*Revue des Energies Renouvelables Vol. 18 N°4 (2015) 701 – 711*

# GA-based solar cell parameters extraction Application to single, double and triple diode models

A. Harrag [1,2*] and S. Messalti [2†]

[1] CCNS Laboratory, Electronics Department
Faculty of Technology, Ferhat Abbas University
Route de Bejaia, Setif 05000, Algeria
[2] Electrical Engineering Department ,
Faculty of Technology, Mohamed Boudiaf University,
Route de Bordj Bou Arreridj, M'Sila 28000, Algeria

(reçu le 20 Novembre 2016 – accepté le 25 Décembre 2015)

**Abstract** - *In this paper, we propose a new technique based on genetic algorithm for the extraction of electrical parameters (the saturation current, the serial resistance, the parallel resistance and the ideality factor). The models with five, seven and nine parameters respectively are considered. The genetic algorithm is used as a tool for optimization to increase the probability of reaching the global minimum solutions in a short time with a very good accuracy based on the minimization of the quadratic error between experimental and theoretical characteristics. The simulation results show that the accuracy of the heuristic approach is effective for modeling in the case of solar modules. The values of squared errors are around zero ($5.8297 \times 10^{-8}$, $3.0751 \times 10^{-7}$ and $1.7243 \times 10^{-5}$ for the five, seven and nine parameters models, respectively). On the other hand, the results were obtained after only seven generations which can be considered very fast for a nonlinear optimization problem with many physical constraints. The results prove that the GA is very suitable for estimating electrical parameters needed for modeling the PV array.*

**Résumé** - *Dans cet article, nous proposons une nouvelle technique basée sur l'algorithme génétique pour l'extraction des paramètres électriques (le courant de saturation, la résistance série, la résistance parallèle et le facteur d'idéalité). Les modèles avec cinq, sept et neuf paramètres sont considérés respectivement. L'algorithme génétique est utilisé comme outil d'optimisation pour augmenter la probabilité d'atteindre les solutions minimales dans un court laps de temps avec une très bonne précision basée sur la minimisation de l'erreur quadratique entre les caractéristiques théoriques et expérimentales. Les résultats des simulations montrent que la précision de l'approche heuristique est efficace pour la modélisation dans le cas des modules solaires. Les valeurs des erreurs quadratiques sont autour de zéro ($5.8297 \times 10^{-8}$, $3.0751 \times 10^{-7}$ et $1.7243 \times 10^{-5}$ pour les modèles cinq, sept et neuf paramètres, respectivement). D'autre part, les résultats ont été obtenus après seulement sept générations qui peuvent être considéré comme un temps très rapide pour un problème d'optimisation non linéaire avec de nombreuses contraintes physiques. Les résultats prouvent que l'AG est très approprié pour l'estimation des paramètres électriques nécessaires pour la modélisation des modules photovoltaïques.*

**Mots-clés**: Modélisation de la cellule photovoltaïque - Algorithme génétique – Extractions des paramètres - Identification.

## 1. INTRODUCTION

The depletion of the fossil fuel reserves and the pollution caused by the conventional energy sources has made necessitous the exploitation of renewable energy sources in order to address the global challenges of clean energy, climate change and sustainable development. Those alternative energy production systems, such as photovoltaic (PV)

* a.b.harrag@gmail.com
† messalti.sabir@yahoo.fr

systems are being supported by many governments and countries on a worldwide basis [1].

Photovoltaic energy is one of the most promising emerging technologies. The cost of PV modules has been divided by five in the last six years; the cost of full PV systems has been divided by almost three. On the other hand, installations of PV systems around the world have been growing at an average annual rate of more than 44 % during the period from 2000 to 2013. Since 2010, the world has added more solar photovoltaic capacity than in the previous four decades. New systems were installed in 2013 at a rate of 100 megawatts (MW) of capacity per day. Total global capacity overtook 150 gigawatts (GW) in early 2014 [2].

Photovoltaic's is the field of technology and research related to the devices which directly convert sunlight into electricity. The solar cell made of semiconductor materials is the elementary building block of the photovoltaic technology. A number of solar cells electrically connected to each other and mounted in a single support structure or frame is called a 'photovoltaic module'. Several modules can be wired together to form an array. Photovoltaic modules and arrays produce direct-current electricity. They can be connected in both series and parallel electrical arrangements to produce any required voltage and current combination [3].

To better understand the acting physical mechanisms within the solar generator (cell, module, array), several methods have been proposed for the identification of the different parameters that affect their characteristics, not only for increase their performance, but also to simulate their behavior and optimize their different characteristics [4-10]. These methods can be classified in two categories: a- deterministic methods involving methods such as least squares [11], Lambert W-functions [12], and the interior-point method [13]; b- heuristic methods such differential evolution (DE) [14], particle swarm optimization (PSO) [15], simulated annealing (SA) [16].

In this paper, we propose a technique based on genetic algorithm (GA) [17] for the extraction of electrical parameters (the saturation current, the serial resistance, the parallel resistance and the ideality factor). The models with five and seven parameters respectively are considered. The genetic algorithm is used as a tool for optimization to increase the probability of reaching the global minimum solutions in a short time with a very good accuracy based on the minimization of the quadratic error between experimental and theoretical characteristics. The simulation results show that the accuracy of the heuristic approach is effective for modeling in the case of solar modules. The values of squared errors are around zero ($5.8297 \times 10^{-8}$, $3.0751 \times 10^{-7}$ and $1.7243 \times 10^{-5}$ for the five, seven and nine parameters models, respectively). On the other hand, the results were obtained after only seven generations which can be considered very fast for a nonlinear optimization problem with many physical constraints. The results prove that the GA is very suitable for estimating electrical parameters needed for modeling the PV array.

The remainder of the paper is organized as follows. In Section 2, the problem of solar cell modeling is defined. Section 3 describes the GA algorithm as well as the problem of solar cell identification translated to an optimization task using this technique. Section 4 presents the simulations results compared to experimental ones. In Section 5, the conclusions are stated.

## 2. PHOTOVOLTAIC CELL MODELING

There are two well-known and widely used models based on the well-known Shockley diode equation [18]: the single-diode model (the five parameters model) and the two-diode model (the seven parameters model). The most common versions of these models are presented below. In addition, in this study we introduce the genetic based extraction for the triple diode model parameters. The triple diode model is a recently used model [19, 20].

### 2.1 The single diode model

It consists of a constant current source, in parallel with a diode, which includes an ideality factor to account for the recombination in the space-charge region. This model accounts for the losses due to the module's internal series resistance, as well as contacts and interconnections between cells and modules. While the shunt resistance of the module models the losses due to the leakage currents across the junction and within the cell due to crystal imperfections and impurities. This model offers good compromise between approximation precision and simplicity [20, 21].

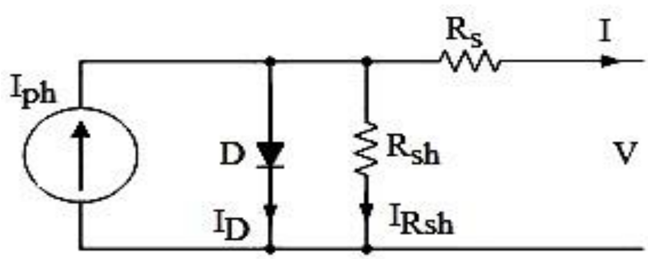


Fig. 1: The single diode model

The mathematical model is given by:

$$I = I_{ph} - I_0 . \left( e^{\frac{V + I.R_S}{n_s . V_t}} - 1 \right) - \frac{V + I . R_s}{R_{sh}} \quad (1)$$

Where, $R_{sh}$ is the module shunt resistance; $R_s$ is the module internal series resistance; $I_0$ is the dark saturation current; $n_s$ is the number of series connected cells in the module; $V_t$ is the module thermal voltage defined by:

$$V_t = \frac{n_s .A.k.T}{q} \quad (2)$$

Where, $n_s$ is the number of series connected cells in the module; $A$ is the diode ideality factor; $k$ is the Boltzmann's constant; $T$ is the temperature; $q$ is the charge of an electron.

### 2.2 The double diode model

It considers an additional diode in the equivalent scheme to account for the losses due to the carrier recombination in the space charge region of the junction, and those due to surface recombination. The double diode model is considered to be more accurate than the single diode model.

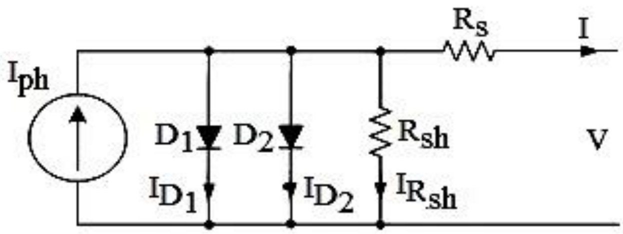


Fig. 2: The Double diode model

The mathematical model is given by:

$$I = I_{ph} - I_{01}.\left( e^{\frac{V + I.R_S}{n_s.V_{t1}}} - 1 \right) - I_{02}.\left( e^{\frac{V + I.R_S}{n_s.V_{t2}}} - 1 \right) - \frac{V + I\ .R_s}{R_{sh}} \quad (3)$$

Where, $R_{sh}$ is the module shunt resistance; $R_s$ is the module internal series resistance; $I_{0i}$ (I = 1 or 2) is the dark saturation current; $n_s$ is the number of series connected cells in the module; $V_{ti}$ (i = 1 or 2) is the module thermal voltage defined by:

$$V_{ti} = \frac{n_s.A_i.k.T}{q} \quad (4)$$

Where, $A_i$ ($i = 1$ or 2) is the diode ideality factor; $n_s$ is the number of series connected cells in the module; $k$ is the Boltzmann's constant; $T$ is the temperature; $q$ is the charge of an electron.

### 2.3 The triple diode model

As in the double diode model, the triple diode model considers an additional diode (3rd one) in the equivalent scheme to account for the contribution of added diode current due to recombination in the defect regions and grain sites.

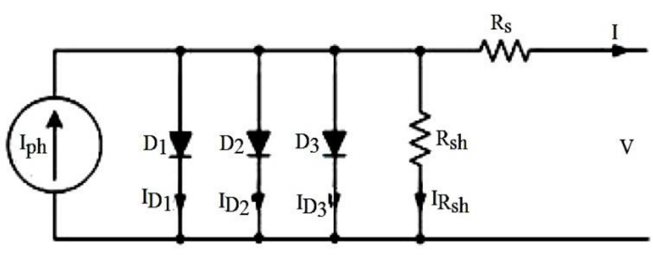


Fig. 3: The triple diode model

The mathematical model is given by:

$$I = I_{ph} - I_{01}.\left( e^{\frac{V + I.R_S}{n_s.V_{t1}}} - 1 \right) - I_{02}.\left( e^{\frac{V + I.R_S}{n_s.V_{t2}}} - 1 \right) - I_{03}.\left( e^{\frac{V + I.R_S}{n_s.V_{t3}}} - 1 \right) - \frac{V + I\ .R_s}{R_{sh}} \quad (5)$$

Where, $R_{sh}$ is the module shunt resistance; $R_s$ is the module internal series resistance; $I_{0i}$ (i = 1 or 3) is the dark saturation current; $n_s$ is the number of series connected cells in the module; $V_{ti}$ (i = 1 or 3) is the module thermal voltage defined by

$$V_{ti} = \frac{n_s . A_i . k . T}{q} \quad (6)$$

Where, $A_i$ ( $i$ = 1 or 23 is the diode ideality factor; $n_s$ is the number of series connected cells in the module; $k$ is the Boltzmann's constant; $T$ is the temperature; $q$ is the charge of an electron.

## 3. GA-BASED PV CELL PARAMETERS EXTRACTION TECHNIQUE

The unknown parameters of the single or the double diode models have to be determined for the given type of cell, whose characteristics are to be reproduced by the model. A number of approaches for cells and module parameter determination can be adopted using the datasheet parameters or measured I/V curves.

### 3.1 Genetic algorithm overview

A genetic algorithm is a search heuristic that mimics the process of natural selection. The idea with GA is to use this power of evolution to solve optimization problems. The father of the original Genetic Algorithm was John Holland who invented it in the early 1970's [23]. His student D.E. Goldberg took care of its implementation in the 80s [24]. In general, genetic algorithm have five basic components, as summarized by Michalewicz [25]:

- A genetic representation of solution to the problem;
- A way to create an initial population of solutions;
- An evaluation function rating solutions in terms of their fitness;
- Genetic operators that alter the genetic composition of children during reproduction;
- Value for the parameters of genetic algorithms.

The genetic algorithm maintains a population of individuals, say $P(t)$, for generation $t$. Each individual represents a potential solution to the problem. Each individual is evaluated to give some measure of its fitness. Some individuals undergo stochastic transformations by means of genetic operations to form the new individuals. After several generation, the algorithm converges to the best individual, which hopefully represents an optimal or suboptimal solution to the problem.

### 3.2 GA-based PV cell parameters extraction technique implementation

The electrical PV cell parameters ( $I_{ph}$, $I_0$, $A_1$, $R_s$ and $R_{sh}$ ) in case of single diode model or ( $I_{ph}$, $I_{01}$, $A_1$, $I_{02}$, $A_2$, $R_s$ and $R_{sh}$ ) in case of double diode model are encoded into binary strings known as chromosomes. The length of strings is set to 80 (5*15) for the single diode model, 112 (7*16) for the two diode model and 144 (9*16) for the triple diode model.

The selection is applied on a population of chromosomes and forms a mating pool. The purpose of parent selection in a GA is to give more reproductive changes to those individuals that are the fit. In our case we use the roulette wheel parent selection.

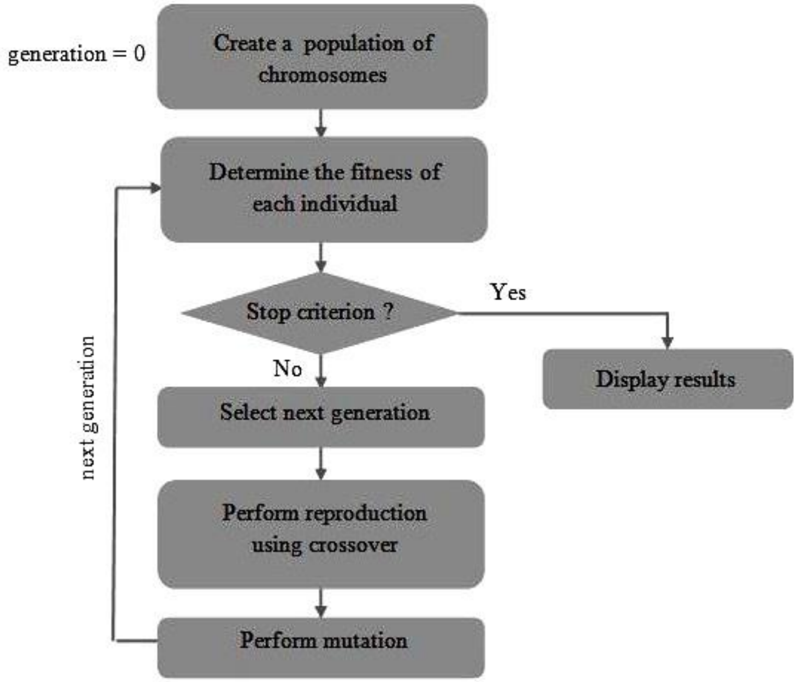


Fig. 4: Basic genetic algorithm

The Crossover operator is applied next to produce new chromosomes. Like in nature, crossover produces new individuals having some parts of both parent's genetic material. For this matter, we apply a single point crossover. The mutation is a genetic operator used to maintain genetic diversity from one generation of a population of genetic algorithm chromosomes to the next one. The fitness of each chromosome is evaluated by converting its binary string into a real value which represents model parameters. Each set of model parameters is to compute the correspondent computed I-V curve. The error criterion which used in the non-linear fitting procedure is based on the sum of the squared difference between the computed and experimental current values.

## 4. SIMULATION RESULTS

The simulated GA algorithm parameters used to initialize the GA algorithm parameters and generating an initial random population of individuals representing the model parameters are defined in **Table 1**.

**Table 1**: GA parameters

| Description | Parameters |
|---|---|
| Population size | 100 |
| Maximum iteration | 100 |
| Crossover probability | 0.5 |
| Mutation probability | 0.02 |
| Number of bits per chromosome | 16 |

The developed algorithm implemented using Matlab environment was tested on two PV modules the 30XLS (**Table 2**) and the 34XLS (**Table 3**).

**Table 2**: 30XLS parameters

| Description | Experimental measured value |
|---|---|
| Module temperature $T_{mod}$ | 35.08 °C |
| Efficiency insolation $E_{eff}$ | 962.15 W/m$^2$ |
| Short circuit current $I_{SC}$ | 5.58 A |
| Open circuit voltage $V_{OC}$ | 21.26 V |
| MPP current Ipmax | 5.119 A |
| MPP voltage Vpmax | 16.78 V |
| Short circuit current (STC $I_{SCO}$) | 5.80 A |
| Open circuit voltage (STC $V_{SCO}$) | 22.03 V |
| MPP current at STC Ipmax | 5.32 A |
| MPP voltage at STC Vpmax | 17.59 V |
| Maximum power Pmax | 93.63 W |

**Table 3**: 34XLS module parameters

| Description | Experimental measured value |
|---|---|
| Module temperature $T_{mod}$ | 32.16 °C |
| Efficiency insolation $E_{eff}$ | 791.25 W/m$^2$ |
| Short circuit current $I_{SC}$ | 4.86 A |
| Open circuit voltage $V_{OC}$ | 21.26 V |
| MPP current Ipmax | 4.44 A |
| MPP voltage Vpmax | 16.90 V |
| Short circuit current (STC $I_{SCO}$) | 6.167 A |
| Open circuit voltage (STC $V_{SCO}$) | 22.03 V |
| MPP current at STC Ipmax | 5.62 A |
| MPP voltage at STC Vpmax | 17.69 V |
| Maximum power Pmax | 99.50 W |

Figures 5 to 10 show the computed and the experimental I-V characteristics for the two considered modules.

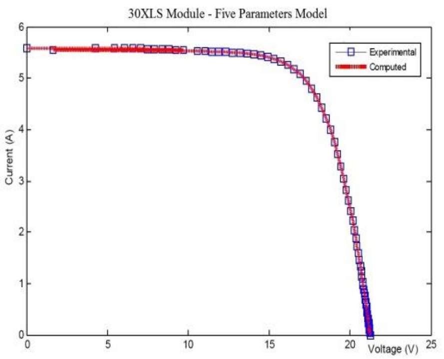


Fig. 5: I-V characteristics for 30XLS module: five parameters model

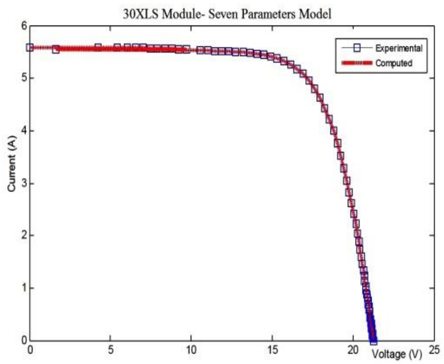


Fig. 6: I-V characteristics for 30XLS module: seven parameters model

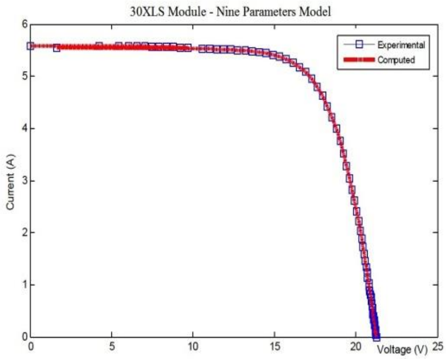


Fig. 7: I-V characteristics for 30XLS module: nine parameters model

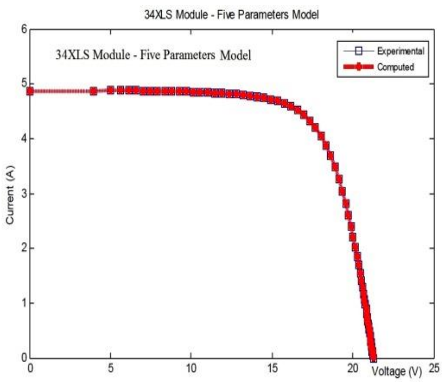


Fig. 8: I-V characteristics for 34XLS module: five parameters model

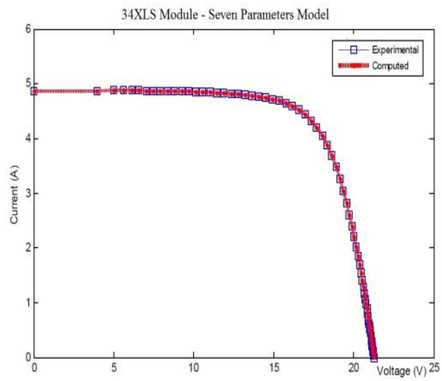


Fig. 9: I-V characteristics for 34XLS module: seven parameters model

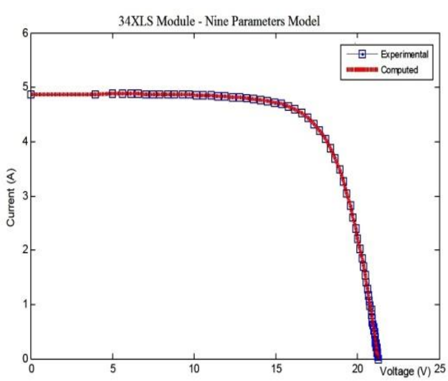


Fig. 10: I-V characteristics for 34XLS module: nine parameters model

**Tables 4**, **5** and **6** give the extracted parameters using the developed genetic algorithm.

**Table 4**: Five parameters model

| Parameter | 30XLS | 34XLS |
|---|---|---|
| $I_{ph}$ | 5.50 A | 4.95 A |
| $I_0$ | $2.55 \times 10^{-8}$ A | $5.98 \times 10^{-8}$ A |
| A | 1.88 | 1.52 |
| $R_s$ | 0.174 Ω | 0.647 Ω |
| $R_{sh}$ | 187.24 Ω | 156.48 Ω |

**Table 5**: Seven parameters model

| Parameter | 30XLS | 34XLS |
|---|---|---|
| $I_{ph}$ | 5.92 A | 4.94 A |
| $I_{01}$ | $6.57 \times 10^{-8}$ A | $6.29 \times 10^{-8}$ A |
| $A_1$ | 1.32 | 1.09 |
| $I_{02}$ | $0.56 \times 10^{-8}$ A | $4.99 \times 10^{-8}$ A |
| $A_2$ | 1.48 | 1.93 |
| $R_s$ | 0.798 Ω | 0.107 Ω |
| $R_{sh}$ | 193.96 Ω | 192.01 Ω |

**Table 6**: Nine parameters model

| Parameter | 30XLS | 34XLS |
|---|---|---|
| $I_{ph}$ | 5.33 A | 5.38 A |
| $I_{01}$ | $6.59 \times 10^{-8}$ A | $3.51 \times 10^{-8}$ A |
| $A_1$ | 1.27 | 1.77 |
| $I_{02}$ | $6.35 \times 10^{-8}$ A | $6.71 \times 10^{-8}$ A |
| $A_2$ | 1.88 | 1.11 |
| $I_{02}$ | $6.10 \times 10^{-8}$ A | $6.42 \times 10^{-8}$ A |
| $A_3$ | 1.58 | 0.67 |
| $R_s$ | 0.524 Ω | 0.345 Ω |
| $R_{sh}$ | 223.76 Ω | 218.70 Ω |

From the obtained figure, we can see that the theoretical $I-V$ characteristics are very close to the experimental measured $I-V$ characteristics. The results prove the effectiveness of the proposed technique to extract with good precision the parameters of the equivalent circuit model. Another important point is the very little needed time to extract these parameters compared to deterministic methods which consider the problem of PV model parameters extraction as a NP-hard optimization problem.

**Aknowledgment-** We thank Mr. Aissa Chouder, senior lecturer at Mohamed Boudiaf University of M'Sila for his invaluable assistance in carrying out this work

## REFERENCES


[1] Report, '*Global Status Report*', 2014.
Available: http://www.ren21.net/portals/0/documents/resources/gsr/2014/

[2] Report IEA, '*Technology Roadmaps Bioenergy for Heat and Power*', 2014.
Available: http:// www.iea.org/publication/

[3] H. Haberlin, '*Photovoltaics: System Design and Practice*', Chichester: John Wiley & Sons, 2012.

[4] M. Chegaar, Z. Ouennough, F. Guechi, and H. Langueur, '*Determination of Solar Cells Parameters Under Illuminated Conditions*', Journal of Electron Devices, Vol. 2, pp. 17 – 21, 2003.

[5] L. Han, N. Koide, Y. Chiba and T. Mitate, '*Modeling of an Equivalent Circuit for Dye Sensitized Solar Cells*', Applied Physics Letters, Vol. 84, N°13, 2433.

[6] W. Xiao, MGJ Lind, W.G. Dunford and A. Capel, '*Real-time Identification of Optimal Operating Points in Photovoltaic Power Systems*'. IEEE Transactions on Industrial Electronics, Vol. 53, N°4, pp. 1017 – 1026, 2006.

[7] D. Sera, R. Teodorescu, and P. Rodriguez, '*PV Panel Model Based on Datasheet Values*', IEEE International Symposium on Electronics, ISIE 2007, June 4-7 2007, Vigo, Spain.

[8] M. Ye, X. Wang and Y. Xu, '*Parameter Extraction of Solar Cells Using Particle Swarm Optimization*', Journal of Applied Physics, Vol. 105, N°9, 094502, 2009.

[9] T. Huld, R. Gottschalg and H.G. Beyer, '*Topic M. Mapping the Performance of a PV modules, Effects of Module Type and Data Averaging*', Solar Energy, N°84, pp. 324 -328, 2010.

[10] T. Easwarakhanthan, J. Bottin, I. Bouhouch and C. Boutrit, '*Nonlinear Minimization Algorithm for Determining the Solar Cell Parameters with Microcomputers*', International Journal of Solar Energy, Vol. 4, N°1, pp. 1 – 12, 1986.

[11] A. Ortiz-Conde, F.J. Garcia Sanchez and J. Muci, '*New Method to Extract the Model Parameters of Solar Cells From the Explicit Analytic Solutions of Their Illuminated I-V Characteristics*', Solar Energy Materials and Solar Cells, Vol. 90, N°3, pp. 352 – 361, 2006.

[12] D.S.H. Chan, J.R. Phillips and J.C.H. Phang, '*A Comparative Study of Extraction Methods for Solar Cell Model Parameters*', Solid-State Electron, Vol. 29, N°3, pp. 329 – 337, 1986.

[13] M.R. Al-Rashidi, M.F. Al-Hajri, K.M. El-Naggar, A.K. Al-Othman, '*A New Estimation Approach for Determining the I-V Characteristics of Solar Cells*', Solar Energy, Vol. 85, N°7, pp. 1543 – 1550, 2011.

[14] I. Kashif and S. Zainal, '*An Improved Modeling Method to Determine the Model Parameters of Photovoltaic (PV) Modules Using Differential Evolution (De)*', Solar Energy, Vol. 85, N°9, pp. 2349 – 2359, 2011.

[15] H. Wei, J. Cong, X. Lingyun and S. Deyun, '*Extracting Solar Cell Model Parameters Based on Chaos Particle Swarm Algorithm', In: International Conference on Electric Information and Control Engineering*, 'ICEICE', pp. 398 – 402, 2011.

[16] K.M. El-Naggar, M.R. Al Rashidi, M.F. Al Hajri and A.K. Al-Othman, '*Simulated Annealing Algorithm for Photovoltaic Parameters Identification*', Solar Energy, Vol. 86, N°1, pp. 266 – 274, 2012.

[17] M. Mitchell, '*An Introduction to Genetic Algorithms*', A Bradford Book The MIT Press Cambridge, Massachusetts, London, England, 1999.

[18] W. Shockley, '*The Theory of P-N Junctions in Semiconductors and P-N Junction Transistors*', Bell System Technical Journal, Vol. 28, pp. 435 - 489, 1949.

[19] Vandana Khanna, B.K. Das, Dinesh Bisht, Vandana, P.K. Singh, '*A Three Diode Model for Industrial Solar Cells and Estimation of Solar Cell Parameters Using PSO Algorithm*', Renewable Energy, Vol. 78, N°6, pp. 105 – 113, 2015.

[20] H. Rezk and E.S.A.M. Hasaneen, '*A New MATLAB /Simulink Model of Triple-Junction Solar Cell and MPPT Based on Artificial Neural Networks for Photovoltaic Energy Systems*', Ain Shams Engineering Journal, 2015.

[21] D. Rekioua and E. Matagne, '*Optimization of Photovoltaic Power Systems: Modelization, Simulation and Control*', Springer-Verlag, London, 2012.

[22] A. Goetzberger and V.U. Hoffmann, '*Photovoltaic Solar Energy Generation*', Springer-Verlag, Berlin, Heidelberg, XII 234 p., 2005.

[23] J.H. Holland, '*Adaptation in Natural and Artificial Systems*', University of Michigan Press, 1975.

[24] D.E. Goldberg, '*Genetic Algorithms in Search, Optimization and Machine Learning*', Addison-Wesley Longman Publishing Co., Inc. Boston, MA, USA 1989.

[25] Z. Michalewicz, '*Genetic Algorithms + Data Structure = Evolution Programs*', Springer-Verlag, New York 1996.