Estimation of solar cell circuit model parameters using an Algorithm based on artificial intelligence

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Abstract- The use of solar photovoltaic systems (PVs) as a clean and affordable source of electrical energy is increasing. In order to improve the performance, control and evaluation of the PV system, it is necessary to accurately design and define the intrinsic parameters of the solar cells, which are the main components of the PV system. Since the electric current versus voltage (V-I) characteristic of the solar cell is nonlinear, its modeling is associated with many problems. Considering that optimization techniques are the best tools for identifying the parameters of nonlinear models, the use of these techniques has been considered. in this article, it is intended to estimate the parameters of the equivalent circuit of the two-diode model of the PV system by using the method based on artificial intelligence. Based on this, at first, using the particle swarm algorithm as a suitable method, 7 parameters of the two-diode model were optimized. In order to check the performance of the particle swarm method, different strategies were considered for it, including PSO algorithm with random inertia coefficient, time-varying inertia coefficient, time-varying learning coefficients, contraction coefficient and average. Next, the Archimedes optimization method as a new algorithm in this field was proposed and investigated, and the parameters of the two-diode model were optimized based on it. In order to check the accuracy of the proposed methods, the results obtained from the optimization of the parameters of the two-diode PV system model were compared with some optimization methods.

Keywords: solar cell system, two diode circuit model, particle swarm algorithm, Archimedes optimization algorithm, mean square error.

1. Introduction

Due to the abundance and non-polluting nature of solar energy, the use of photovoltaic (PV) systems has received much attention. A PV module consists of many solar cells that can be connected in series or parallel. The performance of a PV module mainly depends on the availability of solar radiation and the efficiency of power conversion. These are important characteristics that are affected by many physical parameters such as geographic location, weather conditions, placement and rotation angle of the panel, air temperature, wind speed, etc. [1] Modeling the electrical equivalent circuit of photovoltaic devices is a key tool for efficient design and predicting their electrical performance. In general, three different equivalent circuits are needed to model the output power of the PV system in a specific radiation and limited temperature. These models include the thermal model to find the temperature of the solar cell, the radiation model to find the solar energy absorbed in the PV cells, and the electrical model to calculate the electrical characteristics of the PV system [2]. So far, various models have been made to depict the electrical characteristics of the PV device. Among these models, single diode model and two diode model are very common. The single-diode model, which is used to model the behavior of a PV system, is very useful because of its moderate complexity and relatively good accuracy. The two-diode model has higher accuracy but more complexity [3]. In the two-diode model, the accuracy of the PV system is improved compared to the single-diode model, and the disadvantages of the single-diode model are overcome [4]. The circuit characteristic curves of the electrical model of PV systems are expressed using nonlinear relations. To accurately model the nonlinear characteristic of the V-I curve, every point on the curve must exactly match the experimental values. For this reason, an efficient method to determine the values of circuit parameters of the PV system model is necessary. Since it is difficult to determine these parameters using analytical methods, one way to solve this problem is to consider the ideal electrical model for the PV system [5]. Considering that these parameters change with the change of solar radiation and temperature, this assumption cannot be correct and the obtained models do not have proper accuracy. Another method is to use intelligent programming and optimization algorithms, which are very efficient according to their development. In [6], to find the parameters of the equivalent circuit of the PV system of the single diode model, Gauss Seidel algorithm method is used. A method to estimate the parameters of two-diode model PV system using dynamic algorithm in different weather conditions is proposed in [7]. By using AIS meta-heuristic algorithm, optimization of two diode circuit model parameters has been done in [8 and 9]. Also, the BFA bacteria search algorithm has been used to estimate the parameters of the single-diode model photovoltaic system [10]. In [11], to determine the parameters of the PV system single diode model, the Particle Swarm Optimization (PSO) algorithm is proposed. In addition, the estimation of the parameters of the two-diode PV system model using genetic algorithms and Simulated Annealing algorithm has been investigated in [12]. Using the Artificial bee colony algorithm to determine PV system parameters is one of the other methods presented in this field [13]. In [14], Wind Driven Optimization (WDO) is proposed as a new method to estimate solar PV parameters. The accuracy and convergence time of Pattern Searching (PS), Genetic Algorithm (GA), and

Simulated Annealing (SA) have been compared for single-diode and dual-diode solar PV models. In [15], a flexible particle swarm optimization (FPSO) algorithm is proposed to estimate PV cell model parameters. The performance of this algorithm is that an elimination step is added to the classical PSO. At the beginning of each step, a certain number of worst particles are removed and some new particles are replaced in the new search space. Also, the parameters search space in each particle changes based on the value of these parameters. These changes have increased the performance of the proposed algorithm by adding global search capabilities as well as searching in a sensible space. Extraction of PV parameter was done in [16] using optimization method with honey badger algorithm (HBA) and wild horse optimizer (WHO). PV cells and modules were modeled with single-diode model (SDM) and double-diode model (DDM) and tested with real measurement data. In this reference, Root-mean-square deviation (RMSE) was chosen as the objective function. To determine the parameters of solar PV modules and cells, the chaos game optimization (CGO) method is presented in [17] for the single diode model. The objective function in this paper is also considered based on the root mean square error (RMSE) between the measured and estimated data sets. In [18], an effective meta-heuristic algorithm based on Tunicate swarm algorithm (TSA) is proposed to identify the parameters of PV models. The proposed improved algorithm (ITSA) has two main steps in each iteration: searching the entire search space based on a randomly selected cover and improving the search using the position of the best possible cover. A new intelligent optimization algorithm called mayfly algorithm (MA) has been proposed to effectively identify the diode model of PV cells in [19], which uses the minimum root mean square error (RMSE) as an evaluation index to verify the effectiveness.

This article, it is intended to estimate the parameters of the equivalent circuit of the two-diode model of the PV system by using the method based on artificial intelligence. Based on this, at first, using the particle swarm algorithm as a suitable method, 7 parameters of the two-diode model were optimized. In order to check the performance of the particle swarm method, different strategies were considered for it, including PSO algorithm with random inertia coefficient, time-varying inertia coefficient, time-varying learning coefficients, contraction coefficient, and average. Next, the Archimedes optimization method as a new algorithm in this field was proposed and investigated, and the parameters of the two-diode model were optimized based on it. In order to further compare, the results obtained from the optimization of the parameters of the two-diode model of the PV system for methods such as Bees Algorithm (BA), Pattern search algorithm (PS), Harmony Search algorithm (HS), and Simulated Annealing algorithm (SA) are compared and the method The final optimum was presented.

2. Photovoltaic cell modeling

The electrical equivalent circuit of the two-diode model PV system is shown in Figure (1). The electrical equivalent circuit suitable for this model includes two diodes, a current source, and two resistors in series and parallel. These resistances have an effect on the voltage and current characteristics of the photovoltaic cell. This model is characterized by seven parameters called $R_s, R_{sh}, I_{ph}, I_{d1}, I_{d2}, n_1, n_2$.

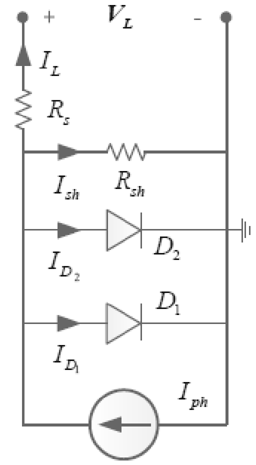

Figure (1): Equivalent circuit of two diodes of PV system

Considering the equivalent circuit of two diodes of the PV system, the formulation of the problem is considered as relations (1) to (3).

$$I_t = I_{p\square} - I_{d_1} - I_{d_2} - I_{s\square} \quad (1)$$

$$I_t = I_{p\square} - I_{sd_1}\left[exp\left(\frac{q(V_t+R_sI_t)}{n_1kT}\right) - 1\right] - I_{sd_2}\left[exp\left(\frac{q(V_t+R_sI_t)}{n_2kT}\right) - 1\right] - \frac{V_t+R_sI_t}{R_{s\square}}$$

$$f(V_t, I_t, x) = I_t - I_{p\square} + I_{sd_1}\left[exp\left(\frac{q(V_t+R_sI_t)}{n_1kT}\right) - 1\right] + I_{sd_2}\left[exp\left(\frac{q(V_t+R_sI_t)}{n_2kT}\right) - 1\right] + \frac{V_t+R_sI_t}{R_{s\square}}$$

In these relationships, I_{ph} is the current source that is placed in parallel with the diode and represents the current generated from sunlight, I_{d1} and I_{d2} are the saturation current of diodes D1 and D2, R_s series resistance represents the internal resistance of the cell and depends on the semiconductor resistance, R_{sh} resistance The parallel is proportional to the dispersion at the P-N junction point and n1 and n2 are the L coefficients of the diodes.

3. Optimizing circuit model parameters of two diode PV system

3.1 Particle swarm optimization algorithm

The particle swarm optimization method is a population-based stochastic optimization algorithm that is modeled from the simulation of the social behavior of a group of birds [20]. The PSO algorithm has several parameters, each of which has an effect on the denoising performance. These parameters are: the number of particles N, the maximum number of repetitions, the learning coefficients 1C and 2C and the inertia coefficient ω. The inertia coefficient has a direct effect on the convergence of the PSO algorithm. In fact, it is possible to change the value of ω to establish a balance between global search and local search. A large value for ω causes the particles in the algorithm to search for newer regions and perform a global search. On the contrary, a small value of ω makes the particles stay in a limited area and actually perform a local search. The right value for ω creates a balance between local and global searches and in most cases reduces the number of iterations required to converge to a suitable solution. According to these conditions, achieving the optimal value of ω is very important. Accordingly, in this article, the PSO algorithm with random inertia coefficients of 1ω, time-varying inertia coefficient of 2ω, contraction coefficient of 3ω, time-varying learning coefficients of 4ω and average of 5ω have been compared as improved methods of the PSO algorithm against the conventional PSO method (IPSO).

3.2 Archimedes optimization algorithm

Currently, meta-heuristic optimization algorithms are often considered to solve complex engineering problems due to their ability to explore and exploit to achieve better results compared to classical algorithms. In this article, the AOA algorithm presented in 2021 is used. The AOA algorithm is a high-performance optimization tool with regard to the speed of convergence and the balance of exploration and exploitation, and it can be used effectively to solve complex problems, and it has a more accurate speed and performance than the Harris Hawks optimization [21]. AOA is a crowd-based algorithm. Like other crowd-based meta-heuristic algorithms, AOA also starts the search process with an initial population of objects with random volume, density, and acceleration. After evaluating the fitness of the initial population, AOA is repeated until the convergence condition is met and the algorithm terminates. In each iteration, the algorithm updates the density and volume of each object. The acceleration of the object is updated based on the conditions of its collision with any other neighboring object. The updated density, volume, and acceleration determine the new position of an object. Below is a detailed statement of the mathematical steps of AOA.

- **Initialization of the population in this algorithm according to equation (4)**

$$O_i = lb_i + rand \times (ub_i - lb_i); \quad i = 1,2,\ldots,N \tag{4}$$

In the above relation, Oi is the i-th object from the total population (N). ubi specifies the upper limit and lbi the lower limit of the search space. The initial size and density of each population is determined randomly. The initial acceleration of the i-th object (acci) can also be calculated from equation (5).

$$acc_i = lb_i + rand \times (ub_i - lb_i) \tag{5}$$

In this step, the initial population will be evaluated and the best fitting part will be selected.

- **In this step, the volume (vol) and density (vol) of each object are updated.**

$$vol^{t+1}{}_i = den^t{}_i + rand \times (den_{best} - den^t{}_i) \tag{6}$$
$$vol^{t+1}{}_i = vol^t{}_i + rand \times (vol_{best} - vol^t{}_i)$$

- **Transfer operator and compression coefficient**

First, the collision between objects occurs and after some time, they try to reach the equilibrium state, which is implemented using the transfer operator TF in the AOA algorithm to transform the search from exploration to exploitation.

$$TF = \exp(\frac{t - t_{\max}}{t_{\max}}) \tag{7}$$

Where, TF gradually increases towards 1. In the above relationship, t is the repetition count and tmax is the maximum repetition value. Also, the density increase coefficient d accompanies the AOA algorithm in local and global search and is calculated from the following equation.

$$d^{t+1} = \exp(\frac{t - t_{\max}}{t_{\max}}) - (\frac{t}{t_{\max}}) \tag{8}$$

If the TF coefficient is less than 0.5, then:

$$\mathrm{acc}_i^{t+1} = \frac{den_{mr} + vol_{mr} \times acc_{mr}}{den_i^{t+1} \times vol_i^{t+1}} \tag{9}$$

In the above relationship, den_i^{t+1} is the density, vol_i^{t+1} is the volume, and acc_i^{t+1} is the acceleration of particle i, and den_{mr} is the density, vol_{mr} is the volume, and acc_{mr} is the acceleration of the random substance. Applying a value other than 0.5 changes the exploration-exploitation behavior. If the TF coefficient is greater than 0.5, then there is no collision between the objects and the acceleration of the object in repetition t+1 is determined from the following equation.

$$\mathrm{acc}_i^{t+1} = \frac{den_{best} + vol_{best} \times acc_{best}}{den_i^{t+1} \times vol_i^{t+1}} \tag{10}$$

Equation (11) is used to determine the percentage of changes and the normalized acceleration coefficient. If the object (i) is far from the global optimum, the acceleration value will be high, which means that the object will be in the exploration stage. Otherwise, the object is in exploitation phase. In the normal case, the acceleration coefficient starts with a large value and decreases with time, helping the search agents to move towards the global best path while moving away from the local optima.

$$\mathrm{acc}_{i-norm}^{t+1} = u \times \frac{\mathrm{acc}_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + 1 \tag{11}$$

- **Location update**

If TF is less than 0.5, then the location of the particle is updated using equation (12) and in this relation, the C1 coefficient is equal to 2. Otherwise, particle optimization can be calculated from equation (26) and in this relation, C2 coefficient is equal to 6 and C3 coefficient is a number between 0.3 and 1.

$$x_i^{t+1} = x_i^t + C_1 \times rand \times \mathrm{acc}_{i-norm}^{t+1} \times d \times (x_{\mathrm{rand}} - x_i^t) \quad (12)$$

$$x_i^{t+1} = x_{best}^t + F \times C_2 \times rand \times acc_{i-norm}^{t+1} \times d \times (T \times x_{best} - x_i^t) \quad (13)$$
$$T = C_3 \times TF$$

The coefficient F in the above relationship is also calculated as follows.

$$F = \begin{cases} 1 & p \le 0.5 \\ -1 & p \ge 0.5 \end{cases} \quad (14)$$
$$p = 2 \times rand - C_3$$

3.3 Optimization parameters and objective function

In order to evaluate the efficiency of the method of determining the parameters of the equivalent circuit of two diodes by different strategies of PSO and AOA algorithm, the volt-ampere characteristic of a 57 mm silicon solar cell has been used. The experimental data was obtained from a system under irradiated 21000 w/m2 at a temperature of 33°C. In the PSO algorithm, the number of particles is 100, the maximum repetition is 500, the learning coefficients are C1=C2=2, and the inertia coefficient is ω=1. In the optimization algorithm, the unknown parameters of the solar cell are considered as a vector $x = [R_s, R_{sh}, I_{ph}, I_{d1}, I_{d2}, n_1, n_2]$ for the two diode model. To evaluate the performance of the algorithm, according to equation (15), the sum of squares criterion is used to determine the difference between the results obtained from the algorithm and the results obtained from the laboratory test.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(f_i(V_t, I_t, x))^2} \quad (15)$$

$f_i(V_t, I_t, x)$ expresses the mathematical relationship of the current-voltage curve of the two-diode model of the photovoltaic system, which is defined in equation (3). The upper and lower limits of the two-diode solar cell parameters are specified in Table (1).

4. Results

4.1 Problem solving by PSO method

By applying the PSO and improved PSO optimization algorithms to the studied system, the values of the optimal parameters and the objective function of the two-diode model using different strategies are given in Table (2). As can be seen, strategies of time-varying inertia, inertia with contraction coefficient, and time-varying learning have obtained the lowest objective function values, which are 0.000942, 0.00083482, and 0.00093917, respectively. As it is evident, the objective function defined for the inertial strategy with the contraction coefficient has obtained the lowest possible value and the best estimate for the parameters of the solar cell. Therefore, PSO-ω3 will be considered for comparison with other optimization methods.

Table (1): Range of parameter changes of 2-diode model

PARAMETER	LOWER LIMIT	UPPER LIMIT
R_s	0	0.5
R_{sh}	0	100
I_{ph}	0	1
I_{d1}	0	1
I_{d2}	0	1
n_1	1	2
n_2	1	2

Table (2): Comparison of results of PSO method with different inertia coefficient

	IPSO	PSO ω1	PSO ω2	PSO ω3	PSO ω4	PSO ω5
Rs	0.352	0.348	0.222	0.455	0.255	0.209
Rsh	51.28	56.88	66.85	91.97	47/94	44.91
Iph	0.993	0.98	0.941	0.99	0.963	0.973
Isd_1	0.483	0.299	0.048	0.282	0.02	0.0264
Isd_2	0.203	0.172	0.263	0.139	0.34	0.264
N_1	1.97	1.34	1.37	1.38	1.67	1.53
N_2	1.35	1.09	1.89	1.87	1.79	1.21
objective function	39398e -6	39414e -6	942 e-7	83482e -7	93917 e-7	39428e -6

Figure (2) shows the V-I characteristic estimation curve of the two diode model by the PSO algorithm with the contraction inertia coefficient compared to the actual volt-ampere characteristic curve. Also, the convergence curve of optimization methods based on PSO is shown in Figure (3). According to the obtained results, although the convergence speed of the random method is higher than other methods, it is the contraction method that obtains the lowest value of the objective function.

4.2 Problem solving by AOA method

The results of estimating the parameters of the two-diode solar cell model using the AOA optimization method are shown in this section. The values obtained from this method for the parameters of the two-diode model are presented in table (3). As can be seen, the value of the objective function in this case has reached 0.00081059, which is reduced by 29% compared to PSO-ω3. The convergence curve of the objective function based on the AOA method is shown in Figure

(4). According to this figure, the convergence speed and accuracy are improved.

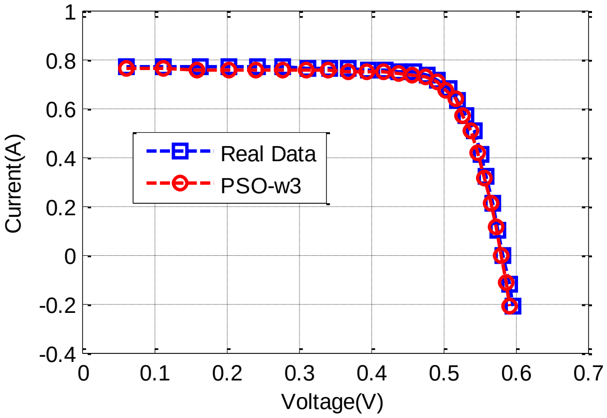

Figure (2): Comparison of V-I characteristic curve of two diode model using parameter estimation by PSO-ω3 method and real data

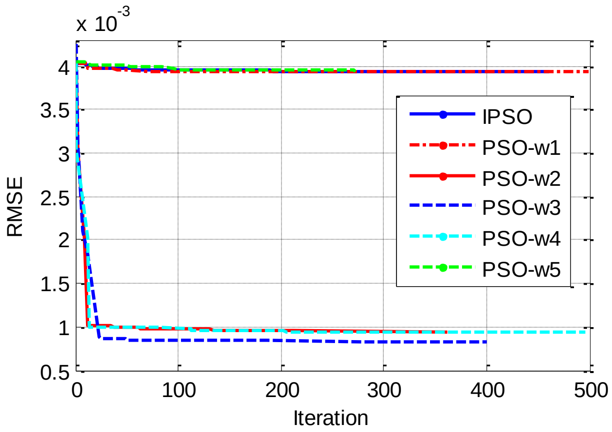

Figure (3): Convergence changes of PSO-based methods

Table (3): Parameters of two diode circuit model estimated by AOA method

parameters	Rs	Rsh	Iph	Isd۱
Amounts	0.14182	55.3774	0.66215	0.34768
parameters	Isd۲	N۱	N۲	RMSE
Amounts	0.77819	1.5545	1.92983	81059e-7

4.3 Comparison of optimization methods

By determining the optimal values of the parameters and the value of the objective function in the single-diode and two-diode models by using the parameters estimation through different PSO and AOA strategies and also the availability of the research results on the case study according to what is considered in this article. is, table (5) is provided. To compare the results, the results presented in [22] based on Harmony Search algorithm (HS), Pattern search algorithm (PS), metal annealing simulation (SA), and Bees Algorithm (BA) were used. According to the obtained results, it has been seen that the PSO-ω3 and AOA methods used in this article have obtained much better results in minimizing the mean square error.

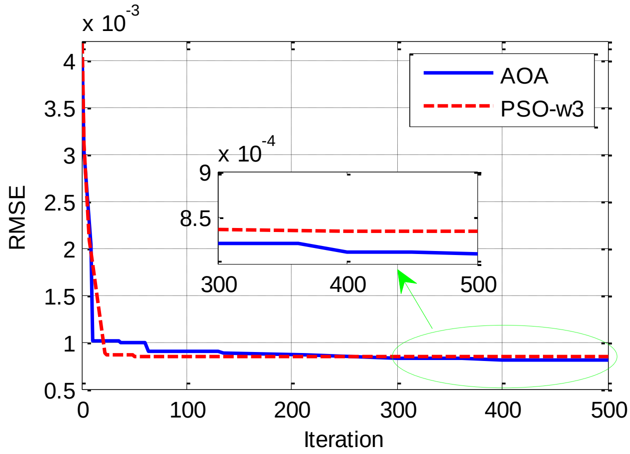

Figure (4): Convergence changes of the AOA method in estimating the parameters of the 2-diode circuit model

Table (4): Comparison of the results obtained from the parameters of the two diode model using different methods

	PSO ω3	AOA	BA
Rs	0.455	0.14182	0.03657
Rsh	91.97	55.3774	54.621
Iph	0.99	0.66215	0.76078
Isd1	0.282	0.34768	0.2671
Isd2	0.139	0.77819	0.3819
N1	1.38	1.5545	1.4651
N2	1.87	1.92983	1.9815
objective function	83482e-7	81059e-7	9834e-7
	PS	SA	HS
Rs	0.032	0.0345	0.0354
Rsh	81.3	43.103	46.827
Iph	0.7602	0.7623	0.7618
Isd1	0.9889	0.4767	0.1255
Isd2	0.0001	0.01	0.2547
N1	1.6	1.5172	1.4944
N2	1.192	2	1.4999
objective function	151e-4	166e-4	126e-5

5. Conclusion

The voltage-current characteristic of PV systems plays a very important role in optimizing the dimensions and maximizing the power extracted from it. Accurate modeling of V-I characteristics of solar cells due to their non-linear nature is considered as an optimization problem and should be solved using intelligent search algorithms. In this article, the PSO algorithm was investigated with different strategies to accurately estimate the parameters of the two-diode model photovoltaic system. Also, the AOA optimization method was used as a new method in this article. Finally, the obtained results were compared with the results obtained from references for the circuit model of two diodes. Some of the most important results obtained are as follows.

- In the common PSO strategy, for the two-diode model, the lowest value of the objective function is 0.0039398.
- In the PSO method with the contraction inertia coefficient, the lowest value of the objective function of the optimization problem is 0.00083482. By comparing the simulation results, it can be seen that the best estimation of the parameters of the equivalent circuit of two diodes, which has led to the greatest agreement with the volt-ampere curve of the real model, has been obtained by using the contraction inertia coefficient method.
- The use of AOA algorithm led to the improvement of the results, and finally, the minimum mean square error equal to 0.0081059 was obtained for this method, which led to a 29% improvement in the accuracy of model parameters estimation.
- Comparing the results obtained from PSO-ω3 and AOA methods with methods performed in references including HS, PS, SA and BA confirms the higher accuracy and better speed of the methods proposed in this article.

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