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New Model of Photovoltaic System Adapted by a Digital MPPT Control and Radiation Predictions Using Deep Learning in Morocco Agricultural Sector

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Abstract:
Solar energy is an essential factor in Moroccan sustainable development, especially in solar pumping in the agricultural sector. It is therefore difficult to dissociate the energy system of a society from its economic development and social development. Solar radiation prediction is useful in giving us a global overview on maintaining the integrity of solar systems. Access to database use makes this process more flexible. Solar forecasts can be generated using various available data sources. There are two major pillars of this data: the exploitation of historical solar radiation data, and the exploitation of other meteorological factors. On the other hand, the choice of data can have an impact on the choice of the model and the approach employed. In this paper we suggest an idea that aims to monitor in real time the situation of solar radiation in Morocco, using Long Short-Term Memory for deep learning models compared with Artificial Neural Networks and Deep Neural Networks to predict the solar radiation with regard to solar pumping in the Moroccan agricultural sector.

Keywords: *Morocco sustainable development, Solar pumping, Deep Learning, Renewable energies, Solar radiation.*

1. Introduction

Morocco has been making great strides in renewable energy, and green process in sustainable development, and especially in solar pumping for its agricultural sector [1]. Recently, in the literature several intelligent algorithms have been used in renewable energy, and for solar pumping prediction for sustainable development [2–5]; Indeed, some Artificial Neural Networks models have been studied for predictions of solar radiation [6–9]. These have the advantage of giving a fast and accurate tracking of the MPP [10–16]. The controller in renewable energy effectiveness depends on the algorithm used and the neural network trained. Articles over the last years were studied renewable energy, and green process in sustainable development using Machine, and deep learning [16–18]. Some authors discuss in different papers the renewable energy using ANN for MPPT control is presented [19, 20].

The algorithms are based on Deep Learning and Machine Learning Approaches or in Empirical and machine learning models for predicting daily global solar radiation from sunshine duration [21–23]. In general, countries are making great strides towards cleaner energy that is more environmentally friendly.

The agricultural sector consumes a large share of energy in Morocco, contributes the most to gross domestic product, and is one of the sectors that employs the most people, especially in rural areas. In recent years, agriculture has made great strides in incorporating renewable energy into its businesses.

In 2010, Morocco's Solar Energy Agency (MASEN) was established, with the goal of providing the country with a clean energy source that replaces 90% of imported energy [24]. Renewable energy is expected to exceed 52% of the country's total energy consumption and production by 2030. The country invests in both solar and wind energy, especially the Noor Solar Station. The investment is estimated at 2 billion euros, all built over the last five years with a total area of 300 hectares [25].

For Morocco, solar energy is an important economic issue in line with the choice of sustainable development. The unchecked cost of traditional energy, which has a negative impact on the environment, doubles the stake. Solar energy is clean, inexhaustible, and beneficial alternative energy consistent with sustainable development. Morocco's determination to be a flag bearer is an advantage in pursuing energy autonomy, not only for our brothers in Africa, but also for other partners in the world who want to provide services and products and share their experiences.

As part of its strategy to promote renewable energies, Morocco prioritizes the expansion and sustainable development of these energies. With abundant solar resources, "potential of 2,600 kWh/m^2/year", and a strategic location in the center of the energy hub (connected to the Spanish power network via two 400 kV/700 MW lines), Morocco offers several investment opportunities in the field of solar energy in thermodynamics and photovoltaics. The Moroccan solar energy project aims to build a total of 2000 MW of solar power capacity in 2020 at five sites: Ouarzazate, AinBni Mathar, Foum Al Oued, Boujdour and Sebkhat Tah.

Solar radiation is the radiation or energy we receive from the sun. For energy systems, a thorough understanding of the availability and variability of solar radiation intensity is fundamental and crucial. This is the fuel of any solar energy system. Due to the growing demand for electricity, several countries have been targeting the renewable energy production market. Morocco is launching a range of projects that will hit about 2000 MW of electricity and plans to make 42% of its energy renewable by 2020 and bring it to 52% by 2030. The kingdom has a high sunshine rate: around 3000 hours of sunshine per year. All projects implemented or under construction offer the country the chance to be the leader in the MENA region in this field.

One of the most well-known projects in Morocco is in Noor, Ouarzazate, which currently has four factories at different stages of development: Noor I is a 160 MW cylindrical-parabolic mirror with 3 hours of thermal storage and an annual production of 520 GWh; Noor II is a 200 MW cylindrical-parabolic mirror with 7 hours of thermal storage and an annual production of 699 GWh; Noor III is a 150 MW tower with 8 hours of thermal storage with an annual production of 515 GWh and Noor IV of 72 MW with an annual production of 125 GWh [25]. Noor has other proposed projects such as Noor Midelt, Noor Tafilalet, Noor PV II, Noor Atlas , Outat El Haj, Ain Beni Mathar, Boudnib, Bouanane and Boulemane) and Noor Argana. A study and analysis of previous solar radiation studies in Morocco are presented in this article. Section 2 presents the solar pumping in the agricultural sector. Next, Section 3 deals with methods for the acquisition of the necessary data for AI models and with artificial intelligence and its axes. Section 4 deals with modeling precise assessment methods. Section 5 provides presentations and algorithms used in solar radiation publications in Morocco. Finally, Section 6 shows the results and discussion.

2. Solar Pumping in the Agricultural Sector

In Figures 1 and 2, the requested sample concerns 500 farmers, 277 of whom use photovoltaic power (PPV) for irrigation and 223 who use other conventional sources of energy. To constitute a representative sample is to ensure that the essential components

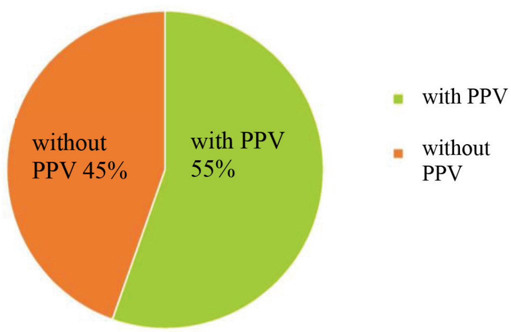

Figure 1. Spire of solar pumping

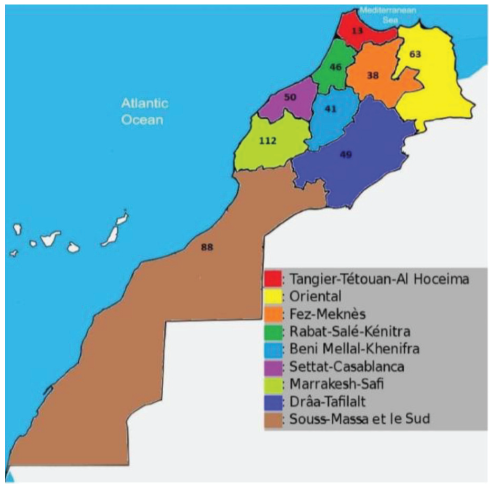

Figure 2. Inventory of the solar pumping in the agricultural sector

Table 1. Reference population distribution without PPV

Without PPV		
Parent population	1,710,000	ha
Sample	2,800	ha
Confidence threshold	95%	
Expected proportion of a response	0.5	
Margin of error	2%	

Table 2. Reference population distribution with PPV

With PPV		
Parent population	1,710,600	ha
Sample	3,300	ha
Confidence threshold	95%	
Expected proportion of a response	0.5	
Margin of error	1.7%	

of its reference population appear in the sample, in identical proportions.

Under this condition, the results observed in the sample can be extrapolated to its entire reference population (see Tables 1 and 2).

The margin of error is:

$$y = \sqrt{\frac{t_p^2 \times P \times (1-P) \times (N-n)}{(N-1) \times n}}$$

n: sampling size.
N: size of the target population, actual or estimated.
P: expected proportion of a response from the population or actual proportion.

In the case of a multi-criteria study (our case), it can be set at 0.5 by default.

tp: Sampling confidence coefficient. The values are associated with confidence intervals.
y: margin of sampling error

Three teams of investigators were trained before the surveys began. The training focused on the operation of a solar installation and on how to address the different questions to the farmers.

Table 3. PPV in the different regions of Morocco

Region	With PPV	Without PPV	Sum
1. Tanger-Tetouan-Al Hoceïma	0	13	13
2. L'Oriental	58	5	63
3. Fez-Meknes	23	15	38
4. Rabat-Salé-Kenitra	8	38	46
5. Béni Mellal-Khénifra	25	16	41
6. Casablanca-Settat	14	36	50
7. Marrakech-Safi	66	46	112
8. Darâa-Tafilalet	29	20	49
9. Souss-Massa et le Sud	54	34	88
Sum	**277**	**223**	**500**

The three teams visited the 500 farmers in a random manner, respecting randomness while also respecting the distribution of the sample by region and by category (with and without PPV). Some difficulties were encountered in the field:

- The difficulty of convincing farmers with PPV to participate in this study;
- The difficulty of estimating energy and water energy and water consumption among farmers;
- Lack of reliability of farmers' statements about lower costs and/or the increase in their income following the installation of PPV systems (Table 3);

The number of farmers visited in each region was chosen according to two criteria (Figure 3):

- The irrigated area of the region (Data sources: MADRPM 2015/2016)
- The presence of the PPV in the region (Data source: field experience)

Due to the rapid rise in implementation and high penetration of solar power in electricity grids worldwide, forecasting of solar radiation production has become a crucial need [1]. We show here the different types of solar radiation forecasting methods available:

- **Stochastic Learning techniques:** In order to forecast shifts in sun angles, these methods are based on recent data from photovoltaic power plants or radiometer outputs.
- **Artificial Neural Network:** ANN deals with meteorological variables taken as inputs to forecast various time scales of solar radiation.
- **Numerical Weather Prediction Method:** This method used the Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) techniques with numerical weather data to forecast the solar radiation.
- **Satellite Image techniques:** This technique is based on the reflection of correctly measured light from the cloud to satellites.
- **Ground based image techniques:** The strategy used the total sky imager (TSI) to present a clear view of cloud shadows for forecasting the solar radiation.

3. Artificial Intelligence Models

In our research, we would concentrate on Artificial Neural Network forecasting, generally in the techniques of Artificial Intelligence, but what are those methods? And what are their effects on predicting solar radiation?

Artificial Intelligence (AI) is a branch of computer science that deals with the development of smart machines capable of executing tasks that usually require human intelligence. With strong prediction and automation capabilities, AI can operate with excellence in several areas.

Machine Learning (ML) goes deeper, as AI tries to emulate human thought. Machine Learning as a branch of AI enables machines to learn without relying on instruction. In fact, in order to recognize patterns, the "machine" is an algorithm that analyzes a volume of data which would be unmanageable for a human being. Machine learning, in other words, allows the machine to be educated to automate tasks that are difficult for a human being, and it can make predictions with this learning.

Deep Learning (DL) may be viewed as a form but more complex of Machine Learning. Deep Learning is a series of algorithms that simulate the human brain's neural networks. The computer learns by itself, but in

Distribution of the sample offer (distributors/installers) by type of sector (Formal/Informal)

Entity	Number
Installer	51
Installer/Distributors	27
Distributors	10
Financial institutions	9
Manufacturer	3
Total	100

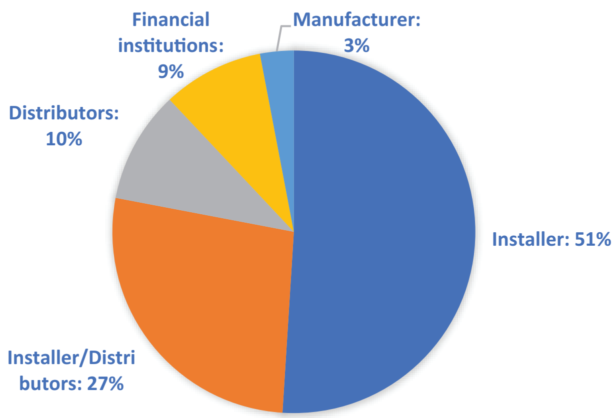

Figure 3. The number of farmers with and without financial institutions

phases or layers, in this technology. The model's depth would depend on the number of layers in the model.

4. DataSET

There are numerous approaches for source data methods that can be used to forecast solar radiation, some of which are:

- **The Prediction of Worldwide Energy Resources (POWER)** is a NASA project with the goal of observing, understanding, and modeling the Earth system to discover how it is changing, to better predict change, and to understand the consequences for life on Earth. The project was initiated to improve upon the current renewable energy data set and to create new data sets from new satellite systems. The POWER project targets three user communities: renewable energy, sustainable buildings, and agroclimatology. They provide two different datasets: meteorology (starting from January 1, 1981, to now) and the solar radiation data (from July 1, 1983, to now).
- **The Copernicus Atmosphere Monitoring Service (CAMS)** provides consistent and quality-controlled information related to air pollution and health, solar energy, greenhouse gases, and climate forcing, everywhere in the world. CAMS offer information services based on satellite Earth observation, in situ (non-satellite) data, and modeling.
- **METEONORM** software is a unique combination of reliable data sources and sophisticated calculation tools. It provides access to typical years and historical time series when we can choose from more than 30 different weather parameters. The database consists of more than 8 000 weather stations, five geostationary satellites, and a globally calibrated aerosol climatology. On this basis, sophisticated interpolation models, based on more than 30 years of experience, provide results with high accuracy worldwide.
- **Local laboratory:** Many universities around the world have already established local laboratories where various sensors (pyrometers, anemometers, pluviometers, radiometers, and thermo-hygrometers) are mounted to capture different meteorological and solar parameters.

5. Model Accuracy Evaluation

Typically, most research papers using methods of Artificial Intelligence use an evaluation algorithm to measure how effective the model is. In this section we will present some of the most used evaluations of model accuracy:

- **Root Mean Square Error (RMSE)** is the standard deviation of the residuals (prediction errors), it is widely used to validate experimental findings in climatology, forecasting, and regression analysis. It detects how oriented the data is around the best fit line. Where *Xobs* observes values, *Xmodel* models values at time/place *i*.
- **R-Squared** (**R2**, or the decision coefficient) is a statistical measure which specifies the proportion of variance in the dependent variable that can be explained by the independent variable. R-squared, in other words, shows how well the data matches the regression model (the goodness of fit).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \overline{y}_i)^2}$$

where n is the number of measurements, y_i the value of the measurement, $\hat{y}_i$ the corresponding predicted value and $\overline{y}$ the mean of the measurements.

- **Mean Absolute Error (MAE)** measures the average magnitude of the errors in a set of forecasts, without considering their direction. It measures accuracy for continuous variables.

$$\mathbf{MAE} = \frac{\sum_{i=1}^{n} |\boldsymbol{y_i} - \boldsymbol{x_i}|}{\boldsymbol{n}}$$

Where y_i is the prediction and x_i is the true value.

- **The mean square error (MSE)** uses the squared difference between measured and forecast values.

$$\mathbf{MSE} = \frac{\sum_{i=1}^{n} (\boldsymbol{Y_i} - \boldsymbol{\hat{Y}_i})^2}{\boldsymbol{n}}$$

Where Y_i is the vector of observed values and $\hat{Y}_i$ is the predicted values.

The authors used various instruments and sensors to gather meteorological parameters (Humidity, Temperature, and Wind Speed). As a result, the authors found that the NARX model with five inputs provides the best efficiency after 10 tested models (Table 4).

In the Benguerir region, some authors [25–29] used multilayer perception (MLP) to forecast global horizontal irradiance for a hot semi-arid atmosphere. For this reason, the authors used data obtained from the weather station located in Green Energy Park, Benguerir, Morocco, formed by different meteorological data (temperature, relative humidity, barometric pressure, wind speed, wind direction, precipitation, and others). Using the correlation coefficient, they find that the global irradiance at the top of the atmosphere and the solar zenithal angle are the most correlated astronomy parameters, and the temperature is the most correlated meteorological parameter with solar irradiance. Author researchers developed an artificial neural network (ANN) model with a multilayer perceptron (MLP) technique to measure the monthly average global solar irradiation on the horizontal surfaces of the Souss-Massa region in Morocco. To train the model, the authors used data from 175 locations spread across the Souss-Massa region for 10 years (1996–2005) provided by the NASA geo-satellite database and Google Maps. The authors have chosen a set of 24 different climate locations to achieve a stable design of the ANN model and validate it for the remaining 151 sites. As a result, the optimal model has 25 nodes in the hidden layer with an RMSE of 0.234 and a correlation coefficient of R 0.988.

Table 4. List of reference papers on solar radiation in some laboratories

Reference	Models	Year	Performance Indicator
3	Artificial neural network optimization for monthly average daily global solar radiation prediction	2016	Mean Absolute Percentage Error (MAPE), range between 1.67% and 4.25%
2	Recurrent neural network model	2017	Training ratio 90; Validation ratio 5; Testing ratio 5, MSE (3.29 10-3) R 0.983 MSETEST (5.27 10-3)RTEST0.961
6	Solar radiation estimation methods using ANN and empirical models	2019	RMSE values of many other similar models range from 2.05 to 4.70 MJ m-2 day-1
7	solar radiation with using ensemble learning algorithm	2019	RMSE between 4.6 and 14.6% in average
23	LSTM	2020	R^2: 91,6%
24	LSTM	2020	MSE/Autumn: 0.0019 MSE/Winter: 0.00301 MSE/Spring: 0.00322 MSE/Summer: 0.0015
Proposed works	LSTM	2022	MSE/Autumn: 0.0005 MSE/Winter: 0.00401 MSE/Spring: 0.00110 MSE/Summer: 0.0040

The authors tested the models for clear and unclear days, the results are very acceptable for clear days with an NMBE of 0.015%, an NRMSE of 0.10% and a correlation coefficient of 0.99, for unclear days the accuracy was an NMBE of 0.14%, an NRMSE of 0.39% and a correlation coefficient of 0.96.

5.1. Random Forest (RF)

Random Forest is a machine learning method and a tweaked algorithm based on a decision tree, including a variety of decision tree fittings for various subsamples of the initial data set at the training level to produce decision trees for computation and to arrange trees for the final outcome.

Bounoua et al. [30] tested 22 empirical and 4 machine learning models to measure Global Solar Radiation at five locations in Morocco (Oujda, Missour, Erfoud, Zagora, and Tan-Tan). The models tested were the Multilayer Perceptron Artificial Neural Network Model (MLP) and three-set methods (Boosting, Bagging, and Random Forest) with some measured meteorological variables and some astronomical parameters (ambient air temperature, relative humidity, wind speed, etc.) were used to train these models. The findings achieved suggest that the temperature and geographic factors model were the more accurate with R: 72.38–93.46%; nMAE: 6.96–17.94%; nRMSE: 9.89–22.39%. The Random Forest (RF) method has also proven to be the highest performing in all stations between the four machine-learning methods.

5.2. Back Propagation Neural Network (BPNN)

Back-propagation is an integral aspect of Artificial Neural Network. It tries to adjust the network weights using the error rate of the past epoch. Proper tuning of the weights helps to reduce the error rate and makes the model accurate by increasing its generalization.

Aghmadi et al. [27] used BPNN with the Empirical Mode Decomposition (EMD) to improve the accuracy of solar radiation estimation and simplify the energy management system. A one-hour data for the year 2018 of Measured Direct Normal Irradiance (DNI) collected from a meteorological ground station located in Rabat, Morocco, is used. Three concept reliability and performance quality criteria are used: MAE, MAPE, and RMSE. The tests of the EMD-BPNN hybrid approach revealed an RMSE of 28.13% and a MAE of 20.99%, much less than other traditional approaches such as the conventional neural network or the ARIMA time series.

5.3. Deep Neural Network (DNN)

A Deep Neural Network is a neural network with a certain degree of sophistication, a technology designed to simulate the behavior of the human brain – specifically, the identification of patterns and the passing of inputs through different layers of simulated neural connections to predict performance using advanced mathematical modeling to process data in complex ways.

Jallal et al. [33] suggested a Deep Neural Network capable of handling the non-linearity and dynamic behavior of meteorological data and providing accurate real-time predictions of hourly global solar radiation. The neural network used hourly data on global solar radiation and meteorological parameters based on the METEONORM data sets of the city of El Kelaa des Sraghna, Morocco. The writers used the Elman neural network (ENN) with the Levenberg-Marquardt Optimizer. With a 99.38% correlation coefficient (R), the Deep Neural Network when implemented proves to be very effective and accurate.

5.4. Long Short-Term Memory (LSTM)

Soufene et al. [34] suggested LSTM enables the simulation of very long-term dependencies. It is based on a memory cell and three gates (Forgotten Gate – Input Gate – Output Gate). The complete activity of the LSTM can be outlined in three steps:

- Detect knowledge from the past, drawn from the memory cell via the forgotten gate;
- Choose, from the current entrance, the ones that will be useful in the long term, via the input gate. These would be applied to the memory cell;
- Collect valuable short-term information from the current cell state to produce the next hidden state via the output gate [34].

Benamrou et al. [23] suggest a very short-term prediction of horizontal global solar irradiation using the LSTM model, using two separate data sources. The first was obtained from the Al-Hoceima, Morocco, Meteorological Station for the duration (2015–2017) and the second was a set of satellite-derived data retrieved from the CAMS dataset around the Al-Hoceima Meteorological Station for the same period. The authors used the RFE (Recursive Function Elimination) approach to find the desired features of the model. Three scenarios were suggested to model solar irradiation using various algorithms (XGBoost, Random Forest, and SVR) to train the features. As a result, XGBoost provided the best output model with an R2 coefficient of 0.916.

Bendali et al. [26] propose a hybrid approach to refine the forecasting of solar irradiance using a Deep Neural Network with genetic algorithm. For this purpose, the authors evaluated Long Short-Term Memory (LSTM), Gate Recurrent Unit (GRU), and Recurrent Neural Network (RNN) models. The genetic algorithm was used to find the most suitable number of window sizes and the number of neurons in each layer. For this work, the Global Horizontal Irradiance (GHI) time series of Fes, Morocco, was used from 2016 to 2019 as a data set derived from the METEONORM Platform. The combination of the genetic algorithm and the LSTM showed the best results for the four seasons of the year evaluated with the MSE and MAE.

6. Modeling a Photovoltaic Generator

6.1. Modeling a Cell

The model of photovoltaic cell equivalent as

$$\mathrm{I} = \mathrm{I_{ph}} - \mathrm{I_d} - \mathrm{I_{sh}} \tag{1}$$

The physics of the PV cell is very similar to the classical p-n junction diode. When the junction absorbs light, the energy of the absorbed photons is transferred to the electron system of the material, resulting in the creation of charge carriers that are separated at the junction. The charge carriers may be electron-ion pairs in a liquid electrolyte, or electron hole pairs in a solid semiconducting material (Figure 4). The charge carriers in the junction region create a potential gradient, get accelerated under the electric field, and circulate as the current through an external circuit. The current squared times the resistance of the circuit is the power converted into electricity.

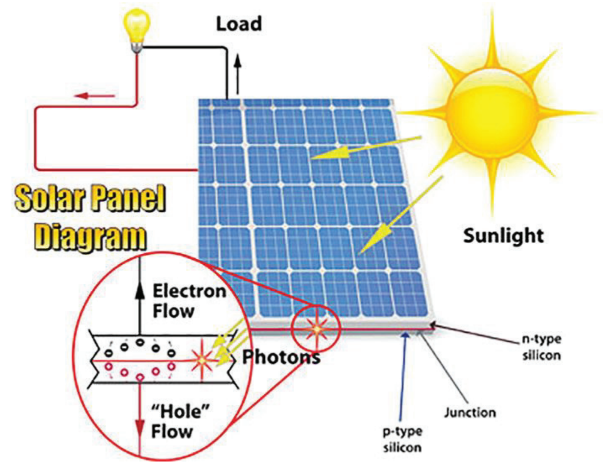

Figure 4. Photovoltaic panel

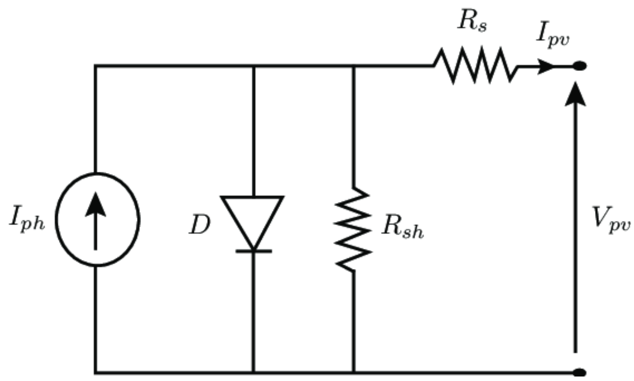

Figure 5. Model of a photovoltaic cell

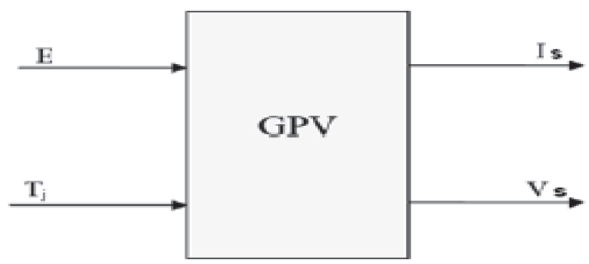

Figure 6. Photovoltaic generator block diagram

The remaining power of the photon elevates the temperature of the cell.

A number of modules make up a typical photovoltaic panel that can be connected in a string configuration in order to achieve desired current and voltage at the inverter input. A number of photovoltaic panels connected in a string configuration is typically known as a photovoltaic array.

Current versus voltage (I-V) characteristics of the PV module can be defined in sunlight and under dark conditions. In the first quadrant, the top left of the I-V curve at zero voltage is called the short circuit current. This is the current measured with the output terminals shorted (zero voltage). The bottom right of the curve at zero current is called the open-circuit voltage. This is the voltage measured with the output terminals open (zero current).

Figure 5 represents the model of a photovoltaic cell, and the block diagram (Figure 6) comprising four parameters can present the equivalent electrical diagram of the photovoltaic generator (GPV). Two input variables, which are the insolation in the plane of the panels E, the junction temperature of the cells Tj, and two output variables: current supplied by the GPV Is, voltage at the terminals of the GPV versus different illuminations and temperatures, we use the following model:

$$I_{cC}(T) = I_{cc}(T_{ref}) \cdot [1 + \alpha(T - T_{ref})]$$

$$I_{ph} = I_{cc}\left(\frac{G}{1000}\right)$$

$$I_{sat}(T) = I_{sat}(T_{ref}) \cdot \left(\frac{T_{ref}}{T}\right)^{\frac{3}{n}} \left[\exp\left(\frac{q.E_{\theta}}{nk}\right) \cdot \left(\frac{1}{T} - \frac{1}{T_{ref}}\right)\right] \quad (2)$$

With:

n is the quality factor of the diode, normally between 1 and 2, k is the constant of Boltzmann k = 1,
α is the coefficient of variation of the current.

Standard illumination, G	1000 W/m2
Standard temperature, T	25°c
Maximum power Pmax	60W
Voltage at Pmax or optimal voltage (Vopt)	17.1 V
Current at Pmax or Optimal current (Iopt)	5.5 A
Short-circuit current Isc	3.8 A
Open circuit voltage Vco	21.1 V
Number of cells in series	36
Forbidden band energy	1.12 ev
Temperature coefficient Isc	65 mA/°c
Temperature coefficient Vco	−80 mV/°c
Power temperature coefficient	(0.5+−0.05)%/°C
Saturation current Isat	20 nA

6.2. Modeling a Module

An elementary cell does not generate enough voltage: between 0.5 and 1.5, according to technology. It usually takes several cells in series to generate a usable voltage.

The module voltage is therefore: $V_m = N_s * V$
V_m: the voltage of the module.
N_s: number of cells in series per module

6.3. Model of a Photovoltaic Chain

For modules mounted in series and in parallel one can write:

$I_{chaine} = I * N_p$
$V_{chaine} = V_m * N_{s-module}$
With: I_{chaine}: the current delivered by a module chain Photovoltaic (A).
N_p: number of modules in parallel.
N_{s_module}: number of modules in series.
V_{chaine}: the voltage at the terminal of the chain (V).

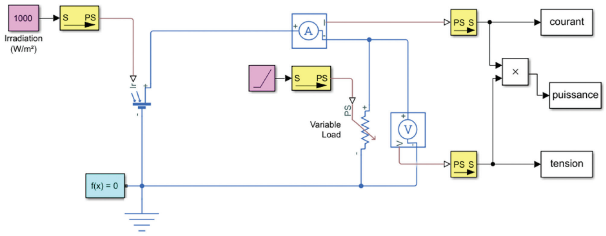

Figure 7. PV generator scheme in MATLAB-SIMULINK

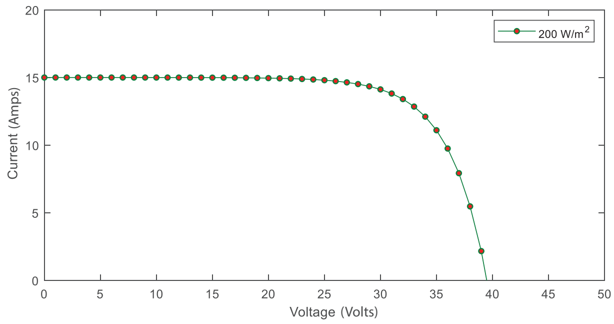

Figure 8. Characteristic I-V of the PV cell

6.4. Model of PV Solar

The photovoltaic generator scheme in the Matlab-Simulink environment represented by:

The simulation results of the photovoltaic generator are represented by Figures 7 through 14. These figures represent the current-voltage and power-voltage characteristics for different illuminations.

Figures 7 and 8 show the influence of illumination on current-voltage and power-voltage characteristics. At a constant temperature, it is found that the current undergoes a significant variation, but against the voltage varies slightly. Because the short circuit current is a linear function of illumination while the open circuit voltage is a logarithmic function.

6.5. Current-Voltage Characteristic

Figure 8 shows the influence of illumination on the characteristic I = f(V). At a constant temperature, it is found that the current undergoes a significant variation, but against the voltage varies slightly. Because the short-circuit current is a linear function of illumination while the open circuit voltage is a logarithmic function.

6.6. Power-Voltage Characteristic

Figure 9 shows the curve I = f(V) of a typical photovoltaic module under constant conditions of irradiation and temperature. The standard irradiation adopted for measuring the response of photovoltaic modules is a radiant intensity of 1000 W/m^2 and a temperature of 250°C.

It is difficult to give a source of current or voltage to a photovoltaic module over the full extent of the current-voltage characteristic. Therefore, the photovoltaic module is considered as a source of power with a point Pm. It is important to note that some solar regulators realize an adaptation of impedance so that at every moment one is close to this point P where the

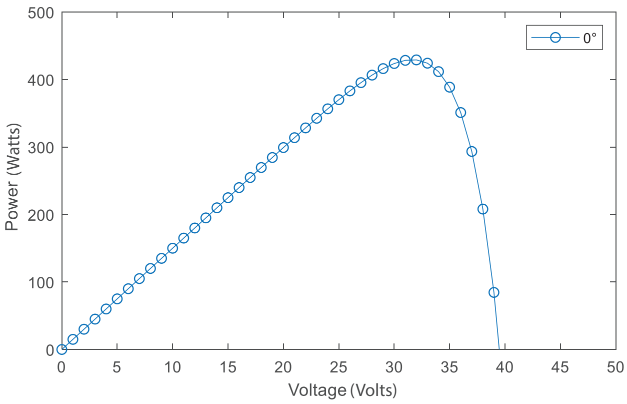

Figure 9. P-V characteristic of the PV cell

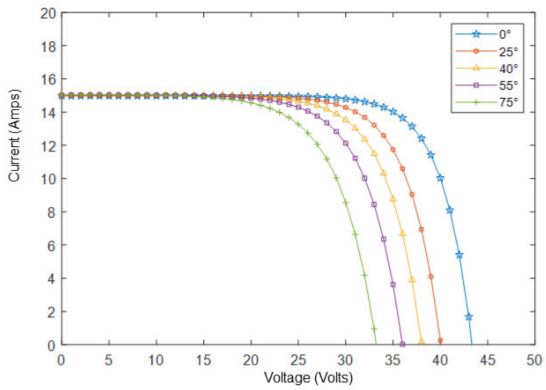

Figure 10. Current-voltage characteristic for different temperature value $I = f(V)$; $E = 1000$ W/m^2

power is found to be maximal. It is therefore interesting to place oneself on this point to get the most energy and thus make the most of the peak power installed.

6.7. Influence of Temperature

The influence of temperature on the characteristic I = f(V). It is essential to understand the effect of changing the temperature of a solar cell on the characteristic $I = f(V)$ in Figure 9. The current depends on the temperature since the current increases slightly as the temperature increases, but the temperature has a negative influence on the open circuit voltage. When the temperature increases the open circuit voltage decreases. Therefore, the maximum power of the generator is decreased.

Figures 10 and 11 illustrate the variation of the power delivered by the generator as a function of the voltage for different values of the temperature, which allows us to deduce the influence of the temperature on the characteristic P = fct(V).

6.8. Influence of Solar Radiation

Figure 12 illustrates the variation of the power delivered by the generator as a function of the voltage for different values of the temperature, which allows us to deduce the influence of the temperature on the characteristic P = fct(V).

Figures 13 and 14 represent the characteristic I-V of a module reflecting the influence of different

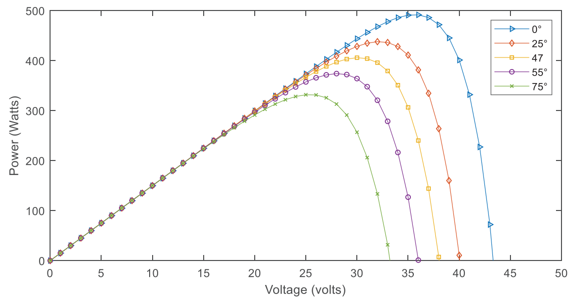

Figure 11. Characteristic power-voltage for different values of the temperature $P = f(V)$; $E = 1000$ W/m^2

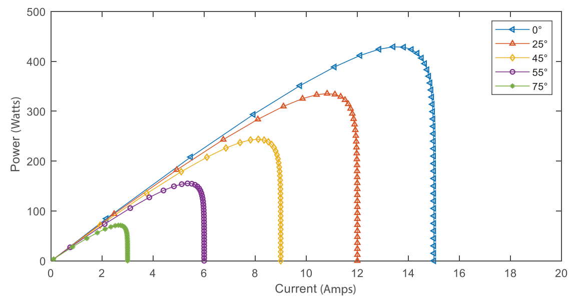

Figure 12. Characteristic power-current for different values of the temperature $P = f(V)$; $E = 1000$ W/m^2

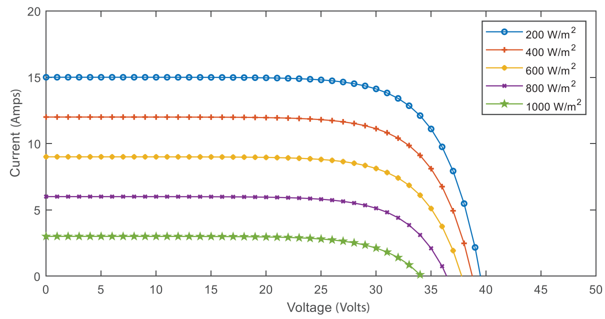

Figure 13. Current-voltage characteristic for different radiation values $I = f(V)$; $T = 25$ Cln

radiation at a fixed temperature: the current of the module is proportional to the radiation, while the open circuit voltage changes slightly with the radiation. The optimum power is also proportional to the radiation.

In Figure 14, we represent the variation of the power delivered by the generator as a function of the voltage for different illumination values, which allows us to deduce the influence of the illumination on the characteristic P.

This paper provided an analysis of forecasting the solar radiation using artificial intelligence techniques in Morocco.

As seen in Table 4, a number of machine learning and deep learning methods have been used. The most widely used methods are machine learning algorithms and, in particular, ANNs. The methods used various model precision performance for different data sources; we can detect the best performance with a decision coefficient R^2 of 99.12%, using data obtained from a local laboratory in the Marrakech region.

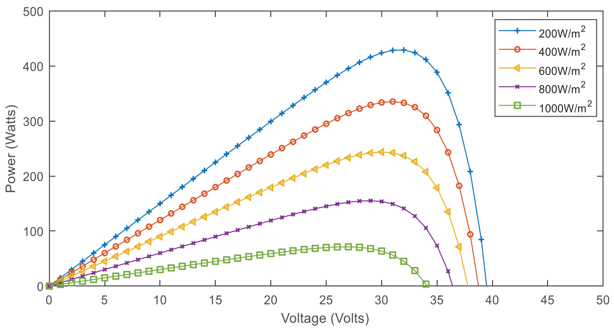

Figure 14. Power-voltage characteristic for different radiation values $P = f(V); T = 25$ C

We also note the rise in the use of deep learning approaches in recent years, as can be seen in Table 4, in particular Deep Neural Networks and Long Short-Term Memory. As well as the ANN case, the best performance had a decision coefficient R^2 of 99.38% using the METEONORM datasets for the Elkelaa des Sraghna region.

From our study, we have seen different choices of geographical, meteorological, and solar input parameters. This choice is the most critical consideration for the reliable and accurate estimation of solar radiation. Unless there are few studies working on this problem, we may take, for example, the cross-correlation function CCF as used by Ettaybi et al. [35], to calculate the correlation between the clear-sky index and each meteorological parameter to determine which one will be used to train the model. In the other hand, Benamrou et al. [23], use the Recursive Feature Elimination (RFE) approach with XGBoost algorithm to find the best features to be used for model learning.

7. Conclusion

Renewable energy has been highlighted as a crucial strategic source for green development in the world. Morocco has an immense solar energy capacity; the Kingdom is implementing a number of policies and initiatives to meet the optimistic goal of 2030 by achieving 52% of overall electricity generation using solar. In conclusion, efforts towards greener energy will always be ongoing as technology doesn't stop advancing and evolving. Since the agricultural sector is one of the most important contributors to our national GDP, it is necessary to find new ways to decrease costs and increase efficiency, all the while making sure to maintain eco-friendly processes and make well-informed decisions.

In order to encourage potential studies in this area, our paper provides an updated summary of predicting solar radiation papers in Morocco. Indeed, due to advances in the AI methods, the efficiency and availability of daily data, and the development of actual solar energy projects, the example of Noor projects as we've seen in the introduction involve more and more studies and applications for solar radiation and for energy systems in general.

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