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Estimation of parameters for one diode solar PV cell using grey wolf optimizer to obtain exact V-I characteristics

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ABSTRACT

This article introduces an adequate method for one diode PV equivalent model to estimate the unknown parameters. Considering this proposal, accurate estimation of unknown parameters can be determined by objective function minimization by applying the outstanding grey wolf optimizer (GWO) algorithm. Mentioned (GWO) algorithm is carried out to estimate the parameters of one diode PV cell and obtained results are compared with those of recent memetic algorithm, simulated annealing, cuckoo search, particle swarm optimization, pattern search and genetic algorithm. Experimental data and simulation results confirm that GWO algorithm is capable of achieving every parameter by enormous accuracy. The results of GWO algorithm outperforms the previous algorithms reported in this consideration.

Keywords: PV cell, parameter estimation, V-I characteristics, GWO and accuracy.

INTRODUCTION

Renewable energy plays a prominent role in minimizing the usage of fossil fuel energy. The enormous occurrence of sunlight makes solar energy the major recourse in renewable energy. This type of energy has properties like infinite availability, low-cost, pollution free, and obtainable in large sector on earth. At this time, because of fossil fuel limitations and their extensive damage on climatic variation, it effectively expanded the solar energy utilization in various parts of the world. For understanding superior characteristics, calculation of enforcement and accordingly one diode PV cell model optimization are required by analyzers for significant mechanism. Modeling of solar PV cell is initially associated with the characteristic curve of voltage and current (V-I). Various models have been proposed to achieve the characteristics of the model under various constraints (Chan et al., 1986; Ortiz-Conde et al., 2012; Ortiz-Conde et al., 2013; Wolf et al., 1977).

The hypothesis considered can be different for various systems including prevalent physical variables. From the reported works, it can be observed that one diode cell model is major in implementing the PV systems. Now-a-days, various methods are available to estimate the parameters of one diode models. Few experiments in this specialization are concentrated on employing numerical and analytical methods to estimate the parameters depending on appropriately selected objective function minimization (Chan et al., 1986; Romero et al., 2012; Orioli et al., 2013; Ortiz-Conde et al., 2006, Chen et al., 2011; Lineykin et al., 2014 & Appelbaum; Peled, 2014).

The major bottleneck of the aforesaid methods is the large probability sliding into local optima and the complicated calculations. In modern generation, due to the advantages in the algorithm optimization (meta-heuristic), these algorithms are extensively employing to estimate the parameters of solar PV cell systems. Considering illustration, genetic algorithm (GA) (Zagrouba et al., 2010 & Ismail et al., 2013), pattern search (PS) (AlRashidi et al., 2011), particle swarm optimization (PSO) (Soon & Low 2012; Wei et al., 2011; Shi et al., 1999), implementation of simulated annealing (SA) (El-Naggar et al., 2012), cuckoo search (CS) (Ma et al., 2013) and employment of memetic algorithm (MMA) (Yoon & WooGeem, 2015) have been reported in literature works.

It is obvious that, each and every algorithm having its own merits and demerits. where, GA generally accepts delay in convergence with respect to time. PSO is flashing, however, the accuracy of the solutions can be frequently improved by changing the iterative numbers (to be accommodated by testing and failure) (Karaboga, 2005). SA major demerits are less probability global optimum identification and sensitivity to primary assumptions. CS is unable to optimize because during the process of optimization it loses its characteristic of higher efficiency levy flight search. Recently memetic algorithm (MMA) is implemented, but having a drawback of global search optimization as it has less search space guaranty exploitation and exploration. Moreover some argumentation moves on various algorithms optimization.

In regular, algorithms having less number of parameters, flashing convergence and bigger probability of sliding against local optimum are recorded as most adequate algorithms. Moreover this is very significant to note that algorithm adequateness mainly built upon a problem can arise while it is functioning to determine. In alternative, it can arise that a particular algorithm to be exceptional in handling by a problem where it is absolutely unexceptional in handling others. Considering this logic along with a general proceeding, analysts employ various techniques to a particular problem to identify the finest method appropriated to deal with.

In general, authors make effort to associate with many algorithms to have better results (Brano et al., 2010 & Villalva et al., 2009). The objective is to handle various systems with different properties to run-over the unfavorable functioning and eventually making the functioning better. Introducing the better adequate algorithm (which has better accurateness, rapid convergence, lesser in parameters number, highest ease concerning usage, etc.) to estimate the parameters of solar PV cell systems is a huge attention in form. The essential objective of this article is to progress a description of GWO algorithm and review it's functioning to estimate the parameters of one diode solar PV cell and correlate the results besides challenging methods.

Here, GWO optimization approaches strictly act like the grey-wolf improvisation process. In this technique, the objective is to reach an exact state. So, the grey-wolf plays best by accustomed alpha, beta, and delta wolves. In a same implementation, optimizer's techniques endeavor maximizing or minimizing the objective function by changing the variables section. Alternatively, grey-wolves process of improvisation could be compared with optimization examine course. The ease of performance of GWO drived with its utilization is method of optimization; GWO has many merits. It is assumptive, enforces various mathematical extremities to give an advanced solution by examining the present solution and it does not desire any data regarding derivative. In this paper, implementation of GWO to identify the parameters for one diode solar PV cell is carried out.

DESCRIPTION OF THE PROBLEM

As considered previously, it is the general process to develop solar cells by one diode systems; moreover by using the approximately selected cost function the parameters of above system are determined. From below initially we describe the analysis of one diode solar cell system and later we bring out the proposed minimized cost function.

Solar cell one diode system

As presented below in Fig.1 one-diode system is popularly practiced to obtain the solar cells V-I characteristics. They are having various semiconductor materials employed for different mechanism of manufacturing. The functioning of solar cell is built upon photovoltaic eventuality, where it expresses the potential difference generation near P-N barrier in feedback to evident or alternative radiation. In case the solar cell is illustrated through sunlight, generation of charge carriers takes place when photons are consumed by semiconductor material. The potential difference between external circuit and current indicates nearing carrier's isolation in the enclosed electric field created by P-N barrier and converges at electrodes. Charge carriers created were identified in formation of electric current, specifically photo current. If there is no effect of photo voltaic, parameters of light are not identified such that photo voltaic cell diode operates like a normal diode. Generally diode current drift is described by Shockley diode equation as follows

$$I_{DC=}I_{de} * [\exp((G + IR_{SE})/JV_{the}) - 1] \quad \text{(a)}$$

By equation (a), (R_{ES}) is series resistance, (G) is the open circuit voltage, (J) is the ideality factor, (I_{ds}) is diode current and (V_{the}) is thermal voltage of photovoltaic cell expressed as proportional to temperature (T)

$$V_{the} = K_{BZ}T_{ep}/_q \qquad \text{(b)}$$

By equation (b), q is the charge of electron ($1.350650 * 10^{-19}$ c), K_{BZ} , is Boltzmann constant ($1.350650 * 10^{-23}$ J/K), and T_{eb} is Temperature concerned for PV-cell in Kelvin. The above figure ensue the superposition principle, sum of dark and irradiance characteristics constitute the total characteristics (Villalva et al., 2009; De Soto et al., 2006 & Easwarakhanthan et al., 1986). By equation (c), terminal current I_{Load} is therefore equal to I_{PV} subtracting from series resistance (R_{ES}) and diode current diverting (I_{DC}).

Process of optimization

In case of working out the problem associated with identification parameters of one diode solar PV cell systems, the below must be taken into consideration:

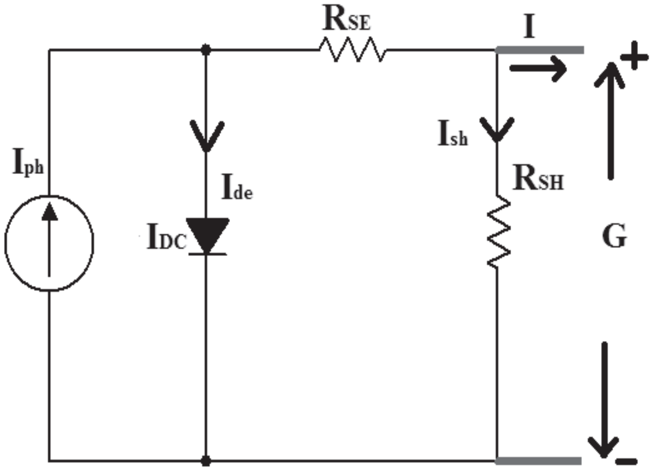

Fig.1 One-diode model equivalent circuit

(i) By means of what to characterize the solution

(ii) By means of what to actuate the search range

(iii) By means of what to develop the minimization (or) maximization of the objective function.

In the present work, every solution is characterized by using the vector W, where W= [$I_{ph}, I_{de}, R_{SH}, R_{SE}$ and J], is assumed for the one diode solar PV cell system. The lower limit as well as the upper limit of the parameters is taken from the reported works and objective function determination is the final stage. In initially, the equation is re-written as equation (c). Depending on the different types of conditions experimental I-V (current –voltage) data points are suitable for datasheets; substitute also continues for examining these amiable procedures, for detailed detection (Slaoui et al., 2013) including their fabricated data points amplified for directly distinct V-I curves cases.

One diode model

The one- diode model is shown in Fig1.

$$I_{Load} = I_{\mathrm{R}h} - I_{de} * [\exp\,(q(G + IR_{SE})/T_{ep} * K_{BZ} * J) - 1] - \frac{G+IR_{SE}}{R_{SH}} \qquad \text{(c)}$$

By equation (3), (I_{Load}) is terminal current, ($I_{\mathrm{R}h}$) is solar cell illumination generated photo current intensity and limits are between (0.6 – 0.8) V, R_{SE} for mass composed silicon cell crystalline is expressed many times to be 0.001 (Dittrich et al., 2014), (R_{SH}) is parallel resistance limits between ($0.2 - 2\Omega m^2$) and (R_{SE}) is Series resistance limits between ($0.5 * 10^{-4} - 2 * 10^{-4}\Omega m^2$) (Astier, 2008). On the basic characteristics of dark current, J is critically considering 1 at large currents and ideality factor of diode is critically 2 including diode saturation current of $I_{OD} = 10^{-5} - 10^{-4}A/m^2$ about 300K consider small current (silicon) (Siddiqui et al., 2013).

Diode ideality factor

Diode ideality factor is based on temperature (Dittrich et al., 2014) and accustomed through the power, analytically derived by (Bensalem & Chegaar, 2013):

$$J_k(T_{ep}) = J_{o,Ref;i}\left(\frac{T_{ep}}{T_{epRef}}\right)^{N^{(i)}} \quad \text{(d)}$$

By equation (d), $J_{o,Ref;i}$, as the pre-factor, $N^{(i)}$ the exponent power. T_{emRef} Mean values of temperature chosen nearly $i.e. 311K$.

Diode saturation current

Diode thermal dependence saturation current, ensues Arrhenius law along with Boltzmann factor dependence (Dittrich et al., 2014):

$$I_{Load;Q}(T_{ep}) = I_{Load0;Q} * \exp\left(-\frac{E_{The}}{T_{ep}K_{BZ}}\right) \quad \text{(e)}$$

By equation (e), here "; Q" is blank; it will be 1 for single diode model that is anxious; E_{The} is the stimulation of thermal energy in order to extract considering for single diode model. Crystalline solar cells (silicon) should have about 1.1ev. The pre-circumstance may be relatively huge, ($e.g. 10^6 A/m^2$) from the literature alternative characterized by equivalence of one diode model (Bayhan & Kavasoglu, 2007) that is specified and built upon energy band gap and diode ideality factor oscillate along temperature.

Photo current

The variation of photo current depends on temperature (Bensalem & Chegaar, 2013) with below equation:

$$I_{ph} = [I_{ph,Ref} + \mu I_{sc}(T_{ep} - T_{epRef})] \quad \text{(f)}$$

By equation (f) standard temperature condition (K), it is noted that $I_{pv,Ref} = I_{pv}$ $(25\ cent)$ is definitely obtained within the parameters limits, so that we can move linearly these parameter to alternatively required different temperatures by usage of coefficient μI_{sc}. Subsequently association can be given by (Siddiqui et al., 2013 & Dittrich et al., 2014). These are proposed for the optical modifier where it no use for the present appliances.

$$I_{Load} = I_{Rh} - I_{de} - I_{sh}$$

$$= I_{RS} - I_{de} * [\exp(q(G + IR_4)/T_{ep} * K_{BZ} * J) - 1] - \frac{G + IR_{SE}}{R_{sh}} \quad \text{(g)}$$

In this sense, R_{SE} denotes resistance in series G denotes operating voltage and R_{sh}, I_{sh} denotes shunt resistance and shunt current respectively. PV cell parameter estimation is the procedure that minimizes the calculated data and the measured data by varying the PV parameter. If the experimental data is up to, then the objective function shown to minimize the RMSE as

$$\text{RMSE} = \sqrt{\frac{1}{K}\sum_{X=1}^{K} F_{obj}(G, I_{Load}, W)^2} \quad \text{(h)}$$

For one diode model, where $W = [I_{RS}, I_{de}, J, R_{SE}, R_{SH}]$

$$F_{obj}(G, I_{Load}, W) = I_{RS} - I_{de} * [\exp(q(G + IR_{SE})/T_{eP} * K_{BZ} * J) - 1] - \frac{G + IR_{SE}}{R_{SH}} - I_{Msd,X} \quad \text{(i)}$$

Finally, the number of variable parameters from (h) and (i) to be optimized is five; they are ideality(J), diode saturation current (I_{de}), photo current (I_{ph}), shunt resistance (R_{SH}) and series resistance.(R_{SE}) From Table.3, it gives measured V-I data (Chan & Phang, 1987) where current data and voltage data are the second and first columns, respectively; for commercial purpose this PV cell is modeled at STC of temperature ($305\ kelvin$) and irradiance ($1000W_{/m^2}$) originally from RTC France with 57mm diameter silicon.

GREY WOLF OPTIMIZER SYNOPSIS

GREYWOLF OPTIMIZER:

This algorithm was proposed by Sayedali Mirjalili (Mirjalili et al., 2014). Grey wolf is associated with canidae family. These are treated as peak beat of prey that means these are dominant regarding meat group. The directors may be females or males, defined as alphas. These are ultimately susceptive for choice accomplishing regarding the sleep, hunts, wakeup etc. The alpha choice governs the bundle. Moreover, different types of character can be seen, where alpha comes after the rest of wolves in the bundle. In the bundle, the entire bundle signifies the alpha by inheritance of tail down. It is to be noticed that alpha wolves alone accessed to match in the bundle; moreover the alpha may not be fundamentally a strong member of the bundle but they must be better in terms of controlling the bundle. The secondary stage in grey wolf's hierarchy is beta. These are the auxiliary wolves that advice the alpha in choice accomplishing or rest bundle action. These wolfs may be males (or) females done by beta whenever the alpha is drowned. All the times the alpha getting respect by beta, but the lower key group is commanded by beta. It performs as act consultant to alpha and is restrained to the bundle. The bottom grading grey wolf is referred to as omega. The omega operates as the character of buck. These should be always surrendering to the rest of the leading wolves and the closing wolves that grant to munch. It can be noticed that omega is not a important wolves, but these are able to lose because of internal battling. This assistance gives the bundle an influence structure. In case the wolf not is referred (beta, alpha or omega), then it is referred (delta (or) subordinate). The subordinate wolves accept alpha as well as beta, but command the omega. Hunters, sentinels, elders, scouts and caretakers pertain to this group. Scouts are important for constrained limits of neighborhood and advocate the bundle in advert danger. Sentinels safeguard and assure the security of the bundle. Veteran is accomplished wolves who is employed to be as beta or alpha. Hunter's advice is given to the alpha and beta in prey hunt and afforded food to the bundle. At last the take careers are authorities for unsteady, ailing and damaged wolves in the bundle.

Moreover the extension to wolf social hierarchy, group hunt is one more fascinating grey wolf's social nature. The GWO mainly has given the following sub division.

1. Social nature
2. Prey enclosing
3. Hunting
4. Invade prey
5. Search for prey

Social nature: In array to design search for prey wolves in GWO developing, we acknowledge the alpha (α) will be a capable solution. Therefore, the next better solutions are designated as beta (β) and delta (δ) correspondigly. The other solutions are pretended to be omega (ω). The hunting of GWO is navigated by α, β, δ and after these three next ω wolves followed. A similar theory can prolonged to exploration having n dimensions.

Prey enclosing: As considered, at the time of hunt grey-wolves enclose the prey. In array to design enclosing act the below equations are suggested:

$$D = \left|\bar{C}.\overline{X_p}\ (t) - \bar{X}(t)\right| \tag{1}$$

$$\bar{X}(t+1) = \bar{X}_p^{-}\ (t) - A.\bar{D} \tag{2}$$

Here t denotes as current iteration, $\overline{X_p}$ represents prey position vector, $\bar{C}$ and $\bar{A}$ show vector coefficients, and $\bar{X}$ be grey-wolf vector position. The vector $\bar{C}$ and $\bar{A}$ determination is shown below:

$$\bar{A} = 2\bar{a}\overline{r_1} - \bar{a} \quad (3)$$

$$\bar{C} = 2\overline{r_2} \quad (4)$$

Here peripherals of $\bar{a}$ are nearly reduced among 2 to 0 upon the iterations of system and irregular vectors $r_1 r_2$ between [0, 1]. Various places over the better agent can be attained with respect to the present position by changing $\bar{C}$ and $\bar{A}$ vectors. It is to be noticed that irregular vectors r_1 and r_2 grant wolves at distance any position among these points. Definitely grey wolfs amend location internally in the region over the prey in each irregular location by equations 3.1 and 3.2. A similar theory can be prolonged to an exploration having n dimensions; the movement of grey-wolves in intense-cubes over the perfect solution is achieved so deeply.

Hunting:

The intelligence of grey-wolves is to identify the position of prey and moreover enclose the system under the leadership of alpha hunting guidance taking place. In some cases the beta and delta efficacy still proceed with hunting. where, in objective exploration we donot have any strategy regarding the optimum position of the prey. In array to design the grey-wolves act, we consider that beta; alpha and delta acquire preferred attainments regarding the prey potential position. So they definitely memorize the initial three prefect solutions achieved so long and impel the rest exploration operator. The below equations are considered for the above.

$$\overline{D_\alpha} = |\overline{C_1}\,\bar{X}_\alpha - \bar{X}|, \overline{D_\beta} = |\overline{C_2}\,\bar{X}_\beta - \bar{X}|, \overline{D_\delta} = |\overline{C_3}\,\bar{X}_\delta - \bar{X}| \quad (5)$$

$$\overline{X_1} = \overline{X_\alpha} - \overline{A_1}.(\overline{D_\alpha}), \overline{X_2} = \overline{X_\alpha} - \overline{A_1}.(\overline{D_\beta}), \overline{X_3} = \overline{X_\alpha} - \overline{A_1}.(\overline{D_\delta}) \quad (6)$$

$$\bar{X}(t+1) = \overline{X_1} + \overline{X_2} + \overline{X_3}/3 \quad (7)$$

It concludes that beta, alpha and delta give the position estimation of prey, and the rest of wolves amend their locations irregularly over the prey.

Invade prey:

As considered, the mentioned grey-wolves attain the hunt through prey invading when its cutoff is approaching. In array to design the system moving the prey, definitely the $\bar{a}$ value decrement occurs. It is noticed that $\bar{A}$ variation bounds is decremented with $\bar{a}$. A alternatively $\bar{A}$ is irregular value between $[-2a, 2a]$ moreover a is reduced between 2 and 0 around the iterations examination. In case the $\bar{A}$ irregular values are among $[-1,1]$. the adjacent location of exploration could be in either its prey or the current location.

Prey search:

The searching process of these grey-wolves depends on the location of delta, beta and alpha. These deviate among them to exploit for prey, coincide to invade prey. In array to design theoretically, we employ $\bar{A}$ along irregular values larger than 1 or lower than -1 to bind the exploit operator to deviate against the prey. This affirms search and accesses the algorithm to examine globally. Generally, vector $\bar{C}$ consists of irregular values between 0 and 2. This integral gives irregular weights to prey in array to imaginarily impose (c >1) or displace (c <1) the consequence of prey with reference to the separation.

This comforts GWO to display an extra irregular and overall accumulation; advantage exploration and prevention of local optima. It is beneficial to acknowledge that will not to be reduced in variation to. We consciously desire to give irregular values at various times in array to assert exploration not all along iterations even also eventual iterations. This element is actually advantageous in consideration of status local optima, particularly in the eventual iterations. The vector may also be treated as a consequence of difficulty to access the prey in essence. This could be absolutely what the vector achieves. Based on the location of the wolf, which can irregularly allow the prey a weight assemble it tough and beyond to access wolves. Adding to this, the exploration procedure begins by generating an irregular grey wolf's population in this algorithm. Every candidate solution modernizes its length against prey. The constraint is reduced between 2 and 0 in array to accentuate exploitation and exploration correspondingly. At last, the algorithm is approached by the achievement of boundary benchmark

Table 1: Lower and upper limits of the parameters

Parameters	Lower limit	Upper limit
I_{PV}	0	1
I_{de}	0	1
J	0	2
R_{SE}	0	0.5
R_{SH}	0	100

SIMULATION RESULTS AND TESTING

Table.1 shows the lower and upper limits of the one-diode PV cell; the proposed GWO is carried out computing under mat-lab circumstances. Experimental V-I characteristic data points of solar cell are employed to determine accuracy. From (Easwarakhanthan et al., 2014) achieved the experimental data and the basic study at standard test conditions (33c and sun 1000 W/m2). The decrement of current process is an essential problem in a pattern to series and parallel resistance (R_{SE} & R_{SH}) respectively.

Case study of solar cell model:

To achieve a complete GWO proposed algorithm evaluation in parameter estimation of solar cell, we consider one diode model. The estimation of the proposed method effectiveness is verified by the achieved V-I characteristics in comparison with experimental V-I characteristics. The data points in this paper which are achieved to characterize V-I are coming from geometrical spaces. The capability, with regards to the extraction of parameters depends on the RMSE, to be noted V-I values and extracted parameters computational time. It is to noted that from different algorithms evaluation of results is concerned with one-diode model test functions, by employing the characteristics of the V-I. To achieve the bigger drain correlation of algorithms, from Table 3 the value of root mean square error is considered for each test function individually. From this table it is noticed that to have better rationality in V-I experimental data points, the one diode models are preferable.

For accurate estimation, different algorithms are applied previously for their good coherence to reduce the RMSE as much as possible. It is noticed that recent memetic algorithm (MMA) is not adequate to have proper solution because of the below associated problems:

(1) It requires more computational time

(2) Not guaranteed in exploitation and exploration search space.

(3) Having prediction to accord the local optima stagnation but local optima prevention is not great.

From the above it is shown to have further solution improvement. V-I characteristic variation takes place with variation of five parameters (I_{PV}, I_{de}(μA), R_{SE}, R_{SH} & J). The upper and lower limits of these parameters are (I_{PV} (1,0), I_{de}(μA)(1,0), R_{SE}(0.6,0), R_{SH}(100,0) & J(2,1)). So, fitness function minimization definitely depends on these five parameters. The optimization pattern is supervised with experimental V-I data points; at the same time dependent significant domain parameters are directly employed on temperature sensitivity. The maximal values of the fitness function are shown Table 2; this table shows conceivable errors and moreover segment concerned global performance of algorithms.

For best fitted parameter closeness, RMSE is based on objective function (h), depending on temperature, expressed for one diode system. In the past to acquire solution, algorithms have been implemented for decrement of RMSE in parameter estimation of solar cell optimization problem. Moreover it is unusual that, modern applied algorithms (recent applied) like memetic algorithm and cuckoo search algorithm admit unsettled fulfillment of estimation parameters accuracy for one diode solar cell. MMA has many applied combination results, in which algorithm combination of simulated annealing with gradient based gives the best RMSE (0.00209) and consequent best cuckoo search (CS) gives (0.00269). This algorithm accustomed PV parameters credited values, but having RMSE which is restricted.

Finally, this confirms that solution accuracy must be further improved. For the justification of the proposed method estimation parameters of one-diode PV cell, effectiveness of GWO method obtained power includes the V-I actual characteristic data points.

One-diode model unknown parameter estimation:

Minimization of cost function from (h) gives parameters unknown for GWO method. Importantly, parameters values are not initiated, so the proposed method is compared with past algorithms RMSE for index classification. Moreover, the algorithm which has low RMSE value is noticed to be the best algorithm. Various algorithms obtained parameters as shown in Table 2. For comparison, the RMSE values are depicted as shown in the table. In this process there is one-diode PV cell, GWO has total number of iterations 1000 and concerned search agents are 50. It is noticed that recent MMA, CS and other algorithms try to reach the closer values concerned with RMSE. It is observed that from the below the range of voltage is between -0.2057V and 0.5900V in consideration of current error, GWO margin relatives having the same values by current error consideration and from Table.3 we can enhance the power related error. From Table 3 GWO produces very good accurateness in between the range (0.3V to 0.59V). The classification of P-V & I-V curves is done by employing GWO algorithm and the characteristic curves are shown in Fig.3 and Fig.4 with experimental curve respectively. From the GWO algorithm curves one can obtain the absolute data points of experimental V-I. The below table shows the GWO method definiteness.

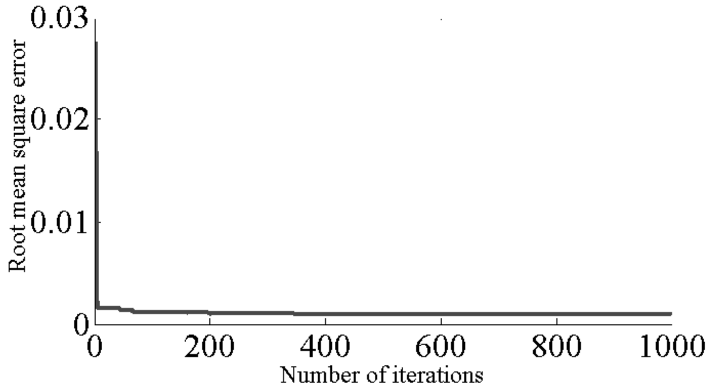

Fig.2 GWO algorithm achieved root mean square error to number of iterations

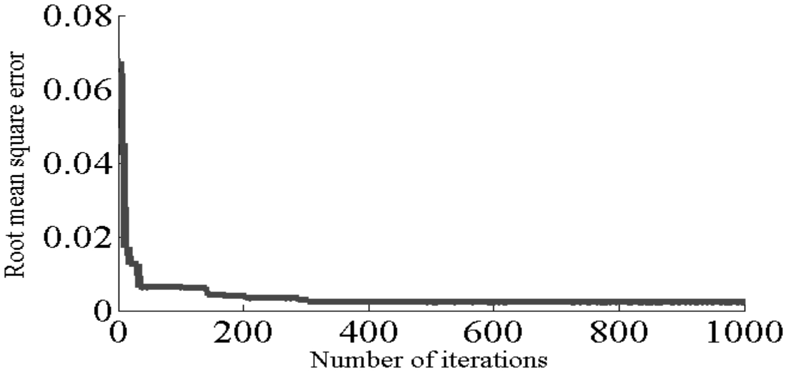

Fig.2.1 CS algorithm achieved root mean square error to number of iterations

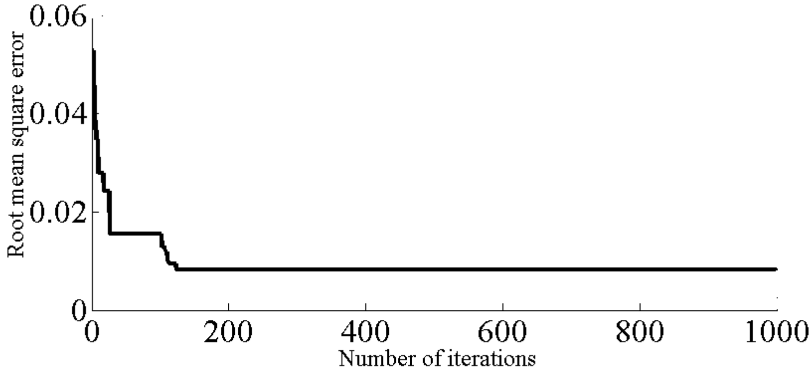

Fig.2.2 PSO algorithm achieved root mean square error to number of iterations

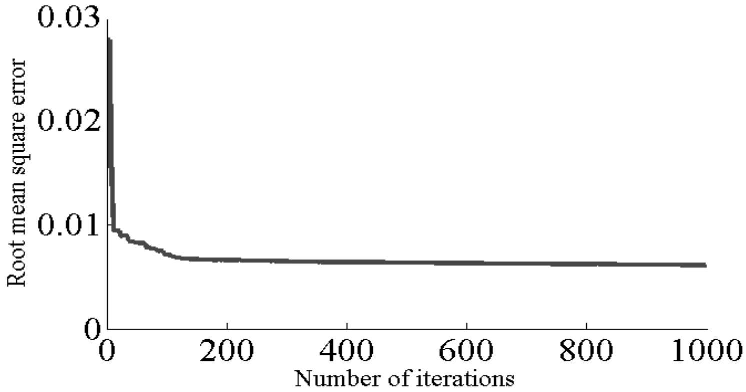

Fig.2.3 PS achieved root mean square error to number of iterations

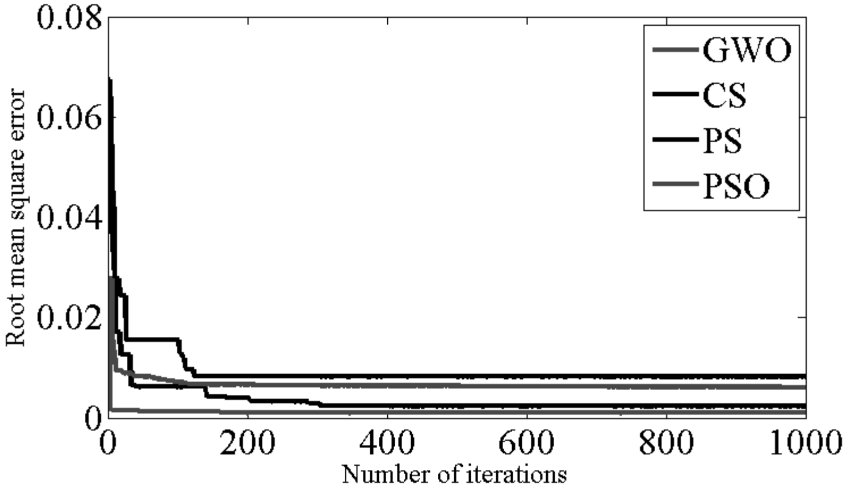

Fig.2.4 Comparison of PS, PSO, CS and GWO algorithms in terms of achieved root mean Square error to number of iterations

Assign every wolf and updating the order of bundles for all iteration to increment the exploration of search space and decrement the local optima stagnation probability. Definitely, the wolves nevermore cost and the GWO convergence can be guaranteed. Flexible number of bundles adjusts the exploitation and exploration. Flexible constant convergence makes acceleration over the bundles around the iteration scheme. The important specification to employ GWO, CS, PSO, and PS algorithms is to estimate the parameters expressed below:

After operating, the total number of runs, the ultimate iterative number is chosen to be. $T = 1000$. The size of population is chosen as. From Fig.2, Fig.2.1, Fig.2.2, Fig.2.3 and Fig.2.4 one can observe the performance in terms of the root mean square error to the number of iterations for the algorithms GWO, CS, PSO, PS and comparison, respectively. In which GWO algorithm converges quickly to reduce the root mean square error.

Flow chart:

The flowchart is shown Fig.2.5. Mathematically, in the initial step of GWO algorithm, the solution vectors were chosen at random from scope of problem. For this process, position of n^{th} grey wolf ($n = 1,2, \dots .SN$) is considered as the subsequent:

$$[X_n = X_{n1}, X_{n2}, \dots X_{nm}] \tag{7.1}$$

where is referred to as the number of grey wolves and stand for the total number of variables from the scope of problem. At every step, employed wolves hunt all over the food sources X_n (i.e. preceding solutions in their recall) to catch the best sources $[V_n = V_{n1}, V_{n2} \dots . V_{nn}]$, moreover the terms of X_n and V_n are associated through the below equation:

$$[V_{ni} = x_{ni} + \phi(x_{ni} - x_{ki})] \tag{7.2}$$

From the above equation, $K(K \neq n)$ is a randomly preferred integer in between $[1, SN]$ and ϕ_{ni} is an arbitrary number with reliable assigning among $[-1,1]$. The obtained solution (new) V_n is replaced with the past one, if here is referred to as m- variable cost function to be reduced otherwise, the past one $X_{n,}$ if $f(V_n) < f(X_n)$, here f is maintained. Obtaining the position of new sources from (7.2) and operating suitable replacements, each new source fitness calculation is obtained from below equation:

$$fit(X_n) = \begin{cases} \frac{1}{1+f(X_n)} & f(X_n) \geq 0 \\ 1 + f(X_n) & f(X_n) < 0 \end{cases} \tag{7.3}$$

where $fit(x_n)$ is referred to as source located fitness at, X_n, $fit(x_n)$ is m- variable cost function to be reduced. Then, wolves process the next iteration dependings on the factor of their food sources. Exactly, initially choosing the probability of food source concerned at x_n referred as P_n is obtained from :

$$P_n = \frac{fit(X_n)}{\sum_{k=1}^{SN} fit(X_n)} \tag{7.4}$$

So, a roulette wheel is taken for achieving the food source to be used by operating wolves in the coming iteration from (7.4). It is to be noted that at every iteration operating wolves select definite wolves by probability and, therefore, few of operating wolves might not be preferred at all, numerous than once. The categorization is limited by a parameter named limit. In this aspect somehow a solution exhibiting a food source is not upgraded after reregulate successive number of iterations, so that food is discarded by its operating wolves and operating wolves affiliate with that source of food, moreover exploring over randomly. The iterative number to release the source of food is similar to the "limit" value; however it is an essential parameter for the grey wolf optimizer algorithm. Definitely any operating wolf that couldnot find a best solution, iteration is identified best wolf that starts to follow to path of best wolf. To add up, at all iteration initially the new location, are achieved from (7.2) and their effectiveness are verified through (7.3). So, definite replacements are shown and selection probabilities are achieved from (7.4). It is definite that by this process low-essence food sources are discarded by active wolf and, with that result, operating wolf moves to find over the location with greater fitness values. The greater fitness value location is recognized as the final solution.

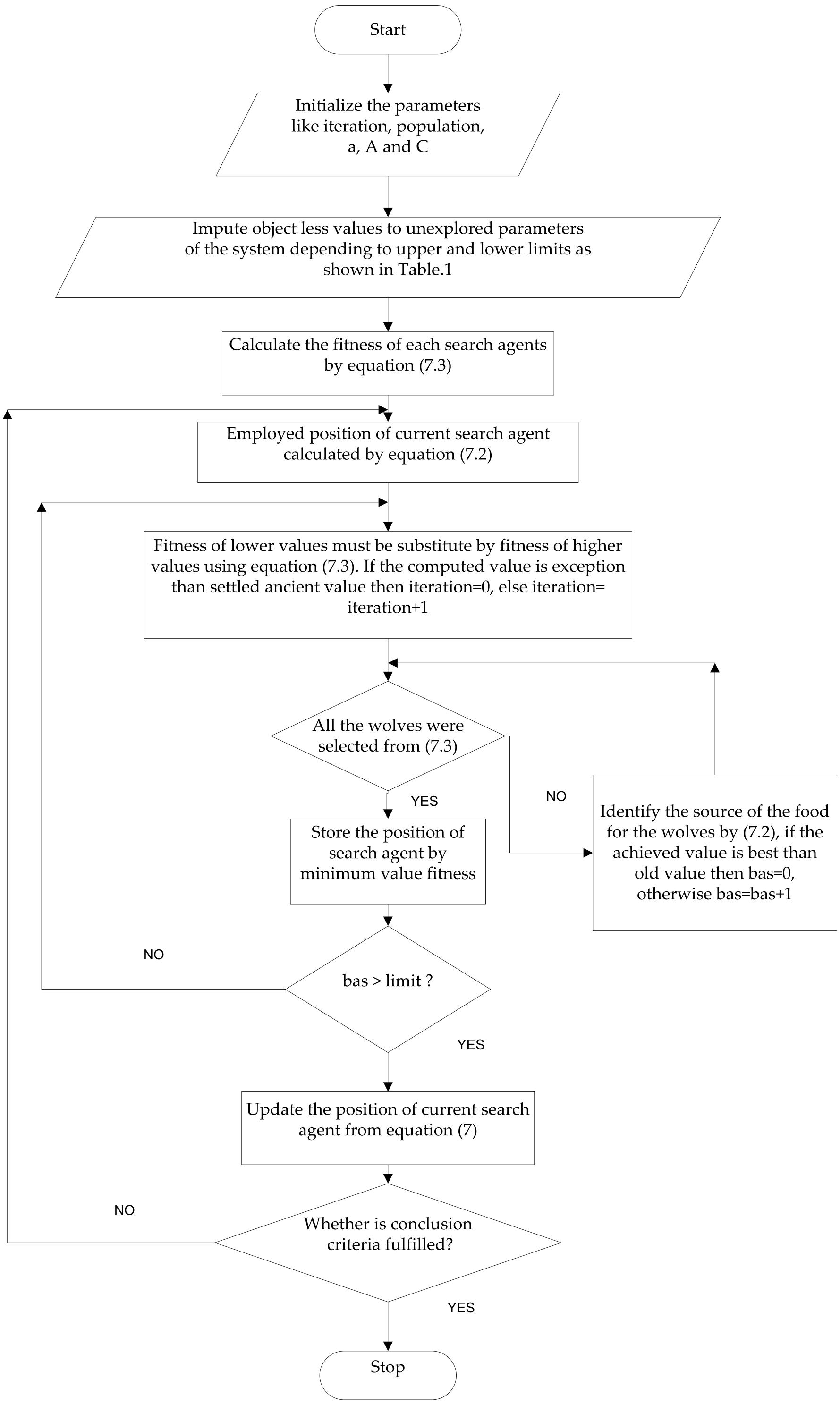

Fig.2.5 Flow chart implementation of GWO for one diode model PV cell

Table 2 : Various algorithms estimated values of parameters unknown for one diode PV cell

S.NO	Param-eters	GA [Ismail et al., 2013]	PS [AlRashidi et al., 2011]	LS [Bouzidi et al., 2007]	PSO [Soon et al., 2012]	CS	MA (best) [Yoon et al.,2015]	GWO
1	I_{PV}	0.755	0.7617	0.7607	0.760798	0.7617	0.7620	0.7607516
2	I_{od} (μA)	0.964	0.9980	0.33	0.322721	0.42	0.45	0.304709
3	R_S	0.0388	0.0313	0.0364	0.036394	0.0380	0.0345	0.0366465
4	R_p	55.4477	56.10	60.241	53.7965	52.8789	43.103	53.03
5	n	1.9807	1.600	1.4816	1.48282	1.4700	1.5172	1.4768
6	RMSE	0.0049	0.08132	0.00477	0.00715	0.001	0.00209	0.000994378

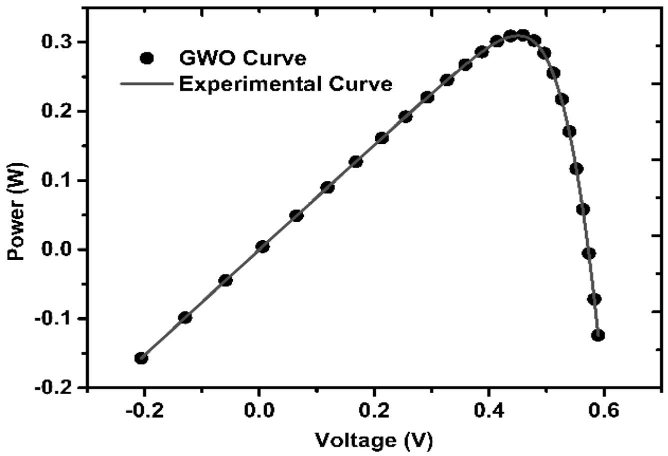

Fig.3 GWO achieved and experimental P-V curve of unknown parameters of single diode PV-cell

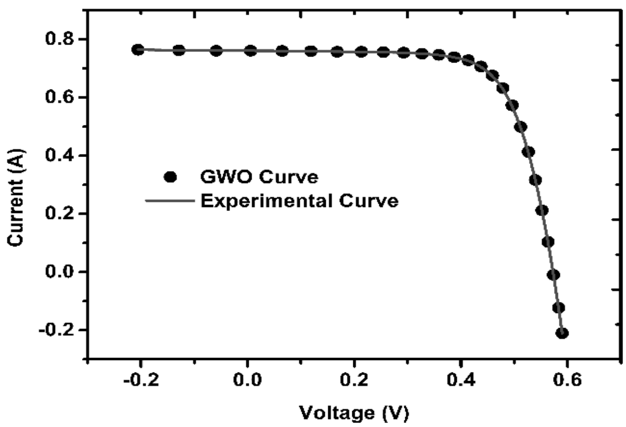

Fig.4 GWO achieved and experimental I-V curve of unknown parameters of single diode PV-cell

As shown in Table 3 the measured currents, calculated currents and power absolute errors are with root means square error indices achieved at various data points for good comparison between the algorithms; equations (x) and (y) below gives minimization of current and power

Minimization of current

$$(MZ_C) = \sqrt{\frac{1}{K}\sum_{X=1}^{K}(I_{Load,X} - I_{Msd,X})^2} \qquad \text{(x)}$$

Minimization of Power

$$(MZ_P) = \sqrt{\frac{1}{K}\sum_{X=1}^{K}(P_{Load,X} - P_{Msd,X})^2} \qquad \text{(y)}$$

As depicted the results in Table.2, further shows memetic and cuckoo algorithms accomplished exceptionally great conclusive performance when compared to past algorithms on PV cell estimation of parameters. GWO having RMSE which is lesser than algorithms applied previously. Memetic and cuckoo search algorithm is applied recently (Ma et al.,2013 & Yoon et al. 2015). The exploration and exploitation balancing is necessary (Tan et al., 2009). GWO algorithm importantly depends on five parameters for optimization. Implementation of GWO algorithm resulted in better performance, mainly because of guaranty in exploration and exploitation search space. Moreover, local optima prevention is very high. At twenty six different points the measured current, calculated current, and current error are shown in Table.3, when GWO is executed. From different inspections calculated and measured sections were shown in this table that concludes the proposed GWO definiteness for one diode solar PV cell to estimate the parameters.

Nomenclature

R_{SE} : Series resistance,

R_{SH} : Shunt resistance

T_{eb} : Temperature ambient

G : Observed operation voltage

L_{Load} : Observed terminal voltage

I_{de} : Current through diode

I_{BZ} : Photocurrent generated from cell

K_{de} : Boltzmann constant (1.380650 × 10 − 23 J/K)

J : Ideality factor of diode

q : Electron charge (1.602176 × 10 − 19 C)

I_{OD} : Saturation current of the diode

I_{SH} : Shunt current

V_{the} : Thermal voltage

Table 3: Calculated and measured data for twenty six various working conditions

Measurd numbers	$V_L^{(V)}$	$I_{Msd.x}^{(A)}$	$I_{calc}^{(A)}$	Current relative error	$P_{Msd.x}$	P_{calc}	power relative error
1	-0.2057	0.7640	0.75216	-9.772e-04	-0.14258	-0.1428953	-0.00014553
2	-0.1291	0.7620	0.75317	-0.0007829	-0.087215	--0.097298564	-0.000072568
3	-0.0588	0.7605	0.74254	-0.00073218	-0.03689	-0.04587524	-0.000041003
4	0.0057	0.7605	0.75218	0.00025712	4.2218e-3	0.00362895	0.0000010912
5	0.0646	0.7600	0.746329	0.00089136	0.048619	0.035421	0.00059269
6	0.1185	0.7590	0.744218	0.0021896	0.072418	0.087256193	0.00012596
7	0.1678	0.7570	0.746816	2.6629e-05	0.1160179	0.268113	0.000003982
8	0.2132	0.7570	0.74218	0.00092663	0.153627	0.158294	0.000182665
9	0.2545	0.7555	0.742968	0.000484829	0.185679	0.186162	0.0001129625
10	0.2924	0.7540	0.746329	0.00036219	0.21890562	0.2158729	0.000115892
11	0.3269	0.7505	0.735186	0.00078296	0.2369851	0.2368426	0.00027621
12	0.3585	0.7465	0.73694	0.000742698	0.2563289	0.2518239	0.00027659
13	0.3873	0.7385	0.72689	0.00150326	0.272519	0.2738294	0.00061302
14	0.4137	0.7280	0.714592	0.00056814	0.297258	0.2961382	0.00022659
15	0.43730	0.7065	0.70426	0.00056217	0.312892	0.2911338	0.000235692
16	0.4590	0.6755	0.66829	7.1029e-05	0.301125	0.3023318	0.0000320985
17	0.4784	0.6320	0.628953	0.00116982	0.297866	0.2961445	0.000501625
18	0.4960	0.5730	0.561895	0.000925228	0.279226	0.2763582	0.00045136
19	0.5119	0.4990	0.4852819	0.000727789	0.244128	0.246318	0.000352846
20	0.5265	0.4130	0.40256	0.000679265	0.203256	0.2078625	0.000351136
21	0.5398	0.3165	0.304271	0.00096529	0.162981	0.1689206	0.00051896
22	0.5521	0.2120	0.206935	5.348e-05	0.123518	0.101294	0.0000298651
23	0.5633	0.1035	0.11628	0.0012695	0.0575031	0.0558296	0.000761892
24	0.5736	-0.0100	0.0072318	0.0011853	-5.628e-3	0.004842651	0.000772986
25	0.5833	-0.1230	0.1106	0.00235891	0.070529	0.069812	0.001356198
26	0.5900	-0.2100	0.207256	0.00163052	-0.1128	0.1129631864	0.0025893

Table 4: Temperature sensitivity analysis

Celsius (Degreecent.)	Kelvin (Degree Kelv.)	I_{PV}	I_{SD}	R_S	R_P	N	RMSE (MMA) [Yoon et al.,2015]	RMSE (GWO)
-5	268.15	0.760766	3.09203e-7	0.0365607	53	1.68611	0.01438	0.00312648
0	273.15	0.760766	3.11822e-07	0.0365608	52.93	1.65711	0.01658	0.000991982
5	278.15	0.760766	3.09076e-07	0.0365608	52.8315	1.62547	0.00520	0.00296722
10	283.15	0.760766	3.10779e-07	0.0365607	52.8315	1.59734	0.01107	0.00298554
15	288.15	0.760766	3.09103e-07	0.0365607	52.877	1.56734	0.01454	0.00866569
20	293.15	0.760766	3.0911e-07	0.0365607	52.8782	1.54255	0.01952	0.00207388
25	298.15	0.760766	3.09055e-07	0.0365609	52.882	1.5165	0.00391	0.00253909
30	303.15	0.760766	3.17146e-07	0.0365602	52.9819	1.49476	0.00203	0.00101329
35	308.15	0.760766	3.17835e-07	0.0305607	52.9906	1.47101	0.01491	0.0110516
40	313.15	0.7626	6.28035e-07	0.0331531	47.406	1.5178	0.00236	0.00214364

Table 4 shows the various temperatures sensitivity analysis of various temperatures between [-5 to 40 deg. Cent]. The exact value for every parameter was obtained using this method that shows accordance of the results with practical data. In this process, variation of temperature is fused into the analysis for obtaining the error fitness in order to measure the optimized values for various parameters. A value that associates with the full range of solar temperatures was therefore computed for every parameter. Various trials were made to identify the execution time for achieving the cell parameters. It is achieved that this time, in various cases, it is below 6 seconds. Nonetheless, as this established method uses the rating of any solar cells, characteristics obtained by manufacturer data sheet to achieve the parameters global value fit the full range of solar temperature variations, initially with these parameters being analysed (off-line). This clearly indicates that in this method, modelling in real time is not required. In various approaches real time modelling is required with change in parameter value under temperatures constraint. In this method modelling access shall be rapid to accord with real time performance.

GWO optimized model in this manuscript achieved nearly exact results for the RTC France with 57mm diameter silicon by consideration of standard test condition (STC), as already explained in Table 3. The obtained simulation results at STC are steady with practical data; these method results are seen under V-I characteristics data. The feasibility of GWO method is justified by correlating the achieved results with various methods in Table.2, the correlation is executed under temperature conditions and GWO performance is verified by correlating with other methods. Different temperature conditions were used to achieve the exact parameters of PV cell. The purpose of various temperature case analyses is to determine the better case that can implement the obtaining of exact precise parameters of PV cell; such parameters are used in simulation program to achieve the experimental data sheet.

In addition, the ultimate fundamental factors of correlation process among GWO algorithm and various methods (or algorithms) are the conversion speed and execution of time till meeting the maximum iteration number. Fig.2.4 shows that GWO algorithm converges to the exact solution rapid than other methods. The execution time of GWO is about 40% of that recent cuckoo search algorithm. Consequently, it must be observed that the GWO algorithm converges to exact solution very fast and better compared with previous algorithms. It is because of meta-heuristic algorithm inspiration of GWO algorithm that comforts it to nevermore lose its exact solutions and converges to solutions quickly.

The final parameters after employing various algorithms when computed for one-diode cell are that, the GWO algorithm has better performance in consider action of execution time, error analysis, and physical behaviour and V-I curves validation.

CONCLUSION

In this paper, the grey wolf optimizer algorithm has been proposed for achieving the exact parameter values of solar cell one-diode equivalent model. The GWO considered every wolf and updated the order of bundles for all iterations to increase the exploration of search space and decrease the exploration local optima stagnation probability. The parameter values of one diode PV cell are extracted in such a process by minimizing the error among the theoretical and experimental data. The V-I data obtained by R.T.C France (57mm diameter) cell is the only essential requirement for this method. Different temperature cases were analyzed for correlation purpose. The better results (obtaining lowest RMSE) are achieved using one diode model with three parameters (shunt resistance, series resistance and photon current). The saturation current and diode ideality of one diode model were estimated to confide the optimally achieved parameters. The exact modeling of PV cell is a definite tool essential for any new studies related to PV applications. It is noticed that the one diode parameters which are achieved using GWO algorithm are very promising and dominant over previously applied algorithms. GWO method in this execution can also be applied to many critical and practical PV models with different systems in future. Finally, it can be concluded that GWO algorithm applied for parameter estimation of one diode PV cell is very much efficient for extracting the accurate values.

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تقدير المعلمات لخلية شمسية كهروضوئية ثنائية الصمام باستخدام خوارزمية GWO للحصول على خصائص V-I الدقيقة

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الخلاصة

تقدم هذه المقالة طريقة مناسبة لتقدير المعلمات غير المعروفة لنموذج ما يعادل خلية كهروضوئية ثنائية الصمام. ووفقاً لهذا المقترح، يمكن تحديد تقدير دقيق للمعلمات غير المعروفة عن طريق تقليل دالة الهدف من خلال تطبيق خوارزمية الذئب الرمادي المتميز (GWO). تم تنفيذ الخوارزمية المذكورة (GWO) لتقدير المعلمات لخلية واحدة كهروضوئية ثنائية الصمام وتمت مقارنة النتائج التي حصلنا عليها مع كل من خوارزمية الممتيك (MA)، وخوارزمية محاكاة التلدين، وخوارزمية بحث الوقواق، وخوارزمية أمثلة أسراب العناصر، وخوارزمية البحث عن نمط والخوارزمية الجينية. وتؤكد النتائج التجريبية ونتائج المحاكاة أن خوارزمية GWO قادرة على تحقيق كل معلمة بدقة هائلة، وتتفوق نتائجها على الخوارزميات الأخرى المذكورة أعلاه.