{6}$$

For the development of the objective function, the errors generated from the above equations i.e. equation (4), equation (5) and equation (6) have been considered. The error equations can be written as

$$Err_{OC} = I_0\left[exp\left(\frac{qV_{OC}}{aKT}\right) - 1\right] + \frac{V_{OC}}{R_p} - I_{PV} \tag{7}$$

$$Err_{SC} = I_{SC} + I_0\left[exp\left(\frac{qI_{SC}R_S}{aKT}\right) - 1\right] + \frac{I_{SC}R_S}{R_p} - I_{PV} \tag{8}$$

$$Err_{mp} = I_{PV} - I_0\left[exp\left(\frac{q(V_{mp}+I_{mp}R_S)}{aKT}\right) - 1\right] - \frac{V_{mp}+I_{mp}R_S}{R_p} - I_{mp} \tag{9}$$

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The objective function that is to be developed must reduce the above-mentioned errors as much as possible. In order to achieve this here, the square error has been considered as the square error provides the best results and the parameters are extracted with greater accuracy. Therefore, the error equation is given as [15]-

$$Err = Err_{OC}^2 + Err_{SC}^2 + Err_{mp}^2 \tag{10}$$

III. PROPOSED METHODOLOGY

3.1 Grey wolf optimizer (GWO)

GWO is an algorithm which is based on population in which the technique used for hunting and the ranks of grey wolves is considered. They usually live in groups of 5-12 members where each member maintains a strict social rank assigned to them as depicted in Fig. 2.

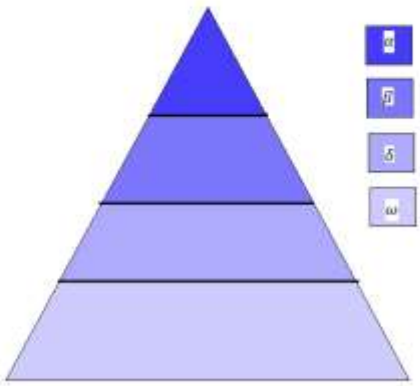

Figure 2: Social hierarchy of grey wolves

There are four varieties of grey wolves which are alpha, beta, delta, and omega and are used for simulation of the rank shown by the leader. The alpha (α) is said to be the most dominating and also the top rank member of the group. The remaining members are beta (β) and delta (δ), which help to keep an eye on the rest of the members who are called as omega(ω). The ω wolves hold the lowest rank among the group. In this algorithm, the hunting is headed by α, β and δ. The ω follows the solutions of the first three wolves. During hunting, the grey wolves surround their prey and mathematically it is written as:

$$\vec{D} = \left|\vec{C}\vec{X}_p(t) - \vec{X}(t)\right| \tag{11}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{12}$$

where, t represents the present iteration, $\vec{A}$ and $\vec{C}$ represents the vector coefficients, $\vec{X}_p$ specifies the location vector of the considered prey and $\vec{X}$ denoted the location vector of the grey wolf. The vectors $\vec{A}$ and $\vec{C}$ are calculated with the help of the following equations:

$$\vec{C} = 2.rand_2 \tag{13}$$

$$\vec{A} = 2\vec{a}.rand_1 - \vec{a} \tag{14}$$

where $\vec{a}$ is decreased linearly from initial value 2 to 0 throughout the cycle of iterations, $rand_1$ and $rand_2$ represent random numbers lying between $(0,1)$. The hunting process of the grey wolves is headed by the α wolf.

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The β and δ wolves not very often go out for hunting. Thus, the mathematical model considers that α, β and δ members possess better information of the presence of prey. Thus, the three best solutions which are obtained initially are stored and the others are asked to update their location based on the best solutions. The following mathematical equations describe the same:

$$\vec{D}_\alpha = |\vec{C}_1\vec{X}_\alpha - \vec{X}| \tag{15}$$

$$\vec{D}_\beta = |\vec{C}_2\vec{X}_\beta - \vec{X}| \tag{16}$$

$$\vec{D}_\delta = |\vec{C}_3\vec{X}_\gamma - \vec{X}| \tag{17}$$

Thus

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\vec{D}_\alpha \tag{18}$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta \tag{19}$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\vec{D}_\delta \tag{20}$$

and finally

$$\vec{X}(t+1) = \frac{(\vec{X}_1+\vec{X}_2+\vec{X}_3)}{3} \tag{21}$$

The grey wolves wait for their prey to stop and attacks it to complete their hunt. In this stage, the fluctuation in the value of $\vec{A}$ reduces because the value of $\vec{a}$ is decreased. When the parameter $\vec{A}$ possess any value randomly lying between $[-1,1]$, then it can be said that the search agent's next location will also be lying somewhere in between current position of the search agent and the position of the prey [16].

3.2 Modified GWO algorithm (mGWO)

This algorithm considers a exponential function as given below for the decay of 'a' over the passage of iterations. The value of 'a' is given by [17]:

$$a = 2\left(1 - \frac{t^2}{T^2}\right) \tag{22}$$

3.3 PSO-GWO algorithm

In this hybrid algorithm, PSO and GWO are used together to crack the optimization problem where first PSO is used to formulate the solution space and compute fitness of each one. The GWO is used to calculate the first three best solutions and positions are updated accordingly. The position of α wolves is considered the final position and the PSO is used to calculate the final result [18].

3.4 CS-GWO algorithm

This algorithm adds up the advantages of the two algorithms. GWO chooses the $rand_1$ and $rand_2$ randomly but this may lead to local minima problem. To overcome this, the optimum control elements are selected with the help of CS. CS-GWO considers the population of wolves and the nests where number of nests are very less as compared to wolves. Conventional CSA has a static problem of building the nests which is overcome by averaging nest building. The position and direction of the pack is estimated with the help of eq. (15-21) and finally applying the same to CSA. Finally, GWO is applied for the selection of optimal scale [19].

3.5 Augmented grey wolf optimizer (AGWO)

In the conventional GWO the parameter a linearly decreased from 2 to 0. As proposed in AGWO, a varies randomly and non-linearly from 2 to 1 which gives a better exploration phase than the exploitation phase.

$$\vec{a} = 2 - \cos(\mathrm{rand}) \times \frac{t}{Max\_iter} \quad (23)$$

Also, in AGWO hunting only depends on α and β wolves. Therefore, considering the equations (15), (16), (18) and (19) the final equation developed as follows [20]:

$$\vec{X}\mathrm{i} + 1 = \frac{\vec{X}_1 + \vec{X}_2}{2} \quad (24)$$

3.6 Enhanced leadership based GWO (EGWO)

GWO faces stagnation problem in local optima. Based on levy-flight an algorithm for local search has been proposed that is called EGWO. This algorithm improves the leadership efficiency of leading hunters. The Levy-flight discovers the auspicious areas to search for better leaders in terms of possibility and suitability. To maintain a stability between exploration and exploitation, a greedy selection search is applied which balances the quality of the wolf pack and resists the wolves to diverge from the auspicious areas of search space.

In the EGWO, the position of i^{th} leading wolf $xi = (xi1, xi2, \ldots\ldots, xin)$ for j^{th} dimension $(j = 1,2,3, \ldots.., n)$ is changed as follows:

$$xij' = xij + \mathrm{par} \times \mathrm{s} \quad (25)$$

where, x_{ij}' is the i^{th} changed leading wolf, par is used for controlling the step length and hence is a control parameter, par is a vector which decreases linearly and numerically par∈(2,0). Range of par is chosen such so that the stability between exploitation and exploration can be maintained par is defined as [21]:

$$par = 2 - 2\left(\frac{t}{max\ iter}\right) \quad (26)$$

IV. RESULTS AND DISCUSSIONS

The PV cells employed for this purpose were manufactured by Kyocera, Solarex, Canadian Solar and the estimation was done at STC. The datasheet for three widely used solar panels is used for the calculation as reported in Qais *et al.* [22]. For obtaining better results, 50 search agents were chosen and the number of iterations performed were 500. The ranges for all the variables which are used are based on literature from Dizqah *et al.* [23]. A comparison is made based on the parameters estimated for each of the cell and has been reported in Table 3. Tables 4-6 shows the best results obtained for the parameters of different solar cells considered when run was performed with GWO and its five variants which are mGWO, PSO-GWO, CS-GWO, AGWO and EGWO.

Table 1: Best results obtained for Kyocera KC200GT Multi-crystalline PV cells

Method	**I_{pv}**	**a**	**R_s**	**R_p**	**I_0**	**Error**
GWO	8.195395	1.340364	0.1485445	209.9009	1.651233e-7	0.0013704

mGWO	8.244977	1.381058	0.1722272	182.3991	2.790184e-07	0.0014065
PSO-GWO	8.203873	1.473237	0.08876554	205.1633	8.176155e-07	0.00092414
CS-GWO	8.226059	1.327125	0.2102793	312.0583	1.397797e-07	0.00021024
AGWO	8.261108	1.310179	0.228446	263.9592	1.098713e-07	0.010754
EGWO	8.214662	1.365439	0.1689877	223.4744	2.293961e-07	**4.5566e-05**

Table 2 : Best Results obtained for Solarex MSX-60 Polycrystalline PV cells

Method	**I_{pv}**	**a**	**R_s**	**R_p**	**I_0**	**Error**
GWO	3.805584	1.472104	0.1331109	492.1394	6.945835e-07	0.00013119
mGWO	3.815001	1.488408	0.1255141	297.4793	8.185409e-07	0.00083147
PSO-GWO	3.791625	1.508785	0.001140375	257.6213	9.985529e-07	0.00026515
CS-GWO	3.825044	1.461875	0.0743655	156.2289	6.104429e-07	0.00088686
AGWO	3.829048	1.509638	0	169.4572	1.003023e-06	0.0012893
EGWO	3.803796	1.467575	0.0636068	223.922	6.530288e-07	**1.5088e-05**

Table 3: Best results obtained for Canadian Solar CS6K-280M Monocrystalline PV cells

Method	**I_{pv}**	**a**	**R_s**	**R_p**	**I_0**	**Error**
GWO	9.4423	1.511171	0.001153572	302.0384	6.133828e-07	0.0003906
mGWO	9.496327	1.474238	0.005014363	148.2569	4.013257e-07	0.0061534
PSO-GWO	9.566547	1.555889	0.09497292	321.3284	9.991277e-07	0.039927
CS-GWO	9.450051	1.444841	0.0425545	301.8122	2.874052e-07	0.0082555
AGWO	9.427309	1.553484	0	232.9428	9.66449e-07	0.017615
EGWO	9.438898	1.524805	0.00287038	410.5201	7.140156e-	**0.00014958**

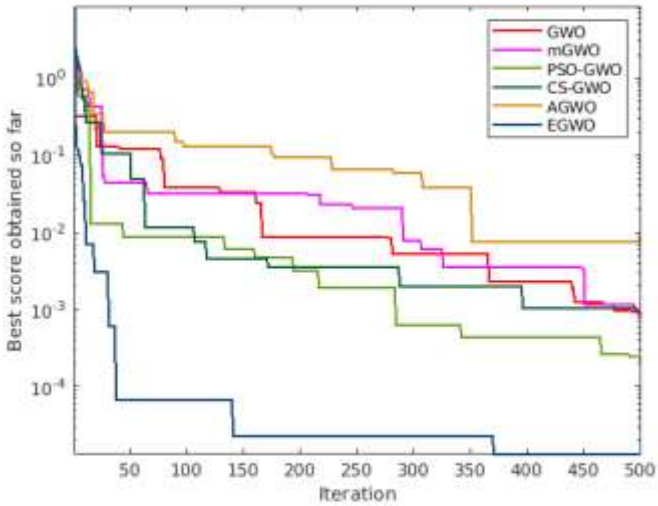

Figure3: Comparison amongst algorithms based on the error obtained for Solarex Polycrystalline PV cells

For determining the results sum of square error is considered and it can be seen very clearly all the above incorporated algorithms provide good results when tested for different types of solar cells. Also, the results obtained so far are best for the EGWO algorithm and the same has been verified from the comparison graphs between the algorithms for each solar panel. One of the convergence curves is shown in Fig. 3 comparing the fitness values of all the algorithms plotted for Solarex Polycrystalline. The least error obtained in each table is highlighted. All the values of the parameters estimated are within the prescribed limits. The difference between the highest and the lowest errors comparing all the panels considered is for the Solarex Polycrystalline and lowest for Canadian Monocrystalline. Out of the three panels the results with lowest error and fastest convergence rate for all the algorithms is obtained for the Solarex Polycrystalline panel. The curves also reveal about the convergence speed of the algorithms which is fastest for the EGWO algorithm and the AGWO provides very poor results for all the panels.

V. CONCLUSION

The objective of this work was to extract the parameters of SDM using GWO, mGWO, PSO-GWO, CS-GWO, AGWO and EGWO and compare the results obtained from them. The three equations are used for the estimation of five parameters of SDM. The square error obtained from the constraints is added and minimized with the help of the above algorithms. The algorithms proved to give very good results for the parameter values and very less error. All the values of parameters obtained were within the limits mentioned in Table 2. The results obtained from the EGWO was better from all the other algorithm as the error was least. There are many new models which have been proposed recently for the modelling of PV cells. Those methods may prove to be more accurate than the SDM as the number of parameters increases. Besides, there are always new algorithms being developed and they may produce better results for the same objective function. For the future scope, new models and algorithms may be incorporated for the solution.

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