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A Dragonfly Algorithm Application: Optimizing Solar Cell Single Diode Model Parameters

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Abstract. This paper provides an overview of optimizing solar cell single diode parameters using Dragonfly Algorithm. The 57 mm diameter commercial (R.T.C. France) silicon solar cell measurement data are taking as the data source for the optimization process. The results produced are compared with NM-PSO and IJAYA algorithms to observe the efficiency, accuracy and reliability of the proposed approach

1. Introduction

Recently, the application of optimization to solve engineering problems has increased significantly. The aims of optimization is to maximize the production efficiency, reduce the production cost or minimizing the errors. An optimization algorithm mostly works by comparing various solutions and executed iteratively to found an optimum or satisfactory solution. The example of engineering problems solve using the optimization algorithms are distributed generation [1, 2], maximum power point tracking [3], harmonic elimination [4] and fuel cell parameters [5–8].

Various optimization methods have been applied to determine the solar cell parameters such as Particle Swarm Optimization (PSO) and their variants [9–13], Ant Lion Optimization [14],Genetic Algorithm (GA) [15], and JAYA [8, 16, 17]. The Dragonfly Algorithm or DA, developed by Mirjalili in 2014 [18] is a bio-inspired optimization algorithm inspired by the static and dynamic swarming behaviours of dragonfly. Since that, the application of DA and its' modified version in solving engineering problems are increasing [6, 19–22]. Hamal et al [6] used the DA to optimize the fuel cell parameters, meanwhile, T. Bashishtha and L. Srivastave [20] apply this algorithm to find the optimal setting of the power system control variables for optimal power flow. Moreover, K. Ghany et al [21] used the hybrid DA with extreme machine learning (ELM) for prediction problem. In this paper, the DA is set to extract the parameters of solar cell single diode model (SDM). The SDM is one of the popular method to model the solar cell and due to its simplicity and accuracy [9, 16, 17].The proposed algorithm is used to determine the SDM parameters of 57 mm France solar cell and the best result is compared with NM-PSO [9] and IJAYA [17] algorithms to further observe the performance.

The remainder of this paper is organized as follows: Mathematical Modelling Section present the mathematical formulation of SDM. Problem Formulation Section describe the objective function selected for optimization process. In Dragonfly Algorithm Section, the proposed DA

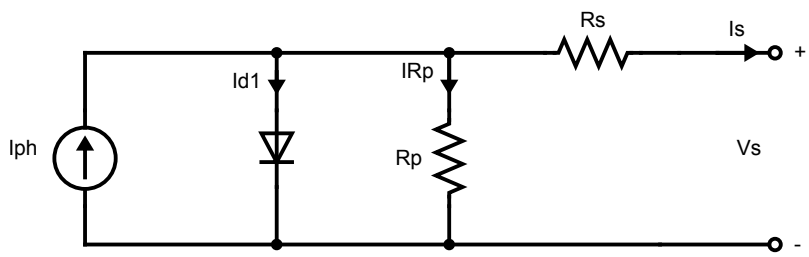

Figure 1. Single diode model equivalent circuit.

are elaborated. In Results and Analysis Section, the optimize SDM model parameters are observed and compared with other optimization approaches. Finally, in Conclusions Section the conclusion and future improvement are drawn.

2. Mathematical Modelling

The solar cell model can be used to predict the behavior of the system operation under different conditions [9, 17, 23]. There are many model being proposed to represent solar cell such as single diode model (SDM), double diode model (DDM) and triple diode model (TDM). However, SDM has become dominant choice in many research works due to its simplicity [9, 13, 15]. There are five unknown parameters namely the ideality factor (a), photovoltaic current (I_{R_p}), reverse saturation current (I_d), series resistance (R_s), and parallel resistance (R_p) need to be determined as shown in figure 1. R_s and R_p represent the sum of structure resistance and the leakage current, accordingly. These parameters are important and normally being determined either by using measurement, analytical calculation or numerical iteration.

Based on figure 1, the output current, I_s can be written as:

$$I_s = I_{ph} - I_d - I_{R_p} \tag{1}$$

By considering Shockley equation for the diode current, I_d and substituting the current of the shunt resistor, I_{R_P}, equation 1 can be rewritten as follows:

$$I_s = I_{ph} - I_o\left[\exp\frac{V_s + I_sR_s}{aV_t}\right] - \frac{V_s + I_sR_s}{R_p} \tag{2}$$

Where, V is the solar cell output voltage, a is the diode ideality factor and V_t represents the thermal voltage which is given as:

$$V_t = \frac{kT}{q} \tag{3}$$

The parameter k is the Boltzmann constant ($1.3806503 \times 10^{-23}$ J/K), q is the electron charge ($1.60217646 \times 10^{-19}$ C) and T is the temperature of the solar cell in Kelvin (K). For determining the parameters using optimization algorithm, the equation (2) is rewritten in the homogeneous form:

$$f(V_s, I_s, x) = I_{ph} - I_o\left[\exp\frac{V_s + I_sR_s}{aV_t} - 1\right] - \frac{(V_s + I_sR_s)}{R_p} - I_s \tag{4}$$

where $x = I_{ph}, I_o, R_s, R_p, a$.

3. Problem Formulations

The objective function is a mathematical equation that describes the output target which corresponds to the minimizing the error between the measured and estimated data. The root mean square error (RMSE) is set as a criterion to quantify the difference between the model results and the experimental data and can be describe as follow [9]:

$$F(\boldsymbol{x}) = \sqrt{\frac{1}{N}\sum_{l=1}^{N} f_l(V_s, I_s, \boldsymbol{x})^2} \tag{5}$$

where N is the number of the experimental data point. The value of $f(V_s, I_s, \boldsymbol{x})$ is calculated for each pair of the experimental data. The upper and lower boundaries of the parameters, used during the optimization process, are shown in table 1 [9].

Table 1. Upper and lower range of the solar cell parameters

Parameter	Lower	Upper
I_{ph} (μA)	0	1
I_o (μA)	0	1
R_s (Ω)	0	0.5
R_p (Ω)	0	100
a	1	2

4. Dragonfly Algorithm

The DA inspired from the static and dynamic swarming behaviors of dragonflies in nature [18]. The exploration and exploitation phases are designed by modeling the social interaction of dragonflies in navigating, searching for foods, and avoiding enemies when swarming in dynamically or statistically [18–20]. There are five factors involved in determining the individual dragonfly position [18–22]; Separation (S), alignment (A), cohesion (C), attraction towards food sources (F) and distraction outwards enemies (E). There are two ways for updating the individual dragonflyâĂŹs position depending on the neighborhood position. If there is no dragonfly in the neighborhood radius, the individual position is updated considering the Levy Flight equation and given as follow:

$$X_{(t+1)} = X_t + Levy(d)X_t \tag{6}$$

where t is the current iteration, and d is the dimension of the position vectors. Otherwise, the new position is calculated as follow:

$$X_{(t+1)} = X_t + \Delta X_{(t+1)} \tag{7}$$

where $\Delta X_{(t+1)}$ is the step vector and can be obtained as:

$$\Delta X_{(t+1)} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{8}$$

where t is the current iteration, s shows the separation weight, S_i indicates the separation of the i-th individual, a is the alignment weight, A_i is the alignment of i-th individual, c indicates the cohesion weight, C_i is the cohesion of the i-th individual, f is the food factor, F_i is the food source of the i-th individual, e is the enemy factor, E_i is the position of enemy of the i-th individual and w is the inertia weight. The flow of the DA execution is summarizes in figure 2. Details explanation of the execution processes can be referred to original paper by Mirjalili [18].

```
begin
    Initialize the dragonflies population X_i(i = 1, 2, ..., n)
    Initialize step vectors ΔX_i(i = 1, 2, ..., n)
    while the end condition is not satisfied
        Calculate the objective values of all dragonflies
        Update the food source and enemy
        Update w, s, a, c, f, and e
        Calculate S, A, C, F, and E
        if a dragonfly has at least one neighboring dragonfly
            Update velocity vector using equation 8
            Update position vector using equation 7
        else
            Update position vector using equation 6
        end if
        Check and correct the new positions based on the boundaries of variables
    end while
end
```

Figure 2. The flow of DA execution.

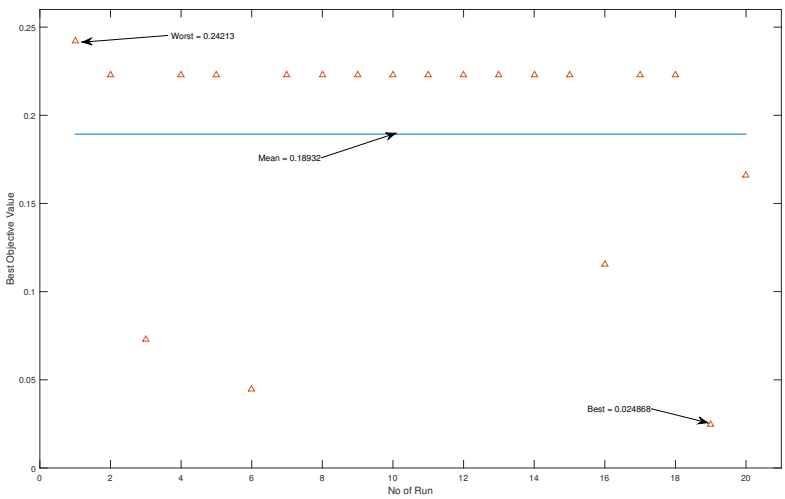

Figure 3. The best objective value distributions for 20 trial runs.

5. Results and Analysis

The performance analysis of DA in estimating SDM parameters of RTC France silicon solar cell at 33 ^{o}C and full sun (irradiation of 1000 W/m^2) is presented in this session. The data for RTC France is taken from [9] and widely used in the literature to test their algorithm [9, 12, 13, 23]. The DA population size is set to be 70 and the maximum number of iteration is 5000 which is similar with setting in [9]. All the simulation work, presented in this paper, made use of MATLAB® 2015a environment, working at Intel® Core™ i5 CPU, 2.5 GHz and 4 GB RAM.

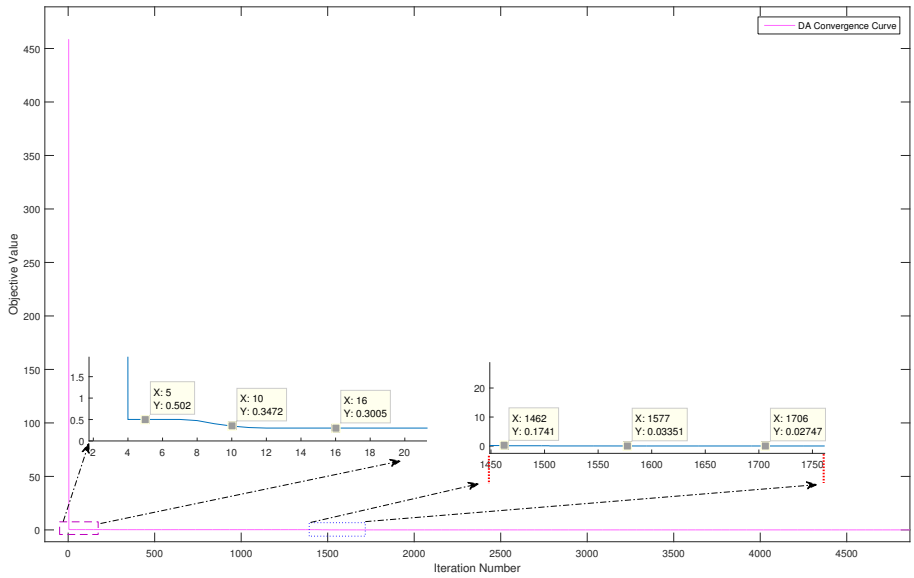

Figure 4. The best objective value convergence curve.

5.1. Optimization Results

The DA has been run for 20 times and the best objective value of each run is plotted in figure 3. Examined this graph, the best, worst and mean objective values are 0.024868, 0.24213 and 0.18932 respectively. The standard deviation value is 0.067286 which is quite big and demonstrating the algorithm inconsistency in optimizing the SDM parameters. The convergence curve for the best objective value is plotted in figure 4. Observing this figure, the DA start to produce lower objective value after 5 iterations and after 1600 iterations it gain the objective value relative stability. Moreover, this curve evidences that the algorithm really fast in obtaining the lower objective value.

To further assess the reliability of the DA, the individual absolute error (IAE) and the relative error (RE) are used. These two indexes are respectively defined by equations 9 and 10.

$$IAE = \left| I_{i,m} - I_i \right| \tag{9}$$

$$RE = \frac{I_{i,m} - I_i}{I_{i,m}} \tag{10}$$

The experimental and calculated data along with the IAE and the RE are given in table 2. The IAE values are less than 3.96×10^{-2} and the RE values are within the range of 0.2883 to 1.8955. These values are relatively high proving that the calculated data are too much difference compared to the experimental data. This indicates that the reliability of optimize parameters is doubtful and DA is not suitable to predict the SDM parameters.

5.2. Comparison with selected algorithms

In this subsection, the results obtained from DA is compared with NM-MPSO [9] and IJAYA [17], and be tabulated in table 3. This table indicates that in terms of the best achieved RMSE,

Table 2. Relative error and individual absolute error for each measurement.

Data	$I_{measured}(A)$	$I_{calculated}(A)$	RE	IAE
1	0.764000	0.764065	-0.043608	0.033317
2	0.762000	0.762648	-0.034137	0.026012
3	0.760500	0.761348	-0.024945	0.018970
4	0.760500	0.760154	-0.014630	0.011126
5	0.760000	0.759061	-0.005845	0.004442
6	0.759000	0.758052	0.001559	0.001183
7	0.757000	0.757103	0.007083	0.005362
8	0.757000	0.756153	0.014935	0.011306
9	0.755500	0.755092	0.020790	0.015707
10	0.754000	0.753659	0.027221	0.020525
11	0.750500	0.751368	0.032386	0.024306
12	0.746500	0.747311	0.039421	0.029428
13	0.738500	0.740047	0.045288	0.033445
14	0.728000	0.727342	0.053995	0.039309
15	0.706500	0.706905	0.055960	0.039536
16	0.675500	0.675260	0.055942	0.037789
17	0.632000	0.630863	0.050218	0.031738
18	0.573000	0.572066	0.034998	0.020054
19	0.499000	0.499468	0.008055	0.004019
20	0.413000	0.413454	-0.027920	0.011531
21	0.316500	0.317163	-0.078810	0.024943
22	0.212000	0.212038	-0.150609	0.031929
23	0.103500	0.102664	-0.288345	0.029844
24	-0.010000	-0.009280	1.895503	0.018955
25	-0.123000	-0.124363	-0.076334	0.009389
26	-0.210000	-0.209125	-0.172532	0.036232
Mean			**0.054832**	**0.021938**

DA has the worst compared to all other optimization algorithms. This possibility due to the stagnation and premature convergence problems which lead to local optima solution rather than global optima as can been seen in convergence curve plotted in figure 4.

6. Conclusion

In this paper, a performance of the DA in extracting the parameters for SDM is investigated. A RTC France silicon solar cell has been used as the case study of this project. The findings show that the DA cannot extract the parameters of SDM and produced unreliable results. That why it cannot surpasses the NM-PSO and IJAYA algorithms. This possibly due to stagnation problem as being displayed at the convergence curve. Even though the DA can jump fast to low objective value but it cannot recovered from this problem, leading to local optimal convergence rather than arriving the global solution. Since the DA alone cannot optimize the SDM parameters, it is essential to improve the DA exploration ability either by hybrid it with local search algorithm or other metaheuristic algorithm that has better exploration capability such as Particle Swarm Optimization (PSO). This improvement will boost the efficiency, accuracy and reliability of the algorithm and at the same time decrease the mean error, standard deviation and average objective values and increasing the success rate value.

Table 3. The comparison of parameters extraction. The minimum RMSE value found by the algorithms is shown in bold.

Parameters	NM-MPSO[9]	IJAYA[17]	DA
$I_{ph}(A)$	0.76078	0.76080	0.77232
$I_o(\mu A)$	0.32306	0.32280	0.13031
$R_s(\Omega)$	0.03638	0.03640	0.00000
$R_p(\Omega)$	53.7222	53.7595	8.2333
a	1.48120	1.48110	1.9979
RMSE	$\mathbf{9.8602}\times10^{-4}$	9.8603×10^{-4}	2.4868×10^{-2}

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