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Adaptive Genetic Algorithm Based Multi-Objective Optimization for Photovoltaic Cell Design Parameter Extraction

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Abstract

In this paper, an enhanced evolutionary computing algorithm has been attempted for photo voltaic (PV) design parameter extraction using adaptive genetic algorithm. The I-V curve fitting approach has been used to find optimal photovoltaic parameters Unlike single objective function based approaches, multiple objective functions including, least mean square error and Pearson residual error optimization are considered to fit the I-V curve. A cumulative fitness function is derived using both objectives that alleviate computational complexity, local minima and convergence. Importantly, Pearson residual error optimization (PRO) optimizes least mean square error (LSE) reduction while alleviating the probability of under/over-fitting that ensures optimal PV design parameter identification

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Keywords: PV Design Parameter Extraction; Adaptive Genetic Algorithm; Multi-Objective Optimization; I-V Curve Fitting.

1. Introduction

To ensure optimal PV system design parameter identification, I-V relationship of the PV cell has always been the

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dominant solution. Generally, lumped parameter circuit model is employed to simulate the characteristics of the PV cell under varied operating conditions. In practice, there are two main types of PV circuit models applied to assess the I-V characteristics; the single diode model and the double diode model. These PV models encompass design parameters namely generated photocurrent, saturation current, series resistance, shunt resistance, and diode idealist factor, as the key design parameters. The selection of the optimal PV design parameters can be of paramount significance to ensure higher Energy conversion ratio (ECR), and hence higher productivity. In practice, the internal series resistance (R_s) in the equivalent PV model causes output voltage to reduce and the output current to increase. On the other hand, R_{sh} causes internal power losses due to flow of current away current away from the output path. Similarly, the other PV design parameters too influences overall productivity and ECR of the PV system. Therefore, the optimal selection of these PV design parameters is of paramount significance. In general, there are two predominant extraction measures to identify PV cell design parameters; the analytical [1–2] and the numerical extraction techniques [3-4]. Analytical PV extraction approaches need information on different key points of the I–V characteristic curve. In fact, the accuracy of these approaches primarily depends on the precise selection of the key points on the I–V characteristics curve. On the contrary, the I–V curve is usually non-linear and hence any wrong selection of the key points might result into errors in the extracted design parameters. To solve these problems authors [5] have applauded genetic algorithm techniques [5]. On the contrary, the numerical technique functions on the basis of certain mathematical approach where it intends to fit the points on the I-V curve. Unlike traditional evolutionary computing techniques [5], in this paper adaptive genetic algorithm (AGA) based multi-objective optimization (MOO) measure has been developed for PV design parameter extraction. One of the prime novelties of MOO system is the optimization of least mean square (LSE) error reduction (for curve fitting) in conjunction with Pearson residual error (PRE) reduction approach, where each of these error reductions have been considered as individual objectives. The overall results confirm that the proposed PV design parameter extraction can be of significant for real time online-offline parameter identification to ensure higher ECR and PV system performance.

The sections of this paper are divided as follows. The section II discusses the related works on evolutionary computing based PV design parameter extraction. The proposed research work or the contribution is discussed in Section III. Section IV discusses the results and analysis. The conclusion and future scopes are in section V. References used in this paper are presented at the end of this paper.

2. Related Work

In last few years, a number of research efforts have been made for optimal PV design parameter extraction. The robustness of the EC algorithms has gained significant attention across academia-industry to use it for various optimization problems. EC schemes can be stated as the iterative approach that incorporates generation growth which is taken into consideration in a pre-derived and targeted random search by means of the parallel processing techniques to retrieve solution. To estimate optimal PV design parameters, different evolutionary computing (EC) algorithms, genetic algorithms(GA) [6-9], particle swarm optimization (PSO) [10-14], simulated annealing (SA) [13-18], Artificial Bee Colony (ABC) [19], Cuckoo search (CS) [20], Bacterial Forging Optimization (BFO) [21,22] algorithms, and many more have been attempted. Research revealed that the generic EC schemes suffer from local minima, convergence issue and dilapidation for decidedly interactive fitness function. In addition authors [12] found that PSO suffers from limitations such as inconstant parameter selection, and huge computations (iterations >10,000). In reference to the efficacy of SA author [18] revealed that the trade-off between the initial temperature and the cooling schedule could not be addressed in practice and therefore SA seems unsuitable for PV parameter estimation. GA was used in [23, 24] to estimate four design parameters of PV model, saturation current, R_s and R_{sh} and the ideality factor for single diode PV model; however issues such as local minima and convergence remain unexplored. To alleviate this, authors [25] derived a hybrid approach using GA and Nelder-Mead (NM), where GA was used to generate the solutions, which was followed by best solution selection using NM algorithm.

No doubt, a number of bio-inspired meta-heuristic schemes have been developed for PV model or cell designs parameter extraction due to its ability to solve the non-linear functions. However, most of these approaches typically apply multiple agents to achieve optimal solution and leads to huge computation time. The key factor to decide efficacy of an EC schemes is its convergence rate [26, 27]. The prime issues such as convergence and local minima during parameter extraction, iterative accumulation of population in subsequent generation etc. can have adverse impact on the estimation of accurate PV design parameters. Similarly, there can be the multiple solutions to fit the curve, however to enable singular optimal solution, the multiple solutions required to be conserved. Meanwhile, the loss in diversity is unwanted, as dealing with all sub-optimal solutions becomes inevitable to identify the global optimum. Such issues can be avoided by augmenting the search space of parameters [28]. However, it might reduce the convergence rate [27, 28]. Moreover, in addition to the optimal solution search, the parameter extraction mechanism requires satisfying varied boundary constraints. Although the extracted parameters give optimal data points for curve fitting on I-V characteristic, the parameters retrieved might not provide exact PV design parameter as for physical PV module design [29]. When applying EC schemes for PV design parameter estimation, introducing multiple objectives to deal with entity issues can be vital [29]. With this motivation, authors [29] used multi-objective evolutionary algorithm (MOEA) based on non-dominating sorting genetic algorithm (NSGA) for silicon solar cell design and estimated the fitness value from the short-circuited current, open-circuited voltage, and the conversion efficiency. Bendib et al. [30] applied multi-objective optimization model to solve ECR optimization problem where the electrical parameters were considered concurrently as distinct objectives. Lakshmi et al. [31] proposed an adaptive meta-heuristic algorithm using DE to solve combinatorial optimization problems, where they compared performance with other techniques such as NSGA-II, Pareto Archived Evolutionary Strategy (PAES) and multi-objective particle swarm optimization (MPSO). They [31] revealed that their approach outperforms other techniques. Recently, a multi-objective GA was proposed in [32] to enhance the control parameters for rigid spacecraft attitude.

Observing literatures, it can be found that introducing a multi-objective optimization solution with distinct targets to enhance computational efficiency as well as accuracy of computation can be of paramount significance for optimal PV design parameter estimation. Enabling a solution to deal with both the convergence and local minima issues as well as reducing the search space to achieve global minima swiftly, without getting conserved can be vital to enhance computational efficiency in PV design parameter estimation. Considering it as first objective to solve, in this paper an enhanced EC scheme, named Adaptive Genetic Algorithm (AGA) has been proposed. The key feature of AGA like adaptive genetic parameters (crossover probability and mutation probability) selection can significantly reduce the search space parameters and hence can achieve sub-optimal solution without letting system converged or saturated. Since AGA estimates genetic parameters based on the current populations having similar fitness value, it can reduce search space iteratively across generations. It enables process swift enough to avoid any convergence probability. Literatures state that converting multiple solutions into a singular optimal solution can't guarantee avoidance of over-fitting and under fitting of the results [29]. Hence, avoiding such issues can be significant to achieve optimal design parameters. With this objective, in this paper a Pearson residual optimization (PRO) technique has been applied that intends to avoid any probable under-fitting or over-fitting of the solutions. In summary, this research work applies AGA to enable swift and precise curve fitting to achieve PV design parameter estimation solutions, while PRO ensures avoidance of any probable under-fitting or over-fitting. Thus, the proposed approach turns out to be a multi-objective optimization measure to estimate optimal PV design parameters for single diode model.

3. Photovoltaic Cell Parameter Extraction

This section primarily discusses the proposed PV design parameter extraction system, including different solar cell modelling, parameter identification for optimization, problem formulation and the proposed AGA based multi-objective optimization (MOO) solution. Before discussing the PV cell design paramter extraction and optimal parameter identification, a brief discussion of the different solar cell design is vital, particularly to identify the paramters to be optimized. The following section discusses the single diode solar cell modeling.

3.1 Single diode PV model

The ease of implementation and the accuracy enable the single diode model as the simplest PV cell design. Single diode PV model comprises five components, including; a photocurrent source, one diode and two resistors including series resistance R_s and shunt resistance R_{sh}. Fig. 1 presents a single diode PV model design.

Now, implementing Kirchhoff's current and voltage rule, the output current of the single-diode PV system can be estimated as (1):

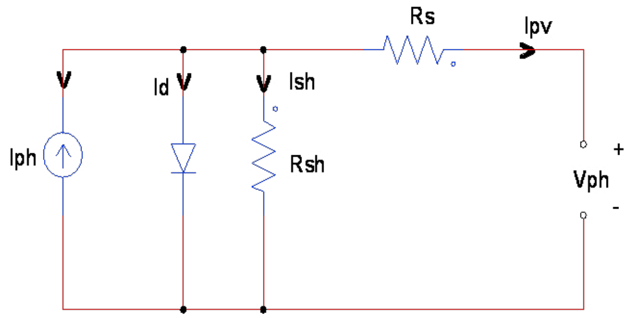

Fig. 1 Single diode PV model

$$i_{pv} = I_{ph} - I_0\left[exp\left(\frac{v_{pv}+i_{pv}R_s}{aV_t}\right)-1\right]-\left(\frac{v_{pv}+i_{pv}R_s}{R_{sh}}\right) \quad (1)$$

Where I_{ph} signifies the photocurrent generated by cell at the standard test condition (STC) and I_o states the reverse saturation current of the diode. The other parameter $V_t\,(kT/q)$ refers the thermal voltage of the PV cell, where k and q represent the Boltzmann constant (1.380650×10^{-23} J/K), and the electron charge (1.602176×10^{-19} C), respectively. Here, the T states the current temperature of *p-n* junction in Kelvin, α represents the diode's ideality factor. The resistive components R_s and R_{sh} represent the series and the shunt resistance, respectively. Here, V_{pv} provides the output voltage of the given PV cell. Thus, considering single diode PV cell design, a total of five electrical parameters (I_{ph}, I_o, R_s, R_{sh} and a) are needed to be estimated.

3.1.1 Single diode parameter estimation

In practice, I_{ph} varies as per solar radiation and the sunshine duration. In addition, it also varies according to the coefficient of temperature at the short current circuit. With the available reference $I_{ph\text{-}Ref}$ (here, Ref represented is known as reference current) on certain standard test conditions (STC) with solar irradiance of G = 1000 W / m^2 and temperature T_{Ref}=25°C, the photo generated current I_{ph} can be estimated as follows (2)

$$I_{ph} = \frac{G}{G_{Ref}}\left[I_{ph\_Ref} + \alpha\left(T - T_{Ref}\right)\right] \quad (2)$$

Where, G represents the solar irradiation received by PV cell [Unit -W/m²], α gives temperature coefficient of the short circuit current (Unit-Amp/K), G_{Ref} is the solar irradiance at STC. The other parameters, T_{Ref} represents the temperature at the STC (i.e., 25°C) and $I_{ph\text{-}Ref}$ gives photo-generated current at the reference STC condition. Typically $I_{ph\text{-}Ref}$ is equivalent to the short circuit current at the standard test conditions. Similarly, the diode reverse current can be obtained using (3).

$$I_s = \frac{I_{cc,Ref} + \alpha\left(T - T_{Ref}\right)}{exp\left[\left(V_{oc,Ref} + \beta\left(T - T_{Ref}\right)/aV_t\right)\right] - 1} \quad (3)$$

Where $V_{oc,\,Ref}$ gives the open circuit voltage, β represents the temperature coefficient of open circuit voltage and $I_{cc,\,Ref}$ signifies the short circuit current at STC. The other constants α and β can be takes as reference from the manufacturer data for the specific photovoltaic cell. Equation (4) and (5) represent the mathematical expression for series and shunt resistance estimation.

$$R_{s0} = -\left(\frac{dV}{dI}\right)_{V-V_{oc}} \quad (4)$$

$$R_{sh0} = -\left(\frac{dV}{dI}\right)_{I-I_{oc}} \quad (5)$$

4. Multi-Objective Optimization based PV Model Design Parameter Extraction

This section discusses the Multi-objective optimization based PV model electrical design parameter extraction technique developed in this paper.

4.1 AGA based PV design parameter extraction

The proposed adaptive genetic algorithm (AGA) based single diode model intends to estimate the optimal PV design parameters defined as binary string by fitting I-V curve points. The generated 0's and 1's are transferred to the five electrical design parameters of the singe diode PV model(I_{ph}, I_o, R_s, R_{sh} and a) estimate the objective function. Providing the initial PV design parameters as the initial population, AGA is executed to perform the least mean square error (LSE) reduction that as a result enables I-V curve fitting.

It is feasible because of its swift convergence rate of the AGA that eventually enables sub-optimal solution retrieval even within a few iterations, without introducing any convergence threat. It reduces the computational time and complexities incurred over unwanted iterations. These binary strings are then used for AGA based PV parameter estimation. Being a multi-objective optimization model, this research work employs two distinct objective functions to estimate optimal design parameters. A brief of these objective functions are given as follows:

4.1.1 Least Mean Square Error (LSE) reduction

Considering the effectiveness of the least square error (LSE) based curve fitting approach for PV design parameters, in this paper, the LSE reduction is considered as the initial objective function. The extraction of the design parameters while retrieving curve fit signifies achievement of the optimal PV design parameters. To reduce LSE, AGA applied equation (6) as the objective function, where LSE is measured as the variation in between the estimated value and the practical simulated current value (say, data).

4.1.2 Residual error (RE) optimization

Enabling LSE minimization by ensuring alleviation of the under-fitting and over-fitting the optimal PV design parameters can be obtained. To ensure optimal solution retrieval, estimating sufficient fitness level plays significance role. The following section briefs the fitness function estimation for the proposed AGA based PV design parameter estimation.

4.2 Fitness function estimation

In order to extract the parameters of the different solar cell models from the I-V data using optimization techniques, here the first need is to define the objective function to be optimized. As stated above in this paper two objective functions; LSE minimization and PRO enhancement are considered. Equation (6) presents the first objective function, i.e., LSE ε to be minimized. Here, ε is derived as the root mean square of the difference between the measured and simulated module current data. For N numbers of I–V data set, mathematically, ε can be presented as (6):

$$\varepsilon = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f_k\left(v_{pv}, i_{pv}, \emptyset\right)^2} \tag{6}$$

Where N represents the number of the experimental I-V data, $\emptyset$ is decision vector which consists of the parameters to be extracted. In case of single diode model the function f (V_{pv}, $i_{pv,}$ $\emptyset$) is given by

$$f_k\left(v_{pv}, i_{pv}, \emptyset\right) = I_{ph} - I_0\left[exp\left(\frac{v_{pv}+i_{pv}R_s}{aV_t}\right)-1\right] - \left(\frac{v_{pv}+i_{pv}R_s}{R_{sh}}\right) - i_{pv} \tag{7}$$

$$\emptyset = \left\{I_{ph}, I_0, R_s, R_{sh}, a\right\} \tag{8}$$

For the double diode PV model, the function f (V_{pv}, $i_{pv\,,}$ $\emptyset$) is given by

$$f\left(v_{pv}, i_{pv}, \emptyset\right) = I_{ph} - I_{01}\left[exp\left(\frac{v_{pv}+i_{pv}R_s}{a_1V_t}\right)-1\right] - I_{02}\left[exp\left(\frac{v_{pv}+i_{pv}R_s}{a_2V_t}\right)-1\right] - \frac{v_{pv}+i_{pv}R_s}{R_{sh}} - i_{pv} \tag{9}$$

$$\emptyset = \{I_{ph}, I_{01}, I_{02,} R_s, R_{sh}, a_1, a_2\} \quad (10)$$

The aim of the extraction procedure is to minimize Eq. (6) with respect to $\emptyset$ (Eq. (8) and Eq. (10)). A smaller value of implies the deviation between the module current and the one computed by the extraction method is small. Ideally, a zero value ε is desired. It can be seen from Eq. (6) that ε is a nonlinear function with no apparent quadratic function. Conventional iterative methods that attempt to solve this problem require the gradient information. Therefore, the presented research work employs proposed AGA based evolutionary computing to solve the problem. As stated, the proposed scheme applies two objectives; LSE reduction and PRE reduction and hence in this paper a cumulative joint fitness estimation model has been derived. Mathematically,

$$F(Cumulative)_{Fitness} = f(LSE) + f(PRE) \quad (11)$$

The overall proposed approach of AGA based PV design parameter extraction is presented in Fig. 2.

i. Selection

In AGA, the cumulative fitness function (11) is calculated based on the considered objective functions (LSE reduction and PRE optimization) that intend to estimate the best possible design parameter identification to fit the I-V curve. As per the fitness value (13), individuals in the population are ranked using the AGA's selection function. In selection, the parent individuals with higher fitness values retain its place for reproduction to form next generation. The individual with high fitness value would have higher probability for being selected for "reproduction". Mathematically, these GA parameters are estimated using following equation (12).

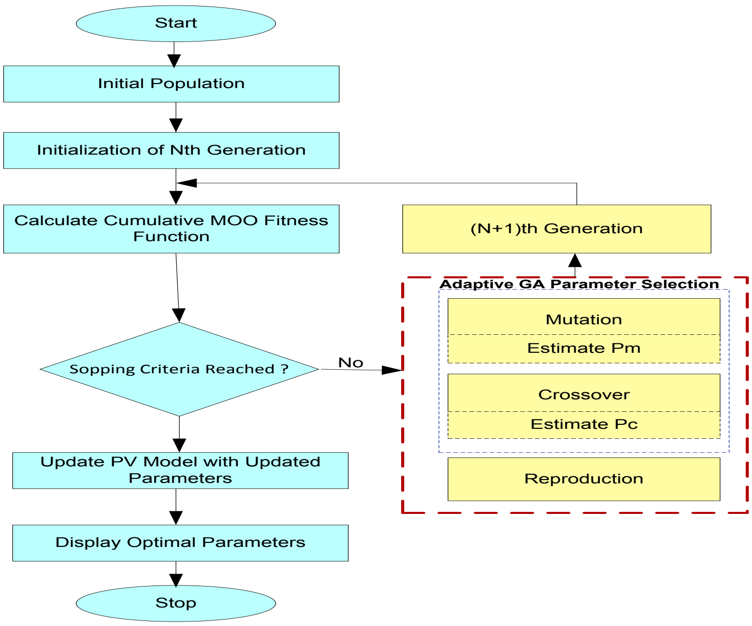

Fig. 2. AGA Based PV Extraction Model

$$(P_c)_{k+1} = (P_c)_k - \frac{C_c * C_{SF}}{5}$$
$$(P_m)_{k+1} = (P_m)_k - \frac{C_m * C_{SF}}{5} \quad (12)$$

In equation (12), $(P_c)_k$ represents the current crossover probability in k^{th} generation, and $(P_m)_k$ represents the mutation probability at the k^{th} generation. The other variables C_c and C_m are the positive constants. In the proposed AGA evolutionary computing model, C_1 and C_2 are selected as 0.01 and 0.001 respectively, however based on problem these values can be selected as any positive constant. The parameter C_{SF} presents the number of chromosomes having similar fitness value. In the proposed PV design parameter extraction or identification model, AGA based optimization continues till the stopping criterion is met or till 95% of the chromosomes achieve similar fitness value. After that the system gets saturated. Due to space constraints, the in depth discussion of the proposed AGA scheme could not be presented in this paper. The overall implementation of the proposed AGA algorithm for initial state point estimation for OPP solution is illustrated in Fig. 2.

5. Results and Discussion

In this paper, an enhanced adaptive genetic algorithm (AGA) based on multi-objective optimization measure was developed for optimal PV design parameter extraction. Two distinct objective functions, least mean error reduction and residual error reduction parameter estimation were considered to derive a cumulative or combined objective functions, with 0.7 and 0.3 proportion (Fitness=0.7LSE + 0.3PRO). In order to simulate the proposed model, the standard temperature condition (STC) manufacturer data were used with pre-defined initial electrical parameter values (synthetic data). The initial parameters for single diode PV model and the double diode PV model are presented in Table 1. The overall simulation model was developed using MATLAB 2015a tools, including SIMULINK SimScape toolbox.

Table 1. AGA based PV design parameters for single diode PV cells

PV Design Parameter	Initial Value	AGA Based PV Parameters
Solar generated Current I_{ph}	3.800	3.900
Diode saturation current I_s	3.000e-07	3.533e-07
Diode Quality Factor α	1.500	1.485
Series Resistance R_s	0.004	0.008
Parallel Resistance R_{sh}	10	10.427
Irradiance used for measurement-G	1000 w/m2	

The developed simulation model has been examined at different temperature conditions or irradiation scenario. I-V characteristics of the PV model at different temperatures (0^0C, 25^0C, 70^0C, and 85^0C) have been obtained with initial PV parameters (Fig. 4) as well as AGA-MOO based optimal identified data (Fig. 5). Being a self-formulated cumulative fitness function, where two objective functions, Least Mean Square Error (LMSE) and Pearson Residual Error Optimization (PRO) has been applied to estimate final fitness value, in this paper a mathematical model (13) with two proportionate constants A and B were used to achieve best possible output.

$$F(Cumulative_{Fitness}) = A(LSE) + B(PRO) \tag{13}$$

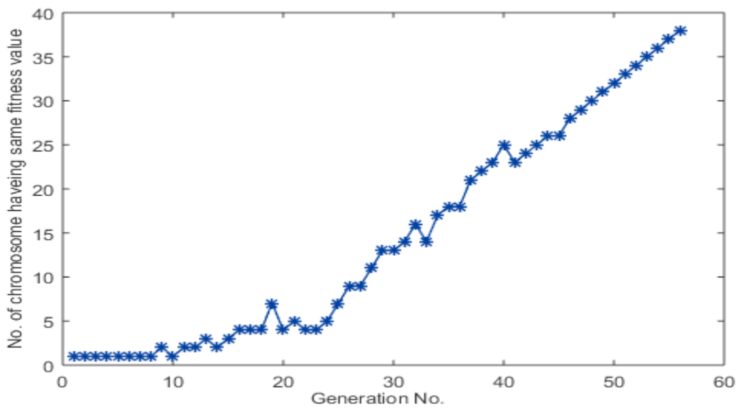

Fig. 3 Variation of the number of chromosomes having same fitness value with generation

It indicates that the proposed AGA-MOO based PV parameter estimation approach is computational as well as time efficient. Here, the performance assessment was done with different combinations and the best outcome with complete I-V cure fit was observed with A=0.7 and B=0.3 combination. Retrieving the optimized PV design parameters, the SIMULINK model was updated and the I-V characteristics were plotted as given in Fig. 5.

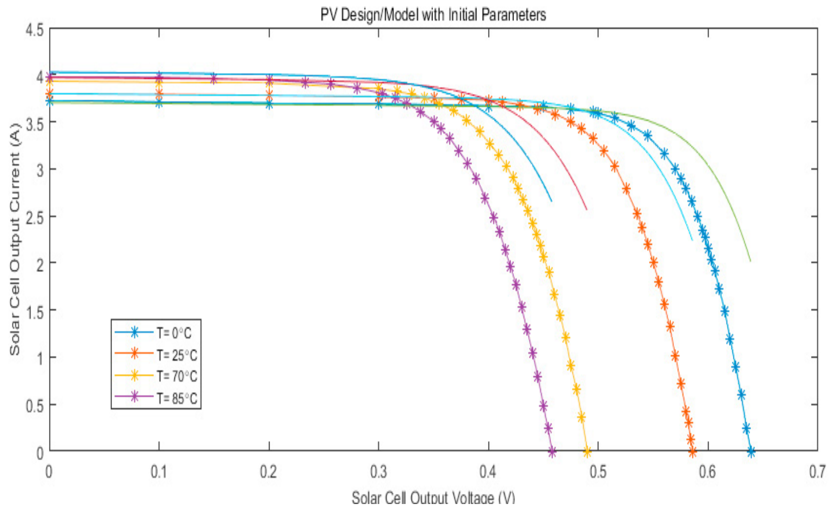

Fig. 4 I -V Characteristics with Initial PV Design Parameters

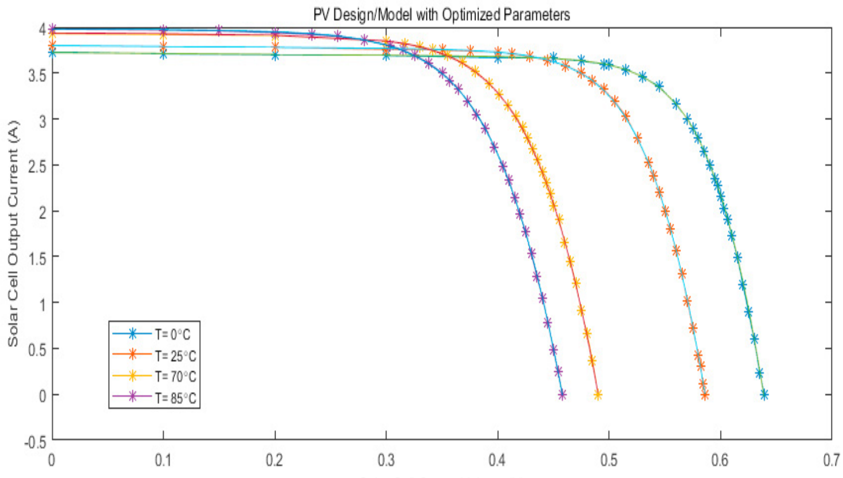

Fig. 5 I-V Characteristics with AGA-MOO Optimized PV Design Parameters

Fig. 4 presents the I-V characteristics curve with initial PV parameters. The results obtained after multi-objective optimization are presented in Fig. 5, where the first (Fig. 4) depicts the initial curve fitting with standard model data used for the case study. Here, the straight lines without "*" signifies the IV characteristics with a standard PV SIMULINK model parameters, while a continuous line connected with "*" refers the curve fit with the initial (non-optimised) data. On the contrary, the complete curve fit with optimised PV parameters can be observed in Fig. 5, which signifies that AGA based MOO achieves optimal PV design parameter extraction. Being noticeable, in Fig. 4 the straight line representing IV characteristics curve for the standard SIMULINK PV model terminates in mid, while curve fit with initial design parameter depicts a complete characteristics pattern or trend. It can be because of selection of the initially assigned parameters. However, eventual results (Fig. 5) confirm complete curve fit that justifies flawless and disambiguate performance. With this reference, the obtained PV electrical design parameters can be considered as the sub-optimal solution to enable ECR efficient solar system. Further, exploring Table 2, it can be found that the optimized parameter leads higher saturation current and hence provide more efficient and reliable power generation.

6. Conclusion

To meet the exponential rise in energy demands, solar energy is considered as the low cost and efficient source of energy. On the other hand, ECR of solar modules does have vital impact on its efficiency and hence applicability. Therefore, selecting optimal design parameters of the PV cells is of paramount significance. Unlike traditional approaches, in this paper, a novel and robust enhanced evolutionary computing algorithm named Adaptive Genetic Algorithm (AGA) has been developed as an improved iterative optimization measure. Being a curve fitting based optimization measure, unlike traditional single objective function based approach, in this work two objective functions, least mean square error (LSE) and Pearson residual error optimization (PRO) have been considered to fit the I-V characteristics curve. The implementation of a novel fitness value with cumulative LSE and PRO as objective functions AGA not only alleviates local minima and convergence issue but also eliminates the under/over-fitting probability, thus assures optimal sub-optimal solution for PV design parameter identification. The simulation with standard solar cell data at standard temperature conditions reveals that AGA based approach fits curve efficiently at different irradiation conditions than the traditional approaches and enables optimal PV design parameters. In future, the effectiveness of the proposed MOO approach can be examined with different operational conditions, evolutionary techniques and PV cells modules to assess the robustness of the proposed AGA-MOO for real time purposes.

Reference

[1] Chan DSH, Phang JCH. Analytical methods for the extraction of solar-cell single- and double-diode model parameters from I–V characteristics. Electron Dev IEEE Trans 1987;34:286–93.
[2] Ortiz-Conde A, García Sánchez FJ, Muci J. New method to extract the model parameters of solar cells from the explicit analytic solutions of their illuminated I–V characteristics. Sol Energy Mater Sol Cells 2006;90:352–61.
[3] Nakanishi F, Ikegami T, Ebihara K, Kuriyama S, Shiota Y. Modeling and operation of a 10kW photovoltaic power generator using equivalent electric circuit method. In: Photovoltaic specialists conference, 2000. Conference record of the twenty-eighth IEEE; 2000. p. 1703–6.
[4] Liu C-C, Chen C-Y, Weng C-Y, Wang C-C, Jenq F-L, Cheng P-J, et al. Physical parameters extraction from current–voltage characteristic for diodes using multiple nonlinear regression analysis. Solid-State Electron 2008;52:839–43.
[5] Moldovan N, Picos R, Moreno EG. Parameter extraction of a solar cell compact model using genetic algorithms. IEEE proceedings of the 2009 Spanish Conference of Electron Devices, 2009 Feb; 382-379.
[6] Zagrouba M, Sellami A, Bouaicha M, Ksouri M. Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction. Solar energy. 2010; 84(5): 866-860.
[7] Moldovan N, Picos R, Garcia-Moreno E. Parameter extraction of a solar cell compact model using genetic algorithms. In: Electron devices, 2009. CDE 2009. Spanish conference on; 2009; 379–82.
[8] Zagrouba M, Sellami A, Bouaïcha M, Ksouri M. Identification of PV solar cells and modules parameters using the genetic algorithms: application to maximum power extraction. Sol Energy 2010; 84:860–6.
[9] Lingyun X, Lefei S, Wei H, Cong J. Solar cells parameter extraction using a hybrid genetic algorithm. In: Third international conference on measuring technology and mechatronics automation; 2011; 306–9.
[10] Ye M, Wang X, Xu Y. Parameter extraction of solar cells using particle swarm optimization. Journal of Applied Physics. May 2009;105(9).
[11] Qin H. Kimball JW. Parameter Determination of Photovoltaic Cells from Field Testing Data using Particle Swarm Optimization. IEEE Power and Energy Conference at Illinois. 2011; 4-1.
[12] Ye M, Wang X, Xu Y. An extraction method of solar cell parameters with improved particle swarm optimization. J Appl Phys 2009; 105:1099–104.
[13] Wei H, Cong J, Lingyun X, Deyun S. Extracting solar cell model parameters based on chaos particle swarm algorithm. In: Electric information and control engineering . 2011; 402-398.
[14] Zwe-Lee G. A particle swarm optimization approach for optimum design of PID controller in AVR system. IEEE Trans Energy Convers 2004;19:384–91.
[15] AlRashidi MR, El-Naggar KM, AlHajri MF, Solar Cell Parameters Estimation Using Simulated Annealing Algorithm. World academy of science, engineering and technology. 2013;7(4):152-149.
[16] AlRashidi MR, El-Naggar KM, AlHajri MF. Extraction of Photovoltaic Characteristics Using Simulated Annealing. International Conference on Advances in Engineering Sciences and Applied Mathematics, May2014.

[17] Ji M, Jin Z, Tang H. An improved simulated annealing for solving the linear constrained optimization problems. Appl Math Comput 2006; 183:251–9.
[18] El-Naggar KM, AlRashidi MR, AlHajri MF, Al-Othman AK. Simulated Annealing algorithm for photovoltaic parameters identification. Solar Energy. 2012; 86(1):274-266
[19] Oliva D, Cuevas E, Pajares G. Parameter identification of solar-cells using artificial bee colony optimization. Energy. 2014; 72: 102-93.
[20] Ma J, Ting TO, Man KL, Zhang N, Guan SU, Wong PW. Parameter estimation of photovoltaic models via cuckoo search. Journal of Applied Mathematics. 2013;2013:8.
[21] Biswas A, Das S, Abraham A, Dasgupta S. Analysis of the reproduction operator in an artificial bacterial foraging system. Applied Mathematics and Computation. 2010; 215(9):3355-3343.
[22] Krishnakumar N, Venugopalan R, Rajasekar N. Bacterial foraging algorithm based parameter estimation of solar PV model. Emerging Research Areas and International Conference on Microelectronics, Communications and Renewable Energy (AICERA/ICMiCR), Annual International Conference on, Kanjirapally. 2013; 6-1.
[23] Harrag A, Messalti S. Extraction of solar cell parameters using genetic algorithm. 2015 4th International Conference on Electrical Engineering (ICEE), Boumerdes. 2015; 5-1.
[24] Dali A, Bouharchouche A, Diaf S. Parameter identification of photovoltaic cell/module using genetic algorithm (GA) and particle swarm optimization (PSO).Control, Engineering & Information Technology (CEIT). 2015 3rd International Conference on. Tlemcen. 2015; 6-1.
[25] Maherchandani JK, Agarwal C, Sahi M. Estimation of Solar Cell Model Parameter by Hybrid Genetic Algorithm Using MATLAB. International Journal of Advanced Research in Computer Engineering & Technology. 2012 Aug; 1(6):81-78.
[26] Wang W, Wu J-M, Liu J-H. A particle swarm optimization based on chaotic neighbourhood search to avoid premature convergence. In: Third international conference on genetic and evolutionary, computing; 2009; 633–6.
[27] Leung Y, Gao Y, Xu Z-B. Degree of population diversity—a perspective on premature convergence in genetic algorithms and its Markov chain analysis. IEEE Trans Neural Networks 1997;8:13.
[28] Amor HB, Rettinger A, Intelligent exploration for genetic algorithms using self organizing maps in evolutionary computation. In: Conference on genetic and evolutionary computation; 2005; 1531–8.
[29] W. T. Huang, C. Y. Chen, Y. Y. Chen, S. C. Hsu and Y. Li, "Multiobjective evolutionary approach to silicon solar cell design optimization," Quality Electronic Design (ASQED), 2013 5th Asia Symposium on, Penang, 2013, pp. 192-195.
[30]T. Bendib, A. Maoucha, F. Djeffal, N. Lakhdar, D. Arar1and and M. A. Abdi, "A multi-objective optimization-based approach to improve the organic solar cell efficiency," 2012 First International Conference on Renewable Energies and Vehicular Technology, Hammamet, 2012, pp. 425-429.
[31] K. Lakshmi, A. R. M. Rao and K. Bhaskar, "Multi-objective adaptive differential evolution algorithm for combinatorial optimisation," Computing Communication and Networking Technologies (ICCCNT), 2010 International Conference on, Karur, 2010, pp. 1-8.
[32] Xuebo Yang, Yanlong Jia and Xintong Chai, "Optimization of control parameters based on multi-objective genetic algorithms for spacecraft attitude tracking control," 2016 IEEE 25th International Symposium on Industrial Electronics (ISIE), Santa Clara, CA, USA, 2016, pp. 1017-1021.