

# Experimental Evaluation of Solar Power Plant Performances for the Choice of a Suitable Photovoltaic System

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## Abstract

The need for energy in many remote locations has led many researchers to look for an efficient and sustainable solution. And this necessarily involves using natural resources that are not limitless. These resources are even better solutions when they are of a renewable nature. Before installing any photovoltaic system on a site, factors such as the type of solar cell to be used or the temperature to be received at the solar panels must be taken into account. In this work, data are supplied by the external data acquisition bench, which is installed on-site. The robustness of the system is based on its ability to respond to sudden changes in insolation. For greater precision in the proposed method, five months are selected: December, January, February, March and April each year for four successive years. These values are used to determine the daily, monthly and annual average power output by the photovoltaic plant. To address this issue, a comparative study was carried out between two cell types: the monocrystalline silicon solar cells (MSSCs) and the polycrystalline silicon solar cells (PSSCs). Performance evaluation and the calculation of certain performance indicators show that the monocrystalline cell is more suitable for setting up a photovoltaic power plant in Ngaoundéré. Simulation results in MATLAB/Simulink reduce the quadratic errors to 0.97. This error is obtained by calculating the discrepancy between the data provided by the NASA site and the experimental acquisition bench installed in this locality. The calculation of the error shows that the method used is suitable not only for extrapolating power to implement the photovoltaic power plant but also for determining the type of cell to be used.

#### **Keywords**

Local Resources, Sustainable Solution, Monocrystalline Cell, The Polycrystalline Cell, Photovoltaic Power Plant

## **1. Introduction**

Cameroon is a country with great potential for photovoltaic solar energy [1]. In the country's northern regions, many areas are isolated from the main electricity grids [2]. As a result, in some rural areas, thermal power plants or other generators are distributed in isolated, decentralized forms. The study of the performance of solar panels used in this rural area provides an overall assessment of the lifetime not only of the solar panels, but also of the entire installation, in order to avoid the expense of implementing this photovoltaic solar system. In fact, there are a number of photovoltaic generators in several localities that have been abandoned, partly because the installation was incorrectly sized, and partly because maintenance is not carried out regularly [3]. What's more, periodic maintenance is not carried out. This neglect automatically leads to many solar power plants coming to a standstill [4]. On the other hand, the problem lies in the use or choice of appropriate components for the installation of solar panels. In this work, a choice is made on the use of photovoltaic cells according to the availability and performance of the chosen site [5]. The University of Ngaoundéré was chosen as the site for an experimental study of solar panels. The results of the experimental study in [6] show that polycrystalline cells are better suited to the Niger locality and can therefore deliver higher yields than polycrystalline cells. In [7], a study shows why most solar fields in rural areas are abandoned when the lifetime of these installations exceeds four years [8]. However, the work in [9] shows that monocrystalline cells are suitable for low-intensity insolation. This is because polycrystalline cells tend to improve yields when the lifetime or operating time is long. On the other hand, in [10], it was shown that polycrystalline cells performed better for daily, weekly and monthly periods. These studies have paved the way for the appropriate choice of photovoltaic installations in the city of Ngaoundéré and attracted producers of the materials.

The focus is on climatic conditions on the one hand, and on performance criteria due to the effects of aerosols on the other [11]. Most often, solar panels are installed haphazardly in rural localities, because no feasibility study has been carried out, either due to a lack of appropriate equipment, or because the local population lacks the appropriate equipment or tools to install these photovoltaic systems [12]. The weekly, monthly and annual assessment of sunshine levels in the city of Ngaoundéré gives us an idea not only of the lifespan of the installation, but also of the choice of equipment in terms of performance for the installation of a large-scale photovoltaic power plant.

The first step is to estimate the daily, monthly and annual data before obtaining

the annual average. The study was carried out over four successive years, with the most acceptable levels of sunshine observed during the months of December, January, February, March, and April.

Knowing the availability of sunlight is important for estimating the performance of a photovoltaic cell. Not only does this help to determine the size of the photovoltaic power plant that can be set up in that locality, but it also enables a decision to be made on whether to combine other sources of energy, itself renewable, in order to raise the power level, or on the choice of the appropriate cell type. It is, therefore, useful to know the characteristics [13], performance and efficiency of this experimental study, as shown in **Figure 1**.



Figure 1. Experimental setup.

# 2. Methodology





The various photovoltaic energy conversion stages are shown in **Figure 2**. Depending on the type of photovoltaic cell, energy is delivered to non-linear loads via two conversion stages: Direct Current to Direct Current (DC/DC) conversion and

Direct Current to Alternative Current (DC/AC) conversion [14]. A Maximum Power Point Tracking (MPPT) control system ensures maximum extraction of the photo power generated [15]. A battery bank is associated with the photovoltaic (PV) system to store continuous energy. This configuration system takes 2 types of solar cells as input: monocrystalline and polycrystalline [16].

# 3. Presentation of the Study Environment and Data Used in the Location

The data acquisition bench installed on the roof of the University of Ngaoundéré enables real-time meteorological data to be extracted during specific intervals of the day. Depending on the station frequency setting, data is generated every 30 minutes or every hour. These data, which are supplied by the University of Ngaoundéré's data acquisition system, enable a comparative study to be made of the data supplied by the NASA site [17]. **Figure 3** shows the location of the real-time meteorological data acquisition site. This site is located in the Adamaoua region of Cameroon. The Cameroonian region of Ngaoundéré is situated in the sub-Sahelian climate zone [18]. Our study was conducted on the University of Ngaoundéré's website. The data were collected and made available by the Institute of University Technology's (IUT) meteorological station from 01 December 2021 to 01 December 2024.



Figure 3. Spatial location of the selected site. (Source: https://www.univ-ndere.cm/)

Table 1	. Geograp	hical p	osition	of the	site.
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Site	Longitude	Latitude	Altitude (m)
Ngaoundéré	13°35′04″ E	7°19′39″ N	1128

In order to carry out this study, data will be collected from December 1, 2021 to December 1, 2024. **Table 1** shows the geographical coordinates of the chosen location [19].

The different stages of electrical energy conversion are given in Figure 2, which

represents the architecture of the system on which our work focuses. We observe that it is important to add a boost chopper and to extract energy in a battery bank. The sensors are installed to collect real-time data or for the acquisition of experimental data.

## 4. Photovoltaic Power Plant System

The power generated from the photovoltaic panel is defined by the cell temperature as a function of the location's ambient temperature and the available solar irradiation [20]. The PV power is used to supply the load directly in case of outages, and/or to charge the battery bank. The maximum available power from the PV with maximum power point tracking (MPPT) for a given surface area of the panel,  $A_{pv}$  (m<sup>2</sup>), and the total irradiation hitting the PV surface, G.

The photovoltaic system is a combination of solar panels, a DC converter and a DC-AC converter stage to supply either direct DC loads or linear or non-light AC loads [21]. **Figure 4** shows the electrical system configuration of the stage for extracting photovoltaic energy from sunlight. This diagram depicted in **Figure 4** allows us to develop a mathematical model of the power of a photovoltaic generator using the photocurrent generated, according to Equation (1) [22].



Figure 4. Electrical circuit of the photovoltaic system of conversion.

$$I_{\text{out}} = I_{\text{In}} - I_0 \left\{ \exp\left[\frac{e}{kT_C} \left(V_{\text{out}} + R_y I_{\text{out}}\right)\right] - 1 \right\} - \frac{V_{\text{out}} + R_x I_{\text{out}}}{R_x}$$
(1)

$$V_{\text{out}} = \frac{\text{AkT}_c}{\text{e}} \ln \left( \frac{I_{\text{In}} + I_o - I_{\text{out}}}{I_o} \right) - R_y I_{\text{out}}$$
(2)

$$P_{\text{Syst}}(\eta) = \eta_{\text{Syst}} A_{\text{Syst}} G_{\alpha}(\eta)$$
(3)

where  $P_{\text{Syst}}(\eta)$  is the generated PV power at time step t (a 1-min time step is used) and  $\eta_{\text{Syst}}$  is the PV panel efficiency and is given by.

$$\eta_{\text{Syst}} = \phi_{\gamma} \left[ 1 - \beta_{\rho} \left( T_{\text{cell}} - T_{\text{STC}} \right) \right]$$
(4)

$$T_{\text{cell}} = T_{\text{amb}} + (\text{NOCT} - 20) \frac{G_{\phi}}{800}$$
(5)

where  $G_{\phi}$  is the module efficiency,  $\beta_{\rho}$  is the photovoltaic panel power temper-

ature coefficient taken as -0.003/°C for silicon cells.  $T_{cell}$  and  $T_{amb}$  are the cell and ambient temperatures (°C), and  $T_{STC}$  is the reference temperature, which is 25°C. The nominal operating cell temperature (NOCT), module efficiency, and temperature coefficient are variables depending on the selected module and can be derived from the manufacturers' datasheets.

## 5. Model Validation using Statistical Performance Indicators

Mathematical techniques such as statistical tests can be used to evaluate models [23]. These include the Root Mean Square Error, the Mean Bias Error, the Mean Absolute Error, the Mean Absolute Relative Error, or the quadratic error, which allow us to evaluate the difference between two data sets, one measured and the other estimated or theoretical. The data collected by the acquisition bench at the University of Ngaoundéré are compared with the data provided by the NASA site, in order to determine the quadratic error.

#### 5.1. Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) gives an idea of the model. When the RMSE is low or close to zero, then the model is reliably feasible. When this value is too high or far from zero, it implies that the estimated values are subject to a lot of error. This is a parameter that must be taken into account in the same way as the quadratic error. Different techniques are used to compare models. The parameter RMSE is the wisely used in methods evaluation. When the value of RMSE is low, it means that the model is better. The formula of the RMSE indicator is given in Equation (6).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} \left( \overline{H}_{obs} - \overline{H}_{exp} \right)^2}$$
(6)

#### 5.2. Mean Bias Error (MBE)

Another parameter is also used to test the feasibility and performance of a method. This is the Mean Bias Error (MBE). When this value is close to zero, the method used has fewer errors. This value needs to be around zero, because when it is too large, it leads to an overestimation of the parameters, and when it is negative, it also leads to an underestimation of the model. This is why statistical analysis can be used to reduce calculation errors or achieve precision based on measurement uncertainties. While values of MBE closest to zero are desirable, this indicator therefore expresses the tendency of the model to overestimate (positive value) and to underestimate (negative value) the global radiation. When the model shows underestimated and overestimated values at the same time, this test does not show the correct performance, which is the drawback; because the values of underestimation and overestimation cancel each other out. The formula of the MBE indicator is given in Equation (7) [24].

$$MBE = \frac{1}{n} \sum_{i=1}^{n} \left( \overline{H}_{obs} - \overline{H}_{exp} \right)$$
(7)

#### 5.3. Mean Absolute Error (MAE)

As for the mathematical tool defined as the Mean Absolute Error (MAE), this parameter needs to be virtually low, *i.e.*, close to zero, for model performance. Taking this value into account, along with the RMSE, gives an idea of the discrepancy between the statistical data used. When you want to measure the error between experimental data and estimated or observed data, it's important to use the MAE. The MAE is the ratio of the sum of the absolute values divided by the number of observations. This quantity is often used in statistics to measure how close the estimated values are to the measured values. In inter-comparisons of mean model performance error and dimensioned evaluations, the authors pointed out some advantages of MAE over root mean square error (RMSE). The formula of the MAE indicator is given in Equation (8) [25].

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \overline{H}_{obs} - \overline{H}_{exp} \right|$$
(8)

#### 5.4. Mean Absolute Relative Error (MARE)

The error is an indicator of the precision of the difference between measured and estimated data. This parameter can be used to assess whether the data has been overestimated or underestimated. This is because when the data is not defined within the normalized interval, it is possible for there to be a large error; consequently, we can easily move away from the solution or the solution search field. Some works state that to get an idea of a model's performance, it is necessary to automatically evaluate the MARE. MARE is known as Mean Absolute Percentage Error (MAPE) when expressed as a percentage. Between measured and estimated solar radiation, this indicator is expressed as an average absolute value. The formula for the MARE indicator is given in Equation (9) [26].

$$MARE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{\overline{H}_{obs} - \overline{H}_{exp}}{\overline{H}_{exp}} \right|$$
(9)

## 5.5. Coefficient of Determination (R<sup>2</sup>)

Many studies point out that we can't decide on the performance of a model until this value of the coefficient of determination or a quadratic error has been determined. This is why it has been shown that knowledge of this value enables a decision to be made on the choice of a model or method when this value is found to be close to 1. To estimate the performance of models, this indicator is often used in statistics. Thus, the models are efficient when the coefficient of determination is close to 1. The formula of the determination indicator is given in Equation (10) [27].

$$R^{2} = 1 - \frac{\sum_{i=1}^{n} (\bar{H}_{obs} - \bar{H}_{exp})^{2}}{\sum_{i=1}^{n} (\bar{H}_{obs} - \bar{H}_{obs(mean)})^{2}}$$
(10)

## 6. Results and Discussion

The results section deals with the power profiles of different photovoltaic solar

cells: monocrystalline cells and polycrystalline cells. The evaluation of the power profiles is first made for one day, and then a comparative study of the data provided over four consecutive months is also carried out, namely, January, February, March and December. An annual average is calculated to determine the power level of the entire energy system.

## 6.1. Assessment of the Daily Output of the Photovoltaic Generator

The power profile of the photovoltaic generator is shown in **Figure 5**, where it can be seen that there is not too much deviation between the two types of solar cells, although the monocrystalline cell seems to produce more energy than the polycrystalline cell. Abundant sunshine is observed between 7 a.m. and 5 p.m.; during this time, the monocrystalline cell estimates power better than the polycrystalline cell around 12 p.m., when peak sunshine is reached.



Figure 5. Daily power profile.

## 6.2. Assessment of the Monthly Output of the Photovoltaic Generator

The monthly power profiles are shown in **Figure 6** for December, **Figure 7** for January, **Figure 8** for February, **Figure 9** for March and **Figure 10** for April. It can be seen that in December, both types of solar cells provide good power extraction, and the power output trends remain virtually identical. The polycrystalline cell provides good power extraction at low irradiation levels, while the monocrystalline cell does not provide good power extraction for sudden changes in irradiation. We also observe a decrease in power during January and February. The intervals between the 17th and 28th of each month show a loss of power. In March, however, power extrapolation was better, and both cell types extracted power from the photovoltaic array with improved performance. This is demonstrated by the fact that in March in Ngaoundéré, the temperature is slightly high [28]. In **Figure 10**, the power profile of the photovoltaic generator shows that the powers produced by the monocrystalline and polycrystalline cell types are almost identical, but the polycrystal-

line cell overestimates power.







Figure 7. Power profile for the month of January.







Figure 9. Power profile for the month of March.



**Figure 10.** Power profile for the month of April.

## 7. Determination of Performance Indicators

Table 2. Data collected for monocrystalline silicon solar cells (MSSC).

Methods	R <sup>2</sup>	MARE	RMSE	MBE	MAE	Power Installed (MW)
First year (01/12/2021)	0. 965	0.002	0.466	0.045	4.111	0.83
Second year (01/12/2022)	0.974	0.023	0.490	0.089	2.012	0.55
Third year (01/12/2023)	0.981	0.047	0.324	0.065	0.452	0.51
Fourth year (01/12/2024)	0. 942	0.002	0.572	0.044	0.44	0.22

Determining the values of the performance indicators listed in **Table 2** gives an idea of the estimation or extrapolation of real-time data. **Table 3** shows the various

parameters determined by the use of the monocrystalline cell. We can see that for the first four successive years, there is a regression or decrease in cell efficiency performance, but this decrease is not too great.

The values in **Table 3**, on the other hand, show that there is a big difference and a gradual decrease in polycrystalline cell efficiency. This shows that when the time of use of photovoltaic generators extends over a long period for polycrystalline materials, it is possible that there is a decrease in solar cell performance [29]. The values of these performance indicators show that not only is the approach or method better for power extrapolation, but it also gives an idea of the feasibility and implementation of a high-capacity photovoltaic generator.

It can be seen that for four successive years, there has been a decrease in the power produced by polycrystalline cells. This regression means that polycrystalline cells are either unsuitable for the chosen site, or do not perform better in these climatic conditions.

Methods	R <sup>2</sup>	MARE	RMSE	MBE	MAE	Power Installed (MW)
First year (01/12/2021)	0.45	0.077	0.237	0.011	1.574	0.71
Second year	0.979	0.056	2.478	0.045	2.001	0.72

0.065

0.077

1.356

3.587

0.085

0.074

3.021

0.444

0.63

0.33

Table 3. Data collected for polycrystalline silicon solar cells (PSSC).

0.9505

0.943

## 8. Conclusion

(01/12/2022) Third year

(01/12/2023) Fourth year

(01/12/2024)

After evaluation over a whole day, we can see that for a sunny day, particularly in February and March-April, there is a drop in performance for generators made from polycrystalline cells, whereas for solar panels made from monocrystalline cells, there is a slight increase in performance is observed, up to 18% in efficiency. These results corroborate studies in the literature which show that monocrystalline solar panels are more resistant and suitable for rural areas with low levels of sunlight. However, not only is the local sunshine low, but the environment is also exposed to dust. However, the performance of monocrystalline cells is quite acceptable, demonstrating the robustness of these materials in the face of adverse weather conditions. The aim is not only to evaluate the performance of monocrystalline cells, but also to assess the performance parameters of amorphous cells for the same locality, in order to gain an idea of the choice of materials for the installation of photovoltaic systems.

## **Conflicts of Interest**

The authors declare no conflicts of interest regarding the publication of this paper.

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