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SENSITIVITY ANALYSIS OF A NEW APPROACH TO PHOTOVOLTAIC PARAMETERS EXTRACTION BASED ON THE TOTAL LEAST SQUARES METHOD

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Abstract

The degradation of photovoltaic modules and their subsequent loss of performance has a serious impact on the total energy generation potential. The lack of real-time information on the output power leads to additional losses since the panels may not be operating at their optimal point. To understand the behaviour, numerically simulate the characteristics and identify the optimal operating point of a photovoltaic cell, the parameters of an equivalent electrical circuit must first be identified. The aim of this work is to develop a total least-squares based algorithm which can identify those parameters from the output voltage and current measurements, taking into consideration the uncertainties on both measured quantities. This work presents a comparative study of the Ordinary Least Squares (OLS) and Total Least Squares (TLS) approaches to the estimation of the parameters of a photovoltaic cell.

Keywords: photovoltaic modules, parameter extraction, total least squares, MPP, sensitivity analysis.

1. Introduction

The continuous increase in energy demand over the last decades is creating a major challenge in energy production. Although multiple sources of energy are currently available [1], most of them present environmental and economic issues. For example, nuclear energy is almost unlimited but presents great risks to the planet and to human beings. Fossil fuels, which are presently considered the major source of energy production, have limited resources which are being depleted. Additionally, their consumption increases pollution and gives rise to the emission of greenhouse gases which is mainly responsible for climate change [2]. However, renewable energies like solar photovoltaic energy, wind energy or hydropower are virtually unlimited and environment friendly [3].

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Photovoltaic solar energy comes from direct transformation of solar radiation into electric energy. This energy conversion is done through *photovoltaic* (PV) cells and is based on a physical phenomenon called the photovoltaic effect which creates an electromotive force when the surface of the cell is exposed to light [1]. A photovoltaic cell should be connected to a maximum power point converter in order to keep track of the maximal produced power [4,5]. Modelling the behaviour of a PV cell requires that properties of solar radiation and of the cell semiconductors [6] are known. In the literature [7, 8], there are several photovoltaic cell models whose purpose is to obtain the *current-voltage* (I–V) characteristic for analysis and performance evaluation of photovoltaic modules. The most common model is based on five parameters: the photocurrent I_{ph}, the saturation current I_s, the ideality factor n, the series resistance R_s and the shunt resistance R_{sh}.

In general, manufacturers do not provide information on model parameters, although they constitute the base for the characterisation of a photovoltaic panel. Moreover, the long exposure of a panel causes it to suffer multiple forms of degradation [9, 10], which also unpredictably changes the values of the model parameters [11–13]. Therefore, identifying the photovoltaic model parameters from the current-voltage measurements is crucial to the characterization of PV panels.

The direct techniques [14,15] use analytical approaches to obtain the parameters from a measured curve, but it requires extensive calculations. Another possibility to directly measure those parameters [16] requires the use of expensive measurement instruments. However, numerous works using different mathematical optimization methods have been proposed [17–26]. In [22] the Levenberg–Marquardt method is used to identify the PV parameters through the minimization of a suitable cost function based on *ordinary least squares* (OLS). In [23] a *Flower Pollination Algorithm* (FPA) is proposed for estimating the parameters of photovoltaic modules and the performance of the proposed extraction technique is tested using three different sources of data. In [21] a method is suggested for extracting the intrinsic parameters of a photovoltaic module by using the *shuffled complex evolution* (SCE) technique for a double-diode PV model. In [18] a combination based on the Grey Wolf Optimizer and the cuckoo search algorithm for parameter extraction of solar photovoltaic models is also developed. This paper [17] presents the *Bacterial Foraging Optimization* (BFO) technique as a new parameter extraction method and compares its results to other methods. In [20] a new version of the wind-driven optimization algorithm, called an *adaptive wind-driven optimization* (AWDO) algorithm was developed and implemented. A *triple-phase teaching-learning-based optimization* (TPTLBO) is proposed in [19] to accurately and reliably extract the parameters of different PV models. In this work [24], the *Coyote Optimization Algorithm* (COA) has been applied to extracti parameters of various models for the solar cell and PV modules. An enhanced heuristic Nelder–Mead algorithm has also been used for photovoltaic parameter identification [25, 26], where the initial simplex and the convergence conditions were modified.

The experimental set up for characterization of a photovoltaic panel requires the use of instruments to measure the panel's output current and voltage. The resulting data from these measurements are always affected by uncertainties which manifest themselves in the form of additive noise. Usually, the cost function used in the optimization is based on the OLS [27] which only focus on quantifying the sum of the difference between the measured current and the estimated current. The resulting algorithm is simple to implement even in the case of implicit non-linear models such as the photovoltaic I–V characteristic. However, this approach results in higher uncertainty of the estimated PV parameters despite its implementation simplicity.

This paper proposes a new method which is based on minimizing the sum of distances not only between the measured and estimated current, but also between the measured and estimated voltage. Therefore, this method relies on minimizing the sum of Euclidean distances between

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the measured and estimated quantities in what is defined as *total least squares* (TLS). The new proposed algorithm is easily implementable for application to non-linear implicit models such as the photovoltaic I–V characteristic. Simulation results of a PV panel are presented to statistically compare the performance of the proposed TLS method with the traditional OLS method. To further highlight the advantages of the TLS proposed method, both methods are applied to experimental data, acquired from a deployed PV panel. The simplicity of the proposed method makes it suitable for real time implementation.

2. Mathematical methodology

2.1. Photovoltaic panel model

There are several physical models of a photovoltaic cell available in the literature [28, 29]. They differ in the number of parameters describing the behaviour of the photovoltaic cell. The non-linear behaviour of a cell can be reproduced by the introduction of one or two semiconductor junctions resulting in the so-called single diode (or five parameters) model [30, 31] and in the two diodes (or seven parameters) model [32, 33]. In this study, the single diode model was chosen to model a PV panel and is represented by the electrical circuit shown in Fig. 1. The circuit contains a current source which models the luminous flux as the photocurrent I_{ph}. The losses of the cell are modelled by a shunt resistance R_{sh} and a series resistance R_s. The diode is characterized by inverse saturation current I_s and the diode's ideality factor n, represents the cells polarization and is responsible for the non-linear characteristics of the model. These five components represent the five internal parameters of the photovoltaic cell that this work aims to extract.

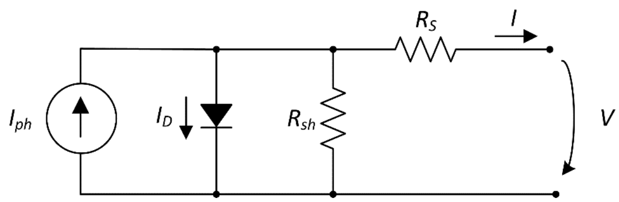

Fig. 1. Single diode equivalent electric circuit of a photovoltaic cell.

The I–V characteristic equation results directly from Kirchhoff's laws and can be written in the form of $f(V, I) = 0$ such that

$$I_{ph} - I - I_s \left[\exp\left(\frac{q(V + IR_s)}{nk_BT} \right) - 1 \right] - \frac{V + IR_s}{R_{sh}} = 0, \tag{1}$$

where I is the output current, V is the output voltage, T is the cell's absolute temperature, q is the elementary charge and k_B is the Boltzmann constant.

2.2. Optimisation of the objective function

The OLS method is widely used for model identification and parameter estimation. The method is based on the best fit, in a least square sense, of a mathematical model to a set of measured data. It consists in the optimization of an objective function $S_{\mathbf{p}}$ which depends on

$\mathbf{p} = \{p_1, p_2, \ldots\}$ (i.e., the set of parameters to be optimized) and is defined as a sum of the square of the distances between the measured data and the model estimated values as

$$S_{\mathbf{p}} = \frac{1}{N} \sum_{k=1}^{N} \left(I_k - \hat{I}_k\right)^2, \tag{2}$$

where I_k is the value of the measured current, $\hat{I}_k$ is the value of the estimated current and N is the number of the data points.

The OLS approach is normally used due to its simple application for both linear and non-linear problems. However, the measured data (output current and voltage) are always affected by uncertainties. Therefore, the objective function should account for the uncertainties of the measured current as well as the uncertainties of the measured voltage which are not included in (2), representing the OLS technique. It is therefore proposed that parameter estimation is performed in the total least squares sense which takes into account both current and voltage deviations due to the measurement uncertainties. The objective function (2) should, accordingly, be modified to

$$S_{\mathbf{p}} = \frac{1}{N} \sum_{k=1}^{N} \left[\left(I_k - \hat{I}_k\right)^2 + \left(V_k - \hat{V}_k\right)^2\right], \tag{3}$$

where V_k is the value of the measured voltage and $\hat{V}_k$ is the voltage estimated by the model.

The difficulty of using this objective function lies in its complexity due to its non-linearity, transcendent and implicit form. In this work, an iterative and simple to implement algorithm for TLS application is presented with a particular focus on photovoltaic characterisation and its parameter estimation. It is also important to mention that even though the problem posed by the characteristic $f(V, I)$ in (1) is nonlinear and implicit, this function is continuous, differentiable and strictly monotone, and its derivative can be calculated with the Implicit function theorem.

The objective of the TLS approach is to find the minimal distance between the measured data point and the estimated curve in an iterative approach as presented in Fig. 2.

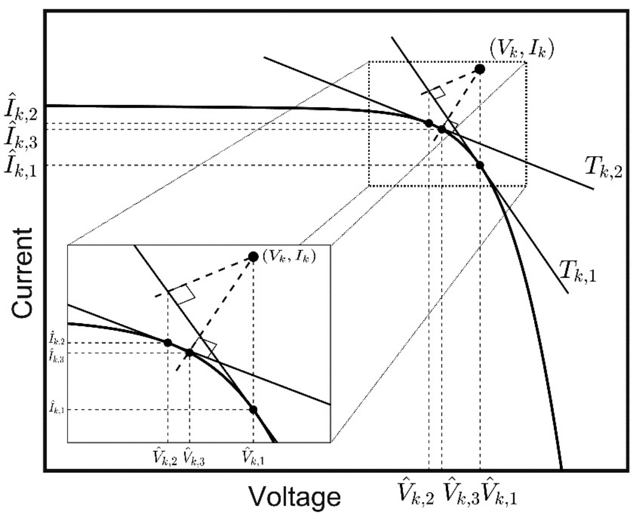

Fig. 2. TLS iterative algorithm illustration of the first 3 iterations.

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To find the point $(\hat{V}_k, \hat{I}_k)$ corresponding to the minimal distance from the measured point (V_k, I_k) to the I–V curve, the algorithm starts by calculating the first estimated point $(\hat{V}_{k,1}, \hat{I}_{k,1})$ which corresponds to the vertical projection of the measured point onto the I–V curve. The first coordinate $\hat{V}_{k,j+1}$ of the next iterative point $(\hat{V}_{k,j+1}, \hat{I}_{k,j+1})$ is the intersection of the tangent line $T_{k,j}$ with the I–V curve at $(\hat{V}_{k,j}, \hat{I}_{k,j})$ and its normal which passes through (V_k, I_k). The coefficient of the tangent is calculated by the derivative of the implicit function (4). The second coordinate $\hat{I}_{k,j+1}$ is the root of $f(\hat{V}_{k,j+1}, \hat{I}_{k,j+1})$.

$$f'(V, I) = -\frac{\partial f}{\partial V} \Big/ \frac{\partial f}{\partial I} \,. \tag{4}$$

This iterative process continues until a stopping criterion is achieved. This criterion is based on two conditions: 1) the difference between two successive distances should be smaller than an imposed tolerance as shown in equation (5); or 2) the maximum number of iterations has been reached. For the sake of clarity and ease of implementation the TLS iterative algorithm is described in the detail in the flowchart in Fig. 3.

$$\left| d_{k,j+1} - d_{k,j} \right| \leq Tol \,. \tag{5}$$

The process described is repeated for each measured data point $(V_k I_k)$ with $k \in \{1, 2, \ldots, N\}$ until the objective function (3) can be computed for a set of parameters $\mathbf{p} = \{p_1, p_2, p_3, p_4, p_5\}$, which in this case corresponds to the 5 parameters of the single diode model. The objective function is then minimized, in the TLS sense, to estimate those 5 parameters using a heuristic search algorithm.

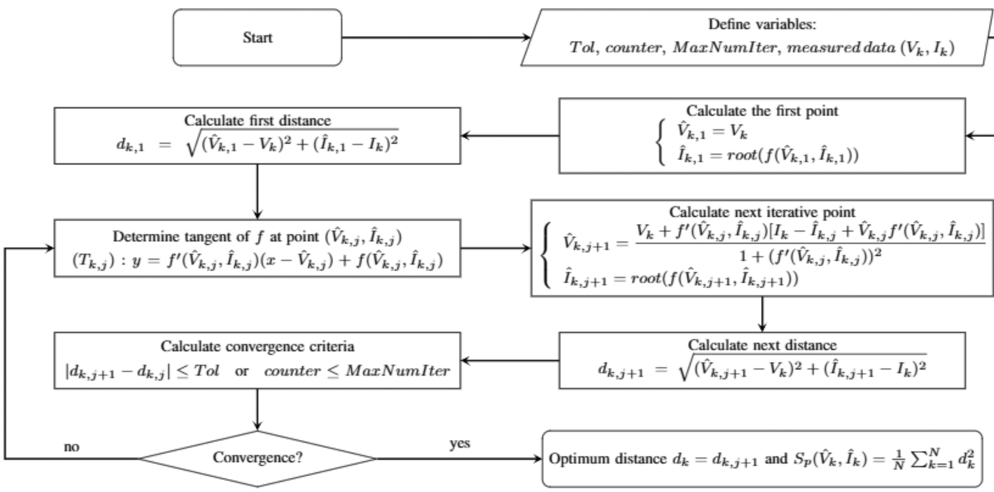

Fig. 3. Flowchart of optimum distance calculation in the TLS approach.

2.3. Parameters estimation

The photovoltaic parameter estimation is done using a non-gradient heuristic search method to minimize the objective function computed by the TLS algorithm presented in the previous section. The Nelder–Mead search algorithm [34] performs a direct search leading to the optimal solution by only evaluating successive values of the objective function. The method uses the concept of a simplex which is a polytope of $m + 1$ vertices in a space with m dimensions. In this work $m = 5$ since the objective is to estimate the 5 parameters of the single-diode model.

The algorithm starts with an initial simplex $\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_{m+1}$ and then a set of linear transformations removes the point of the simplex where the function is maximal and replaces it by a new point which depends on the size and evolution of the simplex.

Figure 4 illustrates the possible steps of the algorithm: reflection; expansion; outside contraction; inside contraction; and shrinking.

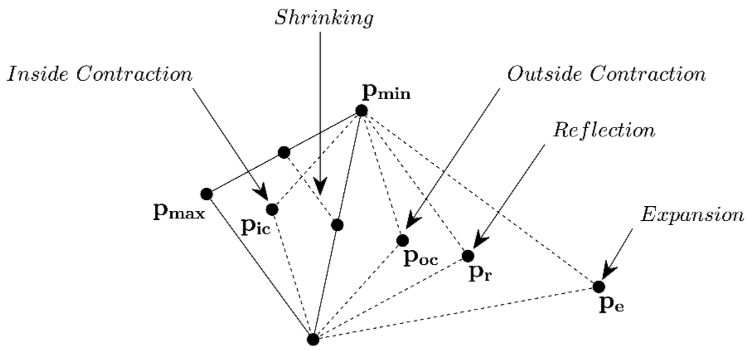

Fig. 4. Illustration of the Nelder–Mead algorithm.

The application of this algorithm to photovoltaic parameter identification is explained in details in [25]. It should be noted that the algorithm's results strongly depend on the stopping criteria and on the initial simplex as discussed in [25].

3. Sensitivity study of the proposed TLS and comparison with OLS

The simulation results presented in this section were obtained for a photovoltaic panel with the reference parameters shown in Table 1. A set of $N = 212$ points (V_k, I_k) were uniformly sampled from the ideal I–V curve obtained with the parameters shown in Table 1.

Table 1. Reference parameters of the photovoltaic panel for the simulation results.

Parameter	Value
I_{ph} (A)	3.95
I_s (nA)	21.6
n	1.2
R_{sh} (Ω)	134.7
R_s (Ω)	0.255

To simulate measurement uncertainties, normally distributed white noise n was added to the sampled voltage and current values according to the system of equations (6) resulting in I_{noisy} and V_{noisy} with n_I and n_V the additive noises for the output current and voltage. The noise standard

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deviation was considered equal for both voltage and current in the range between 1% and 10% of the RMS value of the voltage and current, with steps of 1%. The OLS and TLS approaches were applied to the simulated data to estimate the photovoltaic panel parameters.

$$\begin{cases} V_{noisy} = V + n_V \,, \\ I_{noisy} = I + n_I \,. \end{cases} \tag{6}$$

To perform a statistical analysis, both algorithms were applied to 10000 random noise realizations for each noise level. The results shown in Fig. 5 present the average value of the estimated parameters, in Fig. 6 their standard deviation values and in Fig. 7 the relative error of the estimated results compared with the reference parameters in Table 1.

Figure 5 shows the evolution of the average value of each PV model parameter as a function of noise amplitude. The reference value of each parameter is shown by the dashed line. The average values of all parameters deviate from the reference value as the noise amplitude increases. However, the results from the TLS approach remain closer to the reference value as compared with the results from the traditional OLS approach.

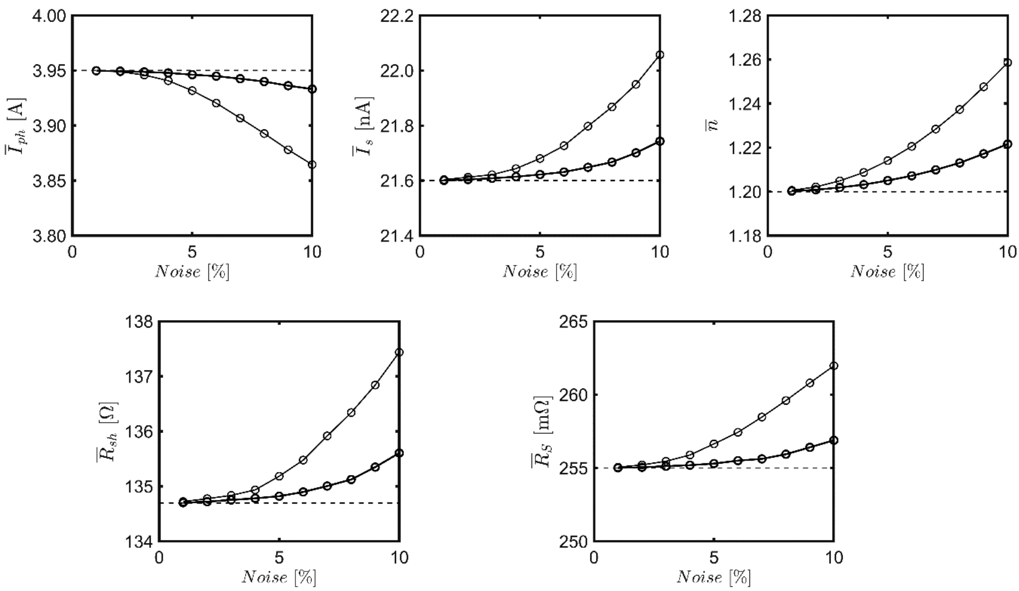

Fig. 5. Average values of estimated photovoltaic parameters. The thin line corresponds to the OLS results, while the thick line corresponds to the TLS results. The dashed line represents the reference value of each parameter.

The better performance of the TLS algorithm is also confirmed by the standard deviation of the estimated parameters as shown in Fig. 6. The thin line represents the OLS results, while the TLS results are shown with the thick line. The standard deviation of the estimated parameters increases with the noise level, but the TLS approach results in standard deviations lower than with the OLS approach.

Figure 7 compares the evolution of relative error of average value of each estimated parameter obtained by each algorithm. The thick line represents the relative error using the TLS method, while the thin line represents the results from the OLS method. These results show that the TLS

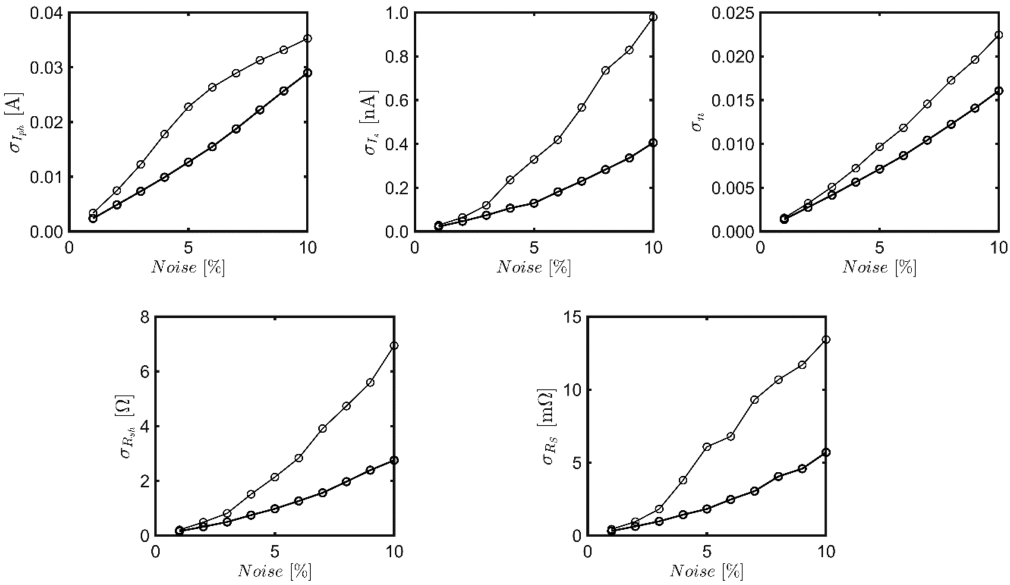

Fig. 6. Standard deviation of estimated photovoltaic parameters. The thin line corresponds to the OLS results, while the thick line corresponds to the TLS results.

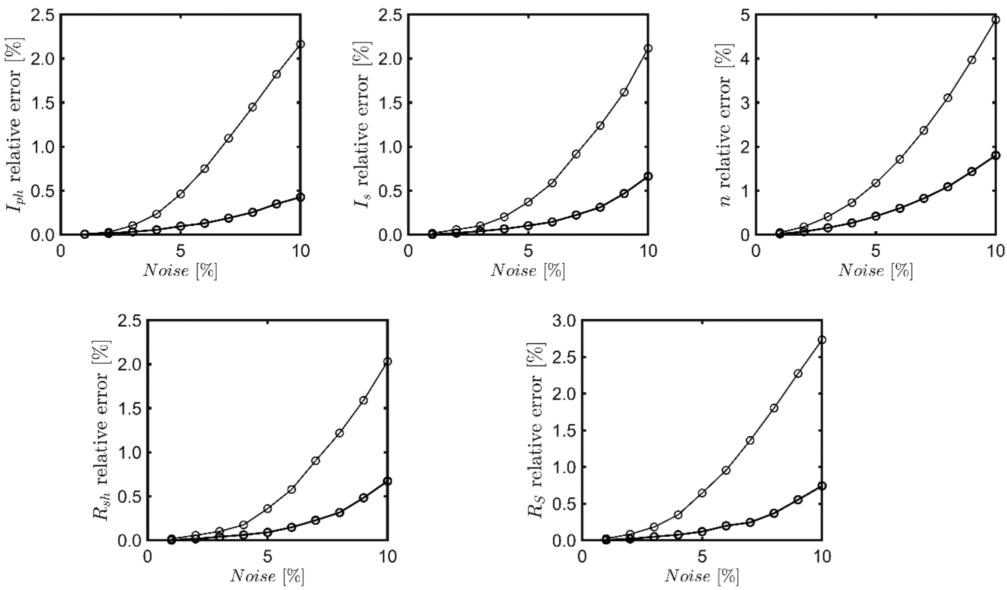

Fig. 7. Relative error values of estimated photovoltaic parameters. The thin line corresponds to the OLS results, while the thick line corresponds to the TLS results.

algorithm estimates the parameters more accurately than the OLS option. Additionally, in general the TLS results present estimation errors which are about 4 times lower than those in the OLS approach.

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4. Experimental setup and results

4.1. Parameters estimation of RTC France cell

The application of the proposed TLS algorithm to calculate the cost function in this paper is established on two different sets of data where it is also compared with the OLS algorithm. The first one is a commercial silicon (Si) cell from R.T.C France, its experimental data was taken at a temperature of 33° and 1000 W/m^2. The electrical characteristics of this model are presented in Table 2. This set of measurement is accompanied with less noise than the set of measurement of I–V tracer which will be represented in the next section.

Table 2. Electrical characteristics of a silicon cell from R.T.C France.

Parameter	Variable	Value
Number of cells	N_S	1
Voltage at $P_{\max}$	V_m (V)	0.4590
Current at $P_{\max}$	I_m (A)	0.6755
Short circuit current	I_{sc} (A)	0.7605
Open circuit voltage	V_{oc} (V)	0.5727

The parameter extraction of this cell dataset was performed using both TLS and OLS cost functions in order to compare their performances. The measured I–V and P–V characteristics are presented in Fig. 8a and 8b by circles, the resulting I–V and P–V curves of the model with the estimated parameters are also shown in Fig. 8a and 8b with a thick line for the TLS results and a thin line for the OLS results. These graphs show that the characteristics obtained in the TLS approach are closer to the measured data than the characteristics obtained in the OLS approach.

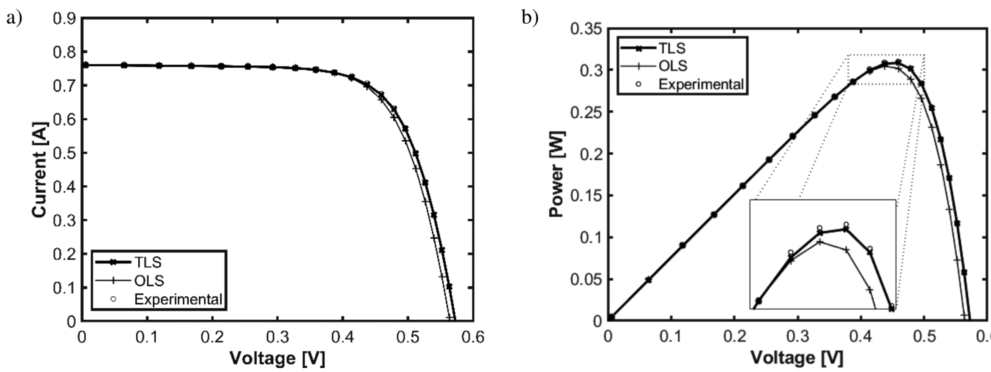

Fig. 8. a) Experimental I–V characteristic along with the characteristics obtained with the TLS and OLS for a silicon cell from R.T.C France. b) Experimental P–V characteristic along with the characteristics obtained with the TLS and OLS for a silicon cell from R.T.C France.

The numerical results are presented in Table 3, where the two methods are compared in RMSE terms which is the value of the cost function using equation (3) for TLS and equation (2) for OLS, and the Relative Error between the maximum output estimated power and the maximum power given by the manufacturer.

Table 3. Results for parameter extraction for an R.T.C France silicon cell.

Method	I_{ph} (A)	I_s (nA)	n	R_{sh} (Ω)	R_s (mΩ)	RMSE	P_{MPP} (mW)	$R_{MPP\ relative\ error}$
TLS	0.76	553.34	1.51	61.31	34.41	9.98e–04	308.51	0.50%
OLS	0.76	552.24	1.52	61.58	34.52	2.08e–03	304.45	1.80%

The value of the RMSE of the TLS is smaller than the one of the OLS by 1.08e–03, and the relative error of the output maximum power of the TLS is 0.50% and the one of the output maximum power of the OLS is 1.80%. This means that maximum power estimated by TLS approach is closer to the experimental value of the power at MPP than the one estimated with the OLS approach with a difference in the relative error of 1.30%.

4.2. Parameter estimation of I–V tracer measured data

To further validate the results of the TLS method and compare it with the performance of the OLS method, both algorithms were applied to data measured from a real photovoltaic panel and the corresponding PV model parameters were estimated. The modular structure of the PV characterization setup consists of an SA-100 OEM solar panel, with characteristics shown in Table 4 provided by the manufacturer, and a CHAUVIN ARNOUX FTV200 I–V curve tracer which measures the I–V and P–V curves of a photovoltaic panel. Additionally, the setup contains a pyranometer with the range of up to 2000 W/m^2 for radiation measurements and a PT-100 sensor for measurement of ambient temperature.

Table 4. Electrical characteristics of the photovoltaic panel used in the experimental setup.

Parameter	Variable	Value
Number of cells	N_S	45
Maximum power	$P_{\max}$ (W)	100
Voltage at $P_{\max}$	V_m (V)	17.6
Current at $P_{\max}$	I_m (A)	5.71
Short circuit current	I_{sc} (A)	6.4
Open circuit voltage	V_{oc} (V)	21

The initial guess for the Nelder–Mead algorithm for both TLS and OLS was calculated following the conclusions from [35], where a study of the impact of internal and external parameters variation was analysed using an error function. Following the guidelines in [35], for better convergence, the photocurrent I_{ph} and shunt resistance R_{sh} initial guess should be lower than the target value, while for the diode parameters, which are the inverse saturation current I_s and the ideality factor n, the initial guess should be higher than the target values. The initial guess of the series resistance R_s does not have a significant effect on the final value of the estimated parameters. The chosen initial guess point is shown in Table 5.

The experiment was performed under an irradiance of 889.58 W/m^2 and at 26°. The I–V and P–V characteristics measured by the curve tracer are presented by circles in Fig. 9a and 9b. The TLS and OLS methods were applied to the measured I–V curve data and the 5 PV parameters of the single-diode model were estimated for each method. The resulting I–V and P–V curves of

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Table 5. Initial simplex used in the Nelder–Mead algorithm.

Parameter	Value
I_{ph} (A)	4.97
I_s (nA)	44.65
n	1.02
R_{sh} (Ω)	179.5
R_s (Ω)	0.521

the model with the estimated parameters are also shown in Fig. 9a and 9b with a thin line for the OLS results and a thick line for the TLS results.

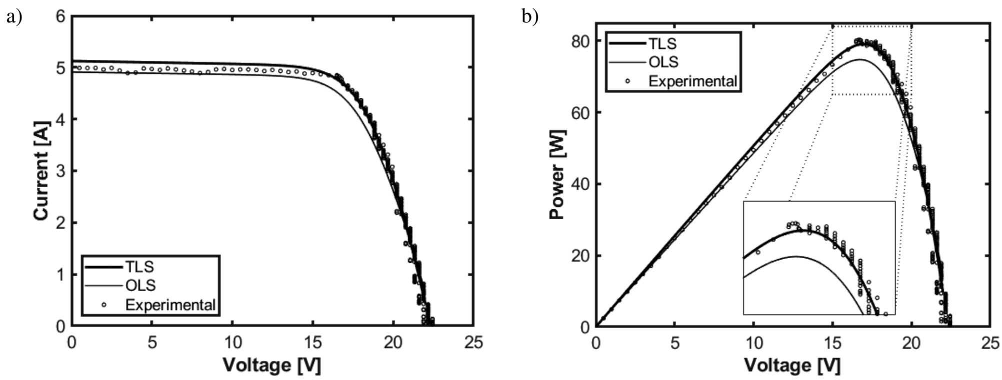

Fig. 9. a) Experimental I–V characteristic along with the characteristics obtained with the TLS and OLS single-diode model estimated parameters. b) Experimental P–V characteristic along with the characteristics obtained with the TLS and OLS single-diode model estimated parameters.

The I–V curve of the single-diode model obtained with the parameters estimated with the TLS method followed the measurements obtained with the I–V curve tracer for all the output voltage range, thus validating the TLS method as a procedure to estimate the PV parameters of a photovoltaic panel. The I–V curve which resulted from the parameters estimated by the OLS method correctly follow the measurements but only for higher output voltages, exhibiting a significant difference at the MPP region of the I–V curve. Analogously, the results for the P–V curve show that the TLS method exhibits a better performance than the OLS method. Of particular importance is the maximum output power point which is underestimated when the parameters used are obtained using the OLS method.

Table 6 represents the maximum iterations the TLS approach needs to converge according to an imposed tolerance; it is the maximum number of all iterations which all the points in the measured dataset need to converge. The imposed tolerance is presented in equation (5). This table proves that this proposed TLS technique can achieve convergence in maximum 3 to 4 iterations, which confirms its rapidity.

Table 6. TLS algorithm maximum convergence iterations.

Imposed tolerance	10^{-1}	10^{-2}	10^{-3}	10^{-4}	10^{-5}	10^{-6}	10^{-7}	10^{-8}	10^{-9}	10^{-10}
Maximum Iterations	2	2	2	2	3	3	3	3	4	4

Table 7 presents the estimated photovoltaic parameters and the maximum power obtained by both TLS and OLS methods, along with the relative error of the maximum power obtained in both approaches. The relative error of maximum power was computed from the maximum measured power by the curve tracer which was P_{MPP} = 80.24 W. Although the exact parameters of the single-diode model are unknown, the maximum power relative error confirms that the TLS method, with relative error of 0.98% allows a more accurate characterization of a solar photovoltaic panel than the OLS approach which presents a relative error of 6.89%.

Table 7. Photovoltaic parameters and maximum power estimated by TLS and OLS methods along with the maximum power and its relative error (the measured maximum power was P_{MPP} = 80.24 W).

Method	I_{ph} **(A)**	I_s **(nA)**	n	R_{sh} **(Ω)**	R_s **(Ω)**	P_{MPP} **(W)**	$R_{MPP\ relative\ error}$
TLS	5.13 A	47.49	1.04	184.93	0.47	79.46	0.98%
OLS	4.92 A	49.71	1.01	219.14	0.64	74.72	6.89%

5. Conclusions

The unavailability of information on the internal photovoltaic parameters and the impact of the degradation phenomena on photovoltaic characteristics make it crucial to estimate those parameters from measurement data.

This paper presents a new method based on minimizing a suitable cost function in the total least squares sense for better estimation of photovoltaic parameters. A comparative study with the classical ordinary least squares approach was also performed. This comparison was performed through a sensitivity analysis of the effect of additive noise on simulated output voltage and current. The average values, standard deviations and relative errors of the estimated single diode model parameters were obtained from 10000 random noise realizations. From the results, it was concluded that the proposed TLS approach shows better precision and accuracy for the photovoltaic parameter estimation.

To further validate the TLS approach, an experimental study was conducted using two different sets of data. The first is from a silicon cell from R.T.C France where the measurements carry less noise than the second set of data which are obtained using an I–V tracer where the measured data is more disturbed. The TLS and OLS methods were applied to the measured data and the single-diode model parameters were estimated. With these parameters the I–V and P–V curves were computed and compared with the original curves measured from a silicon cell of R.T.C France and the I–V tracer. It was found that the TLS method resulted in parameters which yield I–V and P–V curves which closely follow the measurements, especially in maximum power point (MPP) region of the curves.

Additionally, in the comparison of the measured maximum power with the maximum power estimated by the TLS and OLS approaches it was found that the TLS method resulted in a maximum power relative error of 0.50% for the first dataset and 0.98% for the second dataset while the OLS method resulted in a maximum power relative error of 1.80% for the first dataset and 6.89% for the second dataset, thus validating the better performance of the TLS method even for more noised measurements. Besides the simplicity of implementation and rapid convergence of the proposed TLS approach, the benefits of the more accurate parameters and maximum power estimation justify its use in characterization of photovoltaic solar panels.

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