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ScienceDirect

Solar Energy 84 (2010) 860–866

SOLAR ENERGY

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Identification of PV solar cells and modules parameters using the genetic algorithms: Application to maximum power extraction

M. Zagrouba [a], A. Sellami [a], M. Bouaïcha [a,*], M. Ksouri [b]

[a] Laboratoire de Photovoltaïque, des Semi-conducteurs et des Nanostructures, Centre de Recherches et des Technologies de l'Energie, Technopole de Borj-Cédria, Tunis, B.P. 95, 2050 Hammam-Lif, Tunisia

[b] Unité de Recherche RME-Groupe AIA, Institut National des Sciences Appliquées et de Technologie, Tunisia

Received 19 July 2009; received in revised form 18 February 2010; accepted 20 February 2010
Available online 21 March 2010

Communicated by: Associate Editor Igor Tyukhov

Abstract

In this paper, we propose to perform a numerical technique based on genetic algorithms (GAs) to identify the electrical parameters (I_s, I_{ph}, R_s, R_{sh}, and n) of photovoltaic (PV) solar cells and modules. These parameters were used to determine the corresponding maximum power point (MPP) from the illuminated current–voltage (I–V) characteristic. The one diode type approach is used to model the AM1.5 I–V characteristic of the solar cell. To extract electrical parameters, the approach is formulated as a non convex optimization problem. The GAs approach was used as a numerical technique in order to overcome problems involved in the local minima in the case of non convex optimization criteria. Compared to other methods, we find that the GAs is a very efficient technique to estimate the electrical parameters of PV solar cells and modules. Indeed, the race of the algorithm stopped after five generations in the case of PV solar cells and seven generations in the case of PV modules. The identified parameters are then used to extract the maximum power working points for both cell and module.

Keywords: Genetic algorithms; Silicon solar cells; PV modules; Illuminated I–V characterization; Maximum power point

1. Introduction

The algorithms that we use to determine parameters of PV generators (solar cells, modules and arrays) must be efficient and sufficiently accurate for process optimization and photovoltaic systems design tasks. These algorithms are of two types: those that use selected parts of the current–voltage (I–V) characteristic (Charles, 1981, 1985; Laplaze and Youm, 1985; Chan and Phang, 1987) and those that exploit the whole characteristic (Easwarakhanthan et al., 1986; Phang and Chan, 1986; Ikegami et al., 2001; Jervase et al., 2001). The first group of algorithms involves the solution of five equations, derived from considering selected points of the I–V characteristic, i.e. the open-circuit and short-circuit points, the maximum power points and the slopes at strategic portions of the characteristic for different level of illumination and temperature. Although, the exact solution of these equations requires iterative techniques, this method is often much faster and simpler in comparison to curve fitting. The disadvantage of this approach is that only selected parts of the I–V characteristic are used to determine the parameters. The second group of algorithms is based on curve fitting and offers the advantage of taking all the experimental data in consideration. Conversely, it has also the disadvantage of artificial solutions. In fact, the fitting techniques with several parameters are, generally, based on non-convex optimization criterion, and using traditional deterministic optimization algorithms leads to several sets of local minima solutions, and none one of them can describe the physical reality.

* Corresponding author. Tel.: +216 79325160; fax: +216 79325934.
E-mail address: Mongi.Bouaicha@crten.rnrt.tn (M. Bouaïcha).

0038-092X/$ - see front matter
doi:10.1016/j.solener.2010.02.012

Nomenclature

GAs	genetic algorithms	I_i^{exp}	measured current (A)
I_s	saturation current (A)	V_i	measured voltage (V)
I_{ph}	photocurrent (A)	θ	chromosome
R_s	series resistance (Ω)	q	electron charge (C)
R_{sh}	shunt resistance (Ω)	K	Boltzmann's constant (J/K)
n	ideality factor	T	temperature (K)
PV	photovoltaic	G_{sh}	shunt conductance (Ω^{-1})
MPP	maximum power point	IPOP	initial population
I–V	current–voltage	h_i	highest value of parameter
I	theoretical current (A)	l_o	lowest value of parameter
V	theoretical voltage (V)	N_{ipop}	initial number of the population
V_{th}	thermal voltage (V)	N_{par}	number of parameters
χ	cost function (A^2)	ADC	analog digital converter
m	measured points number	DAC	digital analog converter
i	measured point		

In this paper, we present a non-linear least-squares optimization algorithm for the identification of the five electrical solar cell and module parameters from experimental data. This fitting is based on the Genetic Algorithms (GAs) strategy. These algorithms are recently applied in several domains, such as in optimization of large solar hot water systems (Loomans and Visser, 2002), in design and control strategies of PV–Diesel systems (Dufo-Lopez and Bernal-Agustin, 2005), in sizing optimization of hybrid solar–wind system (Yang et al., 2008), etc. For the estimation of the electrical parameters of PV generators, we found that GAs increase the probability of obtaining the best minimum value of the cost function in very reasonable time, and more accurate solution in comparison to the approaches reported in the literature (Ikegami et al., 2001). The identified parameters are then used to extract the working maximum power point (MPP).

2. The one diode model

The theoretical expression of the current crossing a photovoltaic cell versus the applied voltage results from the Schottky diffusion model in a PN junction, and is given by (Charles et al., 1985):

$$I = I_{ph} - I_s\left[\exp\left(\frac{V + R_s I}{nV_{th}}\right) - 1\right] - \frac{V + R_s I}{R_{sh}} \tag{1}$$

where I_{ph} and I_s are the photocurrent and the saturation current, respectively. R_s is the series resistance, R_{sh} is the shunt resistance, n is the ideality factor and V_{th} is the thermal voltage.

The electrical parameters R_s, $G_{sh} = 1/R_{sh}$, I_{ph}, n and I_s are computed from the I–V characteristic under illumination, using the classical one-diode equivalent circuit.

Although a multiple diode model describing all the conduction modes would be more likely for physical interpretation, it may generate many difficulties. In this case, the accuracy of the fitting related to the value of the ending value of the objective function, which corresponds to the admitted absolute minimum can be improved (Ketter and Prawel, 1975). However, the physical meaning of the solution is lost, since the number of parameters becomes high (augmented by 2 for each added diode). In fact, the unicity of the solution cannot be insured. However, precise experiments taking into account different physical phenomena contributing to the electronic transport are suitable to identify all the conduction modes. The single diode model considered here is rather simple, efficient and sufficiently accurate for process optimization and system design tasks. The single diode model can also be used to fit solar modules and arrays where the cells are series and/or parallel connected, provided that the cell to cell variations are not important (Easwarakhanthan et al., 1986). It should be noted, however, that the parameters determined by the one diode model will lose somewhat their physical meaning in the case of solar modules and arrays. Consequently, the precision of each fitting approach will be certainly better in the case of solar cells than that of solar modules, which itself, should be more accurate than that of solar arrays.

3. The genetic algorithms

To numerically treat the I–V curves, we performed a fitting procedure based on the genetic algorithms (GAs). The error criterion which used in the non-linear fitting procedure is based on the sum of the squared difference between the theoretical and experimental current values. Consequently, the cost function to be minimized is given by (Easwarakhanthan et al., 1986; Phang and Chan, 1986):

$$\chi = \sum_{i=1}^{m} [I_i^{exp} - I(V_i, \theta)]^2 \quad (2)$$

where I_i^{exp} is the measured current at the V_i bias, $\theta = (I_{ph}, I_s, R_s, G_{sh}, n)$ is the set of model parameters and $I(V_i,\theta)$ is the predicted current.

Eq. (1) is implicit in I; one way of simplifying the computation of $I(V_i,\theta)$ is to substitute I_i and V_i in Eq. (1). Hence, we obtain Eq. (3).

$$I(V_i, \theta) = I_{ph} - I_s\left[\exp\left(\frac{q(V_i + R_s I)}{nKT}\right) - 1\right] - G_{sh}(V_i + R_s I) \quad (3)$$

In Fig. 1, we give the flow chart of the GAs. The chromosome here is the vector θ containing the five parameters I_{ph}, I_s, R_s, G_{sh}, and n. The initial population (IPOP) of chromosomes is a matrix given by Eq. (4): (Ketter and Prawel, 1975).

$$\mathrm{IPOP} = (h_i - l_o) \cdot \mathrm{random}[N_{ipop}, N_{par}] + l_o \quad (4)$$

where N_{ipop} is the initial number of chromosomes in IPOP, N_{par} is the number of parameters in the chromosome ($N_{par} = 5$ in our case), l_o and h_i are respectively the lowest and the highest values of parameters I_s, I_{ph}, R_s, R_{sh} and n.

The very common operators used in GAs are selection, reproduction and mutation (Haupt and Haupt, 1998; Sellami et al., 2007), which are described as follows:

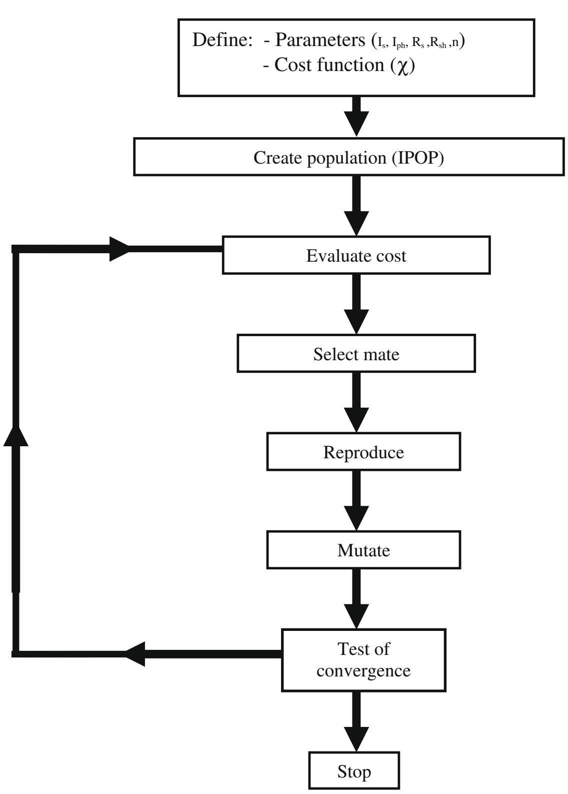

Fig. 1. Flow chart of the genetic algorithms.

(1) *Selection:* This procedure is applied to select chromosomes that participate in the reproduction process to give birth to the next generation. Only the best chromosomes are retained for the next generation of the algorithm, while the bad ones are discarded. There are several methods of this process, including the elitist model, the ranking model, the roulette wheel procedure, etc.
(2) Reproduction/pairing: This procedure takes two selected chromosomes from a current generation (parents) and crosses them to obtain two individuals for the new generation (offspring's). There are several types of crossing, but the simplest methods choose arbitrary one or more points (parameters) in the chromosome of each parent to mark as crossover points. Then the parameters between these points are merely swapped between the two parents.

In our case, each parent is represented by a chromosome containing five parameters. The paring is performed by crossing one, two, three, four and five parameters between the two parents, leading to obtain from these two parents a new generation of 2^5 individuals (chromosomes).

(3) Mutation: It consists of introducing changes in some genes (parameters) of a chromosome in a population. This procedure is performed by GAs to explore new solutions. Random mutations alter a small percentage of the population (mutation rate) except for the best chromosomes. A mutation rate between 1% and 20% often works well. If the mutation rate is above 20%, too many good parameters can be mutated, and then the algorithm stalls. In our case, mutation was applied to all parameters of 4% of chromosomes number. Note that the new value of each parameter should be in the $[l_o,h_i]$ corresponding interval. Consequently, after paring, mutated parameters are engaged to ensure that the parameters space is explored in new regions.

4. Identification of the electrical parameters

We use a homemade GAs program developed on Matlab environment for both PV cell, module and array. For flexibility, we choose to develop this program instead of using Genetic Algorithms and Direct Search Toolbox of Matlab.

4.1. Solar cell parameters

The *I–V* characteristic under AM1.5 illumination was performed using the cell tester CT 801 from Pasan (2004). This cell tester includes in the same compact architecture a single-flash xenon light source, an automatic sliding contact frame, a test chuck with interchangeable plates to fit any cell configuration, a calibrated reference cell, and a Panel-PC type computer. To become a fully featured cell testing unit, it needs to be connected to an external electronic load and flash generator, itself included in a 19” 6U rack. Its single-flash technology gives a negligible heating of the cell, in the tenths of a degree range, much lower than continuous-light testers, so an accurate I–V curve determination can be achieved (Pasan, 2004). In Fig. 2, we give the plot of the I–V curve of a multicrystalline silicon solar cell having a surface area of 4 cm^2.

In the following, we will use the GAs to estimate the cell electrical parameters from the measured I–V curve of Fig. 2. Then, we will compare these results to those established by the Pasan cell tester software version V3.0.

Generally, the time-convergence of the algorithm is influenced by the choice of the IPOP. If coordinates of the absolute minimum of the cost function in the parameter’s space are unknown, initial invidious (IPOP) were generated randomly. The latter were chosen uniformly between the highest and the lowest value of each parameter. In this work, the first generation was started with 14^5 (537824) chromosomes as the initial population (IPOP), where 5 is the number of parameters to be identified. Each parameter in a chromosome has a lowest (l_o) and a highest (h_i) value. Since the interval between l_o and h_i contains an infinite number of value, we started in the simulation with different values such as 200, 100, 50, 25, 15, 10 and 5. We remark that simulation results are similar for all values 200, 100, 50, 25, 15 and 14. For values less than 14, the algorithm leads to a relatively high value of the cost function. For this reason, we choose 14.

After evaluating the cost function for each chromosome, we apply a selection in IPOP (Select mate): only a family of good chromosomes that corresponds to good values of the cost was kept for the pairing (reproduce) and the others (bad) were killed. To ensure that the parameters space is suitably explored, a mutation of 4% in the chromosomes was operated (mutate). At the end of the algorithm, the convergence was tested. If the result (last value of χ) does not give satisfaction compared to a predefined cost minimum ($\chi = 0.000270$ A^2), all below steps are repeated in the second generation and so on. The fitting result is plot in Fig. 3.

Fig. 2. Experimental I–V curve of the solar cell.

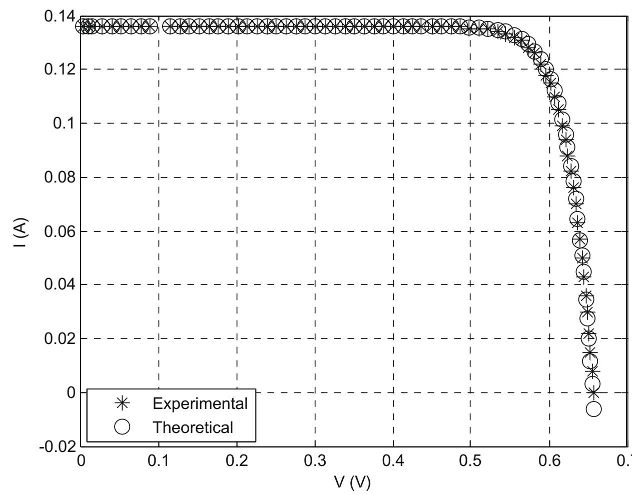

Fig. 3. Adjustment of the solar cell’s theoretical I–V curve to the experimental one using GAs method.

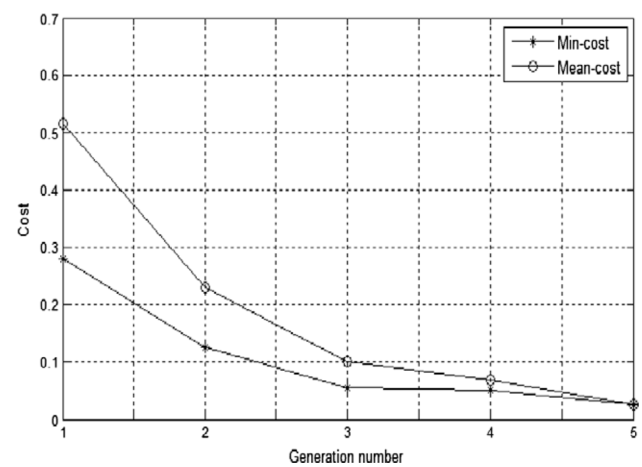

Fig. 4. The mean and the minimum values of the cost function χ versus generation number of the solar cell.

In Fig. 4, we plot the mean and the minimum values of the χ function with respect to the generation number. We can see that beyond the third generation, the cost function becomes stable in a relative good minimum.

The value of the minimum cost was found to be equal to 0.000256 A^2 and was reached after five generations. According to this relatively good value, one can assume that the GAs are very suitable for the estimation of the electrical parameters via the fitting method. In Table 1,

Table 1
Comparison between the electrical parameters of the solar cell determined using GAs and those given by the Pasan CT 801 software.

Electrical parameters	Pasan CT 801	Genetic Algorithms
I_s (A)	Not performed	1.2170×10^{-2}
I_{ph} (A)	0.1360	0.1360
R_s (Ω)	0.2790	0.0363
R_{sh} (Ω)	99999	99050
n	Not performed	1.0196

we compare the electrical parameters resulting from the use of the GAs-based fitting procedure, with those given by the Pasan cell tester software. Hence, the minimization problem is of five parameters (I_{ph}, I_s, R_s, R_{sh}, n), which is a hard problem in fitting procedures. As presented in Table 1, the Pasan software gives only estimations of three parameters (I_{ph}, R_s, R_{sh}) from the five unknown ones. The saturation current I_s and the ideality factor n are not performed. In contrast, using the GAs method, we can estimate values of I_s and n in addition to the other three parameters (I_{ph}, R_s, R_{sh}). Obtained values' using the Pasan software and GAs method are identical for I_{ph} and differs of 1% for R_{sh}. However, value of R_s obtained with the Pasan software is 7.5 times that one obtained with GAs. Regarding the good fitting result in Fig. 3, and taking into account that the R_s effect on the I–V curve is in general observed for voltages near the V_{oc} value, one can argue that the output value of R_s obtained with GAs is reasonable, but no conclusion can be done on the R_s value given by the Pasan software since no fitting is presented.

4.2. PV module parameters

In this case, we use a homemade solar module tester. The system takes advantage of the quick response time of PV devices by illuminating and characterising the samples within a few milliseconds. The tester measures the complete I–V curve of the PV module by using a capacitor load (Sellami et al., 1998). In the meantime, it measures the illumination level, the temperature, the voltage and its corresponding current in order to minimize the quantification errors coming from ADC and DAC conversion. Data are then transferred to the computer that calculates the efficiency, the short circuit current, the open-circuit voltage and the fill factor. The bloc diagram of the PV module tester is given in Fig. 5. We used a commercial 50 Wp PV module manufactured by ANIT-Italy. Testing was performed at 44 °C and 873 W/m^2 illuminations.

The adjustment of the theoretical I–V curve of the PV module to the experimental one using GAs, and the mean and the minimum values of the cost function χ versus generation number are given in Figs. 6 and 7, respectively. In this simulation (PV module), we choose 12^5 chromosomes as IPOP and the predefined cost minimum is $\chi = 0.0700$ A^2.

In the case of the used PV module, the GAs-based fitting procedure of the theoretical I–V curve to the experimental one (achieved using the PV module tester shown in Fig. 5) gives a minimum value around 0.0676 A^2 and was reached after only seven generations. The results of this minimization are shown in Table 2.

5. Maximum power point extraction

In order to extract the maximum available power from PV cell, it is necessary to operate it (the cell) at its maximum power point (MPP). Several MPP methods, such as perturbation, fuzzy control, power–voltage differentiation and on-line method have been reported (Bahgat et al., 2004; Yu et al., 2004; Enrique et al., 2007). These control methods have drawbacks in stability and response time in the case when solar illumination changes abruptly. A direct MPP method using PV model parameters was introduced in Ikegami et al. (2001). However, the validity of obtained result depends on the accuracy of the model parameters; i.e. the criterion for parameters extraction is not convex, and the traditional deterministic optimization algorithm used in Ikegami et al. (2001) leads to local minima solutions. Indeed, in our case, we use the GAs, which belongs to heuristic solutions that represent a trade-off between solution quality and time. The GAs have a stochastic search procedure in nature, they usually outperform gradient based techniques in getting close to the global minima and hence avoid being trapped in local ones.

A derivative of the output power P with respect to the output voltage V is equal to zero at MPP.

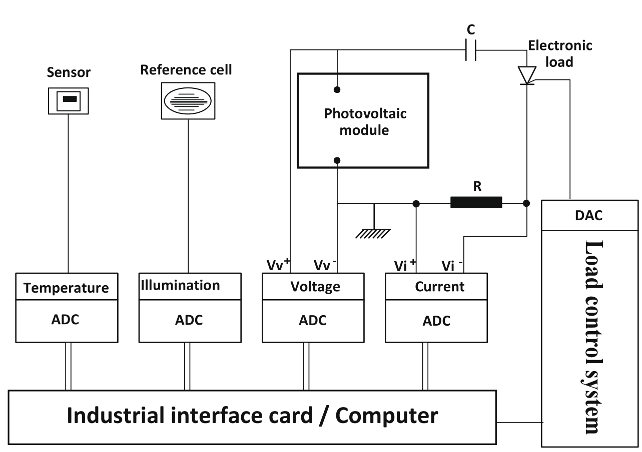

Fig. 5. Block diagram of the PV module tester.

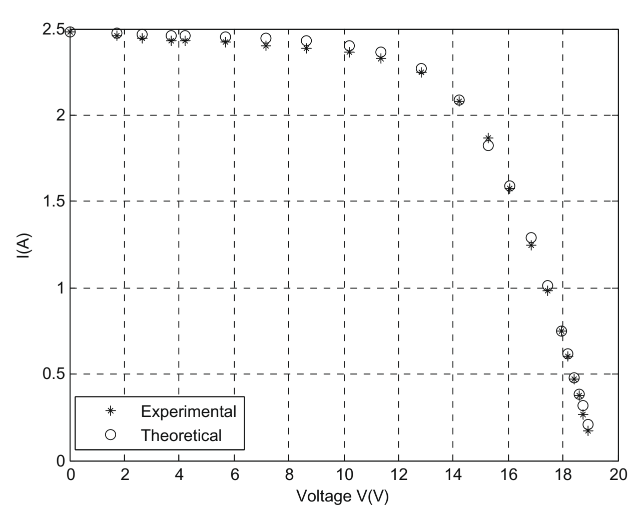

Fig. 6. Adjustment of the theoretical I–V curve to the experimental one using GAs of the PV solar module.

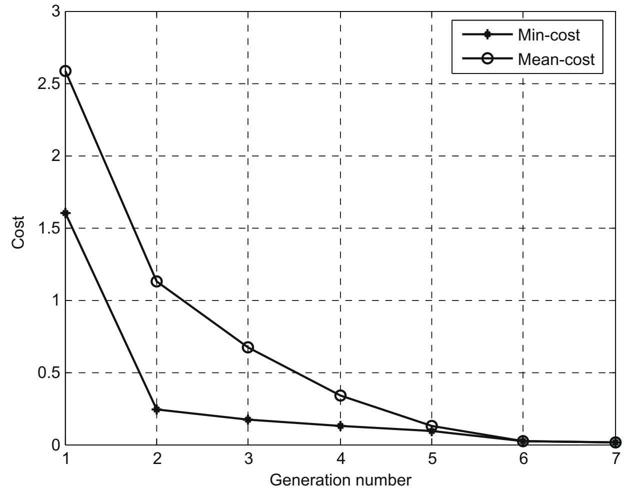

Fig. 7. The mean and the minimum values of the cost function χ versus generation number (case of PV solar modules).

Table 2
Electrical parameters of the PV module obtained with GAs.

Electrical parameters	Values (GAs)
I_s (A)	8.1511×10^{-6}
I_{ph} (A)	2.4901
R_s (Ω)	0.9539
R_{sh} (Ω)	196.4081
n	60.4182

$$\frac{dP}{dV} = I - V\left[\frac{\frac{q}{nkT}\left(I_{ph} + I_s - I - \frac{V+R_sI}{R_{sh}}\right) + \frac{1}{R_{sh}}}{1 + \frac{qR_s}{nkT}\left(I_{ph} + I_s - I - \frac{V+R_sI}{R_{sh}}\right) + \frac{R_s}{R_{sh}}}\right] = 0 \tag{5}$$

If the parameters of the equivalent circuit model are given, MPP is obtained by solving Eq. (5) using standard numerical non-linear method. This can be easily achieved with the optimisation Toolbox of MATLAB software.

In Table 3, we give the current and voltage values corresponding to the maximum power points (MPP) obtained using Eq. (5) and the electrical parameters given in Tables 1 and 2 identified by the GAs. The output results in the case of the solar cell are compared to those provided by the Pasan software. In the case of the cell (Table 3), one can notice that our GAs simulations results differ at least by 5.3% from those given by the Pasan software. In general, the well used procedure to estimate the MPP in cell and module testers is based on the selection of the maximum power from an experimental set of current–voltage multiplication. The accuracy of this statistical approach depends on the precision of the experimental data, which should surround the real value of the MPP. However, our approach presents two advantages; first, it is based on Eq. (5), which is free of these experimental constrains. Secondly, Eq. (5) itself, uses the identified electrical parameters extracted by the GAs that belong to a sophisticated global search method.

Table 3
MPP's coordinates of the solar cell and the solar module and their corresponding powers.

	I_{opt} (A)	U_{opt} (V)	MPP (W)
Cell (using GAs)	0.137	0.571	0.078
Cell (using Pasan software V 3.0)	0.131	0.565	0.074
Module (using GAs)	2.120	14.200	30.104

Obtained results in the case of the PV cell using the Pasan software and the GAs are nearly identical. However, in the case of the PV module, our homemade system is able to measure I–V characteristics, but it is not equipped with sophisticated software to give the electrical characteristics of the module. Consequently, the measured I–V curve of the module is analysed only with the GAs method, and no comparison is performed as shown in Table 3. The credibility of obtained results with the PV module is extrapolated from that one of the PV solar cell, where obtained results with the GAs technique are compared to those obtained using a professional machine (Pasan CT 801).

6. Conclusion

In this work, we applied the genetic algorithms to characterize PV solar cells and modules, particularly for the determination of electrical parameters namely such as the photocurrent, the saturation current, the series resistance, the shunt resistance and the ideality factor. Determination of these parameters starting from the experimental data is formulated in the form of a non convex optimization problem. The resolution of this problem by conventional techniques of non-linear programming, such as the algorithm of Newton Rafson, conducts to less satisfactory results, which depend on the initial conditions leading to local minima solutions. We thus adopted the genetic algorithms (GAs) as an optimization tool. This choice is justified by the fact that GAs overcome problems involved in the local minima in the case of non convex optimization criteria. We used a fitting procedure based on the minimisation of the cost function χ of the theoretical I–V curves from the experimental ones. Initially, we applied GAs to determine values of the electrical parameters of a PV solar cell and a PV module. Theoretically, we assumed a one diode model in the I–V characteristic. Simulation results show that the precision of the fitting approach is better in the case of solar cells than that of solar modules. Hence, values of the minima were found to be equal to 0.000256 A^2 and 0.0676 A^2 for the solar cell and for the module, respectively. These minima were reached after five generations for the solar cell and after seven generations in the case of the module. According to these results, one can assume that the GAs are very suitable for the estimation of the electrical parameters via fitting procedure.

In the case of the solar cell testing, the Pasan's software (V3.0) gives three parameters. However, the GAs-based fitting procedure developed in this work, was achieved using five parameters. Two of the output parameters using GAs are close to those obtained with the Pasan's software. In addition, we estimated two others parameters (the saturation current and the ideality factor) and all results were obtained with a relatively good value of the cost function. Since GAs belong to a global search approach, the minimum value of χ might be the absolute one, or close to it. The maximum power working points were then extracted from the previously identified electrical parameters from the GAs in the case of the cell and module PV generators. Obtained MPP' cell coordinates by GAs are compared to those derived by the Pasan machine, and, are found to be closely identical. The GAs credibility on performing such minimization permits us to use the GAs to estimate the MPP of a solar module, despite the fact that we have no professional software to determine the PV module MPP.

References

Bahgat, A.B.G., Helwa, N.H., Ahamd, G.E., El Shenawy, E.T., 2004. Estimation of the maximum power and normal operating power of a photovoltaic module by neural networks. Ren. Energy 29 (3), 443–457.

Chan, Daniel S.H., Phang, Jacob C.H., 1987. Analytical methods for the extraction of solar-cell single- and double-diode model parameters from *I–V* characteristics. IEEE Trans. Electron Dev. ED-34 (2), 286–293.

Charles, J.P., Abdelkrim, M., Muoy, Y.H., Mialhe, P., 1981. A practical method of analysis of the current–voltage characteristics of solar cells. Solar Cells 4, 169–178.

Charles, J.P., Ismail, M.A., Bordure, G., 1985. A critical study of the effectiveness of the single and double exponential models for *I–V* characterization of solar cells. Solid-State Electron. 28 (8), 807–820.

Dufo-Lopez, Rodolfo, Bernal-Agustin, José L., 2005. Design and control strategies of PV–Diesel systems using genetic algorithms. Solar Energy 79, 33–46.

Easwarakhanthan, T., Bottin, J., Bouhouch, I., Boutrit, C., 1986. Nonlinear minimization algorithm for determining the solar cell parameters with microcomputers. Int. J. Solar Energy 4, 1–12.

Enrique, J.M., Durán, E., Sidrach-de-Cardona, M., Andújar, J.M., 2007. Theoretical assessment of the maximum power point tracking efficiency of photovoltaic facilities with different converter topologies. Solar Energy 81 (1), 31–38.

Haupt, R.L., Haupt, S.E., 1998. Practical Genetic Algorithms. Wiley, New York.

Ikegami, T., Maezono, T., Nakanishi, F., Yamagata, Y., Ebihara, K., 2001. Estimation of equivalent circuit parameters of PV module and its application to optimal operation of PV system. Solar Energy Mater. Solar Cells 67, 389–395.

Jervase, Joseph A., Hadj, Bourdoucen, Al-Lawati, Ali, 2001. Solar cell parameter extraction using genetic algorithms. Meas. Sci. Technol. 12, 1922–1925.

Ketter, Robert L., Prawel, Sherwood P., 1975. Modern Methods of Engineering Computation. Mac Graw-Hill Book Company.

Laplaze, D., Youm, I., 1985. Modélisation d'une cellule photovolta: détermination des paramètres à partir de la caractéristique courant-tension sous éclairement. Solar Cells 14, 167–177.

Loomans, Marcel, Visser, Huib, 2002. Application of the genetic algorithm for optimisation of large solar hot water systems. Solar Energy 72 (5), 427–439.

Pasan Cell Tester CT 801 operating manual, 2004. (www.pasan.ch).

Phang, Jacob.C.H., Chan, S.H. Daniel, 1986. A review of curve fitting error criteria for solar cell *I–V* characteristics. Solar Cells 18, 1–12.

Sellami, A., Ghodbane, F., Andoulsi, R., Ezzaouia, H., 1998. An electrical performance tester for PV modules. Proc. WREC (Florence, Italy) 3, 1717–1720.

Sellami, A., Zagrouba, M., Boua, M., Bessa, B., 2007. Application of genetic algorithms for the extraction of electrical parameters of multicrystalline silicon. Meas. Sci. Technol. 18, 1472–1476.

Yang, Hongxing, Zhou, Wei, Lu, Lin, Fang, Zhaohong, 2008. Optimal sizing method for stand-alone hybrid solar–wind system with LPSP technology by using genetic algorithm. Solar Energy 82, 354–367.

Yu, G.J., Jung, Y.S., Choi, J.Y., Kim, G.S., 2004. A novel two-mode MPPT control algorithm based on comparative study of existing algorithms. Solar Energy 76, 455–463.