Accurate Estimation of PV Cell Equivalent Circuit Parameters with Evolutionary Algorithms

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Abstract

Accurate estimation of equivalent circuit parameters in photovoltaic (PV) cells is of great importance to improve the efficiency, performance and cost effectiveness of PV systems. It also allows better monitoring and modeling of the system's behavior over time. To achieve this, two different evolutionary algorithms, Harmony Search (HS) and Genetic Algorithm (GA), were used and the performances of both algorithms for two different temperature values were compared with previous studies in the field. The results obtained revealed that the temperature value is effective for HS and GA in estimating the parameters of the double diode equivalent circuit model. These findings highlight the effectiveness of the proposed optimization methodology and highlight that temperature values are important in choosing the algorithm to be used and that HS and GA are a powerful tool to optimize the parameters of the PV cell equivalent circuit and therefore improve the output current.

1. Introduction

Renewable energy sources present a significant alternative for satisfying the escalating global energy demand. Among these sources, solar energy emerges as a prominent option due to its clean and boundless nature. Photovoltaic (PV) panels enable the conversion of solar energy into electricity. Consequently, the optimization of PV systems assumes paramount importance to enhance the efficacy of solar energy utilization. Within this optimization process, the accurate estimation of equivalent circuit model parameters for PV cells is crucial.

PV cells consist of semiconductor (SC) materials, giving rise to non-linear characteristics in terms of current-voltage or power-voltage relationships. Considering this, numerous equivalent circuit models have been proposed in the literature for the purpose of PV cell modeling. These models encompass the single diode model, double diode models, empirical models, and more. The nonlinear characteristics exhibited by PV cells hold significant importance when aiming to maximize their output. The optimization of equivalent circuit parameters for PV cells has a direct impact on enhancing the efficiency, performance, and cost-effectiveness of PV systems. Moreover, it facilitates the monitoring and modeling of system behavior over time. Optimization refers to a process employed to identify the most suitable solution within specified constraints, tailored to one or more specific objectives. Given the limitations associated with mathematical methods in terms of flexibility, evolutionary algorithms have gained prominence in the field of optimization. Evolutionary algorithms offer greater flexibility and ease of use, making them increasingly preferred in optimization processes. They possess a high aptitude for discovering solutions, rendering them particularly suitable for addressing complex problems where traditional mathematical methods are inapplicable.

Evolutionary algorithms (EAs) draw inspiration from natural processes and have been developed for specific purposes, leveraging their superior performance. Among the array of evolutionary algorithms available, particle swarm optimization (PSO) and genetic algorithm (GA) are particularly favored in the context of PV systems. Both PSO and GA have demonstrated their efficacy in optimizing PV systems, providing valuable insights into parameter tuning, system design, and performance improvement [1,2].

Numerous EAs and their variants have been employed for parameter estimation of PV modules. In [2], a hybrid GA-PSO is utilized to extract parameters for the single diode PV model. Ketkar et.al. introduced the Artificial Bee Colony (ABC) algorithm for estimating parameters in the double diode model [3], where a modified version of ABC demonstrated superiority over the traditional approach. In [4] and [5], the performance of PSO algorithm is investigated to estimate parameters for three diode cell model and single/double diode cell models, respectively; revealing the impact of EA usage for improving solar energy system performance. In [6], Salp Swarm Algorithm (SSA) is proposed for parameter estimation in both single and double diode solar PV models. In [7], the enhanced Levy flight bat algorithm (ELBA) was employed for single and double diode modeling of three benchmark PV sources: the RTC France silicon cell, the STM6-40 monocrystalline silicon module, and the PVM 752 GaAs cell, whose experimental data were provided by NREL. In [8], a new algorithm, named Whippy Harris Hawks Optimization (WHHO), was proposed to enhance the performance of cell model parameter estimation considering three types of commercial PV modules and including the effect of temperature and irradiance changes. Another work [9] represents a method of extracting single diode model parameters from PV solar cells using differential evolution and the three-point curve fitting approach. The single diode model is simple and easy to implement, whereas the double diode model has superior accuracy, which acquiesces for a more precise forecast of PV systems performance as proven by research [10]. In [11] Harmony Search (HS) algorithm was employed for single and double diode parameter extraction. Three HS variants are used to extract the optimal parameters of both the single and double diode models. It is revealed that the accuracy of the double diode model is slightly more than that of the single diode model. Results obtained using HS variants are quite promising and superior, especially when compared to the other methods. In this work, a comparative analysis between single diode and double diode models of PV solar cells is carried out to enhance the conversion efficiency of PV solar systems.

Based on the literature review conducted, a particular aspect was observed in the study [2], where the I_D diode saturation current was disregarded in the single diode PV cell model. To address this limitation, our study opted for the utilization of a seven-parameter double diode model, which accounts for the absence of the I_D current. The parameter values for this seven - parameter double diode PV cell were determined through the employment of the HS and GA. While the single diode model offers simplicity in design and ease of operation, the double diode model is known to provide higher efficiency [10].

Subsequently, the performance of both algorithms was evaluated to determine the most suitable model for future research endeavors in this field. Notably, during the examination of previous studies, there was a lack of mention regarding whether the results obtained were trapped in local minima or not. This is noteworthy as early convergence and local minima are considered disadvantages of the HS and GA algorithms. To address this limitation, repeated runs were conducted. The consistency of the algorithms was assessed by constructing box-whisker plots based on the outcomes of these runs. Minimizing the cost function by identifying the optimal own parameters for HS and GA is crucial for enhancing the effectiveness and accuracy of these evolutionary algorithms in parameter estimation for the PV cell double diode equivalent circuit model. In addition, compared to the studies conducted with HS and GA in the literature, the effect of temperature on the performance of the algorithms in parameter optimization of single and double diode cells was investigated and comparisons were made regarding the error results of two different temperatures.

The fundamental objective of the present study is to obtain an effective and accurate estimation methodology for the PV cell double diode equivalent circuit model and to enhance the output current and voltage by utilizing the parameter values derived from the HS and GA. This lays the groundwork for future research, where the performance of PV system employing a boost converter driven by PV cells will be investigated using the optimized parameter values obtained through evolutionary algorithms. The anticipated outcome is an improved output current and voltage, leading to enhanced efficiency and performance of the boost converter circuit.

2. Photovoltaic Cell Model

A solar cell is a thin SC wafer containing a p-n junction. Its primary function is to harness the PV effect, which enables the conversion of solar energy into electrical energy. When sunlight impinges upon a solar cell, the photons within the radiation carry energy, leading to the creation of electron-hole pairs within the SC material.

Due to the SC nature of solar cells, their current-voltage and power-voltage characteristics exhibit non-linearity. Consequently, various equivalent circuit models have been developed to accurately represent their behavior in modeling and analysis. These models provide a means to capture the complex electrical characteristics of solar cells and facilitate their inclusion in system-level simulations and optimizations. By utilizing equivalent circuit models, the non-linear behavior of solar cells can be effectively captured.

Fig. 1 indicates an equivalent model for PV cells, which is called the double diode model [3, 5, 6, 7]. PV cell is modeled by the current obtained from the sun and the current flowing through diodes 1 and 2, together with the resistance linked parallel to the diode, and the resistance attached to the output of the circuit. The output current of this equivalent circuit is I, and the output voltage is V. The output current is calculated using "(1)". By substituting “(2)”, “(3)” and “(4)” in “(1)”, the current equation “(5)” of the double diode model is generated.

$$I = I_{PV} - I_{D1} - I_{D2} - I_{sh} \tag{1}$$

$$I_{D1} = I_{SD1}\left[\exp\left(\frac{q(V+IR_s)}{kTa_1}\right) - 1\right] \tag{2}$$

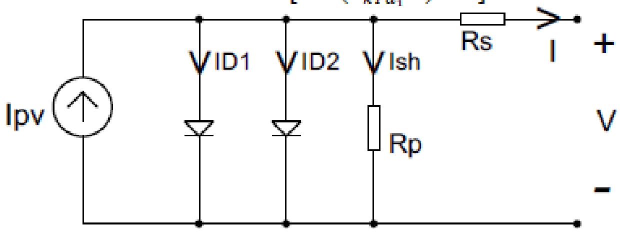

Fig. 1. Double-diode model of a PV cell

$$I_{D2} = I_{SD2}\left[\exp\left(\frac{q(V+IR_s)}{kTa_2}\right) - 1\right] \tag{3}$$

$$I_{sh} = \left[\frac{V+IR_s}{R_P}\right] \tag{4}$$

$$I = I_{PV} - I_{D1}\left[\exp\left(\frac{q(V+IR_s)}{kTa_1}\right) - 1\right] - I_{D2}\left[\exp\left(\frac{q(V+IR_s)}{kTa_2}\right) - 1\right] - \left[\frac{V+IR_s}{R_P}\right] \tag{5}$$

In these equations, I_{SD} represents the reverse saturation current of the diode, q is the charge of an electron, k is the Boltzmann constant, T is the temperature of the p-n junction in Kelvin, and a is the ideality factor of a diode.

Using “(5)” as actual output current and characteristic data from RTC France Solar Cell [7], optimization algorithms aim to calculate the optimal values of seven different parameters which are I_{PV} , I_{D1} , I_{D2} , R_S , R_P , a_1 and a_2 by minimizing the cost function, which is explained in Section IV.

3. Evolutionary Algorithms

3.1. Harmony Search

HS is a music-based meta-heuristic algorithm which was developed in 2001 by Geem et al [12]. The search process is iterative and follows five steps. The first step involves determining the parameters for the HS. And followed by generating a random solution equal to the size of the harmony memory. The third step entails the creation of a new solution through inspiration. The fourth and final steps are the evaluation of the new solution and controlling the number of iterations, respectively [12].

Harmony memory is a crucial component of this algorithm. Optimal solutions in memory are transferred to the next iteration, attempting to approach the optimum. Harmony memory consideration rate determines the ratio at which the decision variable will be selected from a value in the harmony memory, and this ratio is in the range of {0,1}. The pitch adjustment ratio is the sum of the adjacent values of a note value selected from the harmony memory that determines whether to review. In the literature, both linear and nonlinear PAR functions are found, but generally, the following linear pitch adjustment function is used.

$$X_{new} = X_{old} \pm rand(0,1) * bandwidth \tag{6}$$

3.2. Genetic Algorithm

GA was introduced by John H. Holland [13] and popularized by David Goldberg in 1989 [14], which is based on Darwin's theory of evolution. It calculates the suitability value of individuals by repeating the selection, crossover, and mutation processes until a stopping criterion is met and ensures that the most suitable individual is selected. Selection is the process of choosing candidate solutions from the population to be used as parents for the next generation. Crossover is a genetic operator used to combine genetic material from two or more parent solutions to create new candidate solutions. Mutation, on the other hand, is a genetic operator used in genetic algorithms to introduce new genetic material into the population by randomly altering one or more genes in a candidate solution [13, 14].

4. Equivalent Circuit Optimization with EA

The cost functions to be used in these algorithms are required to optimize the equivalent circuit parameters with GA and HS. The cost function is a mathematical model for an optimization problem. This function is used to measure the quality of the solution to the problem and determine how good the solution is. In this study, minimizing the cost function, which is the root mean square error (RMSE) between the target current, and the actual current is aimed at. The target current is *0.7603* A which is the characteristic data from the R.T.C. France solar cell [7].

$$Cost\ Function = \left(\sqrt[2]{\left(\frac{\sum_{i=1}^{N} (I_{Target} - I_{Actual})^2}{N} \right)} \right) \quad (7)$$

Here, N is the number of candidate solutions in evolutionary algorithms. The constraints used for cost function parameters are provided below. These constraints are selected from the R.T.C. France solar cell [15], where units for currents and resistors are A and Ω, respectively.

$$0 \leq I_{PV} \leq 1 \quad (8)$$

$$0 \leq I_D \leq 10^{-6} \quad (9)$$

$$1 \leq a \leq 2 \quad (10)$$

$$0 \leq R_S \leq 0.5 \quad (11)$$

$$0 \leq R_P \leq 100 \quad (12)$$

5. Simulation Results

The obtained parameter values on double diode cell model are evaluated by means of accuracy. Simulation results of GA and HS based estimation of model parameters are investigated in the following. The simulation was carried out using the 1.30-1,50 GHz Intel(R) Core(TM) i7-1065G7 CPU with 16 GB RAM on a PC with the MATLAB R2021b simulation environment. The resulting parameter values were obtained from the radiation (1000 W/m^2) and two different operating temperature (33℃ - 50℃) of a commercial RTC France silicone solar cell. Here, two different temperature values are used in order to compare how the temperature impacts the algorithms' output.

Considering the HS algorithm, the following parameter settings were adopted after trial-and-error sequences:

- The harmony memory size is 50, indicating the number of solutions stored in the harmony memory.
- The HS iteration number is 50, representing the number of times the HS process was repeated.
- Number of new harmonies: Two values were utilized, namely 50 and 40, indicating the number of new solutions generated in each iteration.
- The harmony memory consideration rate is 0.75, indicating the proportion of solutions in the harmony memory that are considered for generating new solutions.
- The Pitch adjustment rate is 0.3. PAR manages local search in a narrow area. As PAR approaches 0, local diversity decreases, and as PAR approaches 1, it begins to gain random search properties.
- The bandwidth is determined as 0.04 times the range of parameter values.
- Bandwidth dump ratio is 0.995, indicating the rate at which the bandwidth is reduced in each iteration.

Considering the GA algorithm, the following parameter settings were adopted after trial-and-error sequences:

- The iteration number is 50, indicating the number of generations or iterations in the genetic search process.
- The population size is 20, representing the number of candidate solutions (individuals) in each generation.
- The crossover probability is 0.7, indicating the likelihood of two individuals producing offspring.
- The mutation probability is 0.06, indicating the likelihood of mutation occurring for an individual.
- The mutation parameter is 0.3.

The selected parameter values aim to set a balance between exploration and exploitation while ensuring efficient convergence towards optimal solutions.

5.1. Double Diode Equivalent Circuit Simulation Results

The determination of the own parameters of EAs is done by obtaining the minimum cost function value at the end of the iterations. The abovementioned own parameters are set for GA and HS, 50 iterations are carried out to observe the decrement characteristic of cost function value with respect to increment of iteration number. Following the completion of these iterations, the best objective function values at 33℃ were obtained as $2.23x10^{-9}$ for the HS and $9.08x10^{-8}$ for the GA. At 50℃ , the best objective function values were obtained as $1.02x10^{-7}$ for the HS and $8.58x10^{-10}$ for the GA.

The variation of the error according to iteration number at 33℃ is illustrated in Fig. 2, showcasing the convergence behavior of the evolutionary algorithms and their respective effectiveness in minimizing the cost function. Since the cost function is minimized, actual current is obtained such that the difference from target current is also minimized. The actual output currents are obtained as ***0.7593*** A for HS and ***0.7526*** A for GA. Consequently, the double diode equivalent circuit parameters are obtained with evolutionary algorithms using equation "(5)" and are provided in Table 1 alongside the results reported in [7]. A comparison of the RMSE values obtained with GA and HS, as well as the $9.82x10^{-4}$ error value from [7], reveals that the results obtained in this study yield lower error values. Based on this comparison, it can be concluded that the equivalent circuit parameters derived from HS and GA are more effective for the purpose of the integration of a boost converter to the output of the PV module, as planned for the subsequent phase of this study. These findings highlight the significance and practical relevance of the obtained parameters, suggesting their potential for optimizing the performance and efficiency of the boost converter within the PV system.

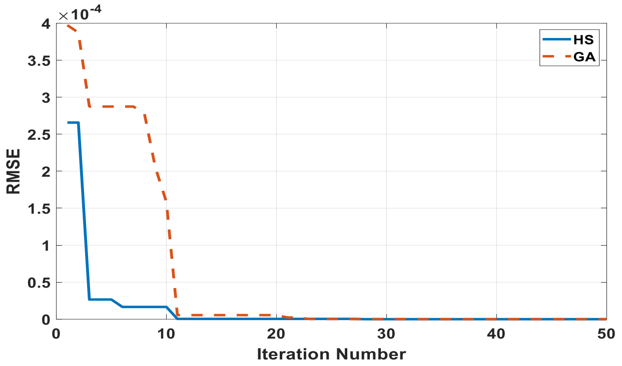

Fig. 2. Cost function minimization of HS and GA for Double Diode PV Cell Model

Table 1. Double diode cell model parameter values obtained with evolutionary algorithms

Equivalent Circuit Parameters	HS	GA	ELBA[7]
Ipv (A)	0.7603	0.7608	0.7607
Id1 (μA)	0.0003	0.0020	0.749
Id2 (μA)	0.0006	0.0018	0.226
Rs (Ω)	0.0031	0.4745	0.0367
Rp (Ω)	34.65	83.19	55.485
a1	1.789	1.199	2
a2	1.387	1.304	1.45

Subsequently, we conducted a comprehensive analysis of the performance of the GA and HS through 25 independent runs maintaining the own parameters of the EAs. The objective is to assess the consistency and robustness of both algorithms and evaluate the variation of RMSE values throughout each independent run. Considering 25 runs, at 33℃ the average cost function value is obtained as *1.75x10^{-7}* for HS and *2.57x10^{-6}* for GA. At 50℃ the average cost function value is obtained as *3.34x10^{-6}* for HS and *3.77x10^{-6}* for GA.

To visualize the variation in error across these 25 runs, box and whisker plots were generated and presented in Fig. 3 and Fig.4. These plots provide a comprehensive overview of the distribution and central tendencies of RMSE values obtained from each algorithm at different temperature. The box represents the interquartile range, while the whiskers extend to the minimum and maximum values. The upper and lower ends of boxes represent the 75th and 25th percentiles. The median is depicted by the red line. Outliers are data with values beyond the ends of the whiskers. By examining these plots, we gain insights into the overall performance and stability of GA and HS in achieving the desired optimization results over multiple runs.

When we examine the box whisker graphs at 33℃, we can observe that the box spacing of the HS algorithm is smaller, that is, the RMSE values obtained because of the HS algorithm are closer to each other. However, when the temperature value is increased to 50℃, it turns out that the RMSE values obtained because of GA are more consistent.

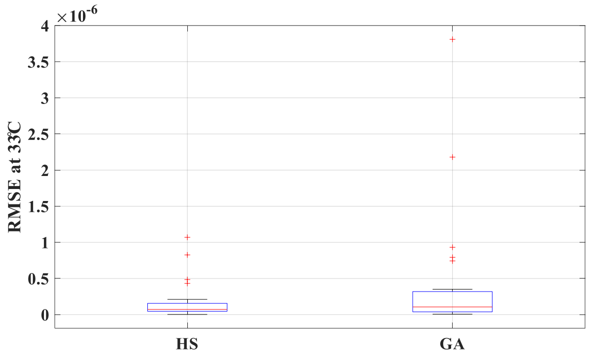

Fig. 3. Box and whisker plots for comparing EA performances for Double Diode Model Parameter Values over 25 runs at 33℃

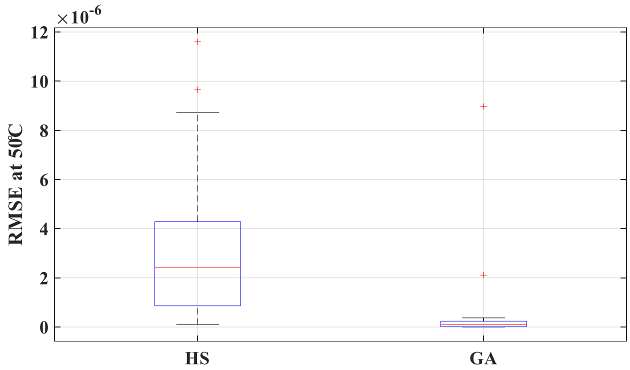

Fig. 4. Box and whisker plots for comparing EA performances for Double Diode Model Parameter Values over 25 runs at 50℃

6. Conclusions

The optimization of equivalent circuit parameters in PV cells and panels remains a focal point of research in renewable energy sources. While significant progress has been made, the exploration of optimization techniques for PV cells continues to be a popular area of investigation in the literature considering improved effectiveness in renewable energy system design.

This paper introduces a comprehensive analysis of EA usage for calculating the values of solar cell parameters that directly influence the conversion efficiency, power conversion, and characteristic curve of the PV cell. The HS and GA methods are employed in this study and have proven to be effective in optimizing the double diode equivalent circuit parameters of the R.T.C. France cell. The results obtained from these methods surpass those published in previous studies, highlighting their efficacy in achieving superior outcomes.

The application of HS and GA have been studied previously for the optimization of double diode equivalent circuit model parameters but temperature changing has not been considered. In this study , temperature value was changed and observed how results have been changed. At different temperatures, algorithms performance has changed. Because of that situation HS was better than GA when standard test conditions, but when temperature was increased GA have been become consistent and error values has decreased. Not only the best results but also multiple independent runs have taken into account to validate the accurate estimation performance of the proposed methods. Evolutionary Algorithms (GA and HS), which are constructed with the selected own parameters are very successful tools for cost effective and accurate estimation of equivalent circuit parameters with constraints.

Overall, this research presents powerful and efficient approaches for double diode equivalent circuit parameter optimization in PV cells, contributing to improved output current and characterization of solar energy systems. By leveraging the equivalent circuit parameters derived from HS and GA, the study is planned to be extended in order to achieve better integration of the boost converter driven by PV cells for enhanced power conversion and improved system performance.

7. References

[1] J.J Soon, K.S. Low , "Photovoltaic model identification using particle swarm optimization with inverse barrier constraint," IEEE Transactions on Power Electronics ,27, 2012.

[2] C. Saravanan, M.A. Panneerselvam, "A comprehensive analysis for extracting single diode PV model parameters by hybrid GA-PSO algorithm," Int Journal of Computer Applications, 78, 2013.

[3] M. Jamadi,F. Merrikh-Bayat, M. Bigdeli, "Very accurate parameter estimation of single- and double-diode solar cell models using a modified artificial bee colony algorithm," Int J Energy Environ Eng, 2016.

[4] V. Khanna, B.K. Das, D. Bisht, Vandana, P.K. Singh,"A three diode model for industrial solar cells and estimation of solar cell parameters using PSO algorithm," Renew Energy, 2015.

[5] A.H. Elsheikh, M. Abd Elaziz, "Review on applications of particle swarm optimization in solar energy systems" Int. J. Environ. Sci. Technol. 16, 1159–1170, 2019.

[6] R. B. Messaoud, "Extraction of uncertain parameters of single and double diode model of a photovoltaic panel using Salp Swarm algorithm," Measurement,Vol.154, March 2020.

[7] L.M.P. Deotti, J.LR. Pereira, I.C.S Júnior, "Parameter extraction of photovoltaic models using an enhanced Lévy flight bat algorithm", Energy Conversion and Management, 221, 2020.

[8] M. Naeijian, A. Rahimnejad, S. M.Ebrahimi, N. Pourmousa, S.A. Gadsden, "Parameter estimation of PV solar cells and modules using Whippy Harris Hawks Optimization Algorithm", Energy Reports, 7, 4047-4063, 2021.

[9] S.M.Ebrahimi , E. Salahshour , M. Malekzadeh , F. Gordillo, "Parameters identification of PV solar cells and modules using flexible particle swarm optimization algorithm", Energy, 2019.

[10] R. Herbazi , Y. Kharchouf , K. Amechnoue , A. Khouya, A. Chahboun, "Solar photovoltaic cell parameters extraction using differential evoluation algorithm" , Proceedings, 2020.

[11] A. Askarzadeh , A.Rezazadeh, "Parameter identification for solar cell models using harmony search-based algorithms", Solar Energy, 2012.

[12] Z.W.Geem, J.H.Kim, G.V.Loganathan, "A new heuristic optimization algorithm: harmony search", J. Simulation 76(2), 60–68, 2001.

[13] J. Holland, "Adaptation in Natural and Artificial Systems". Ann Arbor, MI: Univ. Michigan Press, 1975.

[14] D. E. Goldberg, "Genetic Algorithms in Search, Optimization and Machine Learning," Kluwer Academic Publishers, Boston, MA, 1989.

[15] T. Easwarakhanthan , J. Bottin , I. Bounhouch & C. Boutrıt, "Nonlinear Minimization Algorithm for Determining the Solar Cell Parameters with Microcomputers", International Journal of Solar Energy, 4:1, 1-12.