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AN OUTDOOR PLATFORM FOR PV AGEING STUDIES: ELECTRICAL PARAMETERS EXTRACTION FROM IV CURVES

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Abstract

Accurate models for solar technologies are essential to evaluate the lifetime, ageing and degradation modes of these devices, depending on local climatic constraints. In this context, the DURASOL project aims to provide more sophisticated tools and methods for solar industries, based on studies in multi-site facilities with indoor and outdoor platforms under diverse and complementary climates. For solar cells and modules, simple diode modelling allows to determine several electrical parameters from IV curves: the series and shunt resistances, the photocurrent, the reverse saturation current of diode and the diode ideality factor. These parameters can be used for various applications such as analyze of performance losses, quality control and devices improvements. In this paper, we focus on their extraction through a Particle Swarm Optimization algorithm. Three approaches are compared, based on a direct optimization of the five electrical parameters and on the use of the short-circuit current I_{sc} and the open-circuit voltage V_{oc}. The tests realized on a synthetic IV curve show that the use of V_{oc} leads to a more robust and accurate model with both exact and noisy data.

Keywords: *Photovoltaic, Simple diode model, IV curve, Parameters extraction, Particle Swarm Optimization*

1. Introduction

The markets of solar technologies as photovoltaic (PV) are rapidly growing. However, long term performance and reliability remain major issues to provide warranties, develop insurance and subsidy programs, evaluate a long term investment risk or help the customer to choose between manufacturers. Therefore, methods for evaluating the lifetime, ageing and degradation modes of these technologies are necessary. Most of the time, simple assumptions of a constant and linear degradation rate performance per year are made for PV modules (Vázquez and Rey-Stolle, 2008). The impacts of non-linear and non-uniform degradations as well as their sources require further studies.

Environmental conditions and local climate have an important impact on PV energy efficiency and its evolution over time (Jordan et al., 2012; Jordan and Kurtz, 2013). Even well qualified modules can degrade more than expected when exposed to outdoor conditions (Sharma and Chandel, 2013). These degradations can be correlated to various stresses affecting solar modules lifetime such as temperature (heat, freezing, night-day cycles…), mechanical stresses (wind, snow load, hail…), atmosphere (salt mist, dust, sand, pollution…) and humidity (rain, dew, frost, fog…). Moreover, it must also be considered that each stress may show up some singular ageing effect as well as it can combine with other stresses. As an example, Mekhilef et al. (2012) focus on some environmental factors (dust, humidity and air velocity) and show that they should not be studied separately as their effects are linked up and each of them impacts the other two. Skoczek et al. (2009) also present the results of electrical performance measurements of hundreds crystalline silicon photovoltaic modules, following long-term continuous outdoor exposure. An important outcome is that visual inspection is generally not enough to track the module degradation and by no means answer the question of module lifetime. Advanced diagnostic tools are thus required to measure the degradations, quantify them and also explain the phenomena.

For PV technologies, some electrical parameters allow to analyze performance losses and lead to more

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accurate models and simulations. The extraction and interpretation of these parameters has a variety of important applications. They can, for example, be used for quality control during production or to provide insights into the operation of the devices, thereby leading to improvements in devices (Gottschalg et al., 1999). In this paper, we will focus on the series and shunt resistances R_s and R_{sh}, the photocurrent I_{ph}, the reverse saturation current of diode I_0 and the diode ideality factor n which can be obtained from IV curves through the monitoring of solar cells and modules. The variation of these parameters over time can be correlated to specific degradations (delamination, discoloration…) and thus allow to assess the ageing effects and the impact of environment. In their review of photovoltaic degradation rate methodologies, Phinikarides et al. (2014) present a list of possible sources of performance losses and their impact on some of these parameters. For example, the series resistance has a significant effect on both the fill factor and the conversion efficiency. The shunt resistance is crucial to photovoltaic system performance, especially at reduced irradiance levels (Priyanka et al., 2007). Inaccurate determination will provide a misleading interpretation on the impact of each parameter and lead either to an overestimation or underestimation of the degradation. The main difficulty of this type of study is thus to define measurement and extraction methods with a sufficient robustness and precision.

For this purpose, the DURASOL project aims to provide more sophisticated tools and methods for the PV, ST and CSP industries. This project, supported by the French National Research Agency as an "Invest for Future, EQUIPEX", relies on multi-site facilities with several indoor and outdoor platforms under various and complementary climates. It aims to compare analysis of indoor and outdoor ageing, determine accelerating ageing factors depending on climatic constraints and develop analysis methods for degradation mechanisms. On the medium term, it will provide deeper insight and understanding of degradation mechanisms allowing to design and manufacture new components with longer life-time and higher performances. As a first step, we focus on this paper on the extraction of electrical parameters through simple diode modelling.

2. IV curves processing

2.1. Measurement protocol

In order to get reliable information on a solar device, it is required to set up a robust measurement protocol. Depending on the method used for the calculation of electrical parameters, an important accuracy will be needed. As an example, curve fitting method needs to calculate the differential value dV/dI from the experimental data, which requires a very smooth IV curve (Zhang et al., 2011).

According to Gottschalg et al. (1999), there are three standard measurement strategies for measuring the IV characteristics of PV solar devices. One can apply the voltage in regularly distributed steps, control the current in regularly distributed steps or measure with a variable resistance load. Comparing the different measurement strategies clearly shows that it is better to measure devices with constant voltage steps. In the context of DURASOL project, we have opted for a measurement method based on the application of a voltage with a specific step. This is done with a test bench for PV characterisation through current-voltage measurements. This IV bench is connected to photovoltaic modules, on an outdoor platform which is being installed at the SPE Laboratory UMR CNRS, University of Corsica, France (Fig. 1). The site is located in a coastal zone (distance from the sea of less than 400 m) with a Mediterranean climate and exposed to salty sea spray. In addition to the current and voltage measurements, each module is also equipped with a temperature sensor (PT100) and the surrounding conditions (ambient temperature, solar radiations, wind speed and direction…) are measured on the platform. This facility allows to plot and back up the modules IV curves with a 5 minutes time step and at least 100 points per curve for a given temperature and irradiance. These parameters can be changed depending on the accuracy needed and the aim of the study. The only limitation here is to ensure that the computation time for each IV curve is not too high (of about 1s) in order to avoid variations of surrounding conditions during measurement.

Fig. 1: DURASOL platform at SPE Laboratory, University of Corsica

2.2. Single diode model

To study solar cells and modules, it is common to represent them with an electrical analogy. For electrical engineering applications, simple diode models are usually suitable (Askarzadeh and Rezazadeh, 2012; de Blas et al., 2002). This type of model allows extracting several electrical parameters: the series and shunt resistances R_s and R_{sh}, the photocurrent I_{ph}, the reverse saturation current of diode I_0 and the diode ideality factor n. These parameters influence the behavior of the IV characteristics and give information on solar device performance. Fig. 2 shows an equivalent circuit of a solar module based on a simple diode model.

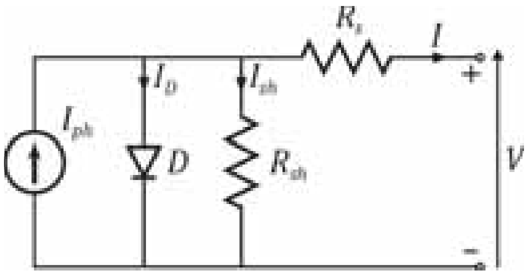

Fig. 2: Equivalent circuit of a solar module (simple diode model)

In this circuit, the current I can be simply expressed as:

$$I = I_{ph} - I_D - I_{sh} \qquad \text{(eq. 1)}$$

With:

$$I_D = I_0 \left(e^{\frac{q(V+IR_s)}{nkT}} - 1 \right) \qquad \text{(eq. 2)}$$

$$I_{sh} = \frac{V + IR_s}{R_{sh}} \qquad \text{(eq. 3)}$$

Which leads to the transcendental equation:

$$I = I_{ph} - I_0 \left(e^{\frac{q(V+IR_s)}{nkT}} - 1 \right) - \frac{V + IR_s}{R_{sh}} \qquad \text{(eq. 4)}$$

This equation is then resolved by an exact explicit method based on the Lambert W-function $W(z)$ (Jain, 2004):

$$I = \frac{R_{sh}(I_{ph} + I_0)}{(R_s + R_{sh})} - \frac{nkT}{qR_s}W(z) - \frac{V}{R_{sh}} \quad \text{(eq. 5)}$$

With:

$$z = \frac{qI_0}{nkT}\frac{R_sR_{sh}}{(R_s + R_{sh})}e^{\left(\frac{R_{sh}}{(R_s+R_{sh})}\frac{q[V+R_s(I_{ph}+I_0)]}{nkT}\right)} \quad \text{(eq. 6)}$$

The solution of this equation is obtained by the algorithm proposed by Fritsch et al. (1973). This method allows to express the current as a function of the voltage, the temperature and the five electrical parameters that we need to determine.

3. Parameters extraction methodology

From the experimental equipment presented in the previous section, it remains five unknown parameters that appear in (eq. 5). Their accuracy will depend on both the precision of the experimental data and the robustness of the method used for their determination. In addition to the measurement protocol, the main part of this work is thus to establish and validate a robust method for parameters extraction.

In the last decades, this problem has been treated frequently in literature with different methods which can be classified into three categories: analytic, iterative and evolutionary computational methods. Among these methods, we will focus in evolutionary algorithms which are the best suited with varying weather conditions (Tamrakar and Gupta, 2015). For this problem, we observe a large variety of algorithms such as Genetic (Jervase et al., 2001), Pattern Search (AlRashidi et al., 2011), Differential Evolution (Ishaque and Salam, 2011), Penalty-based Differential Evolution (Ishaque et al., 2012), Harmony Search (Askarzadeh and Rezazadeh, 2012), Simulated Annealing (El-Naggar et al., 2012) or Chaotic Asexual Reproduction Optimization (Yuan et al., 2014). In this paper, we propose the use of a Particle Swarm Optimization (PSO) algorithm which has been validated by several authors (Macabebe et al., 2011; Qin and Kimball, 2011; Sandrolini et al., 2010; Ye et al., 2009). According to Ye et al. (2009), this technique is accurate, fast, and easily applicable for the parameter extraction of solar cells from illuminated IV characteristics. Moreover, it does not particularly necessitate initial guesses as close as possible to the solutions, which is an important point as we can study a large amount of different PV solar devices. The interest of PSO algorithms for applications in power systems has also been demonstrated by Del Valle et al. (2008).

3.1. PSO configuration

The Particle Swarm Optimization is a metaheuristic which is trying to improve a candidate solution by successive iterations. It is inspired by social behaviour of living organisms such as bird flocking. The members of the population, the particles, are initially dispersed in the search area with random coordinates (position and velocity). At each iteration, the fitness of each particle is evaluated. The algorithm keeps in memory the best solution of each particle and the best solution obtained so far by any particle in the population. This information is then used to update the velocities and positions of all particles to improve the solution. Indeed, the choice of the PSO parameters will have a large impact on optimization performance (calculation time and accuracy). However, PSO algorithms use less parameters compared to other methods such as artificial neural networks and basic principles allow to define some of them more easily. Since 2006, the Standard Particle Swarm Optimization (SPSO) gathers these principles (Maurice Clerc, 2012; Zambrano-Bigiarini et al, 2013). Here, we use the following configuration for standard optimizations:

- Number of iterations: *variable;*
- Number of particles in swarm: 40;
- Cognitive acceleration coefficient: 2.8;
- Social acceleration coefficient: 1.3.

These parameters can always been modified depending on the problem and expectations. As an example, a compromise can be found between calculation time and accuracy by changing the number of iterations and particles.

3.2. Methods

According to the approach chosen in this paper, the most direct method would be to extract the five electrical parameters from (eq. 5) using a PSO algorithm. However, it is known that some of these parameters are interrelated or correlated to other parameters such as the short-circuit current I_{sc} or the open-circuit voltage V_{oc}. The advantage of these two variables is that they can also be obtained by measurements.

If we set the current to 0 in (eq. 4), the voltage takes the value of the open-circuit voltage V_{oc}:

$$I_{ph} - I_0\left(e^{\frac{qV_{oc}}{nkT}} - 1\right) - \frac{V_{oc}}{R_{sh}} = 0 \qquad \text{(eq. 7)}$$

If we set the voltage to 0 in (eq. 4), the current takes the value of the short-circuit current I_{sc}:

$$I_{ph} - I_0\left(e^{\frac{qI_{sc}R_s}{nkT}} - 1\right) - \frac{I_{sc}R_s}{R_{sh}} = I_{sc} \qquad \text{(eq. 8)}$$

From these two equations, it is possible, for example, to express n in terms of V_{oc} or I_{sc}:

$$n = \frac{qV_{oc}}{kT\ ln\left(\frac{-V_{oc}}{I_0R_{sh}} + \frac{I_{ph}}{I_0} + 1\right)} \qquad \text{(eq. 9)}$$

$$n = \frac{qR_sI_{sc}}{kT\ ln\left(\frac{-I_{sc}R_s}{I_0R_{sh}} + \frac{I_{ph} - I_{sc}}{I_0} + 1\right)} \qquad \text{(eq. 10)}$$

This approach allows to extract only four parameters with the PSO algorithm and to determine the fifth with (eq. 9) or (eq. 10). Moreover, it should increase the robustness of the optimization if we have reliable data for V_{oc} or I_{sc}.

4. Application

4.1. Comparison with a synthetic IV curve

In order to test the methods proposed in this paper, it is interesting to work with a synthetic IV curve. This approach presents many interests. First, this type of curve corresponds to perfect curve (without measurement noise) and allows to assess the maximum accuracy which can be reach by the model. As we know the exact value of all the parameters it is also possible to evaluate the accuracy of each of them and their impact on overall model performance.

Here, we use a set of parameters representative of a silicon solar cell (at $T = 306\ K$) and reported in several literatures (Ye et al., 2009):

- $I_{ph} = 0.7608\ A$;
- $I_0 = 3.223 \times 10^{-7}\ A$;
- $n = 1.4837$;
- $R_s = 0.0364\ \Omega$;
- $R_{sh} = 53.76\ \Omega$.

It is also required to determine V_{oc} and I_{sc}, which are used in this method. The exact value of I_{sc} can be directly calculated from (eq. 5) using the Lambert W-function. From this equation, it is also possible to extract the value of V_{oc} using a numerical solver such as *fsolve* function in MATLAB environment.

To determine the best approach, we compare the three possibilities presented in 3.2. The first consists in the application of a PSO algorithm to extract the five parameters from the IV curve. The other two are based on the same PSO algorithm but use V_{oc} and I_{sc} for the calculation of the diode ideality factor n with (eq. 9) or (eq. 10). In each case, we set the same initial values and boundaries:

- $I_{ph} = \max(I) \in [\max(I)\,; 1.02\max(I)]\,A$;
- $I_0 = 1 \times 10^{-6}\,A \in \left[1 \times 10^{-10}\,; 1 \times 10^{-4}\right] A$;
- $n = 1.5 \in [1\,; 2]$ (not used when calculated with V_{oc} or I_{sc});
- $R_s = 1\,\Omega \in \left[1 \times 10^{-5}\,;\ 1 \times 10^{2}\right] \Omega$;
- $R_{sh} = 1\,\Omega \in \left[1 \times 10^{-3}\,;\ 1 \times 10^{5}\right] \Omega$.

The initial values are quite far from the researched parameters and the boundaries are large enough to match different types of solar cells.

To compare these methods, we run 10 simulations with 1000 iterations and 40 particles in each case. First, we focus on the error made on the current *I* by calculating the Mean Absolute Error (MAE) for each simulation. All the results are presented in Fig. 3 and show important variations between the three methods.

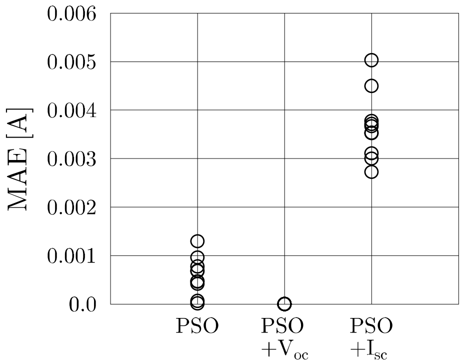

Fig. 3: Performance of the three methods on 10 simulations

The use of the PSO to extract the five parameters provides a MAE between 1.45×10^{-5} and $1.29 \times 10^{-3}\,A$. Even if these errors seem quite low, their differences show that the method is not particularly robust. Moreover, these errors still have an important impact on the electrical parameters, as seen in Fig. 4. As an example, the most impacted parameter, I_0, has a relative error varying between 1.80% and 244%. If we need a very high precision on parameters (relative error lower than 2% for each parameter), only one simulation in ten fulfilled this condition here. To ensure this precision each time, it will thus be necessary to run many simulations which will be time consuming if we apply this method on several solar modules with a low time step. It should also be noted that we did not observe any effect of error compensation between parameters. In each case, the lowest error on current is obtained when each parameter is the closest to its real value. We thus clearly observe that the optimization of this method to further reduce the error is not meaningless and will lead to a better extraction of parameters.

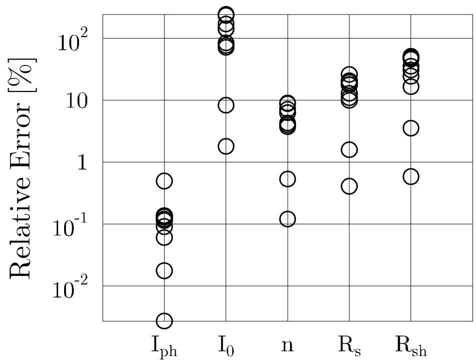

Fig. 4: Relative error of electrical parameters extracted by PSO on 10 simulations

As shown in Fig. 3, the addition of (eq. 9) with V_{oc} calculation significantly improves the performance of the optimization. We observe that all simulations tend to the exact solution, with a MAE of about 1.45 ×

$10^{-17}\,A$, leading to a perfect extraction of all electrical parameters. This method is thus more robust and could be further improved by determining the best algorithm complexity (number of particles and iterations) while maintaining a high precision. The Fig. 5 also shows that much less iterations are necessary to reach a satisfying result. If we are looking for a MAE of about $10^{-5}\,A$, which corresponds to a near perfect extraction of parameters, we observe that 150 iterations are enough when we use the PSO combined with (eq. 9). If necessary, this result allows to bring an important decrease of calculation time.

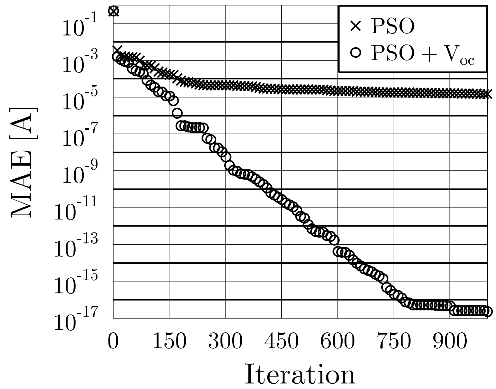

Fig. 5: Evolution of MAE depending on number of iterations

The third case, based on the addition of (eq. 10) with I_{sc} calculation, does not share the same results. Even if the approach is similar, the MAE is varying here between 2.72×10^{-3} and $5.03 \times 10^{-3}\,A$. This precision is thus not satisfying compared to the other methods and does not allow to obtain a reliable extraction of parameters. This difference comes from a stability problem due to the use of (eq. 10). In order to solve this equation, it is necessary to have a positive logarithm and thus:

$$\frac{-I_{sc}R_s}{I_0R_{sh}} + \frac{I_{ph} - I_{sc}}{I_0} + 1 > 1 \qquad \text{(eq. 11)}$$

Which leads to:

$$\frac{1}{I_0}\left(I_{ph} - I_{sc}\left(1 + \frac{R_s}{R_{sh}}\right)\right) > 0 \qquad \text{(eq. 12)}$$

As I_{ph} is known to be very close to I_{sc}, this equation will often lead to a negative result and thus to an impossible solution during the optimization, decreasing its performance. To improve this method, it is possible to define more efficiently the boundaries and the initialization of the PSO algorithm. However, these conditions will change depending on the technologies studied and this lack of robustness is not suitable for this type of model. Here, the use of V_{oc} appears to be a more robust and reliable method.

4.2. Impact of uncertainties

In the application proposed in the previous section, we used a synthetic IV curve which has allowed to determine the exact value of all parameters. In a real case, even with high accuracy measurements, we have to deal with uncertainties. Here, we want to assess the impact of V_{oc} uncertainties on current and thus on electrical parameters extraction. As the ideality factor n is calculated from V_{oc}, the uncertainties on this parameter necessarily induce a loss of precision. In Fig. 6, we present this impact on the optimization (MAE on current I). In each case, 10 simulations have been run with a percentage error x such as $V_{oc,er} = V_{oc} \pm x(\%)V_{oc}$. We still observe the robustness of the method as all simulations tend to the same result for a given error x. However, it should be noted that a very high precision on V_{oc} is required to obtain reliable results. Indeed, this parameter appears to be very sensitive as we observe an almost linear relationship between the errors on V_{oc} and I.

The applicability of this method thus highly depends on both the precision of measurements and the precision desired for electrical parameters. For our application, we estimate that a MAE of about $10^{-4}\,A$ is more than enough to obtain a reliable extraction of electrical parameters. Here, it allows to extract all parameters with the following relative errors: 5.03×10^{-3} % for I_{ph}, 6.65 % for I_0, 0.42 % for n, 1.58 % for R_s and 0.57 % for R_{sh}. However, it still requires an error of less than 0.1 % on V_{oc}, which may be difficult to achieve.

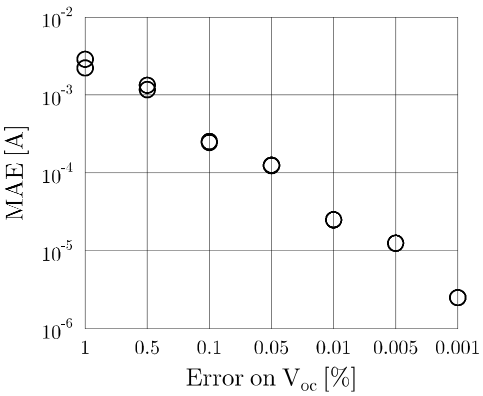

Fig. 6: MAE on current I depending on the error on V_{oc}

With higher error on this parameter, the standard method (direct optimization of all electrical parameters by PSO) could lead to a decrease of overall uncertainty. It is thus needed to compare also these two methods with more realistic IV curves, which may be subjected to measurement noise. For this purpose, it is possible to add a noise in current to assess its impact on parameters extraction. Here, we add a white Gaussian noise with a variance of 0.01, as presented in Fig. 7.

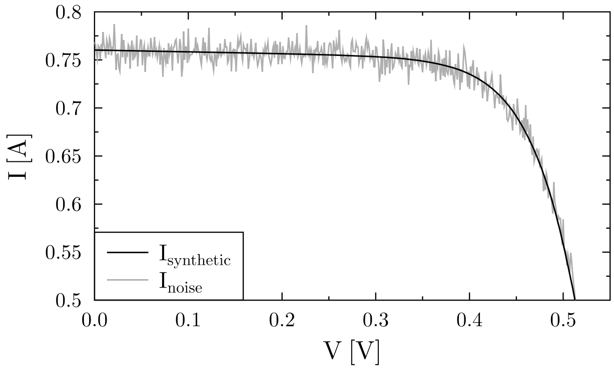

Fig. 7: Synthetic and noisy IV curves (zoom between 0.5 and 0.8 *A*)

In this case, it seems necessary to modify the boundaries of I_{ph}, as $\max(I)$ is no more an accurate value to rely on. We now use the following boundaries: $I_{ph} \in [0.95 \max(I)\,;1.05 \max(I)]\ A$, which are broader than the previous ones. For the noisy IV curve, the two methods present an identical error on current I, with a minimal MAE of about $7.67 \times 10^{-3}\ A$ on ten simulations. However, as in the previous cases, we still obtain a better robustness of the optimization by using the V_{oc}. Moreover, the electrical parameters are also more accurate with this method, as presented in Tab. 1. The only exception is observed for I_{ph} but the error remains low and the difference is not significant.

Even with noisy IV curves, the method proposed in this paper, based on the use of V_{oc}, still appears to be the best choice to extract the electrical parameters. These results could be probably improved with data processing such as filtering and smoothing which is a perspective of this work and will be assessed on real IV curves.

Tab. 1: Comparison of the two methods on a noisy IV curve

	Real values	PSO	PSO + V_{oc}	Relative Errors (%) PSO	Relative Errors (%) PSO + V_{oc}
I_{ph}	$0.7608\ A$	$0.7600\ A$	$0.7619\ A$	0.11	0.14
I_0	$3.223 \times 10^{-7}\ A$	$7.597 \times 10^{-7}\ A$	$2.464 \times 10^{-7}\ A$	135.71	23.54
n	1.4837	1.5737	1.4574	6.06	1.78
R_s	$0.0364\ \Omega$	$0.0298\ \Omega$	$0.0372\ \Omega$	18.13	2.07
R_{sh}	$53.76\ \Omega$	$83.55\ \Omega$	$42.73\ \Omega$	55.42	20.51

5. Conclusion

In this paper we proposed an alternative method to extract the electrical parameters from IV curves with a single diode model. The calculation of the diode ideality factor based on the open-circuit voltage allows to improve the parameters extraction with a Particle Swarm Optimization algorithm. In comparison with a direct optimization of all parameters, which is often used, this method provides much more accurate results. With a synthetic IV curve, it is possible to reach a MAE on current of about $10^{-17}\ A$, leading to a perfect extraction of parameters. This method is also more robust, as we reach similar precision for each simulation with less iterations. Even if a high accuracy on the open-circuit voltage is needed to obtain such results, we observed that it is still applicable for noisy IV curves which are more representative of real measurements.

In the framework of DURASOL project, this study will be applied on real IV curves from different solar PV devices. The next step of this work will thus focus on the real data processing (filtering and smoothing) and on their interpretation. The main contribution will concern the use of this valuable information in order to assess correlations between PV degradations and environmental conditions.

6. Nomenclature

Name	Symbol	Units
Temperature	T	K
Voltage	V	V
Open-circuit voltage	V_{oc}	V
Current	I	A
Short-circuit current	I_{sc}	A
Photocurrent	I_{ph}	A
Reverse saturation current of the diode	I_0	A
Diode ideality factor	n	-
Series resistance	R_s	Ω
Shunt resistance	R_{sh}	Ω
Boltzmann constant	k	$m^2.kg.s^{-2}.K^{-1}$
Elementary charge	q	C

7. Acknowledgements

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