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VARIABILITY AND SENSITIVITY OF TWO MODELS USED TO ESTIMATE PHOTOVOLTAIC PRODUCTION

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Abstract. *Photovoltaic energy has shown a relevant growth of participation in the electric sector. However, the availability and reliability of photovoltaic systems are intrinsically intertwined with climate and can be influenced by changes. The study presented here investigates the variability and sensitivity of two models used to estimate the photovoltaic production potential (P_{pv}). Statistical analyses from the perspective of variability revealed that the difference between the P_{pv} estimated by these models reaches 7.11%. As for sensitivity, in the context of changes in ambient temperature, the relative difference in P_{pv} between models can be up to 4.28%, whereas in the context of changes in solar irradiation, the relative difference can be up to 18.37%. The consideration of the variability and sensitivity of the main sets of equations used to estimate the potential of photovoltaic energy production can help optimize the discussion of studies in this research area.*

Keywords: *Solar energy, performance rate, climate change, PV modeling.*

1. INTRODUCTION

Renewable energy is a fundamental tool to advance towards the United Nations Sustainable Development Goal number 7, which implies universal access to affordable, reliable, and modern energy (Feron et al., 2017). Renewable energy can also help reduce global greenhouse gas emissions and thus mitigate climate change. Among renewable energy projects, decentralized projects based on solar photovoltaic (PV) systems have the potential to contribute to climate change adaptation, climate resilience, energy security and social justice (Feron et al., 2021). However, the sensitivity of renewable energy systems to future climate variability is a source of uncertainty that can complicate energy planning and jeopardize investments in the energy sector.

Changes in the frequency of days with high air temperature or cloudy days can substantially alter the yields of photovoltaic systems. The photovoltaic production potential (P_{pv}) describes the performance of photovoltaic cells in relation to their nominal power generation capacity according to the actual conditions of the environment (Jerez et al., 2015). P_{pv} depends on the solar resource available at the site, air temperature, wind speed, cloud cover, aerosols, spectral distribution of incident irradiation, angle of incidence of irradiation and operating efficiency of system components (Kafka and Miller, 2019).

Different models to estimate PV production have been developed, from simple models with few input parameters to more complex models with extensive PV module modeling procedures (Klise and Stein, 2009). It is common to classify them into two categories: 1) power models and 2) models based on the equivalent electrical circuit of the photovoltaic cell (Djamila and Ernest, 2012). In the present study, we focused on the models of the first group due to their simplicity and wide adoption in the economic feasibility studies of PV plants around the world.

Among the existing models, there are those that consider several meteorological variables, as is the case of the work by Sawadogo et al. (2020), as well as those who opt for more simplistic models, such as the one by Gunderson et al. (2015). Equations (1), (2) and (4) are used by the first work and Eqs. (3) and (4) are used by the second work. It should be clear that "model" is being used for "set of equations".

$$\eta_{cell} = \eta_{ref}\left[1 - \beta\left(T_{cell} - T_{ref}\right)\right] \tag{1}$$

$$T_{cell} = a_1 + a_2 T_a + a_3 G_{tot} + a_4 W + a_5 R_h \tag{2}$$

$$\eta_{cell} = constant \tag{3}$$

$$P_{pv} = NPI \cdot A \cdot \eta_{cell} \cdot G_{tot} \cdot f_{temp} \tag{4}$$

where NPI is the number of modules considered, A is the area of a PV module, η_{cell} is the efficiency of the PV module, where η_{ref} is the reference efficiency, G_{tot} is the solar irradiance, and f_{temp} is the operational loss factor , β is the coefficients of temperature defined by the cell material and structure, and T_{cell} and T_{ref} are respectively cell temperature and the reference temperature of 25 °C (Skoplaki and Palyvos, 2009; Zondag, 2008; Evans, 1981; Tonui and Tripanagnostopoulos, 2008), T_a is ambient temperature in °C, W is the wind speed at the earth's surface in m/s, R_h is the relative humidity in %. According to TamizhMani et al. (2003), the system-specific regression coefficients are $a_1 = 1.57$ °C, $a_2 = 0.961$, $a_3 = 0.0289$ °C.m²/W, $a_4 = -1.457$ °C.s/m and $a_5 = 0.109$ °C/%.

It can be observed that there is no consensus in the literature on which set of equations should be used to estimate photovoltaic production potential (P_{pv}), and there is a gap in comparing the main models used.

The selection of these two models – Sawadogo et al. (2020) and Gunderson et al. (2015) – was made specifically with the aim of comparing the results of a model that uses different meteorological variables with a model that disregards such influences, even though the dependency is evident, as illustrated by the influence of ambient temperature. which is disregarded in the model used in Gunderson et al. (2015). Therefore, the objective of this study is to analyze the variability and sensitivity of the two sets of equations used to estimate P_{pv} aforementioned.

2. METHODOLOGY

2.1 Determination of the models used

The models were defined based on what was presented in Eq, (1-4). The M1 model considers different meteorological variables, the M2 model used by Gunderson et al. (2015) considers the PV cell efficiency to be constant, so there is no equation to define cell temperature, nor for the operational loss factor. In Table 1, there are the models effectively compared, with focus on its equations.

Table 1. Models effectively compared.

#	Equations		
	Temperature	**Efficiency***	**PV production**
M1	Eq. (2)	Eq. (1)	Eq. (4)
M2	-	Eq. (3)	

*f_{temp}=η_{ref}/η_{cell}.

2.2 Meteorological data

The data used were made available by the Brazilian National Institute of Meteorology (INMET) from the historical database. Data from the conventional weather station (OMM code 82798) and the automatic weather station (OMM code 81918) belonging to the city of João Pessoa, capital of the state of Paraíba, Northeastern Brazil, were used for the comparison. Monthly and daily data for the period between January 1961 and December 2021 were collected. The selected parameters were average air temperature, solar irradiation (converted to solar irradiance to enable the analyses performed here), average wind speed and relative humidity.

The data in their integral form were organized by parameter in spreadsheets and then subjected to a quality control process to check for and eliminate errors derived from technical or data transmission problems. From then on, all the data were arranged monthly, using only complete years, that is, years in which data were obtained in all months, from January to December.

2.3 Calculation of photovoltaic production potential (P_{pv})

After defining the models to be compared, using the climatic parameters detailed above and a chosen photovoltaic solar module, the photovoltaic production potential was calculated. The photovoltaic solar module selected was the Axitec AC 260P/156-60S model, commonly used in the region. Table 2 shows the technical characteristics of the solar module (AXITEC, 2016). In the case of relative difference analyses, the chosen photovoltaic module does not have significant impacts, so a solar module with well-known characteristics was used.

P_{pv}, as a function of meteorological variables, was calculated from Equations (4) (Notton et al., 2005) with Equation (3) or with Equations (1) and (2).

The calculations were performed considering 100 modules. The calculation of average P_{pv} uses daily data of T_a and G_{tot} to establish the monthly average, and only then performs the calculations using the equations identified previously.

Table 2. Characteristics of the photovoltaic solar module.

Manufacturer and model: Axitec AC-260P/156-60S			
Photovoltaic cell technology	Polycrystalline silicon	**Solar irradiance coefficient**	$\gamma = 0.12$
Number of modules	$NPI = 100$	**Temperature coefficient**	$\beta = 0.0042/°C$
Nominal power	$P_n = 260\ Wp$	**Solar irradiance**	$G_{\beta,ref} = 800\ W/m^2$
Module area	$A = 1.63\ m^2$	**Cell operation temperature (*)**	$T_{ref} = 25\ °C$
Efficiency	η_{cell}=16%	**Nominal operating cell temperature**	$NOCT = 45\ °C$

(*) Under standard test conditions established by the manufacturer.
Source: AXITEC (2016).

2.4 Variability analysis

The variability analysis sought to check how different the results from each of the two models compared can be. Such difference was quantified from the relative difference between each pair of models, considering the lowest value to establish reference (Equation 5). Thus, the final value was calculated as an average for the months of the year.

$$RDV = \frac{\sum_{i,j=1}^{months} \frac{|X_j - X_i|}{lowest(X_j\ ;\ X_i)} * 100}{n°\ months} \tag{5}$$

where X_j is the result of the variable in analysis of model j, X_i is the result of the variable in analysis of model i, and RDV is the relative difference of variability in %.

It was opted for a relative analysis to remove the influence of the magnitude of the data involved in order to allow the result obtained here to be compared with those extracted from meteorological data of other regions.

2.5 Sensitivity analysis

The sensitivity analysis sought to check how different the results from each of the two models compared can be when the variables air temperature and solar irradiance are altered. Such difference was quantified based on the relative difference between the reference value and the value after artificial alteration (Equation 6) of the meteorological variables (Table 3). Thus, the final value was calculated as an average for the months of the year.

$$RDS = \frac{\sum_{i=1}^{months} \frac{|X_{i,alt} - X_i|}{X_i} * 100}{n°\ months} \tag{6}$$

where X_i is the reference result of the variable in analysis of model i, $X_{i,alt}$ is the result after artificial alteration of the variable in analysis of model i, and RDS is the relative difference in sensitivity in %.

The variables air temperature and solar irradiance were forcibly altered, as described in Table 3, in order to identify the individual sensitivity of each model. The values were chosen so that this forced change contemplates the situations of the maximum and minimum averages of the samples of each variable. The magnitudes used were defined based on the variances of the climatic data.

Table 3 – Conditions for the sensitivity analysis of the compared models.

Conditions	Air temperature	Daily solar irradiance
C1	$T_a = T_{a,measured}$	$G_{tot} = G_{tot,measured}$
C2	$T_a = T_{a,measured} - 10°C$	$G_{tot} = G_{tot,measured}$
C3	$T_a = T_{a,measured} + 10°C$	$G_{tot} = G_{tot,measured}$
C4	$T_a = T_{a,measured}$	$G_{tot} = G_{tot,measured} - 41.6667\ \mathrm{W/m^2}$
C5	$T_a = T_{a,measured}$	$G_{tot} = G_{tot,measured} + 41.6667\ \mathrm{W/m^2}$

3. RESULTS AND DISCUSSION

3.1 Variability of the models

From Figures 1 and 2, it is possible to observe that, despite using exactly the same climate database, the outputs of each of the two models analyzed have some distinctions that deserve to be pointed out. M2 is a most optimistic model, predicting values up to 7.11% higher than those estimated by the M1 model. Its predominant factor is accounting for the influence of meteorological variables, mainly ambient temperature, which is not considered by the M2 model.

The annual production (Figure 2) follows the same behavior of the monthly production, as expected, and the production estimated by the M2 model is 6.08% higher than that calculated by the M1 model.

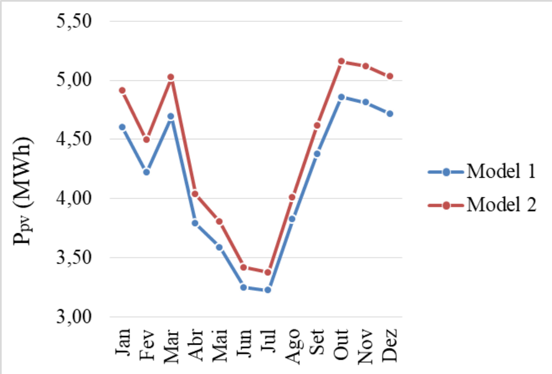

Figure 1 – P_{pv} values per month for the PV production in the city of João Pessoa, PB, Brazil, between the years 1961 and 2021 for 100 Axitec AC 260P/156-60S PV module.

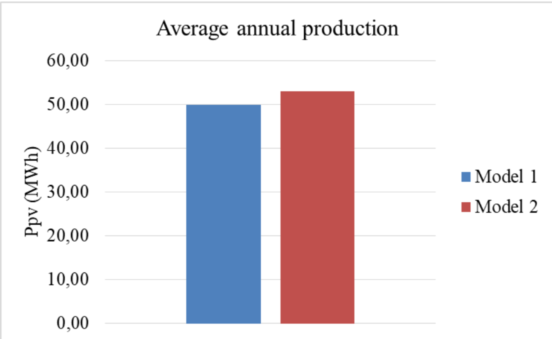

Figure 2 – Average annual P_{pv} values for PV production calculation models in the city of João Pessoa, PB, Brazil, between the years 1961 and 2021 for 100 Axitec AC 260P/156-60S PV module.

3.2 Sensitivity analysis

3.2.1 Sensitivity to changes in T_a

It was observed that the curves of the graph for P_{pv} (Figure 3) move linearly downwards with the increase of temperature (Condition C3) and upwards with its decrease (Condition C2).

The magnitude of these changes, for M1 model, was +4.28% between conditions C2 and C1 and -4.28% between conditions C3 and C1. Calculating the sensitivity of the M2 model under these conditions is meaningless given its independence from the T_a. The order of magnitude of the changes relative to a specific variable can also be determined by the first-degree partial derivative of the equation that models it.

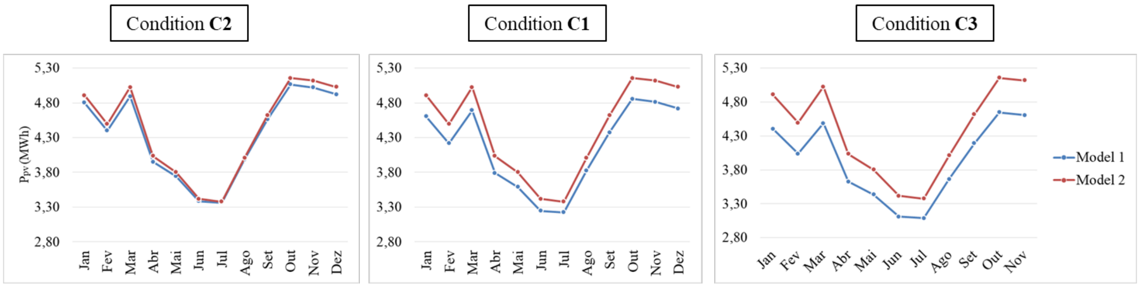

Figure 3 – Conditions to evaluate the sensitivity of the parameters to the variation of the average air temperature for the two PV production calculation models studied.

3.2.2 Sensitivity to changes in G_{tot}

It was observed that, as G_{tot} increases, the curves of the graph for P_{pv} (Figure 4) move linearly upwards with the increase of solar irradiance (Condition C5) and downwards with its decrease (Condition C4).

The increase in irradiance causes the increase of P_{pv} in the M2 model to be more significant than in the M1 model. The increase of 41.6667 W/m² in G_{tot} causes an increase of 18.37% in P_{pv} for the M2 model and of 17.93% for the M1 model, an absolute difference of 0.44%. The increments in P_{pv} for all models were significant and would be plausible in cases of future reductions in local cloudiness.

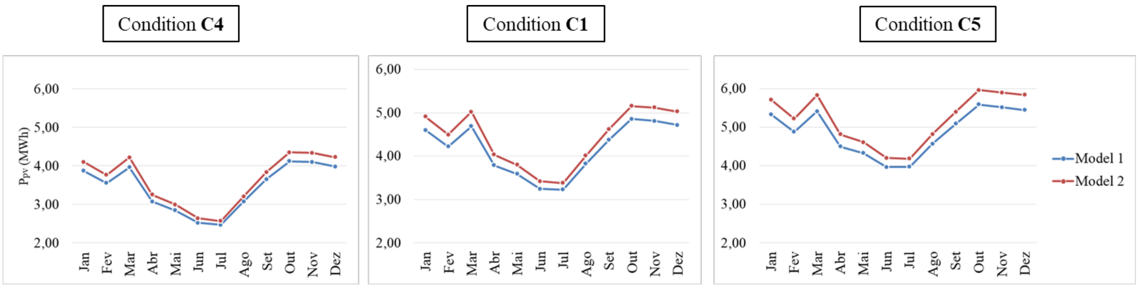

Figure 4 – Conditions to evaluate the sensitivity of the parameters to the variation of solar irradiance for the two PV production calculation models studied.

3.3 Overview

The M1 model, which considers more variables: T_a, G_{tot}, W and R_h, is in line with the findings of Bhattacharya et al. (2014) and Kazem et al. (2012), who showed that T_{cell} is sensitive to W and also to R_h. '

TamizhMani et al. (2003) showed that the correlation between the results of the M1 model and experimental observation is greater than 0.9. The study that used the M2 model makes it clear that the goal was to be robust by considering that the efficiency of the module does not depend on meteorological factors (Gunderson *et al*., 2015). In a complementary way, Mekhilef et al. (2012) showed two situations in which humidity can impact the performance of the PV cell: 1) effect of water vapor particles, because the water droplets on the cell reflect solar irradiance and 2) entry of moisture into the solar cell casing.

The variability of results among the various methodologies for estimating P_{pv} is not something new. In 2011, Podewils (2011) conducted a study with 18 software programs that estimated the P_{pv} of three PV plants, which showed differences of up to 20%. Such magnitude is similar to that calculated for the variability of the M2 model compared to the M1 model.

Recently, Fuster-Palop et al. (2022) compared the results obtained from a power model (they used Equations 1 and 6), a statistical model (MLR) and a machine learning model (RF) for a PV plant in the west of Olmedilla de Alarcón (Cuenca, Spain), of 60 MWp. This plant is the largest so far analyzed based on the performance reported in the literature. The power model showed point errors greater than 5%, but an annual error of 1.81%, in line with what was observed in this study. They concluded that statistical models provided better precision than the power model. However, their use is conditioned on the availability of measured data from the PV plant, which is not possible in the planning phase, before the plant goes into operation.

Morais et al. (2021) conducted a study with an PV plant of IFPI at the campus of Floriano (Piauí, Brazil) of 171.6 kWp, with 660 modules of 260 Wp. The authors used three solar irradiation databases (INMET, SWERAS and ABES) together with a methodology similar to that of the M6 model, and two software programs (Pvsyst and Solergo) to compare estimates of electricity generation. Morais et al. (2021) concluded that the choice of methodology for calculating P_{pv}

estimates can directly influence the results of economic feasibility analyses. Investments are made based on, among several factors, the internal rate of return (IRR), and the authors showed that under one methodology the IRR would be -0.87%, while in the other it would be 2.52%. That is, one indicates loss and the other, profit. Given this situation, it is easy to visualize the possible impacts derived from errors of P_{pv} estimates and, therefore, the importance of knowing the most conservative and optimistic models.

4. CONCLUSIONS

This study analyzed two sets of equations known in the scientific literature to estimate the photovoltaic energy production from meteorological variables. In addition, it analyzed the variability and sensitivity of these sets of equations when there is variation in weather conditions.

The first P_{pv} model studied (M1) has been used by Sawadogo et al. (2020) which equations for efficiency and temperature of the PV cell were developed by Lewis and Kirkpatric (1970) and TamizhMani et al. (2003), respectively; the second (M2) has been adopted by Gunderson et al. (2015). Both of them were analyzed from the perspective of variability and sensitivity. The analysis became more succinct for that used by Gunderson et al. (2015), who, due to the lack of a corresponding equation, could not define cell temperature.

The statistical analyses showed that the two sets of equations generate different results, although they use the same database, which was expected since these equations were obtained empirically.

Under the climatic conditions of the city of João Pessoa (Paraíba, Brazil), the M2 model is the most optimistic, estimating the highest values for P_{pv}. The estimated annual difference in P_{pv} between the two models reached 6.08%.

The sensitivity analyses showed that, due to the different sensitivities, the variability among the models is altered with the change of T_a and with the change of G_{tot}. The M2 model, because of how it was designed, has no sensitivity to temperature change and remains unchanged, while the M1 model has its P_{pv} moved upwards when temperature decreases and downwards when temperature increases. The 10°C increase in T_a causes a reduction in P_{pv} of 4.28% for the M1 model. On the other hand, the M2 model has the highest sensitivity to changes in G_{tot}. The increase of 41.6667 W/m² in G_{tot} causes an increase in P_{pv} of 18.37% for the M2 model and 17.93% for the M1 model.

The importance of determining the variability and sensitivity of the main sets of equations used in the literature to estimate the potential of photovoltaic energy production from meteorological variables has been highlighted. The outputs of the analyzed models show distinctions and sensitivities that can significantly influence the conclusion of studies in this research area. There are variations and sensitivities of such magnitude that can alter the conclusion of statistical analyses that aim to identify the trend of photovoltaic energy production in a given region. These divergences can, in turn, reformulate feasibility analyses and compromise the reliability of photovoltaic energy systems, thus leading to economic and socio-environmental changes.

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