Experimental results and simulation with TRNSYS of a 7.2 kWp grid-connected photovoltaic system

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Abstract

This paper presents a dynamic model and experimental results of a 7.2 kWp photovoltaic (PV) installation located at the Polytechnic University of Valencia (Spain). The modelling of the monocrystalline cells has been realised in TRNSYS and has been validated during an extensive experimental campaign from January 2001 to March 2003, using the data of a fully monitored PV field. The simulation results with TRNSYS provide an accurate prediction of the long-term performance. In addition to the dynamic models, algebraic methods such as the constant fill factor have also been applied.
In the design of PV systems, there are several important uncertainties which have to be taken into account, such as the reduction of power with respect to the nominal power under standard test conditions (STC), the choice of the meteorological database, and the models for the calculation of the radiation on tilted surface and of the cell temperature. These aspects are analyzed thoroughly in this paper, as well as the problems inherent to the PV power injection into the grid.

Keywords: Monocrystalline PV, experimental installation, model, TRNSYS

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NOMENCLATURE

I_{mp}^*	Maximum power point current (A) at reference conditions	$I_{L,ref}$	Module photocurrent at reference conditions (A)
V_{mp}^*	Maximum power point voltage (V) at reference conditions	$R_{s,ref}$	Module series resistance at reference conditions (Ω)
V_{oc}^*	Open circuit voltage (V) at reference conditions	$R_{sh,ref}$	Module shunt resistance at reference conditions (Ω)
I_{sc}^*	Short circuit current (A) at reference conditions	P_{mp}	Power at maximum power point (W)
α_{Isc}	Temperature coefficient of the short circuit current (A/K)	G_{eff}	Global incident irradiance (W)
β_{voc}	Temperature coefficient of the open circuit voltage (V/K)	G^*	Irradiance in reference conditions (W)
T_{NOCT}	Module normal operating cell temperature (ºC) ; irradiance 800 W/m^2; ambient temperature 20ºC; Wind speed 1m/s	T_c	PV module temperature (ºC)
P_n	Nominal power (W)	T_b	Back-side temperature of the PV panels (ºC)
P_{min}	Minimum grid connection power (W)	ΔT_e	Mean temperature difference between the front and back of the panel at reference conditions
V_{mp}	Maximum power point voltage (V)	V_m	Maximum input voltage (V)
f	Frecuency (Hz)	V_{output}	Output voltage reference (V)
t_{pmp}	Time to reach the maximum power point (s)	$G_a(0)$	Annual global irradiation on horizontal surface (kWh/m^2/year)
V_{gm}	Maximum voltage of generator (V)	$E_{a,DC}(0)$	Annual PV energy production (MWh/m^2/year)
I_{gm}	Maximum current of generator (A)	T_a	Ambient temperature (ºC)
V_{goc}	Open voltage of circuit generator (V)	V	Wind speed (m/s)
I_{gsc}	Short circuit current of generator (A)	a_{ref}	TRNSYS reference parameter [16] (V)
L_{nom}	Nominal power loss (%)	$P^*_{mp,corr}$	Corrected power output (W) in Eq. (1) with respect to STC
$I_{o,ref}$	Diode reverse saturation current at reference conditions (A)	$P_{mp,measured}$	Measured power output (W) of the PV field under real operating conditions
STC, *	Standard Test Conditions (global irradiance of 1000 W/m^2, spectral distribution AM 1.5, PV module temperature of 25ºC)		

1. INTRODUCTION

In the design of a PV system, several significant uncertainties have to be considered. Identical PV installations in very close locations have shown a significant difference in the energy output [1] which shows the importance of taking several loss factors and uncertainties into account. In order to predict the energy production of PV systems, the following input data is usually available:

- Characteristics of the installation and its surroundings (tilt angle, orientation, inverter characteristics, external shadings...). The optimisation of the tilt angle and orientation has been studied thoroughly in literature [2], [3].
- Meteorological data: depending on the database, for a same location, the values of radiation or ambient temperature may differ significantly [1], [4], [5]. Furthermore, the surrounding buildings often create shadows on the PV field and reduce the energy production. The shadows should thus be considered in the design of PV fields.
- Manufacturer characteristics of the PV panels. The information which is usually available refers to the reference Standard Test Conditions (STC). However, real operating conditions are completely dynamic [6-7] and cannot be modelled without a temperature and radiation dependent model. The available manufacturer data is subject to dispersion in the fabrication process [8], and the predicted power under STC is very often over-estimated [9], [10].

Using the previous input data, many different simulation programs have been used for the calculation of the PV performance. These models involve algebraic methods (Osterwald [11], Araujo [12] and Green [13]) or numerical tools such as PVSYST [14] or PVSIM [15].

In this paper, the simulation tool which has been chosen is TRNSYS [16] as in former studies from Mondol [17], [18] or Hussein [2]. With TRNSYS, the behaviour of PV panels can be predicted under real, dynamic conditions, hereby providing an interesting tool to evaluate the long-term performance of a PV installation [19]. Moreover, TRNSYS has an extensive library of dynamic models which simplify the modelling of hybrid installations (e.g. PV combined with other renewable energy sources, hydrogen storage as energy buffer system, etc...).

Among published work on models of PV cells [6], [20] a four or five parameter model is often used [17] based on an equivalent circuit of a one diode-model. This approach is useful to predict the energy production of monocrystalline PV power plants [21] and requires very few parameters.

The simulation results have been validated during an extensive experimental campaign between January 2001 and March 2003. The PV power plant, with a nominal peak power of 7.2 kWp, has been fully monitored and has hereby provided the necessary data for the validation of the model in an hourly, weekly and monthly basis.

2. DESCRIPTION OF THE PV POWER PLANT

The PV power plant is located in Valencia, Spain (39ºN 28ºW), and is represented in Fig.1. It is installed on the roof of the Escuela Técnica Superior de Ingeniería del Diseño, at the Polytechnic University of Valencia. The solar field has an azimut angle of 20º west and an inclination of 30º with respect to the horizontal plane. The rooftop is as high as the surrounding buildings and thus there are no shadows on the solar field. The PV power plant is composed of 234 monocrystalline silicon panels from ATERSA, model A-75 (built in 1998) with the technical characteristics given in Table 1.

The system is connected to the grid by means of a four wire three-phase connection. The inverter is a single phase Tauro PRM from ATERSA. Table 2 shows the most relevant features of the power inverters. Two inverters per phase are connected between the neutral wire and the corresponding phase. The solar field is distributed in six groups of 32 panels with eight panels in serial connection and four groups in parallel connection. This configuration provides as input to the inverters: V_{gm} = 136 V; I_{gm} = 17.6 A; V_{goc} = 168 V; I_{gsc} = 19.2 A

42 modules are connected panel by panel to a laboratory which carries out experimental tests of new power electronics systems. The three inverters connected to the four wire three-phase system are monitored with the Data Acquisition (DAQ) System shown in Table 3. The latter system is a Darwin model from the company YOKOGAWA, and has 50 input analog channels. The DAQ system measures the voltage, current (with appropriate conditioning), temperature and the three-phase

power (by means of a specific DU400-22 module). This module measures the three voltages and currents (using a current 20/5 transformer) and calculates the power which is injected into the grid. Finally, the DT300 module communicates with the system by means of RS-422/485.

With the DAQ system, the DC voltage (using a resistive divider to control the voltage range) and the DC current (using a shunt resistor) are measured every hour. The back-side panel temperature is measured by means of 5 J-type thermocouples which are distributed uniformly in the PV field (Fig. 1). The 5 thermocouple measurements show a high correlation coefficient (0.96) and thus their mean value has been applied in the simulations (section 4.5).

The solar radiation is measured with a solar calibrated cell from ATERSA which has the same technology as the PV modules and is placed on the same plane. Thus, any shadows, spectral or dirt losses can be neglected because they are already included in the irradiance which is measured by the coplanar cell.

Finally, several atmospheric parameters are measured by means of a weather station from DAVIS INSTRUMENTS. Every 30 minutes, the ambient temperature, wind speed and direction, relative humidity and barometric pressure are measured. Table 4 shows the most relevant characteristics of the weather station.

3. SYSTEM MODELLING

A dynamic model has been implemented in TRNSYS [16] following the scheme which is given in Fig. 2. TRNSYS has a weather database to predict the behaviour of PV installations in many locations such as in Valencia.

In this work, two different approaches have been used. In case (a), the PV power output is calculated using the METEORONORM weather data as inputs for the PV module (Type 194). The approach (b) is similar, but the meteorological inputs are in-field monitored data. These two models allow for an *a priori* and *a posteriori* analysis of the results. This approach has helped to quantify the uncertainties which are involved in the modelling of a PV field, such as the choice of the weather data and the radiation or temperature models.

The components or types shown in Fig. 2 are based on mathematical models written in FORTRAN. The standard inputs or outputs which are used in the simulations have been numbered in Fig. 2.

As mentioned previously, a 5-parameter model [22] has been used in both of the approaches (a) and (b). In TRNSYS [16] more simplified PV models are available (i.e. type 94) but the 5-parameter model is the most reliable and up-to-date model of TRNSYS.

In order to calculate the five reference parameters (a_{ref}, $I_{o,ref}$, $I_{L,ref}$, $R_{s,ref}$, and $R_{sh,ref}$), five pieces of information are needed, and they are usually provided by the manufacturer for STC: the short circuit current (I_{sc}*), open circuit voltage (V_{oc}*), current and voltage at the maximum power point (I_{mp}* and V_{mp}*, respectively) and the slope of the I-V curve at the short circuit point (α_{Isc}). The two models (a) and (b) in Fig. 2 are based on the same 5-parameter model and differ only in the meteorological data file for *a priori* (meteorological data) and *a posteriori* studies (measured weather data) respectively.

Both types 194 and 210 are “photovoltaic arrays” and determine the maximum power point from I-V curves in the operating conditions which are given by the meteorological inputs.

Type 194 “Photovoltaic Array” requires the following inputs: total incident radiation on tilted surface (1), ambient temperature (2), array slope (4), beam, sky diffuse and ground diffuse radiation on tilted surface (5, 6, 7), incidence angle on tilted surface (8) and wind speed (9). The radiation inputs (5, 6, 7) are calculated internally in Type 109 by means of a radiation processor which calculates in-plane irradiances from the total horizontal irradiances. Only energetic losses such as angular, spectral and temperature losses are considered in this type [16].

Type 210 is also a standard TRNSYS component [16] and calculates the PV power output. The authors have modified the FORTRAN code to receive as inputs the cell temperature and direct in-plane irradiances. The inputs are the in-plane irradiances (1) from the calibrated cell and the module temperature (11), and can be either a monitored input or a calculated variable (section 4.5). Consequently, type 210 predicts the maximum power point without the use of a global-diffuse correlation model, a tilted surface radiation model, an incidence angle modifier or any air mass modifier calculations.

Type 9-c “Data Reader” reads in-plane irradiances (1), module temperature (2) and a failure file (3) which has been created from the YOKOGAWA system in order to reproduce the real in-field failures of the grid connexion. Type 25-b “Output File printer” computes hourly, daily and monthly results in an external file and Type 65-d “Online Graphical Plotter” is used to plot the maximum PV power point (1) and the energy PV output (3).

4. RESULTS AND DISCUSSION

The PV installation which is analyzed has been in operation since 1999. The experimental campaign which is analyzed covers from January 2001 to March 2003. The experimental data has been first filtered in order to eliminate anormal values in the measured currents, voltages or radiations.

4.1 Performance of the PV installation

During the whole experimental campaign and after discarding the experimental points with power transmission failures, the mean energy output of the photovoltaic system was 627 kWh/month, with a mean radiation on tilted surface of 5,79 MWh/month.
The output of the inverters is controlled by a thermal-magnetic circuit breaker that switches off the contact if the frequency or amplitude of the grid voltage is out of range. The re-activation of the solar plant is done manually and the delay in the activation has caused several failures in the energy production. For these reasons, as illustrated in Fig. 3, during 33% of the experimental campaign the installation did not supply any power to the grid.
The monthly PV efficiency varied between 10.2% (July 2001) and 11.4% (January 2003), with an average of 10.9% (without including June 2001, August 2001 and August 2002 where the installation was not under operation). It should be stressed that the theoretical efficiency under STC, according to the manufacturer specifications is 12.9% higher than the mean in-field efficiency of the installation.

4.2 Analysis of the PV output with algebraic and numerical methods

According to manufacturer specifications, the tested panels should deliver a PV power output of $P^*_{mp,manufacturer}$=7.2 kWp ± 10 % under STC. However, the real operating conditions are completely dynamic due to the temperature, wind speed and radiation fluctuations. Hence, in order to compare the real nominal power of the panels, the measured PV power data has to be corrected [11] to account for the difference between the real operating conditions and the STC. Even for points near to STC, the measured power is usually less [9-11] than in the manufacturer specifications, among others, due to a lower installed power and to cabling losses [4]. In *a priori* studies, an accredited independent laboratory (such as the CIEMAT in Spain) can provide the I-V curve and the required electrical parameters with a good precision (± 2-3 % for P_{mp}).

In this study, the PV output was evaluated *a posteriori*, and thus in a first phase, the real PV performance under quasi STC was quantified. Among the whole experimental data, the power measurements within an irradiance band of 950-1050 W/m² were analyzed for time intervals close to the solar mid-day (± 2h) and under clear sky. The power was corrected using the following equation, valid for crystalline silicon panels [11]:

$$P^*_{mp,corr} = \frac{P_{mp,measured}}{\left[1-0.0035\cdot(T_c-25)\cdot\frac{G_{eff}}{1000}\right]} \quad (1)$$

According to PV literature [8], [11], the temperature factor can vary between -0.003 and -0.005 ($^{\circ}C^{-1}$). As the PV manufacturer (ATERSA) does not provide this information, a coherent value of 0.0035 has been assumed.

The results show that under quasi STC, the PV plant provides 6.6 kWp with a standard deviation of 130 W instead of 7.2 kWp (for a confidence interval of 95%: 6.6 kWp ± 3,9%). This mean nominal power loss of 8,3 % with respect to the manufacturer specifications is in coherence to literature [4] and has been included in the simulations. The effect of the dirtiness on the panel surface is already included in the coplanar irradiance cell. The TRNSYS model [16] also takes into account any temperature or spectral losses. Thus, the 8.3 % power loss can be attributed to the following aspects. The ohmic losses are generally less than 2% and contribute to the reduction in the system efficiency according to the energy efficiency institute IDAE. In addition, it has been shown [8] that the mismatch losses (the PV modules are not strictly identical) can lead to significant power differences. Furthermore, there are also losses in the tracking of the maximum power point which may lead to a power reduction of up to 3%.

Fig. 4 shows the hourly measured values of PV power output (white spots) and the corrected values by means of Eq. (1) (black spots). It can be observed that, throughout the studied irradiance range, the corrected values are regularly distributed around the value of 6.60 kW (black circle). The double-standard deviation (giving a 95% confidence interval) has been represented with an error bar.

In Figs. 5 and 6, the correlation between the PV energy output and the incident irradiation has been analyzed, both on a daily and on a monthly basis. The linear behaviour (R^2_{daily}=0.88 and $R^2_{monthly}$=0.98) justifies the use of the mentioned nominal loss coefficient (L_{nom}=8.3 %) within a wide irradiance range.

As in former studies of crystalline modules [6], [12], algebraic methods have also been applied such as Osterwald's method, the variable or constant fill factor approach (CFF) and the approximate maximum power point method [12]. The following hypotheses have been assumed:

- The short-circuit current depends exclusively and linearly on the irradiance:

$$I_{SC} = \frac{G_{eff}}{G^*} \cdot I^*_{SC} \tag{2}$$

- The open-circuit voltage depends exclusively on the cell temperature and decreases linearly for increasing temperatures:

$$V_{OC} = V^*_{OC} - \beta_{V_{oc}} \cdot (T_C - 25) \tag{3}$$

- A constant fill factor (CFF) is assumed for constant ratios of V_{mp}/V_{oc} and I_{mp}/I_{sc}.

Among the tested algebraic methods, the best agreement has been reached with Osterwald's method and the CFF approach, both of them providing almost identical results. For more clarity, in the next paragraphs only the results of the CFF method are discussed.

The fill factor quantifies the deviation between the ideal I-V curves and the measured curves and derives from the parasitic series and shunt resistances. Empirical expressions have been proposed for the calculation of the fill factor, but often a constant fill factor is assumed throughout the whole operating conditions [20]:

$$P_{mp} = P^*_{mp} \cdot \frac{I_{SC} \cdot V_{OC}}{I^*_{SC} \cdot V^*_{OC}} \quad (4)$$

Low irradiances are rejected by the PV system, which has to provide sufficient power to compensate the inverter losses [20]. Thus, for the validation of the CFF approach, only the incident global irradiances higher than 250 W/m² have been considered. Although irradiances lower than 250 W/m² correspond to 47% of the in-plane daytime irradiances, they only contribute to 9.0% of the total irradiation and to 5.2% of the total PV power output.

Fig. 7 shows the measured and predicted instantaneous PV power output. The power output has been calculated using the CFF algebraic method including the previously described nominal power losses. As may be inferred from the high R^2 correlation coefficient (0.97), there is a very good agreement between the predicted and measured power output.

The CFF model results have been compared statistically with the measurements using two normalised parameters: the root mean square error percentage (RMSE) and the mean bias error percentage (MBE) which are defined as:

$$\%RMSE = 100 \cdot \sqrt{\frac{\sum_{i=1}^{N}(P_{Ti}-P_{Ei})^2}{N}} \Big/ \frac{1}{N}\sum_{i=1}^{N} P_{Ei} \quad (5)$$

$$\%MBE = 100 \cdot \frac{\sum_{i=1}^{N}(P_{Ti}-P_{Ei})}{N} \Big/ \frac{1}{N}\sum_{i=1}^{N} P_{Ei} \quad (6)$$

Where P_{Ti} is the i^{th} theoretical (calculated) point of maximum power (W)

P_{Ei} is the i^{th} experimental (measured) point of maximum power (W)

N is the number of measurements

The RMSE (+5.68%) and the MBE (+0.08%) show a good acccuracy of the CFF model. Fig. 7 shows that the model slightly over-predicts the PV power output at low irradiations and under-predicts the performance at higher insolations.

Fig. 8 compares the measured PV output with the predicted values using the TRNSYS model (b) and the analytical CFF method. The results indicate that for low irradiances, the PV output is over-estimated by both models. For in-plane irradiances above 500 W/m^2, the TRNSYS model and the CFF method slightly under-estimate the PV power output. However, regarding the whole duration of the measurement campaign, the energy production predicted by both models is more accurate. The total in-field PV production was 16.93 MWh, whereas the TRNSYS model and the CFF model predict 17.41 MWh (+2.8%) and 17.76 MWh (+4.9%) respectively.

Fig. 9 shows a comparison of the measured and predicted PV power output with the TRNSYS models (a) and (b). As discussed before, using as input files the manufacturer data and the local meteorological data (model (b) in Fig. 2) induces a high overestimation of the PV energy output with a monthly average difference of +11.5 %. Nevertheless, the TRNSYS model including the 8.3% loss factor agrees much better with the measurement data.

As could be expected, the use of the measured irradiance on tilted surface as input data provides a better prediction of the PV output, but in *a priori* studies, the choice of a weather database is inevitable.

The TRNSYS model predicts the PV output reasonably well given the fact that several power losses are not taken into account (e.g. errors in maximum power point tracking).

A good prediction is performed with model (b) using the corrected STC data (Eq. (1)), as can be observed in Fig. 9. The monthly average error in the measurement campaign is only 2.2% (minimum: 0.4% in February 2002 and maximum: 11.9% in December 2001). It is important to note that the maximum difference between the predicted and measured monthly energy PV output reached 63 kWh with a monthly average difference of 16 kWh. In general terms, the 5-parameter model provides a simple tool to predict accurately the yearly PV production.

Fig. 9 clearly shows the failures of the connexion between the PV field and the grid. For instance, in June and August 2001 there was no PV power output as can be understood from the failures which are shown in Fig. 3. The peaks of the PV power output which are observed in Fig. 9 correspond to months with a grid connexion availability (Fig. 3) of more than 90 %.

4.3 Meteorological database

In the simulation of a PV system, the designer requires input weather data. Very often, local measurements are not available and a meteorological database is used.

Any prediction of solar radiation is subject to an uncertainty due to the natural variability of this phenomenon [1], [20]. Not only the predictions of solar radiation are hard to predict, but there are also significant differences between databases.

In this article, 5 different meteorological databases have been studied: PVGIS, Satelight, NASA, Atlas Solar Radiation, and Meteonorm. Table 5 shows the annual irradiation on horizontal surfaces for each database. Additionally, the yearly energy PV production has been calculated with TRNSYS, using the Perez Model for the calculation of the in-plane irradiation [23], and assuming that the PV installation is connected to the grid with no failures.

Regarding the irradiation on horizontal surface, non negligible differences may be observed between the databases; the minimum value is achieved with PVGIS (1521 kWh/m²) and the maximum value is given by the NASA (1701 kWh/m²). This difference of 180 kWh/m²/year (-10.6%) has a direct impact on the yearly PV production. Thus, it is important for any PV designer to take into account that the choice of one database or another may provide significant differences in the predicted energy output.

Fig. 10 illustrates the interannual fluctuations of the solar irradiation. The distribution of the yearly global irradiation average $G_a(0)$ is shown for the period 1984-2005. In coastal zones such as Valencia, the interannual variability of the yearly global irradiation is higher than in continental zones [5]. In this time period, the yearly global irradiation varies from 1534 kWh/m² in 1989 to 1724 kWh/m² in 1994, with an average of 1643 kWh/m². The five mentioned databases provide irradiation values which are approximately included in this irradiation band. PVGIS and NASA database present approximately the minimum and maximum values in this band.

The 5 weather databases provide a total PV output within a band of ± 11%, which corresponds approximately to the interannual difference in the irradiation (Fig. 10). Thus, any PV designer must take into account the significant uncertainty in the prediction of the solar irradiation.

4.4 Calculation of the radiation on tilted surface

The calculation of the radiation on tilted surface derives from the radiation on horizontal surface. This calculation involves the use of a global-diffuse correlation and of a tilted surface radiation model to estimate the direct, diffuse and albedo components of the radiation on tilted surface. Global-diffuse correlations have been analyzed in literature and they often induce a daily root mean square error (%RMSE) higher than 20% which, *a priori*, justifies the election of any available global diffuse-correlation for the studied location.

In this study, the 4 most extended tilted surface radiation models have been analyzed. The Hay and Davies model [24] accounts for both circumsolar and isotropic diffuse radiation. The Reindl Model [25] contains a slight modification of the Hay and Davies model adding a correction for high angles of panel inclination. The Pérez model [23] accounts for circumsolar, horizon brightening, and isotropic diffuse radiation using empirically obtained brightness coefficients. The isotropic sky model (Liu and Jordan model) assumes that the diffuse radiation is uniformly distributed over the complete sky dome [26].

In Fig. 11, the impact of each radiation model on the predicted PV output is shown. The differences between the radiation models with respect to the Pérez model have been calculated in % on the y-axis. On a monthly basis, the Reindl model and the Hay and Davies model provide a similar PV output power in comparison to the Pérez model. However, the Liu and Jordan model presents a higher discrepancy, particularly in winter where the difference with respect to the Pérez model reaches 8.5%.

On a yearly basis, the Pérez model predicts the highest PV output (16.67 MWh), whereas the Liu and Jordan provides the lowest PV output (15.85 MWh), and hence the choice of one radiation model or another can lead to differences in the PV output of up to 4.9%. These deviations between different radiation models are in agreement with published literature [27-28]. It should be pointed out that the isotropic sky model (mode 1 in TRNSYS) under-predicts systematically the diffuse radiation and is consequently not recommended for general use [3]. The discrepancy between the three anisotropic models is only 1.4 % of the total energy output predicted by the Pérez model, and thus the choice of any of them in the simulations can be reasonably well justified in any *a priori* study.

4.5 Calculation of the cell temperature

The reference front-side cell temperature (T_c) can be calculated [29] using the measurements of the mean back-side temperature of the panels (T_b), using Eq. (7):

$$T_C = T_b + \frac{G_{eff}}{G_{ref}} \Delta T_E \quad (7)$$

The PV panels are glass/tedlar-based and have temperature gradient between the front and back-side of ΔT_e = 3ºC [29] under STC.

The cell temperature is directly correlated with the weather conditions and depends on parameters such as the wind speed, radiation and ambient temperature. In this study, different models (valid for the described PV field) have been analyzed in order to quantify their impact on the predicted PV output. Direct in-plane radiation measurements are used as inputs in these simulations.

Generally, semi-empirical correlations are used to weight the influence of each weather variable such as the ambient temperature (T_a), the local wind speed (V) or the solar radiation flux (G_T).

J. A. Skoplaki [30] recently published an interesting review on the correlations which have been proposed in literature. Among the reported correlations, 5 different temperature models have been analyzed; the first two linear regressions are explicit correlations, whereas the last three models (Sandia, Servant and TRNSYS) are based on implicit methods. The temperature models have been analyzed during daytime, for irradiances higher than 250 W/m^2.

Table 6 shows the accuracy of the different models regarding the temperature prediction in itself, and its effect on the predicted PV power output. The measured PV output has been compared with the simulation results of Type 210 using the measured in-plane irradiance as input. The results indicate that the choice of the temperature model is only relevant on a daily basis but has a small effect on the annual predicted PV output. The linear regression model 1 provides nevertheless the best agreement in terms of the MBE (-0,48%) and of the RMSE (+9,20%).

Fig. 12 illustrates the correlation between the predicted module temperature and the measurements during the whole experimental campaign. The Sandia model provides a better agreement than the TRNSYS model by decreasing the RMSE in 37% and by reducing three times the error in the PV output prediction. Although none of the temperature models provide an accurate agreement with the hourly measurements of the cell temperature, they do not have an important effect on the predicted PV output (Table 6). The models tend to under-predict the cell temperatures at high irradiations and hence, an over-prediction is observed in the PV output prediction.

5. CONCLUSIONS

In this paper, a 7,2 kWp monocrystalline installation has been studied. The experimental results from January 2001 to March 2003 have been analyzed, and have been compared with a 5-parameter PV model. The dynamic model developed in TRNSYS provides a good agreement with the experimental results.

Under quasi STC, the in-field performance of the installation is significantly lower than the specifications from the manufacturer (8,3% power loss). For an accurate long-term prediction of the PV performance, the models must include the ohmic and mismatch losses, and the errors in the tracking of the maximum power point. The experimental measurements have also shown important power transmission failures due to the manual activation of the thermal-magnetic circuit breaker which controls the PV power injection into the grid.

The results of this work have shown that in the design of a PV system, the following external uncertainties should be taken into account:

- The choice of the weather database and the interannual fluctuations can lead to an 11% difference in the PV output prediction. Hence, the weather prediction is one of the most important uncertainties in the simulations.
- The choice of the radiation model may provide differences of up to 5% in the predicted power output.
- The calculation of the module temperature with different models has provided very similar results in the total power output (differences of less than 1%). The choice of temperature models is more important on a daily basis, but not so relevant in the calculation of the long-term performance of a PV installation.

Besides a dynamic TRNSYS model, algebraic methods have also been analyzed. Due to the previous external uncertainties, the results have shown that simple algebraic models can be as accurate as detailed dynamic models for the prediction of the long-term energy production in *a priori* studies.

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REFERENCES

[1] Labed S., Lorenzo E. The impact of solar radiation variability and data discrepancies on the design of PV systems. Renewable Energy 2004; 29 (7): 1007-1022

[2] Hussein H.M.S., Ahmad G.E., El-Ghetany H.H. Performance evaluation of photovoltaic modules at diferent tilt angles and orientations. Energy Conversion and Management 2004; 45 (15-16): 2441-2452

[3] Caamaño E., Lorenzo E. Modelling and financial analysis tools for PV grid-connected systems. Progress in Photovoltaics: Research and Applications 1998; 4 (4): 295-305

[4] Luque A., Hegedus S. Handbook of Photovoltaic Science and Engineering 2003. John Wiley & Sons, Chichester: 915-927

[5] Šúri M., Huld T., Dunlop E.D, Albuisson M., Lefèvre M., Wald L. Uncertainties in photovoltaic electricity yield prediction from fluctuation of solar radiation. Proceedings of the 22nd European Photovoltaic Solar Energy Conference 2007, Milan: 3553-3557

[6] Fuentes M., Nofuentes G., Aguilera J., Talavera D.L., Castro M. Application and validation of algebraic methods to predict the behaviour of crystalline silicon PV modules in Mediterranean climates. Solar Energy 2007; 81 (11): 1396-1408

[7]. Kim J.-Y., Jeon G.-Y., Hong W.-H., The performance and economical analysis of grid-connected photovoltaic systems in Daegu, Korea. Applied Energy 2009; 86 (2): 265-272

[8] Zilles R. Modelado de generadores fotovoltaicos. Efectos de la dispersión de parámetros. Doctoral Thesis. Universidad Politécnica de Madrid, 1993

[9] Durisch W., Tille D., Worz A., Plapp W. Characterisation of photovoltaic generators. Applied Energy 2000; 65 (1-4): 273‑284

[10] Durisch W., Bitnar B., Mayor J.C., Kiess H., Lam K. H., Close J. Efficiency model for photovoltaic modules and demonstration of its application to energy yield estimation. Solar Energy Materials & Solar Cells 2007; 91 (1): 79–84

[11] Osterwald C.R. Translation of device performance measurements to reference conditions. Solar Cells 1986; 18 (3-4), 269–279

[12] Araujo G.L., Sánchez E.. Analytical expressions for the determination of the maximum power point and the fill factor of a solar cell. Solar Cells 1982; 5 (4): 377-386

[13] Green M.A. Solar Cells: Operating Principles, Technology and System Applications 1982. Prentice-Hall, New Jersey: 96-97

[14] Mermoud A. Use and validation of PVSYST, a user-friendly software for PV-system design. 13th European Photovoltaic Solar Energy Conference 1995, Nice; 23-27: 736-739

[15] King D.L., Dudley J.K., Boyson W.E. PVSIM: a simulation program for photovoltaic cells, modules and arrays. 25th IEEE Photovoltaic Specialists Conference 1996, Washington: 1295-1297

[16] Klein S.A. et al. TRNSYS 15, A Transient Simulation Program. Solar Energy Laboratory 2000, University of Wisconsin, Madison, Wisconsin

[17] Mondol J.D., Yohanis Y.G., Norton B. Comparison of measured and predicted long term performance of a grid connected photovoltaic system. Energy Conversion and Management 2007; 48 (4): 1065-1080

[18] Mondol J.D., Yohanis Y.G., Smyth M., Norton B. Long-term validated simulation of a building integrated photovoltaic system. Solar Energy 2005; 78 (2): 163–176

[19]. Mondol J.D., Yohanis Y.G., Norton B. Optimising the economic viability of grid-connected photovoltaic systems. Applied Energy 2009; 86 (7-8): 985-999

[20] Lorenzo E. Radiación solar y dispositivos fotovoltaicos. PROGENSA 2006; 2: 173-197

[21] Celik A.N., Acikgoz N. Modelling and experimental verification of the operating current of mono-crystalline photovoltaic modules using four- and five-parameter models. Applied Energy 2007; 84 (1): 1-15

[22]. Zhou W., Yang H., Fang Z. A novel model for photovoltaic array performance prediction. Applied Energy 2007; 84 (12): 1187‑1198

[23] Pérez R., Ineichen P., Seals R. Michalsky J., Stewart R. Modelling daylight availability and irradiance components from direct and global irradiance. Solar Energy 1990; 44 (5): 271–289

[24] Hay J.E., Davies J.A. Calculation of the solar radiation incident on an inclined surface. First Canadian Solar Radiation Workshop Proceedings 1980: 59–72

[25] Reindl D.T., Beckman W.A., Duffie J.A. Evaluation of hourly tilted surface radiation models. Solar Energy 1990; 45 (1): 9–17

[26]. Liu B.Y.H., Jordan R.C. The long term average performance of flat-plate solar-energy collectors. Solar Energy 1963; 7 (2): 53-74

[27]. Daniel W.M., Pelland S., Poissant Y., Morris R., Hutchinson M., Papadopol P., Lawrence K., Campbel K. Spatial insolation models for photovoltaic energy in Canada. Solar Energy 2008; 82 (11): 1049-1061

[28]. Mondol J. D., Yohanis Y. G., Norton B. Solar radiation modelling for the simulation of photovoltaic systems. Renewable Energy 2008; 33 (5): 1109–1120

[29]. King D.L., Kratochvil J.A., Boyson W.E., Bower W.I. Field Experience with a new Performance Characterization Procedure for Photovoltaics Arrays. 2nd World Conference on Photovoltaic Solar Energy Conversion Proceedings 1998, Vienna

[30]. Skoplaki E., Palyvos J.A. Operating temperature of photovoltaic modules: A survey of pertinent correlations. Renewable Energy 2009; 34 (1): 23-29