DYNAMIC MODEL PARAMETER ESTIMATION IN PHOTOVOLTAIC MODULES

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Abstract

In the present work, it is sought to develop a tool that allows perform the parameter estimation of a representative model of photovoltaic panels to give a future implementation and field testing. The development of the algorithm was carried out in MATLAB/Simulink, using as a reference the On-line work Identification of Photovoltaic Arrays' Dynamic Parameters, where the methodology for the application of the Dynamic Regressor Extension and Mixing is delivered, from DREM, in a circuit model that includes the effect of parasitic capacitance.

The operation of the tool was evaluated through a block that simulates the operation of a photovoltaic panel, for which, its parameters, the temperature and irradiance values. From the voltage and current signals, the designed tool is executed and the development of three estimators for different photovoltaic models, which are capable of calculate the values introduced from the voltage and current signals.

On the other hand, the response of the estimators designed was also tested against changes in the operation of a photovoltaic panel, achieving the estimate in approximately 10 [ms]. Given the results obtained, using a block that represents the operation of a photovoltaic panel, the experimental setup began, which includes the attachment of a boost converter, therefore, it is expected to evaluate the tool with voltage signals and experimental stream in the near future.

Keywords: Photovoltaic modules, Dynamic model, Model Parameter

1. Introduction

A photovoltaic panel can be represented by an equivalent circuit, being the single diode model -SDM- (figure 1) highly used in the specialized literature, is characterized by having at least one ideal diode; therefore, its behavior is explained based on semiconductor theory (Nelson Jenny, 2003, Maria Carmela Di Piazza, and Gianpaolo Vitale, 2013, Arno Smets et al., 2016, and Carlos Cardenas et al., 2021) , which is formulated through five parameters that allow its behavior to be emulated (G.Yang et al., 2014).The fundamental parameters for the SDM model are the factor of diode ideality (η), photoinduced current (Iph), diode saturation current (Id), series resistance (Rs), parallel resistance (Rh), and thermal voltage (Vt), (Vt=(NskT)/q, where q is electron charge ($1.602\times10{-}19$C), k is Boltzmann constant (($1.318\times10{-}23$J/K), Ns is number of cells in series and T is the temperature in Kelvin), which vary depending on environmental conditions and natural wear and tear due to operation, as well as its power and photovoltaic profile. In this way, by using real voltage and current information, together with the implementation of different resolution techniques, it is possible to estimate the parameters of the photovoltaic panel.

The Single Diode Model has been very successful in predicting the behavior of photovoltaic modules, with a smaller number of computational resources. Furthermore, it can be applied easily to model different types of photovoltaic cells, modules or chains. While this model has some impressions at low irradiance levels, the SDM is used very often to model photovoltaic generators based on crystalline silicon (Giovanni Petrone et al., 2017). It can be obtained equation 1, which relates voltage and current in a PV panel, as shown in figure 1.

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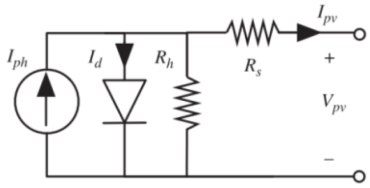


Figure 1: Single Model used to represent a module [A-D]

$$Ipv = Iph - Id * \left[e^{\left(\frac{Vpv+Ipv*RS}{\eta VT}\right)} - 1 \right] - \frac{Vpv+Ipv*Rs}{Rth} \qquad \text{Eq (1)}$$

In the literature it is possible to find different methods that allow estimating the parameters of the SDM, being the analytical solution methods (Cubas Javier et al., 2013, Shiyezi Xiang et al., 2021) and the techniques of optimization most used (Shigeomi Hara et al., 2022). The analytical methods are dependent on the STC initial conditions defined in their equivalent mathematical model, which if not defined adequately, will not allow observing the variations in the profiles as well as the changes in power, temperature and irradiance under conditions non-standard.

On the other hand, the heuristic and metaheuristic estimation techniques, most used in parameter extraction, are algorithms based on bacteria foraging, artificial bee swarm optimization, hybrid flower pollination algorithm, among others. Although, these techniques allow the estimation of the parameters of a photovoltaic panel, is not feasible as a response to different operating scenarios because its solution is due to the reduction and great restrictions in the search space, That is, the search space does not have wide ranges that guarantee the search techniques estimation in the face of substantial changes in irradiation and its power levels (G.Yang et al., 2014).

Therefore, the most realistic model formulation based on the SDM, together with the development of estimation techniques that are capable of characterizing the photovoltaic panel for any operating point, is a solution based on dynamic model.

2. Dynamic PV Model

The dynamic proposed model incorporates the wave effect in the current and voltage product of the power converters that are widely used in this type of technologies and the parasitic capacitance of the photovoltaic plant, which is incorporated as a new element in the process of estimating the parameters of the model (Alexey Bobtsov et al., 2023). Generally, the operation of photovoltaic panels involves the use of converters, whose objective is to track the maximum power point (MPPT). Inevitably, the use of this technology causes a ripple current high frequency from the photovoltaic panel (Giovanni Petrone et al., 2017). Experimental tests have demonstrated that the use of these converters give rise to a characteristic dynamics different from those obtained in traditional mathematical models (such as the SDM or DDM) (Tsung-Hsi Wu et al., 2016, Yao-Ching Hsieh et al., 2019). Thus, the incorporation of a capacitance and resistance parasite in the SDM model, as shown in Figure 2, plays a fundamental role in the synthesis of the V-I curves, since it is possible to replace the nonlinear static curves by a nonlinear dynamic curve with orbits around the points of static operation (Cubas Javier et al., 2013), as shown in Figure 3.

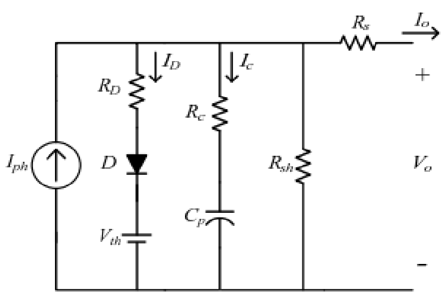


Figure 2: Single Model used to represent PV dynamic operation [8 - 2].

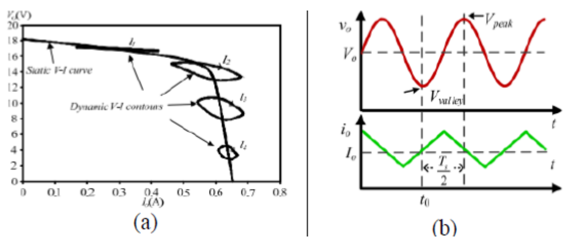


Figure 3: IV Curve (a) and voltage-current signals (b) for zone II of the IV curve [9 - 1].

From Figure 3 it is observed that the region where the PV current is less than Impp, the operation is similar to the static curves, which is due to the fact that the voltage of the capacitor approaches that of the diode. On the other hand, when the instantaneous current exceeds the Impp (and consequently, the voltage is lower than the Vmpp), the parasitic capacitance plays a important role in the V-I characteristic.

The Dynamic Regressor Extension and Mixing – **DREM**- procedure consists of two stages: Firstly, the generation of new forms of regression through the application of a dynamic operator to the original data of the original regression. Secondly, an adequate mixture of these new data to obtain the desired final regression form, to which standard parameter estimation techniques are applied (Stanislav Aranovskiy et al., 2016, Romeo Ortega et al., 2016). The procedure is applied in two different scenarios: Firstly, for linear regression systems, it is used to generate a new parameter estimator whose convergence is guaranteed without a condition persistence of excitation (PE) in the regressor.

The second scenario corresponds to the estimation when the parameters enter from non-linear form to the regression, such as the online estimator of the parameters which are part of the power coefficient function of wind turbines, which corresponds to an identification problem for a nonlinear system, nonlinearly parameterized and not excited. The above aims to control the wind turbine to make the most of the wind energy (Alexey Bobtsov et al., 2020).

3. Methodology

An algorithm has been developed in Simulink Matlab 2022a which allows to identify the parameters of the dynamic model of different photovoltaic panels in different stages, from operation under conditions of irradiance and temperature, until the estimation of the model parameters in study. Figure 4 shows the stages of the proposed alghorisim.

The photovoltaic module has as output signals Vpv and Ipv, where the first variable is defined by the equations not linear, the current Ipv current is defined as a mean value corresponding to the maximum power point, with a sine wave of 5% and a frequency of 20 [kHz]. Along with the Ipv current and the environmental conditions, the parameters of model which are estimated through different analytical techniques, based on the use of the static curves of the photovoltaic panels.

The Stages of the algorithm developed are the following: i.- From the time-varying signals Ipv and Vpv, they enter the block that represents the algebraic conditioning that is carried out on the elementary equations of the model. The key to designing the estimator is to derive a linear regression equation - LRE - $z(t) = \Omega T\ \theta + \epsilon t$

ii.- The estimate is made for the first four elements of the vector θ (which has information about the parameters of the photovoltaic model under study), where the DREM procedure transforms the initial LRE into a set of LREs for each of the unknown parameters, introducing the dynamics extensions. iii.- Once the vector θi is estimated, the mapping of the vector η is carried out using the expression $[\eta i] = [\theta i+1]$, $\{n=1,2,3\}$. $\eta 4 = \theta 3- \theta 1\ \theta 2$. $\eta 5 = \theta 1$

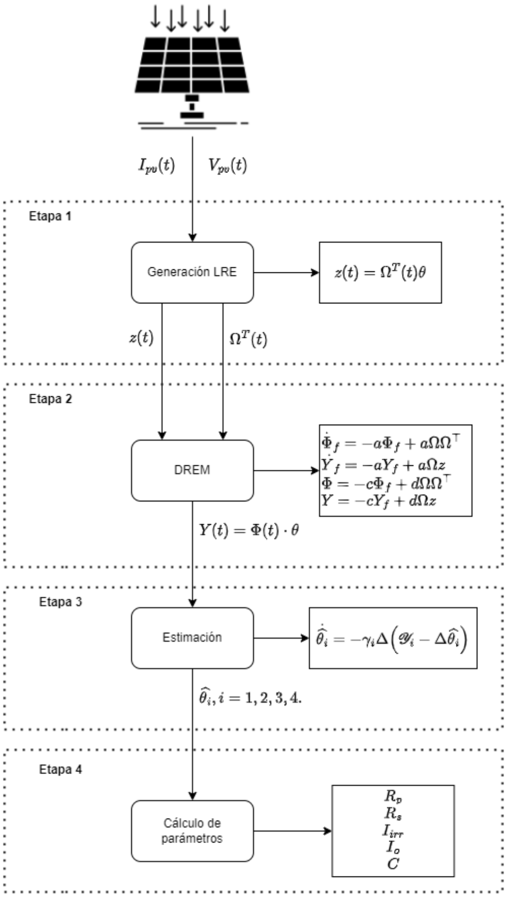


Figure 4. Stages of the algorithm developed for estimation.

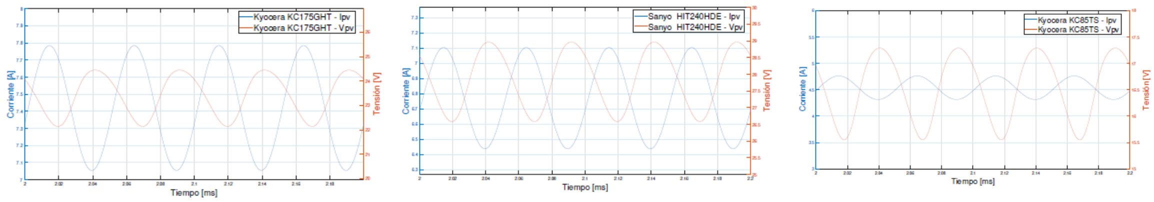
4. Results

Once the methodology used for the estimation is understood, three PV modules were selected and their respective parameters are identified, being detailed in table 1. It should be noted that the parameters of the selected panels correspond to those obtained through different estimation techniques, where two of them are based on the SDM model, that is, they lack the parasitic capacitance of the model used in this work, therefore an arbitrary capacitance of 1.2 [μF] was incorporated. The latter is done in order to simulate an operation, and verify if the tool is capable of estimating the entered parameters.

Table 1: Characteristic parameters of the selected photovoltaic panels

Parameter	Kyocera KC85TS	Kyocera KC175GHT-2	Sanyo HIT240HDE
Iirr [A]	5	8.11	7.3925
RSh[Ω]	112.55	83.30	139.2965
Rs [Ω]	0.2747	0.2836	0.4249
Io [nA]	10.57	0.1066	0.08258
Ns [-]	36	48	48
Ŋ [-]	1.1287	0.9474	1.1244
C [μF]	0.6	1.2	1.2
Ipv [A]	4.54	7.42	6.77

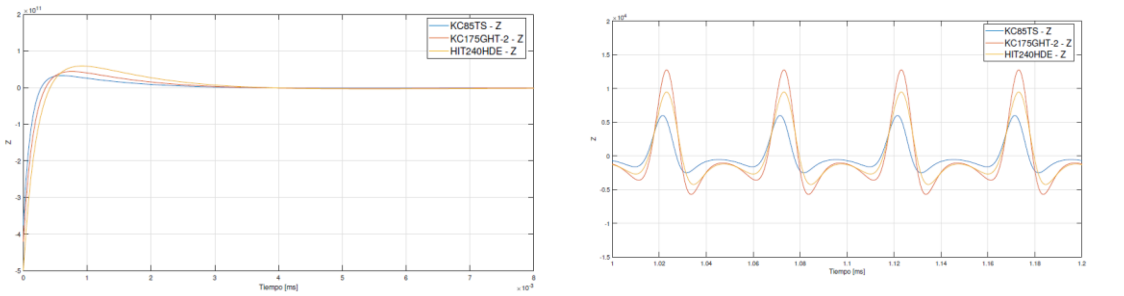
Once the PV moludes have been selected, the current corresponding to the point of maximum power is used for a standardized irradiance and temperature condition, as shown in Table 1 as Ipv. Figure 5 shows voltage and operating current for the different modules selected.



(a) KC1175GHT **(b) Sanyo HIT240HDE** **(c) SV120 E HC89**

Figure 5 Voltage and operating current for the different modules selected.

4.1.- Lineal Regression Estimator. Once the Ipv current of each model has been defined, the process external to the tool is executed, which seeks to define the voltage and current signals that will be used in the designed estimator. After obtaining the voltage and current signals, the filter is tuned with $\lambda = 6{\cdot}105$ and the execution of the linear regression stage LRE begins. Recalling the composition of the scalar z, its dynamics will be subject to Vc and Ipv, therefore, considering that for the panel programming $vc(0) = 0$ was considered, the following dynamics are obtained in the first moments of simulation, as shown in figure 6.



a) Dynamic behavior of the scalar resulting from LRE **b) Steady-state behavior of the scalar resulting from LRE**

Figure 6 Dynamic and Steady-state behavior of the scalar resulting from LRE

From Fig. 6a it can be observed that for the different models, responses of orders of magnitude 10^{11} are reached, subsequently reaching their steady state at 0.004 ms. However, unlike the initial dynamics of the scalar, in steady state, it exhibits oscillations of several orders of magnitude smaller, as shown in Fig. 6b, where it is evident that the dynamics in the three curves are similar. For the KC85TS model, its oscillations are on the order of 10^4, while for the other two models, these oscillations are on the order of 10^2 (for illustrative purposes, the signals were weighted by a factor of 100).

The transient phenomenon already described is repeated for the vector Ω resulting from the linear regression, which represents a challenge when programming the next stage of the process, since abrupt responses (during the transient) can conflict with the integrating elements of the process, slowing down the process or leaving the simulation indeterminate.To address these indeterminacies, it is introduced a delay (2 [ms]) between both stages to work with the signals in their steady state.

***4.2 DREM*:** The signals resulting from the linear regression estimator are used for the formulation of dynamic equations. To carry out this process, it is necessary to define the coefficients a, c and d, in addition to running an algorithm capable of formulating different combinations of coefficients, simulating and storing the results of each simulation, to subsequently choose the combination that allows convergence to the desired solution.

Prior to the execution of this stage, the coefficients $a = c = d = 10$ are defined, which will allow to obtain the time evolution of the matrix and vector resulting from the dynamic extension, that is, Φ and Y respectively. Once the matrix and vector resulting from the extension have been obtained (for the selected combination of coefficients a, b, and c), For the first scenarios, the following coefficients were selected for the estimation: $\gamma 1 = \gamma 2 = 200$; $\gamma 3 = \gamma 4 = 400$

The result of this first combination of coefficients (a, b, and c) yields curves whose growth resembles an exponential curve starting at 10 ms. On the other hand, during the initial stages of the simulation, the estimation shows components of an order of magnitude equal to 10^{-70}, subsequently exhibiting exponential growth and reaching orders of magnitude between 10^{-28} and 10^{-36}. The magnitude of these values may suggest a high order of magnitude for the parameters of the model under study, especially in the initial stages of the simulation.

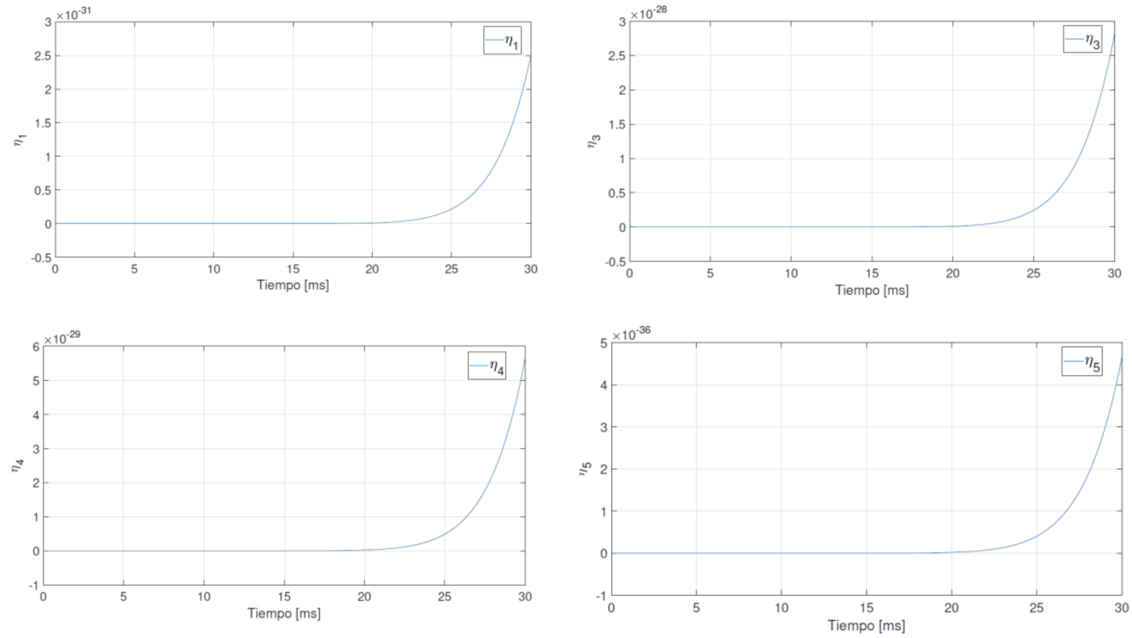


Figure 7 Temporal evolution of coefficients η1-4, during the first combination of coefficients a, c and d.

After estimating the vector θ, the vector η is mapped using, resulting in Figure 7.

Having obtained the components of the vector η and remembering that each of its coefficients contains information about the parameters of the circuit model, it is proceeded to perform the final estimation of the parameters. For visualization purposes, saturation will be applied to each estimated parameter, and in this way, only a range of 0.1 to 10 times the original value of the parameter will be displayed in figure 8.

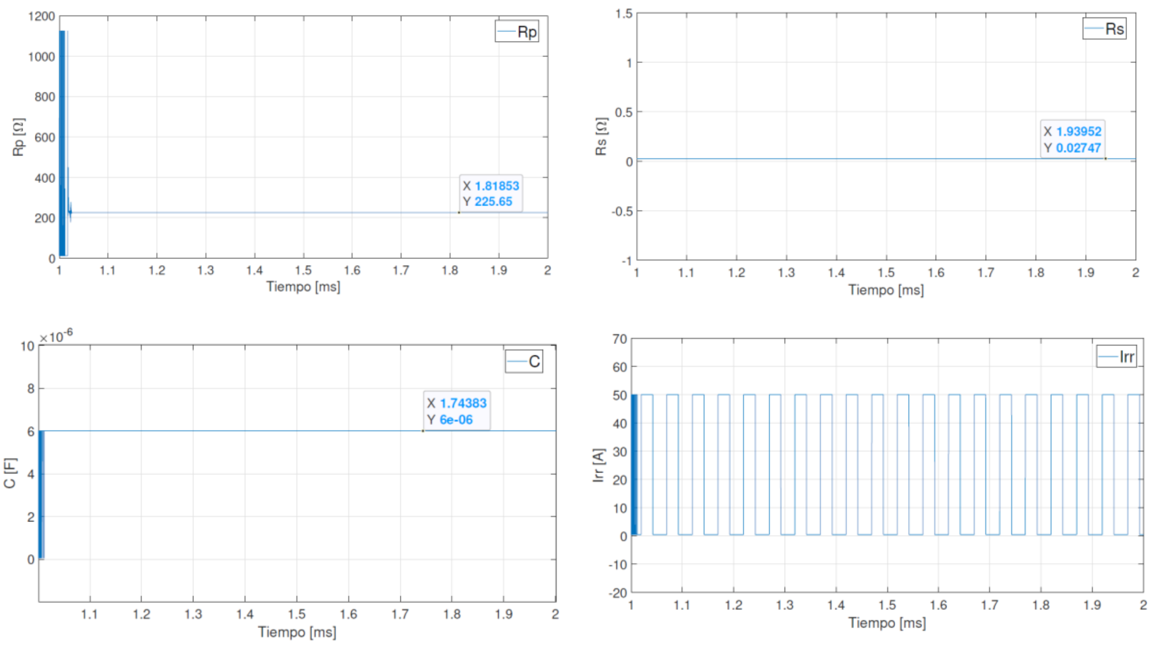


Figure 8 Shunt resistance, Series resistnce, Parsitic capacitance, and Irradiance current obtained for the first combination of coefficients a, c and d.

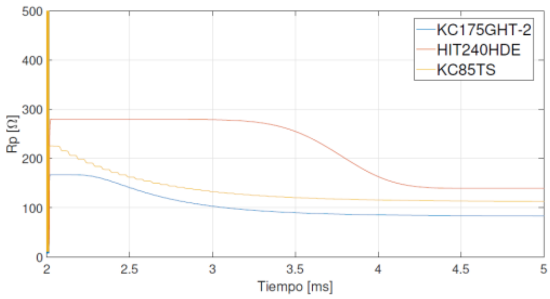
From Figure 8, it can be observed that during the initial stages of the estimation, the shunt resistance reached the saturation limits, before converging to a value of 225.65 Ω, which is equivalent to 198% of its actual value (112.55 Ω). On the other hand, the parasitic capacitance and series resistance can be observed that they do not converge, and their values remain fixed at the upper and lower saturation limits, respectively. Finally, for the irradiance and saturation current, the signals oscillate between both limits, failing to achieve the expected convergence.

Faced with this situation, the algorithm generates different combinations of coefficients a, c, and d, and stored the final values of the estimated parameters, the following combinations were selected:

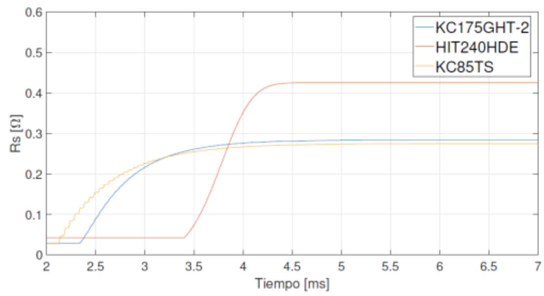
Table 2: Combination of coefficients a, c and d selected for estimation.

PV Module	a	b	d
Kyocera KC85TS	105	103	102
Kyocera KC175GHT-2	104	106	101
Sanyo HIT240HDE	103	106.5	102

4.3 Parameters Estimator: During the transient estimation of the shunt resistance, it is evident that the response in the 3 panels exceed the established limits (0.1 and 10 times the value original resistance), which implies a saturation of the response for the 3 scenarios studied, therefore, for illustrative reasons it was necessary to limit the transients in the range from [0 to 500]. Regarding the estimation times for each model, the combination of coefficients chosen allows a convergence in less than 5 [ms], which can be adjusted by the designer. On the other hand, it is evident that the behavior of the curves is similar, since these start at a higher value (leaving aside the transient), to subsequently decay to its stationary value, as shown in figure 9.



Shunt resistance for the 3 panels under study



Series resistance for the 3 panels under study

Figure 9: Shunt resistance estimates for the 3 panels under study

From Fig. 9, it can be observed that the choice of coefficients for the KC175GHT and KC1185TS modules allows the curves to be saturated at their lower limit up to 2.25 ms, subsequently experiencing growth to their respective steady-state values. On the other hand, for the HIT240HDE module, the curve is saturated at its lower limit up to 3.4 ms, after which it experiences growth resembling a straight line with a positive slope. Furthermore, for all three models, convergence to the values used in the operation occurs at approximately 5 ms.

Regarding the estimation of parasitic capacitances, it is observed that for all three models, the curves are saturated at the upper limit, and then experience an exponential decay to their original value. Furthermore, it can be seen that, like the two previous parameters, the curve of the HIT240HDE model is saturated for a longer period of time; therefore, the possibility of performing an adjustment the coefficients a, c and d, and thus reducing saturation times shown in figure 10.

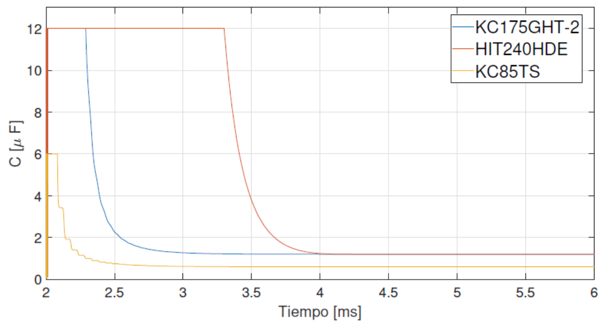


Figure 10: Estimation of parasitic capacitance for the 3 panels under study

For the photo-induced currents, shown in Fig. 11, it can be observed that for the 3 models, the curve oscillates between the saturation limits and then converges to its respective value, where the convergence times vary depending on the model.

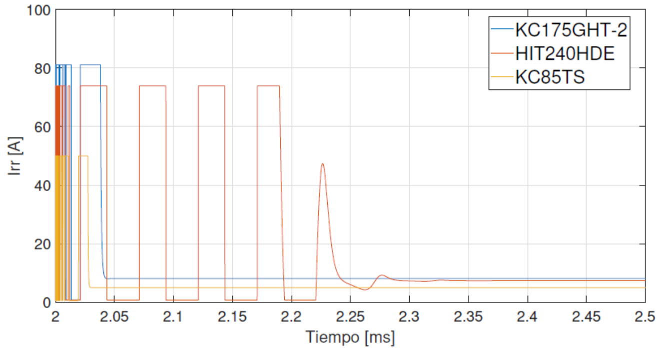


Figure 11: Estimation of the photovoltaic current for the 3 panels under study

Finally, for the saturation current, shown in Fig. 12, where it is possible to observe that the curves oscillate between the established limits and converge at 6 ms, being the variable that takes the longest to reach its final value. It should be noted that for illustrative reasons and in order to appreciate the behavior of the saturation current estimation, the results of the KC175GHT and HIT240HDE models were weighted by 100.

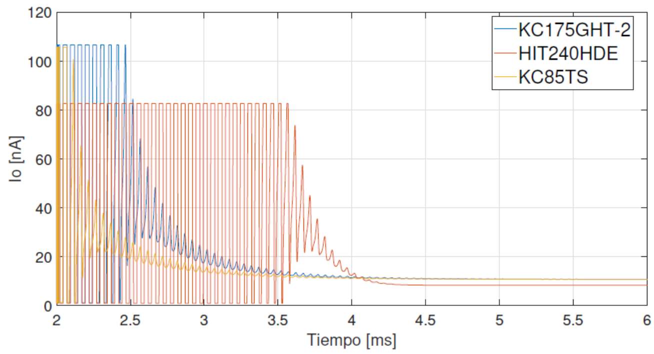


Figure 12: Estimation of the photovoltaic current for the 3 panels under study

So far, the curves of the different models for a specific parameter are like each other, with the convergence times being the distinguishing elements. That said, the developed algorithm is capable of estimating the values used in the operation, with voltage, current, and datasheet information being the essential elements for the estimation.

5. Conclusions

As a result of parameters of photovoltaic panels, the formulation and implementation of models that can characterize photovoltaic installations in different operating conditions, and the estimation techniques of the respective parameters, are becoming a critical task for the efficient use of technology.

The developed tool allows the estimation of parameters of the dynamic model, which corresponds to a non-linear system with non-measurable state variables. The Estimation was undergone for 3 different modules, where tuning was necessary of the coefficients a, c and d. The latter was done with the help of an external element, which allows generating different coefficient vectors, in addition to storing the estimated parameters for each scenario executed. The estimated parameters in each photovoltaic panel, coincide with those introduced in the dynamic model (which allows extract the voltage and current variables, measurements necessary for the estimator), by therefore, the developed estimators are capable of adequately responding to the model.

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