

Full Length Research Paper

Evaluation of PV performance prediction model in tropical environment in Senegal

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Many authors in the literature have worked on models for producing PV module performance, but the question of a climate-specific model is problematic. Some studies have shown more appropriate models for any PV module technology, while others have highlighted models that are more appropriate for a given climate. The aim of this work is to evaluate our model which is based on the I-V characteristic and their accuracy was assessed versus one-year of ground measurement from a system of PV module at different time resolutions. To predict the performance of PV modules in crystalline silicon in a sahelian climate in Senegal, the results obtained experimentally and those of the model were compared. The monthly nRMSE is 17.33% during the rainy season and 17.46% in dry season. There was a good correlation of the model, with a coefficient of 0.88 in January and 0.94 in September.

Key words: PV module, short-circuit current, open circuit-voltage, maximum power output, I-V curve.

INTRODUCTION

Renewable energy is an important part of daily energy consumption today. Among renewable energy resources, solar photovoltaic (PV) represents the fastest growing resource for electric power generation (Ellabban et al., 2014; Panwar et al., 2011; Oliva et al., 2017). Due to their high installation cost, many studies are focused on modeling of PV modules and consequently PV systems (Rosell and Ibáñez, 2006) (Ismail et al., 2013). In photovoltaic (PV) system design it is necessary to predict the potential output of a given solar cell array in various conditions (Jakica, 2018; Roy, 2018; Yadav and Chandel, 2017; Evans, 1981). PV power prediction modeling methods can be classified into two general approaches: deterministic methods which use physics-based models and require detailed design and rated performance information regarding the PV system (Hesse et al., 2017;

Moslehi et al., 2018; Scioletti et al., 2017); and data-driven approaches which require PV power output measurements (Moslehi et al., 2018; Voyant et al., 2017; Wang et al., 2007; Zhao et al., 2018; Pierro et al., 2017). The latter category includes statistical models, linear or time series models, and artificial intelligence techniques (Raza et al., 2016). Another simplified method for predicting the long-term average conventional energy displaced by a photovoltaic system is presented (Kow et al., 2016; Muhsen et al., 2017). Commonly, models and methods are adjusted to PV module and then obtained results are scaled to PV systems to estimate the payback period of PV systems (Adamo et al., 2009; Bastidas-Rodriguez et al., 2013). A detailed discussion about the characteristics of PV cell model parameter estimation problem, estimability and identifiability of the model

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Figure 1. Photovoltaic platform of measurements.

parameters of PV cells is available (Azqhandi et al., 2017; Campanelli and Hamadani, 2018; Ryu et al., 2018). A number of past works have described different simplified methods of estimating the long-term average performance of photovoltaic systems or system components (Nishioka et al., 2003) (Jones and Underwood, 2002; Evans, 1981). Other relevant studies evaluated forecasting models for crystalline silicon PV systems subject to mismatch losses (Almonacid et al., 2011; Malvoni et al., 2017; Sundaram and Babu, 2015). Given the accuracy of the measurements, expected CV-RMSE of hourly power output prediction over the year varies between 3.2 and 8.6% when only climatic data are used (Moslehi et al., 2018). For economic reasons, the choice of the technology, the specific environmental conditions of a model is a real challenge. Some authors have worked on comparing several models for a given climate (Hajjaj et al., 2018) while other works have evaluated a model for a specific technology or climate. However, there is information that the appropriate model for specific climates is still not enough especially in African context.–In this work, the aim is to propose a mathematical model that predicts the performance of PV systems in a sahelien climate. The evaluation of this model will provide additional information for the future installations of PV systems in the locality.

MODEL AND METHODOLOGY PRESENTATION

Photovoltaic platform

The system which is the subject of our study is installed in the laboratory of the Dakar Polytechnic University as shown in Figure 1. This system was tested during one year (2012) in the climate of Senegal (Sahelian climate). During the measurements of each month, a typical day was used which represents the monthly average of the days of the month. Therefore, each month is represented by a day called a typical day.

The data were measured in each month and only the average

day of the month is recorded. The choice of the average day is to do the monthly average of the parameter studied like (I_{sc} , V_{oc} , P_{max} irradiation G_i , the ambient temperature T and the relative humidity) where: I_{sc} is the short circuit-current; V_{oc} the open circuit voltage.

The model description

At normal level of the solar irradiance, the short circuit current can be considered equivalent to the photocurrent I_{ph} , that is, proportional to the solar irradiance G (W/m^2). But this may result in some deviation from the experimental result, so a power law having exponent α is introduced to record the non-linear effect on which the photocurrent depends on. The short circuit current of the PV module is not strongly temperature dependent. The short-circuit current of the module can be calculated by the following relations (Quintana et al., 2002):

$$I_{sc} = I_{sc0} (G/G_0)^\alpha \tag{1}$$

In (1), I_{sc0} and I_{sc} are the short circuit current of the PV module under radiation G_0 and G respectively, G_0 is the radiation at STC and α translates the nonlinear effects due to the photocurrent.

Using Equation (1) we can determine the expression of the coefficient α_i by:

$$\alpha_i = \frac{\ln \left(\frac{I_{sc_i}}{I_{sc0}} \right)}{\ln \ln \left(\frac{G_0}{G_i} \right)} \tag{2}$$

Where I_{sc0} and I_{sc_i} are the short-circuit current under illumination $G_0 = 1000W / m^2$ standard and an illumination G_i of the different illuminations of the day. The average monthly exponent is

$$\alpha = \frac{1}{n} \sum_i \alpha_i \tag{3}$$

Where n represents the number of coefficients α_i

The relationship of the open-circuit voltage to irradiance is known

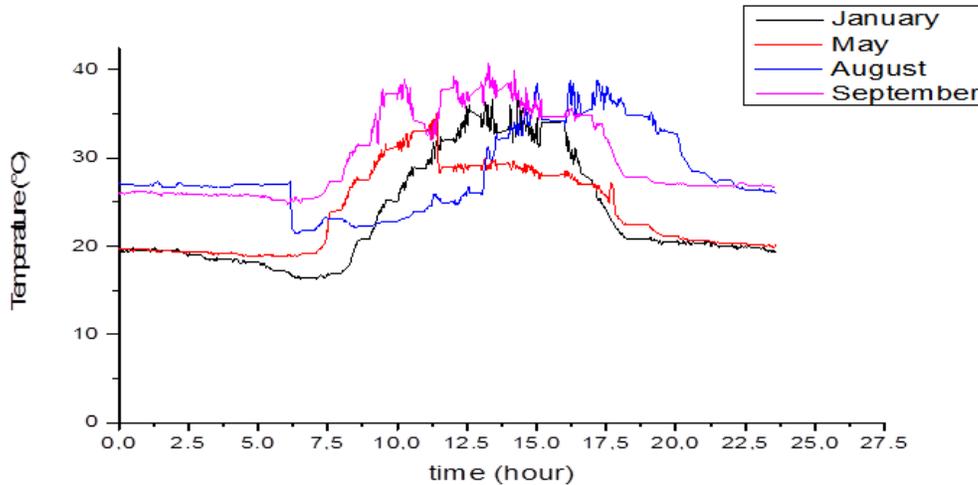


Figure 2. Ambient temperature during four months in the year (2012).

to follow a logarithmic function based on an ideal diode equation, and the effect of temperature is due to the exponential increase in the saturation current with an increase in temperature (Castaner et al., 2002). This conclusion causes some difficulties in replicating the observed behaviors of the tested PV modules. Additional terms or some amendatory parameters must be introduced to account for the shunt resistance, series resistance and the non-ideality of the diode and then take into account the effect of temperature, the open-circuit voltage V_{oc} at any given conditions can be expressed by:

$$V_{oc} = \frac{V_{oc0}}{1 + \beta \ln\left(\frac{G_0}{G}\right)^\beta} \left(\left(\frac{T_0}{T}\right)^\gamma\right) \tag{4}$$

Where V_{oc} and V_{oc0} are the open-circuit voltage of the PV module under the normal solar irradiance G and the standard solar irradiance G_0 ; β is a PV module technology specific related dimensionless coefficient and γ is the exponent considering all the non-linear temperature-voltage effect. In order to calculate the parameter β , the PV module temperature is assumed to be constant. According to equation (2), the coefficient β_i between the standard illumination G_0 and an illumination of the day G_i can be determined by:

$$\beta_i = \frac{\left(\frac{V_{oc0}}{V_{oc}} - 1\right)}{\left(\ln\left(\frac{G_0}{G_i}\right)\right)} \text{ and} \tag{5}$$

$$\beta = \frac{1}{n} \sum_i \beta_i \tag{6}$$

Where, β_i is the value of the coefficient which takes into account the dimension of the module under illumination G_i . To determine the coefficient γ_i of the relation (2), it can be considered that the illumination is substantially equal to a constant.

$$\gamma_i = \frac{\ln\left(\frac{V_{oc0}}{V_{oc}}\right)}{\ln\left(\frac{T_1}{T_0}\right)} \tag{7}$$

$$\gamma = \frac{1}{n} \sum_i \gamma_i \tag{8}$$

RESULTS AND DISCUSSION

The ambient temperature of the period of measure is shown in Figure 2

We have in each period of measure showed the evolution of the ambient temperature and the humidity during the two seasons. The humidity of the period of measure is shown in Figure 3.

The parameter determination in dry season and rainy season

The different values of coefficient during the two seasons are summarized in Table 1.

Estimation of parameter in January

This is given in Figures 4 to 6.

Estimation of parameter in May

This is given in Figures 7 to 9. There is a good correlation between method and experience in January. The correlation R^2 in January is around 0.88.

Estimation of parameter in August

The drop of the power and short circuit in Figures 10 to 12

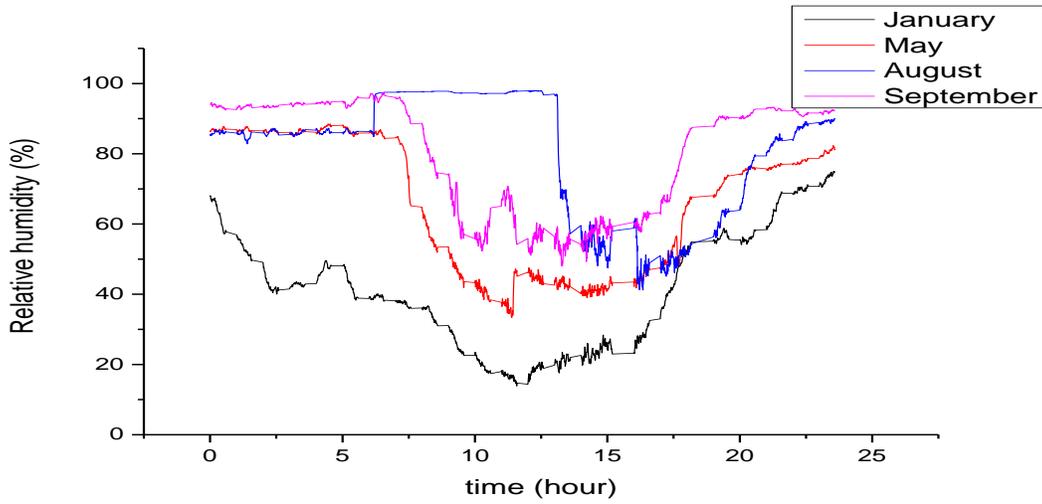


Figure 3. Relative humidity during four months in the year (2012).

Table 1. Estimation of parameter in dry season and rainy season in the year (2012).

Month	α	β	γ
January	2.70	0.46	0.06
May	1.15	-0.07	0.60
August	0.39	0.21	0.28
September	1.12	0.46	0.12

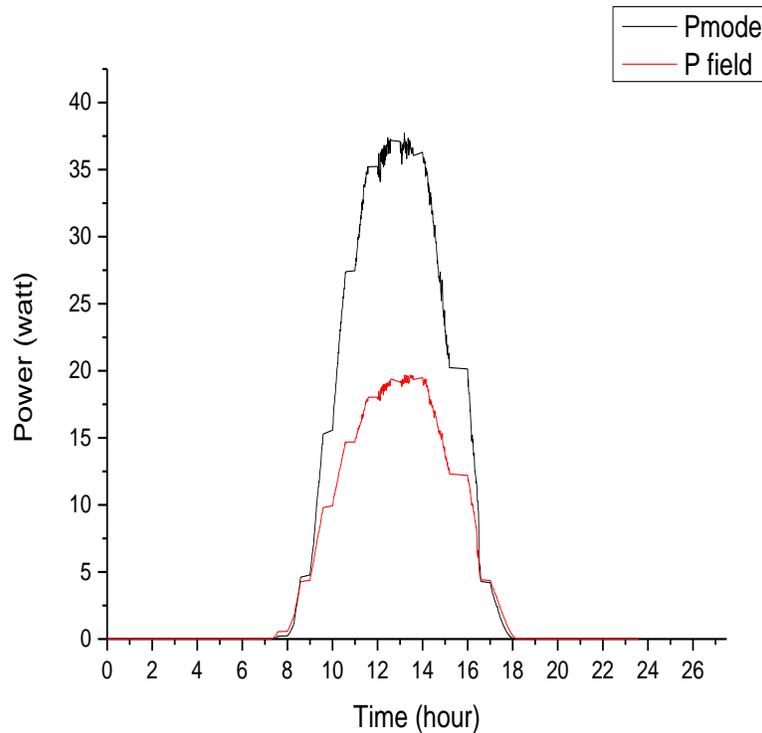


Figure 4. Comparison between the measured and model power.

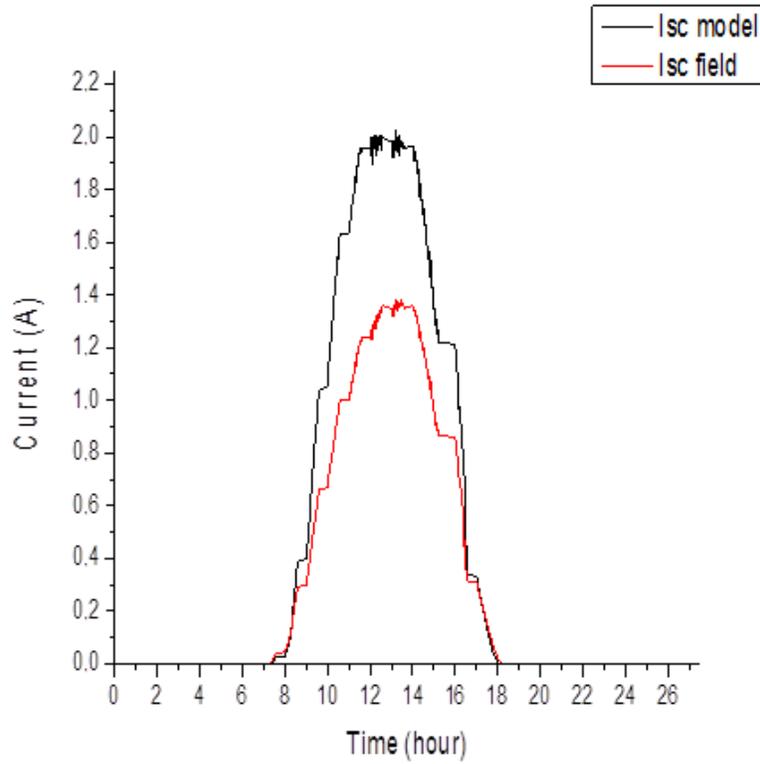


Figure 5. Comparison between the measured and the model short circuit.

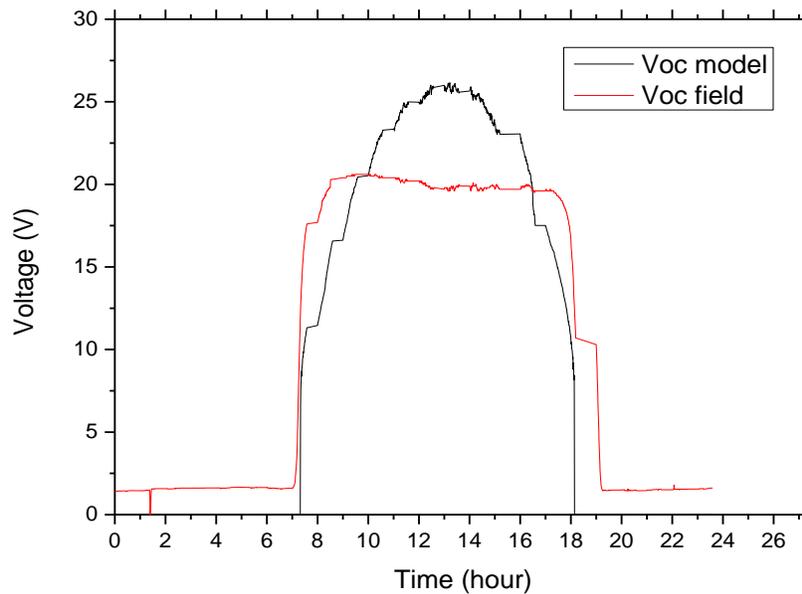


Figure 6. Comparison between the measured and the model and open circuit voltage.

represent the sudden change in weather, cloudy or not during these two months in Senegal.

In September there is rainy season in Senegal. We have a lot of rain and the weather change automatically. It is

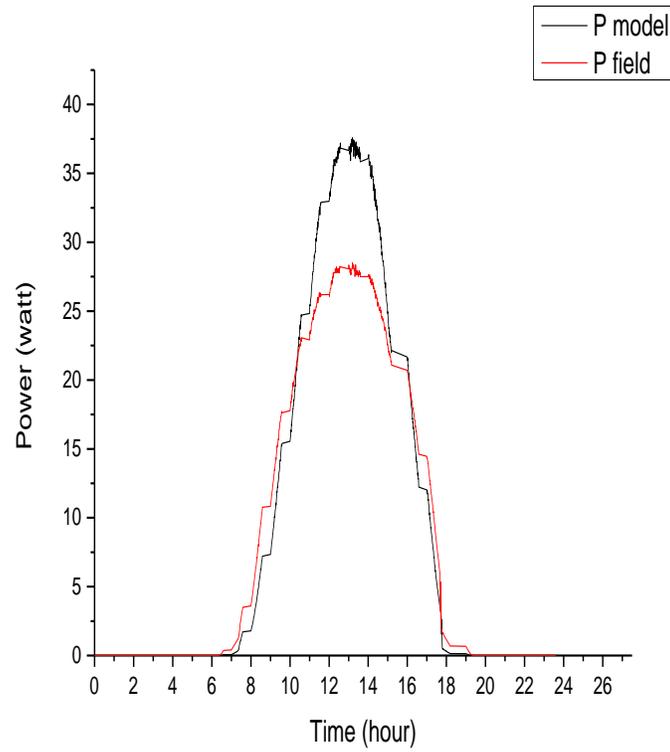


Figure 7. Comparison between the measured and the power model.

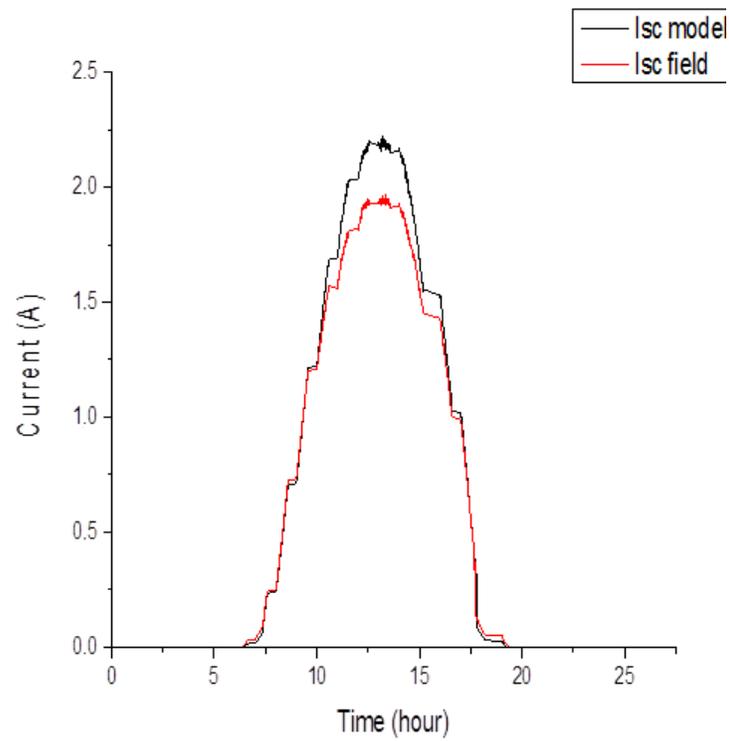


Figure 8. Comparison between the measured and the short circuit current model.

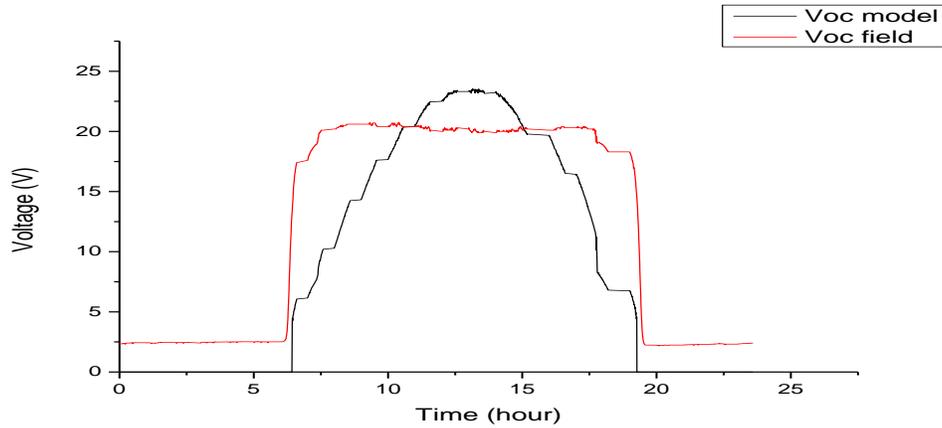


Figure 9. Comparison between the measured and model open circuit voltage.

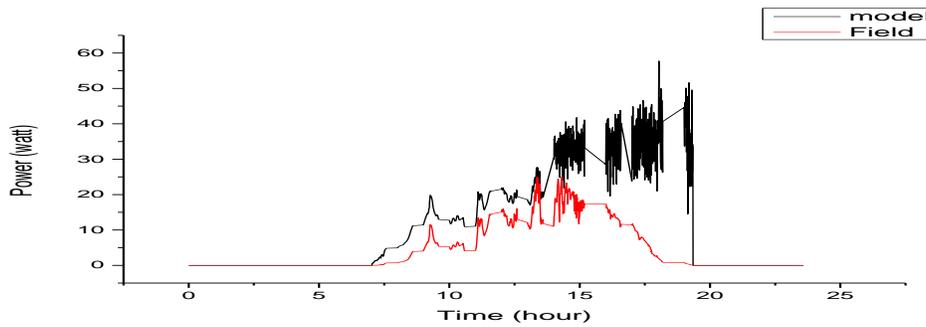


Figure 10. comparison between the measured and model output power.

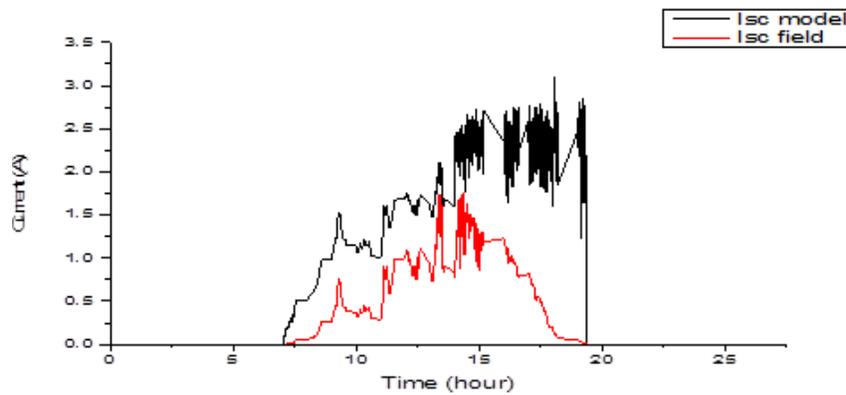


Figure 11. comparison between measured and mode short circuit current.

more difficult to predict the performance on September than in the other months.

Estimation of parameter in September

This is given in Figures 13 to 16. There is correlation coefficient R^2 under these study conditions in dry and

rainy season.

$$R^2 = 1 - \frac{\sum_i (y_{imeasu} - \bar{y}_{exp})^2}{\sum_i (y_{imeasu} - \bar{y})^2}$$

(9)

Where, y_i is the field measured data, \bar{y} is the arithmetic

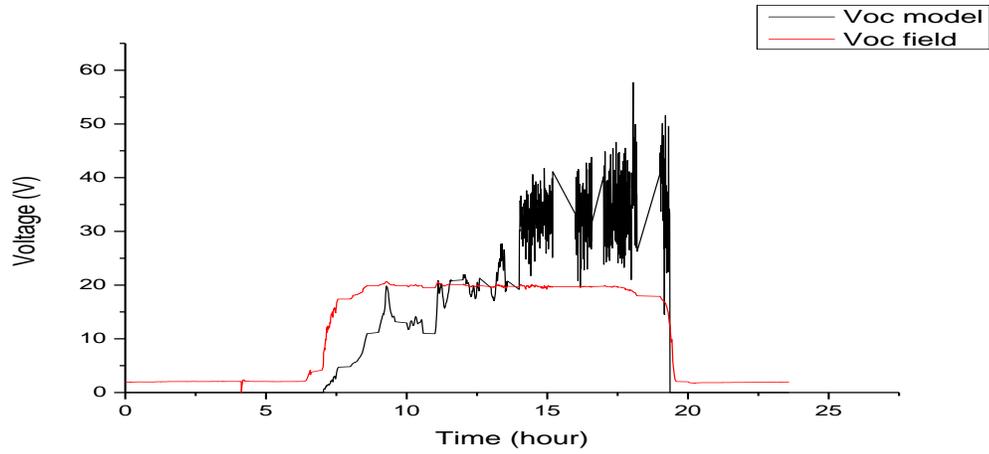


Figure 12. comparison between the measured and model open circuit voltage.

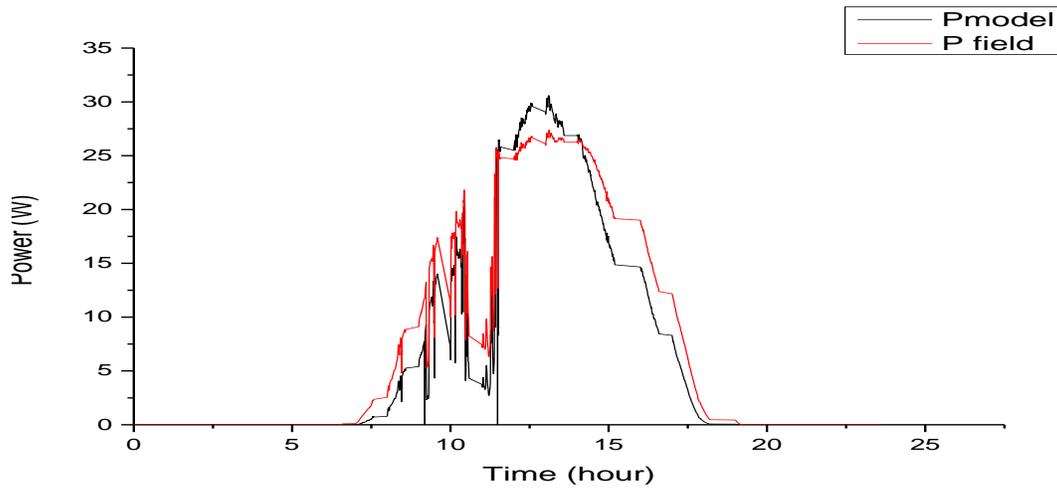


Figure 13. comparison between measured and model output power

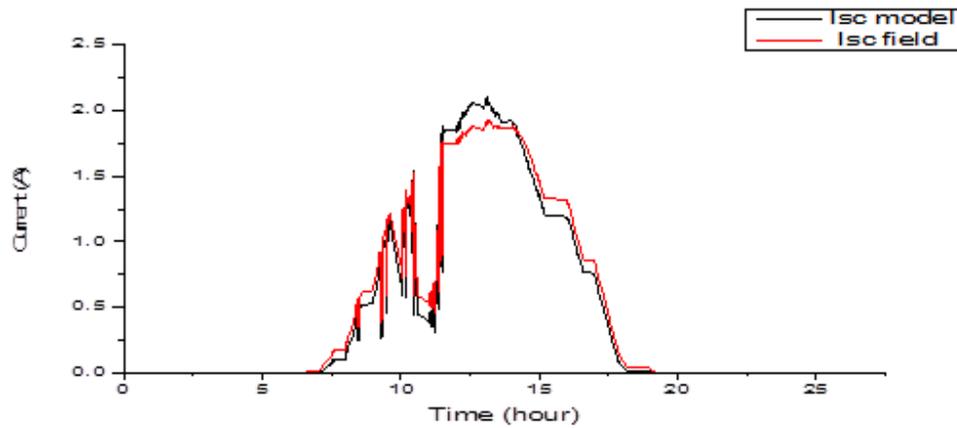


Figure 14. comparison between measured and model short circuit.

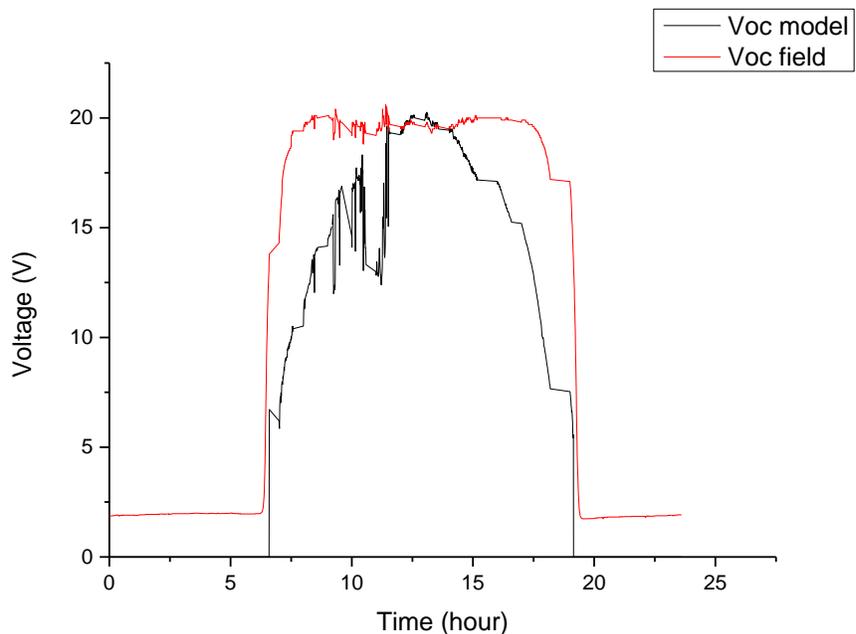


Figure 15. comparison between measured and model open circuit voltage.

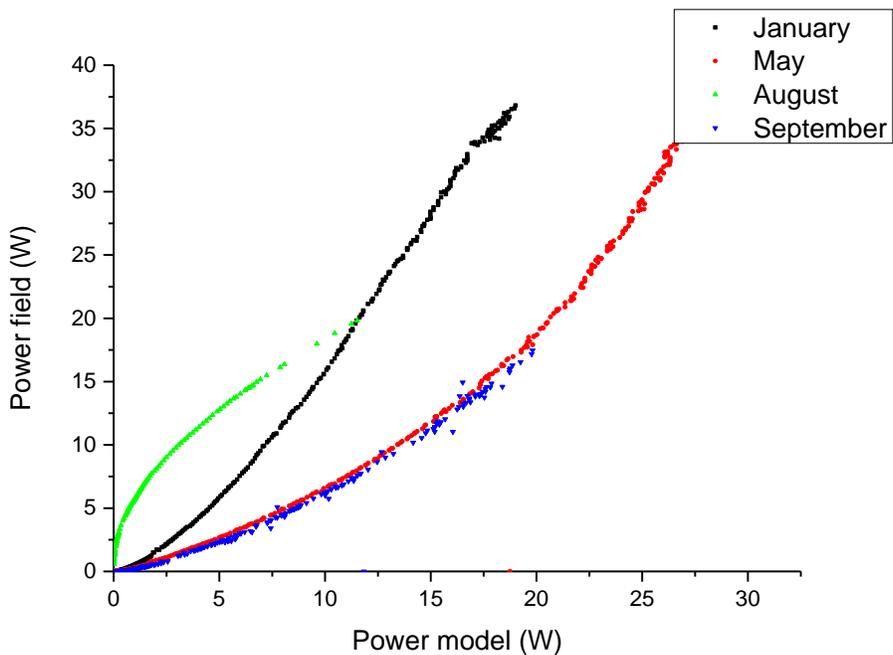


Figure 16. Correlation between the measured and simulated power-data in the two seasons.

mean of the field data, \hat{y} is the mathematical model value. The correlation coefficient R^2 is 0.88 in January, 0.90 in May, 0.76 in August and 0.94 in September. A good correlation is shown by the model. The lower R^2 in

August is a measurement error of the module temperature in the rainy season, due to the rapidly changing irradiance caused by passing cloud; the PV module temperature changes quickly, up and down

which is laminated on the black surface of PV module.

To facilitate the comparative analysis of our model, the standardized technique of assessment is used.

$$nRMSE = \left(\frac{1}{N} \sum_{i=1}^N \frac{|y_{measu,x} - y_{pred,x}|}{y_{measu,x}} \right) * 100$$

Generally, to provide better information on the prediction model, normalized root mean square error nRMSE is used. The results held for the nRMSE during the rainy season are 17.33% for May. However, during the dry season, the nRMSE found is 17.43%.

Conclusion

The type of climate in which the module is installed strongly influences module performance. To predict the energy production of a PV system, it is imperatively important to have a system output of at least one year. This model is purely specific to the Sahelian climate. The results showed a good correlation between the model and the experimental values.

CONFLICT OF INTERESTS

The authors have not declared any conflict of interests.

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