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Estimation models of photovoltaic module operating temperature under various climatic conditions

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ABSTRACT

Accurate control of the operating temperature is essential for achieving optimal efficiency in the use of solar panels. The normal operating cell temperature (NOCT) is a widely used method for estimating module temperature, but it is not always accurate for all conditions. In this paper, the authors propose four different models for estimating module temperature using various techniques including neural networks, a linear method proposed by Ross, and a Fitting method. The objective is to find more accurate methods than the normal operating cell temperature (NOCT) model. The results show that all four models provide good agreement between measured and calculated module temperatures, with $R^2 > 0.91$ and root mean square error (RMSE) < 3.74 for clear days, and considering the resources of time, cost, and expertise necessary for simulating or evaluating the proposed model, the two models based on neural networks (NN) offers a more cost-effective solution, by utilizing straightforward mathematical skills, the RN model demonstrates applicability in any environment, making it a preferable choice over the NOCT model for predicting polycrystalline photovoltaic module temperature under different climatic conditions. The proposed models can be used to estimate PV module temperature with good precision under different climatic conditions.

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1. INTRODUCTION

To predict the energy production performances of photovoltaic (PV) modules and to investigate the real PV system characteristics, it is important to develop an appropriate mathematical model in order to estimate the operating temperature of the PV module depending on several climatic parameters. In the literature, several PV module temperature prediction methods have been developed [1]–[5], the famous used method is built on the normal operating cell temperature (NOCT), which can be found in the PV module datasheet. This simple method is the most used, but its disadvantage is that it is defined in particular meteorological conditions (800 W/m², Tamb=20 °C), moreover certain studies have shown that the NOCT is a variable value and depends on many parameters as; month, time of year and site [6], [7]. The researches developed two different models, one considers the parameter of the wind speed and the other without this parameter, to estimate the outdoor PV module operating temperature [8]–[10]. Wang *et al.* [11] presented an enhanced environmental artificial neural network (ANN) technique to forecast the PV module electrical behavior, by joining various neural networks. Tina and Scrofani [12] presented two different mathematical techniques, one is electrical and the other is thermal, they were joined to obtain the module temperature using actual data in the field. Muzathik [13] developed a simple model which does not require any difficult techniques, this model is based on a simple method to determine the temperature of the PV cell, the efficiency of the new temperature estimation procedure is studied through simulations and its validity is verified by experiments on photovoltaic modules. Massaoudi *et al.* [14] presented a study that allows a temperature forecast based on a real weather-related data.

The present study proposes an intelligent model based on neural networks (NN) that takes into account the variation of solar irradiation over time and ambient temperature to estimate the operating temperature of PV modules with greater accuracy. The proposed NN model is validated by comparing its simulation results with the experimental data, and by comparing it with three other models based on different computational techniques: NOCT, Ross, and fitting, as well as the classical method based on NOCT. This comparison aims to demonstrate the superiority of the proposed NN model over other methods for estimating the operating temperature of PV modules. Our findings suggest that the proposed NN model is more accurate for estimating PV module temperature under different climatic conditions, and can provide a valuable tool for predicting energy production in real PV systems.

2. METHOD
2.1. Experimental data

The experimental study in this work was carried out on a measuring bench installed at the solar equipment development unit, *Unité de Développement des Equipements Solaires* (UDES), Algeria, as shown in Figure 1, which contains a characterization bench of PV modules in outdoor conditions Figure 1(a). The values of the voltage, the current, the irradiance and the temperature are collected with a regular step of about five minutes, the interface simultaneously collects information from the PV modules and the values are measured with good uncertainties. The measurements obtained are saved in a hard disk of a microcomputer connected to the acquisition interface Figure 1(b). The photovoltaic module selected is based on a polycristallin silicon with a maximum power of 135 W. In this study, the PV module temperature estimation models were made using an experimental database recorded in 2020 at UDES site in the region of Bouismail, Algeria, where three months were selected; January, July and November, including around 2,000 values for each month. The simultaneous variation of irradiation and ambient temperature as well as the high number of values (about 6,000) make the database rich and usable to have reliable prediction models.

(a)

(b)

Figure 1. Characterization bench of PV modules in outdoor conditions: (a) electronic load and computer for data acquisition and (b) characterization bench for photovoltaic modules at UDES, Algeria

2.2. Proposed models
2.2.1. NOCT

It is the nominal operating, cell temperature. The NOCT value of a solar module indicates the temperature that the cells of the panel reach at 20 °C of an ambient temperature and an irradiation of 800 W/m². In (1) shows, how to calculate the PV module temperature Tm depending on the NOCT as suggested by many researchers [15]–[20]:

$$Tamb + (NOCT - 20) \times (G/800) \tag{1}$$

where: G, is the irradiation in W/m² and Tamb, is the ambient temperature (°C).

2.2.2. Ross model

This model was suggested by Ross [21], it uses an explicit formula for the PV module temperature estimation Tm, from the ambient temperature Tamb and the irradiation G, as shown in (2).

$$Tm = Tamb + K.G \quad (2)$$

This is a linear equation, where: the "k", presents the value of the slope of: ΔT (ΔT=Tm-Ta) against the irradiation, usually its value is founded to be 0.02 to 0.05 [22], various parameters affect the value of “k” [23]. For this study, the coefficient k was calculated, Figure 2 shows the ΔT variation versus the illumination with the linear dependence of the selected three months data. In this case, the obtained value of the coefficient k is equal to: 0.03.

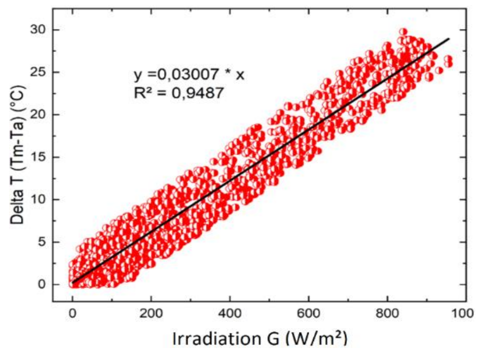


Figure 2. ΔT versus solar irradiation G data for the three months January, July, November 2020

2.2.3. Fitting model

It is a model that we developed with the curve fit application on MATLAB that offers a supple interface which can fit various type of curves and surfaces. The following (3), is obtained by the curve fit application from MATLAB to obtain the module temperature “Tm”.

$$Tm = -0.7279 + 0.03001 \times G + 1.035 \times Tamb \quad (3)$$

2.2.4. Neural networks model NN

The NN, are considered as an adequate technique for the resolution of estimation and prediction problems as shown on several researches [24]–[27]. The definition of the network architecture is essential to obtain a performing system. This consists of making a compromise between the complexity of the network by reducing the number of hidden units and the number of neurons for each layer. The objective is to create a model based on NN in order to forecast the temperature of photovoltaic module, for that we created two models based on the neural networks, one is general NN which is adapted for all seasons and the second one is specific NNs model which is specific for each season, the three seasons chosen are; winter, summer and autumn. Figure 3 shows, the proposed three layers network, where the input variables are; the ambient temperature (Ta) and the irradiance (G), and the output used variable is the PV module temperatures (Tm).

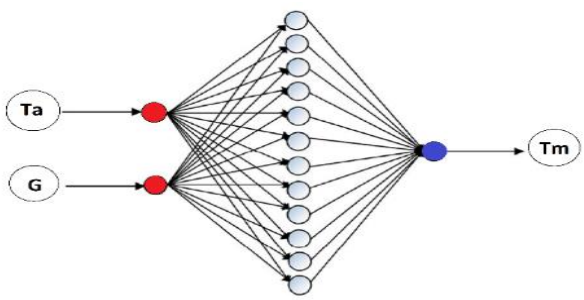
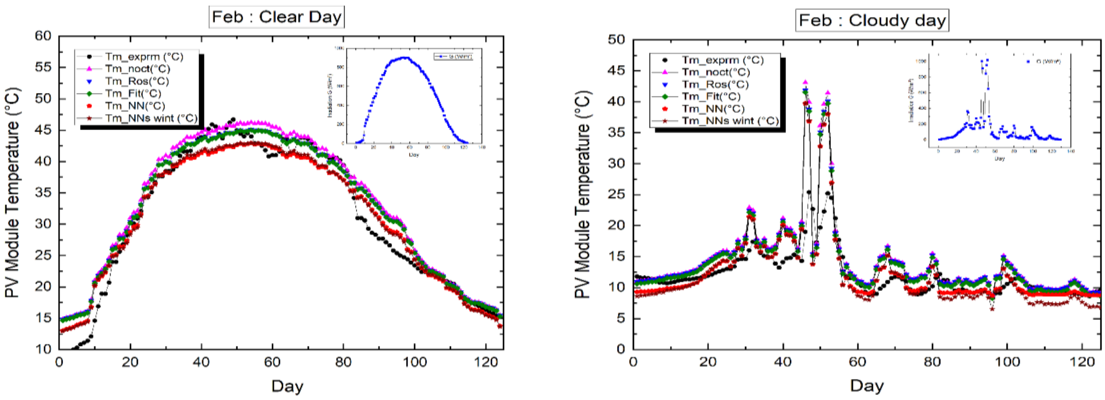


Figure 3. Neural network structure of the proposed NN model

3. RESULTS AND DISCUSSION

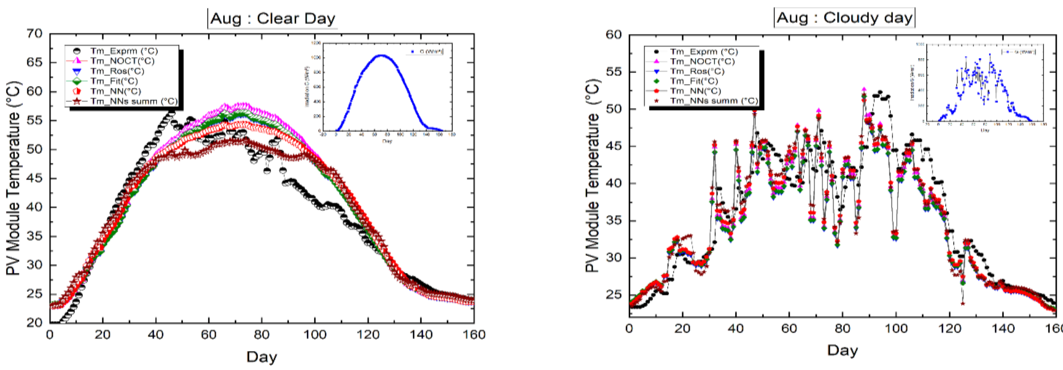
The proposed models are based on experimental data taken in three months: January, July and November 2020, which present the seasons: winter, summer and autumn respectively. In order to study the accuracy of the proposed models, the validation was done using two different days; clear and cloudy, but for three different months which are: February, August, and October 2020 which represent the same seasons studied, the choice of these values make them considered as new values for the models, this approach is important for studying the accuracy of the models. Figure 4 shows the calculated values of the estimated PV module temperature obtained by all the proposed models; Tm_Ros, Tm_Fit, Tm_NN, Tm_NNs, compared with those obtained by the NOCT, Tm_NOCT and the measured temperatures Tm_exprm. This validation is made for a clear day Figure 4(a) and another cloudy day Figure 4(b) for the month of February, for the month of August, it is presented in Figure 5 for the clear day Figure 5(a) and the cloudy day Figure 5(b) and for the month October is shown in Figure 6 for the clear day Figure 6(a) and the cloudy day Figure 6(b).

To study the accuracy of the models the difference between the calculated values and those of the measurement were identified by the calculation of the root-mean-square error, root mean square error (RMSE) and the determination factor "R^2", these coefficients are presented in Figures 7-9 for the months: February, August, and October respectively, for February the Figure 7(a) present the clear day and the cloudy day Figure 7(b), for August the clear day Figure 8(a) and the cloudy day Figure 8(b) and for October the Figure 9(a) present the clear day and the cloudy day in Figure 9(b). According to these results, it was found that the proposed models estimate better the values of the PV module temperature than the NOCT method, in particular for the method based on the NN neural networks, which presents a better accuracy compared to the other models. Table 1 shows, the statistical evaluation for the developed methods for three months, comparing to literature, our developed models provides better results compared with those found for NOCT and Sandia models [8], especially in the R^2 and RMSE for the two months of February and October, where the NOCT provides less efficiency, this confirms the necessity of developing other methods more accurate and efficients than the NOCT method. It was also found that there is no significant difference between the general neural network method NN and that specific for each season NNs, this translates into the importance of having a large amount of data for the general NN model more than that of NNs which is based on a reduced amount of data from each season, but it remains important in certain climatic conditions which require an estimate per season.



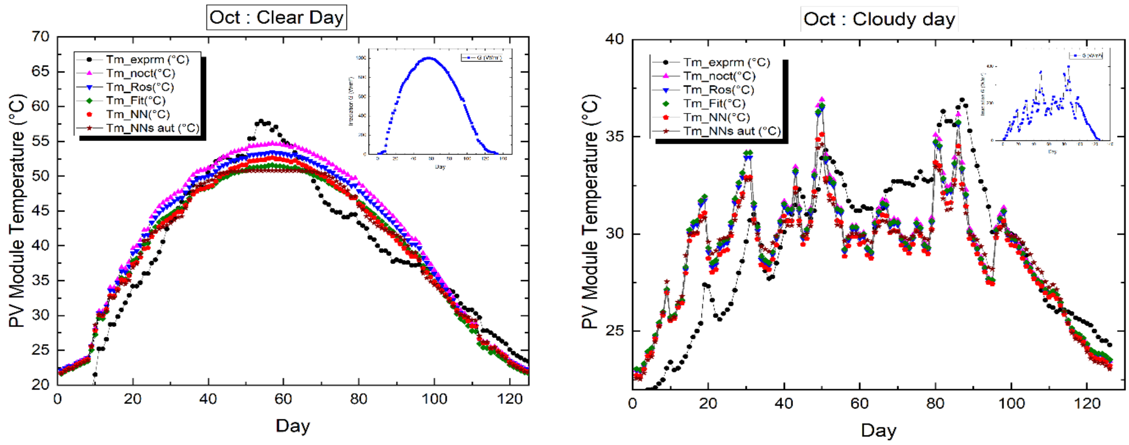
(a) (b)

Figure 4. PV module temperature for all models, in February: (a) clear day and (b) cloudy day



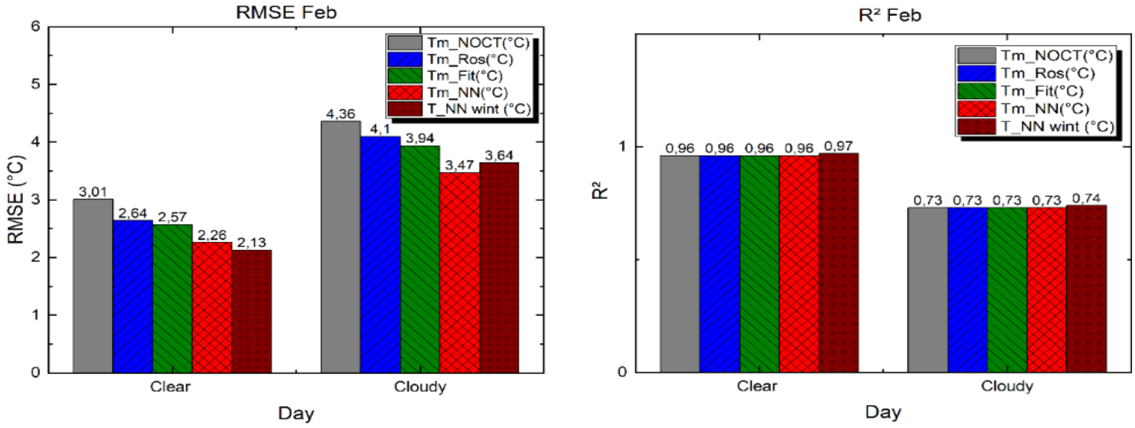
(a) (b)

Figure 5. PV module temperature for all models, in August: (a) clear day and (b) cloudy day



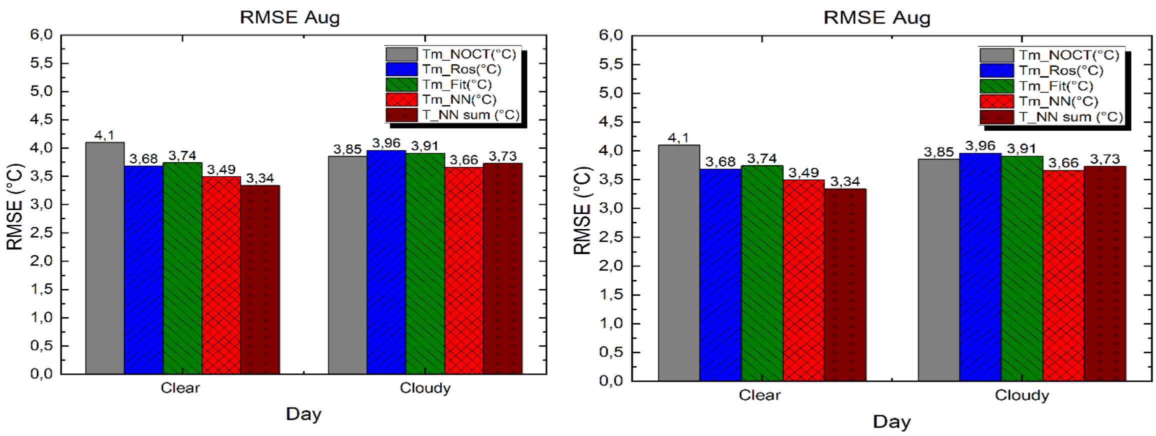
(a) (b)

Figure 6. PV module temperature for all models, in October: (a) clear day and (b) cloudy day



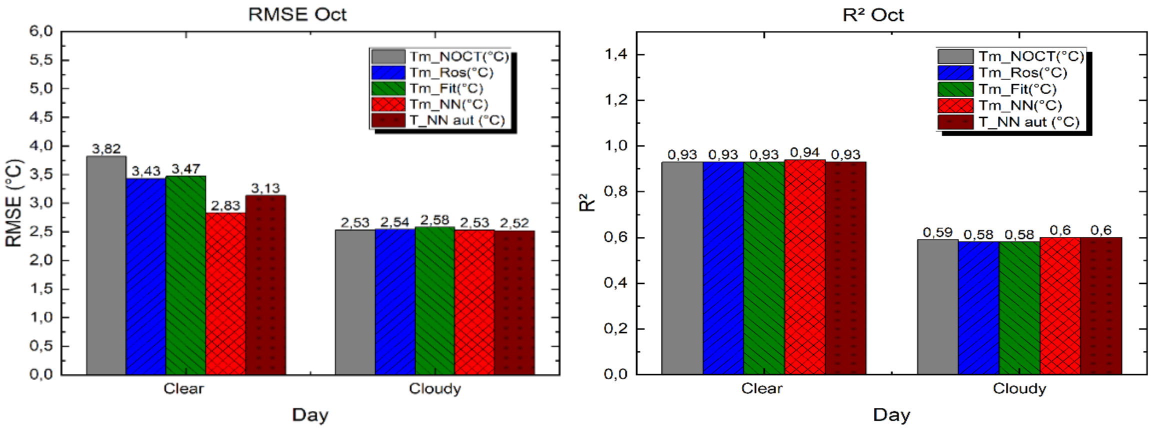
(a) (b)

Figure 7. Predicted PV module temperature errors for all models, in February: (a) root-mean-square ‘RMSE’ and (b) the determination factor ‘R²’



(a) (b)

Figure 8. Predicted PV module temperature errors for all models, in August: (a) root-mean-square ‘RMSE’ and (b) the determination factor ‘R²’



(a) (b)

Figure 9. Predicted PV module temperature errors for all models, in October: (a) root-mean-square 'RMSE' and (b) the determination factor 'R^2'

Table 1. Statistical evaluation (SE) for the developed methods

	February		Augest		October	
	R^2	RMSE	R^2	RMSE	R^2	RMSE
NOCT model	0.9663	3.0116	0.9151	4.1097	0.9312	3.8273
Ross model	0.9693	2.6434	0.9149	3.6883	0.9307	3.4342
Fitting model	0.9696	2.5763	0.9148	3.7402	0.9303	3.4798
NN model	0.9698	2.2608	0.9202	3.4960	0.9438	2.8388
Sandia [8]	0,87	2,44	0,91	0,82	0,95	2,5
NOCT [8]	0,52	4,7	0,57	1,86	0,79	2,33

The results show that the RN model demonstrates applicability in any environment, making it a preferable choice over the NOCT model. Its simplicity not only streamlines the implementation process but also reduces the associated expenses. The RN model provides a cost-effective alternative that can be easily applied in various settings compared to the NOCT model. Based on this work, we wholeheartedly recognize the importance of bridging the divide between theoretical research and practical implementation. Keeping this objective in focus, we are dedicated to delving deeper into real-life application scenarios within the results and discussion sections. Our aim is to provide more comprehensive insights, fostering a better understanding of the practical implications stemming from our research findings, and we are fully committed to elevating the article's relevance and applicability in the dynamic landscape of global energy transformation.

4. CONCLUSION

In this study, different models are proposed for the photovoltaic module temperature prediction, these models are based on different techniques; two models based on NN; one which is general and the other is specific for each season, a model based on a linear method proposed by Ross and another model based on the method of fitting. It was found that there is a very good promise between the measured module temperature and that calculated by the four models; Ross, fitting, general NN and NNs, where $R^2>0.91$ and $RMSE<3.74$ for the clear days, the four models proposed can be used for the PV module temperature prediction with a good degree of accuracy, given the time, cost, and expertise required to simulate or evaluate the proposed model, the model based on the networks of NN neuron is more cost effective with corresponding applicability in any environment by applying simple mathematical skills, because they use intelligent and developed techniques based on deep learning especially when using a big experimental data, this work helps to improve the models for predicting the electrical performance of PV modules/systems, using the estimation of the PV module temperature under various climatic conditions. These models, which range from advanced machine learning techniques to hybrid models, have demonstrated higher accuracy and reliability compared to traditional models. The use of these improved models will help optimize the design and operation of PV systems, and enable more accurate energy yield predictions, which are essential for the sustainable development of renewable energy sources.

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