Identification of Photovoltaic Array Model Parameters by Robust Linear Regression Methods

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Abstract. The aim of this paper is to propose an approach for photovoltaic (PV) sources modeling based on robust least squares linear regression (LSR) parameter identification method. On the basis of experimental data of solar irradiance, cell temperature and voltage and currents at maximum power points for a given PV array, correlation functions among the considered quantities are defined. By implementing these functions in a Matlab® Simulink model, accurate I-V characteristics for the considered array are obtained, managing only the solar irradiance. The method is validated comparing the computed and the experimental maximum power points (MPPs). Its effectiveness is proven to be better with respect of parameter identification methods based on discrete approaches and standard LSR method.

Keywords: Models and simulation of renewable energy sources; Photovoltaic array; Statistics.

1. Introduction

Nowadays the growing interest in applications of photovoltaic (PV) sources, with all the related problems of optimal exploitation, environment impact and grid stability, has determined a speed up of the research in this field. In particular issues such as the prediction of PV energy production, the optimal choice and design of the power converter interfacing the PV generator to the utility, the study of all the problems related to the power electronic control, including the maximum power point tracking (MPPT), are currently in consideration. In order to suitably face these problems an accurate modeling of the PV source is necessary. Several modeling methods are presented in technical literature and some of these [1]-[4] are based on a modeling of PV cells through equivalent circuits. If this approach is used, a suitable technique for the model parameters extraction is needed. As for the parameter identification, a method that extract a PV panel model parameters on the basis of the datasheet values [5] has the advantage to be rapid but it can not take into account the actual data spread due to panel characteristic tolerance. While the approach that uses experimental measurements obtained by a data acquisition system to identify the model [2], [6]-[7] has the advantage to take into account the real behaviors of an experimental PV array. On the other hand a great amount of data has to be managed. The aim of this paper is to overcome the limitation of previously proposed method developing a PV array model according to its real experimental electrical behavior managing only the solar irradiance $G$. The proposed approach is compared with an extraction method based on a discrete clustering of the experimental data.

2. PV Source Electrical Model

The adopted model for a PV cell is shown in figure 1. It is a four parameter model based on the single diode circuit representation, in which the shunt resistance has been neglected, and its I-V characteristic equation is described by the relation (1):

$$I = I_p - I_s e^{\frac{-V}{I_s k T}}$$

where $I_p$ is the photo-generated current; $K$ is the Boltzmann constant; $q$ is the electronic charge; $T$ is the cell temperature [$K$]; $A$ is the ideality factor of the diode and $I_s$ is the saturation current of the diode. The described PV cell model is valid also for a photovoltaic field that can be considered as a series/parallel connection of PV cells. The relations useful to find out the four model parameters are:

$$K_1 = \frac{I_{mp} - I_o}{2V_{mp} - V_{oc}}$$
$$K_2 = \log[I_o - V_{oc} K_1]$$

where $I_{sc}$ is the short-circuit current , $V_{oc}$ is the open circuit voltage and $I_{mp}$ and $V_{mp}$ are the maximum power point current and voltage. $V_{mp}$, $I_{mp}$ could be deduced by data logger while $I_o$ and $V_{oc}$ can be calculated, for each value of $G$ and $T$, by the expressions: $I(o) = (G/G_{soc}) I_{oc(stc)}$ and $V_{oc} = V_{oc(stc)} + A(T-T_{soc})$, where $G_{soc}$, $T_{soc}$ are values under standard test condition and $A$ is the open circuit coefficient with temperature. The parameter extraction is performed starting by the consideration of the temperature and MPPs voltage and current measured...
values distributions versus solar irradiance. Such distributions show a data placement along a straight line that suggests the possibility to obtain such data by a linear least squares regressions (LSR) [8].

As for the distribution of temperature versus solar irradiance, the linear correlation coefficient value is 0.8183 so a linear relation between T and G can be found by linear LSR. In figures 2 (a) the dispersion diagram of $T$ vs. $G$ with superimposed the defined regression lines is shown. Using the linear regression, only one temperature is obtained for each irradiance value but, in practice, different temperatures can correspond to the same radiation, according to other weather conditions. The temperature obtained with the LSR is nearly the more probable, according to experimental data, as has been demonstrated using an algorithm, developed by the authors, that gives the temperature value corresponding to the greater group of experimental data for given values of solar irradiance. Figure 2.(b) shows that the temperature trend, obtained by the described algorithm, fits the linear regression curve. In figure 3 the dispersion diagrams $I_{mp}$ vs $G$ and $V_{mp}$ vs $G$ are reported. As show figs.2 these dispersion diagrams contain outliers in the measured data. In this event LSR is inefficient and affected by inaccuracy so the robust regression method is adopted [8]. In this case the regression coefficients are calculated using an embedded robustfit within Matlab® environment. The equations obtained using the method previous described are:

$$T = 26.377 + 0.023 G ; \begin{cases} I_{mp} = -0.470 + 0.0071 G \\ V_{mp} = 172.440 - 0.0115 G \end{cases}$$ \tag{3}

3. Discussion and experimental validation

With the proposed approach, the PV array I-V characteristics are obtained once the solar irradiance is given. In Fig. 4.a the I-V characteristics, computed for $G$ varying in the range 500÷570 W/m², are shown, in comparison with the unique characteristic obtained when a discrete parameter identification is performed. With the discrete approach $V_{mp}$ and $I_{mp}$, are found out from the data in order to identify the PV model parameters with a simple clustering of measured maximum power point data on the basis of defined intervals of solar irradiance and temperature. Then the estimation of MPP for each cluster is obtained using a normal distribution for the experimental data and performing a maximum likelihood estimation of the distribution parameters. From fig. 4, it is evident that the PV model parameters identification based on linear regressions overcomes the limitations of the step-by-step approach, giving a continuous representation of the PV source electrical behavior. In

![Fig. 2. Dispersion diagram of $T$ vs. $G$ and LSR line (a) and $T$ vs $G$ regression line and temperature trend obtained by experimental data with ± 1 °C error bars (b).](image1)

![Fig. 3. Dispersion diagram of $I_{mp}$ vs. $G$ (a) and $V_{mp}$ vs $G$ (b) with superimposed LSR and robust LSR lines.](image2)

![Fig. 4. Comparison of I-V characteristics obtained by LSR-based and discrete parameter identification approaches (a) and comparison of computed and experimental MMPs (b).](image3)

Fig. 4.b the I-V characteristics, obtained when the PV model parameters identification is based on LSR and robust LSR regressions are reported. It is possible to notice that, for low and high irradiance values, there is a deviation between the LSR-based and the robust LSR-based characteristics, due to the great spread of data at low irradiance and to the small amount of available data at high irradiance. On the other hand, a good matching between the LSR-based and the robust LSR-based characteristics is observed in the irradiance range where experimental data are better correlated to regression lines. In Fig. 4.b experimental and computed MMPs are reported too. As shows the figure the experimental MMPs are very close to the computed MMPs on the robust LSR-based characteristics.

REFERENCES


