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PHOTOVOLTAIC OUTPUT POWER FORECAST USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This article presents a method for predicting the power provided by photovoltaic solar panels using feed forward neural network (FFNN) of a photovoltaic installation located in the city of Mohammedia (Morocco). An almost one-year experimental database on solar irradiance, ambient temperature and PV power were used to study the prediction ability of the power produced by artificial neural networks. To verify this model, the coefficient of determination (R^2), the normalized mean squared error (nRMSE), the mean absolute error (MAE), and other parameters were used. The results of this model tested on unknown data showed that the model works well, with determination coefficients lying between 0.99 and 0.998 for sunny days, between 0.961 and 0.965 for cloudy days and between 0.88 and 0.93 for rainy days.

Keywords: *Photovoltaic Installation, Feed Forward Neural Network, Artificial Neural Networks*

1. INTRODUCTION

To cope with the increase in its energy bill, Morocco has launched an ambitious plan to increase the part of renewable energies to 42% of installed electricity capacity in 2020 and to 52% in 2030, mainly by solar and wind resources. The objective is to promote energy efficiency, contributing to the reduction of greenhouse gases and simultaneously reduce the country's heavy dependence on fossil fuel imports [1-2].

The geographic location of Morocco represents an important advantage towards exploiting solar energy potentials, with an annual value of average solar irradiation could reach 2600kWh/m²/year [3]. Solar energy, particularly PV, is one of the major projects in Morocco, with projects aiming at a capacity reaching 2000 MW of solar power in different sites: Ouarzazate, Ain Bni Mathar, Foum Al Oued, Boujdour and Sebkhat Tah. [2]

Solar photovoltaic technology is nowadays one of the easiest energy technology, for both design and installation process.Besides, solar photovoltaic energy has an important CO^2 mitigation factor as well as a high reliability and low-cost maintenance. [4-5]. Several PV module technologies exist, including monocrystalline, polycrystalline silicon cells and amorphous silicon cells, (CIS), (CdTe), as well as cells based on compounds termed as GaAs and InP, which belong to the category of multi-junction cells. Alongside these established channels of solar cells, new channels based on the use of dyes or organic materials have emerged, but these latter are still in their beginning. The Si, CIS, and CdTe sectors are currently the only ones being used extensively [6-7].

PV production depends on climatic factors, namely the temperature and the amount of global solar radiation incident on PV modules [8], but the latter presents a source of uncertainty for the designers of PV generators, this is mainly due to the lack of long series of data, poor quality data, the quality of measuring instruments and also the non-uniform nature of solar radiation over time, which can create anomalies in the design and sizing photovoltaic of systems [9-10]. In addition, one of the main challenges of the massive integration of photovoltaic is the ability to accurately predict the electrical energy produced by PV systems. [11]

Several approaches to production forecasting can be found in the literature. We cite direct and indirect methods and they can be divided into three categories: physical, statistical and soft-computing [12].

Physical methods attempt to create analytical models based on geographic and meteorological parameters. [13-14]. Statistical approaches attempt to establish a mapping link between historical data and the real power produced by the PV system to minimize the errors. [15-16]. But these approaches are somewhat limited because they are unable to produce short-term and real-time predictions. [17]

Thus, several studies have indicated that soft-computing methods perform more competitively than the other methods cited earlier [18-19-20].

Among the most useful methods for predicting the power produced by a PV system, we quote the method of artificial neural networks (ANN). It seems to be a very promising alternative to solve this kind of difficulties, especially for complex, non-linear or multi-variable problems.

ANN techniques have been widely used for modelling, simulation, prediction and optimization of complex systems, for several energy systems, including photovoltaic systems. [20]. Recently, ANN models have been used in the prediction of electrical power produced in many locations with different climates. Relevant research has been conducted in different countries [21-25], but no work has been done in Morocco.

The aim of this article is the modelling and prediction of the power generated by a photovoltaic installation of 2.04 kWp on the roof of the Faculty of Science and Technology of Mohammedia, Morocco using the ANN models. The developed neural model can be used to predict and model the power produced by the photovoltaic system and to analyze the performances in terms of electrical energy delivered to the network.

2. SITE INFORMATION AND SYSTEM DESCRIPTION

Mohammedia, located at 33 ° 41 '23' North and -07 ° 23' 23 East, in Morocco, is a port city on the west coast of Morocco between Casablanca and Rabat in the region of Casablanca-Settat.

It is located on the coast of the Atlantic Ocean, 24 km north-east of the economic capital of the Kingdom of Morocco, possess a high solar energy potential. The annual average radiation is around 1910 kW h/m^2.

Figure 1:The PV plant installed on the roof

The PV system under study is installed on the roof of the research building in the Faculty of Science and Technology of Mohammedia. It consists of 8 modules in monocrystalline silicon, mounted in a series. The installed capacities total 2.04 kWp. The electrical diagram of the system is shown in Figure 1 and the system installed in Figure 2.

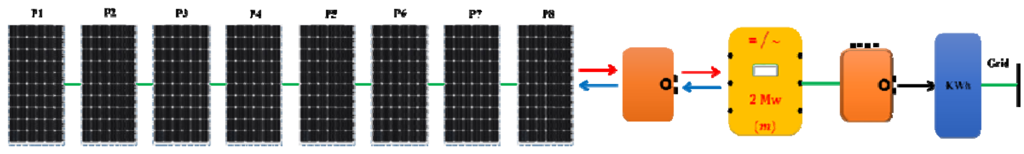

Figure 2: Schematic diagram of solar photovoltaic plant at Mohammedia, Morocco

Tableau 1: PV panel properties

Trademark	SOLARWORLD
Model	SUNMODULE
Solar cell	mc-Si
Maximum power at STC	255 Wp
Optimum operating voltage	31.4V
Optimum operating current	8.15A
Open circuit voltage	37.8V
Short circuit current	8.66A
Temperature coefficient of maximum power	-0.45%/°C
Module efficiency	15.2 %.

The modules are fixed with a south orientation and an inclination angle of 30 °, the PV generator injects electricity into the grid throughout a Sunny boy inverter 2000 HF SMA with a nominal efficiency of 96.6%. The specifications of the studied module and the inverter are represented in table 1 and 2, respectively.

Tableau 2: Inverter specifications

Inverter model	SB 2000HF30
Max PV power	2100 W
Max voltage	700V
Nominal voltage	220V/230V/240V
voltage range	180V-280V
Grid frequency; range	50/60 Hz
Max. output current	8.3 A
Max input current	12.0 A
Maximum efficiency	96%

2.1 Data Base Description:

The meteorological station consists of a set of sensors that record and provide physical measurements and meteorological parameters related to climate change (Figure 3).

The variables measured are the ambient temperature, the horizontal and inclined irradiation and both the speed and direction of the wind. In addition, the station permits the automatic collection and measurement of DC and AC power from the PV array through the inverter. Measured data is saved in CSV files at five-minute intervals; an average is then made for 1 hour.

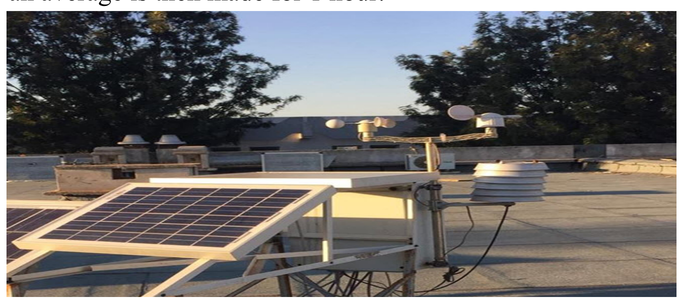

Figure 3: Meteorological data instrumentation.

The global incident irradiance (G_I), the ambient temperature (T_{am}), and the AC current power (P_{AC}) produced during one year at the platform site are shown in Figures 4,5 and 6 with a time scale of one hour.

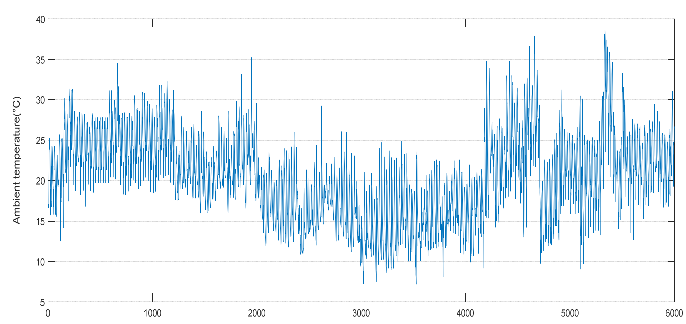

Figure 4 : Experimental ambient tempertaure (T_{am})

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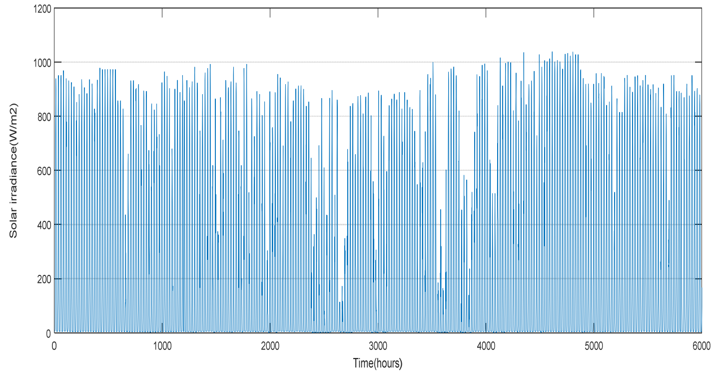

Figure 5: Experimental global incident solar irradiance (G_I)

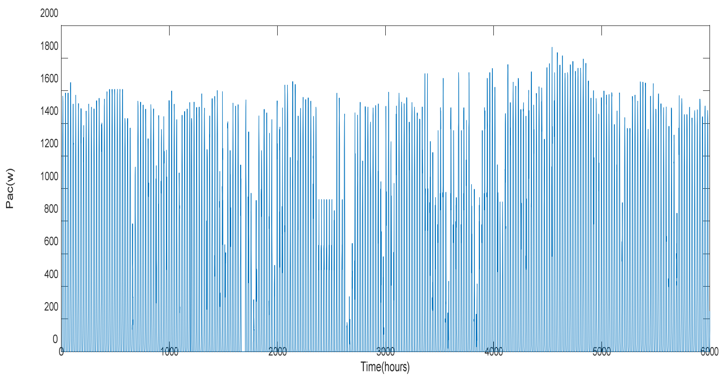

Figure 6: Hourly averaged AC current power (P_{AC})

ANNs, which can be in the form of a hyperbolic, sigmoid, exponential or radial basic function.

These layers are generally classified according to their architecture. There are two main categories: feedback neural networks and feed forward neural networks [27]. FFNNs are the most used multilayer neural networks; the diagram of this type of network is shown in fig 7.

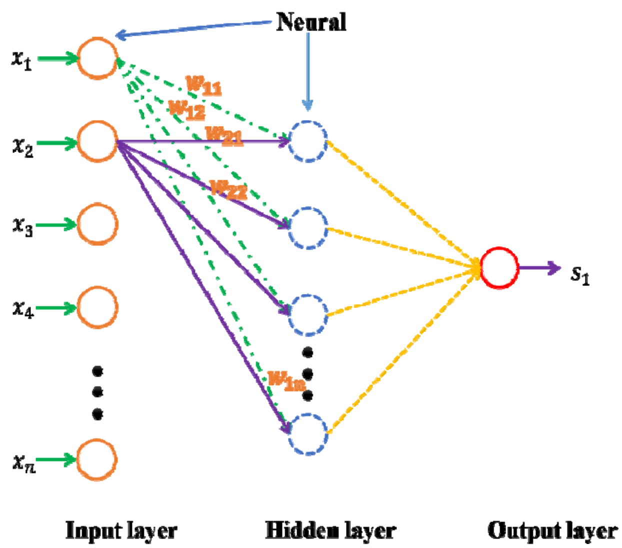

Figure 7: Feed forward neural network

3. ANN

The artificial neural network method is based on the non-algorithmic, massive parallel learning technique, rooted in biological neurons, consisting of layers of parallel units called neurons. These neurons are able to link inputs and outputs using a historical database so that they generate outputs when these ones are missing [10-26].

A neuron is composed of an input layer that receives the data, an output layer where the data that supposed to be calculated is sent, and one or more hidden layers that connect the input with the output layers, which can be translated by the followed equation (1):

$$Z_i = -f\left(\sum_{j=1}^{N} w_{ij} xj\right) \qquad (1)$$

The function f is called the activation function of the neuron. It models the behavioral nature of the system or the physical approach modelled by the

4. METHODOLOGY

To forecast the power produced by the PV system, the feed forward neural network has been designed and formed using the MATLAB software and the neural network toolbox implemented on MATLAB. A simplified diagram of this network is shown in figure 8

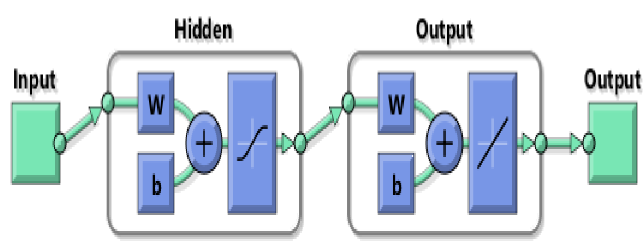

Figure 8: Diagram of the used Feed forwared neural network in MATLAB

In this paper, the predicted data is derived using an ANN algorithm of FFNN typology, whose formation is a back-propagation based on the

Levenberg-Marquardt (LM) minimization method to adjust the weights so that the network produces the required output for the given input data. (see fig 9).

The input layer of our network consists of the ambient temperature (T_{am}) and the solar irradiance (G_I), while the output layer ANN consists of a unit associated with the AC power produced by the photovoltaic system (P_{AC}) (see fig. system networks), the relation between the input parameters and the output can be expressed by the following relation {Pac = f (T_{am}, G_I)}. For this, a database of 274 days from 1/10/2016 to 31/10/2017 have been selected. The other days were discarded due to a variety of reasons such as system malfunctions, updates, etc.

Overall, the selected data has been divided into two parts, 80% for the training and the rest for testing and validating the neural network.

Before proceeding with the network formation process, a pre-treatment of the network training data was established, through a normalization of the input and output data between -1 and 1 using the equation n°2.

$$I_{Normalized} = \frac{2*(I_{actual}-I_{max}-I_{min})}{I_{max}-I_{min}} \quad (2)$$

Where I_{actual} is the original data value; $I_{Normalized}$ is the normalized data; and I_{min} and I_{max} are the minimum and maximum values of the input data, respectively.

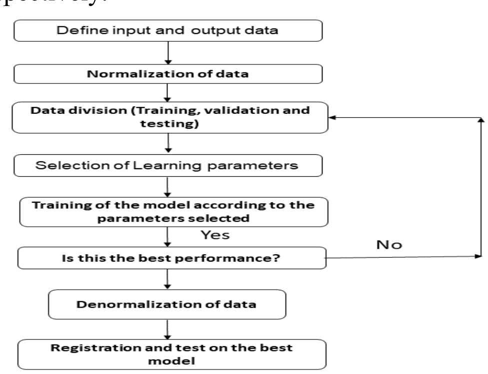

Figure 9: The flowchart of output PV power forecasting

4.1 Evaluation Index

To predict the PV power produced, many methods exist to verify the effectiveness of a predictor. In this paper, the method used is called "cross-validation". Thus, we used statistical parameters for comparison. The tools used are described below:

- Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{t=1}^{m}(P_{AC,m}-P_{AC,f})^2}{\sum_{1}^{m}(P_{AC,m}-\overline{P})^2} \quad (3)$$

- Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(P_{AC,M}-P_{AC,F})} \quad (4)$$

- Mean Absolute error (MAE):

$$MAE = \frac{1}{m}\sum_{t=1}^{m}\left|P_{AC,m}-P_{AC,f}\right| \quad (5)$$

- Normalized mean Absolute error (nMAE):

$$\text{nMAE}=\sum_{t=1}^{m}(P_{AC,m}-P_{AC,f}) \quad (6)$$

- Normalized Root mean square error (nRMSE):

$$nRMSE\ \% = \frac{\sqrt{\frac{1}{m}\sum_{t=1}^{m}(P_{AC,M}-P_{AC,F})^2}}{\max(P_{AC,M})}.100 \quad (7)$$

- Mean Bias Error (MBE):

$$MAE = \frac{1}{m}\sum_{t=1}^{m}(P_{AC,m}-P_{AC,f}) \quad (8)$$

Where $P_{AC,f}$ is the foresting output PV power, $P_{AC,m}$ is the actual measured PV power. $\overline{P}$ is the rated output PV power. N represents the hours of the forecasting horizon.

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5. RESULTS AND DISCUSSION:

This section treats the results of the prediction of PV power by artificial neural networks. For this purpose, a network of the FFNN type has been formed to generate a model for predicting the PV power produced by the photovoltaic system described above.

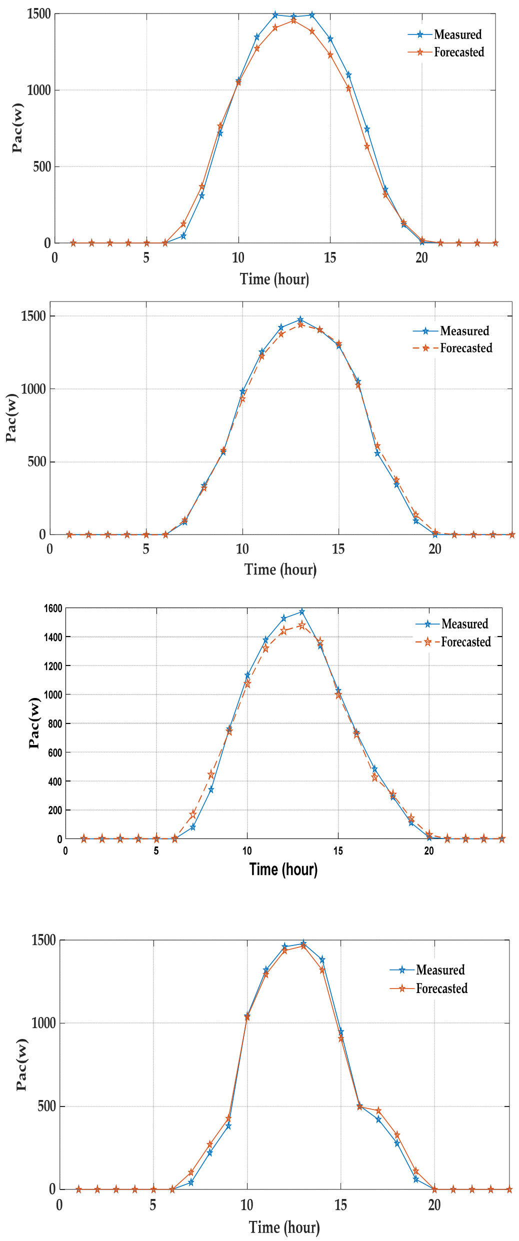

Figure 10: Predicted and measured output PV power(P_{AC}) as a function of time for sunny days

The construction of a prediction model by ANN involves the formation of its network using input and output data from a real system, and then testing it with different data. After several trials, the best configuration corresponds to the model with two nodes in the input layer (incident solar irradiation and ambient temperature) and 5 neurons in the hidden layer. In the learning process, the training was repeated several times, and for several numbers of hidden neurons.

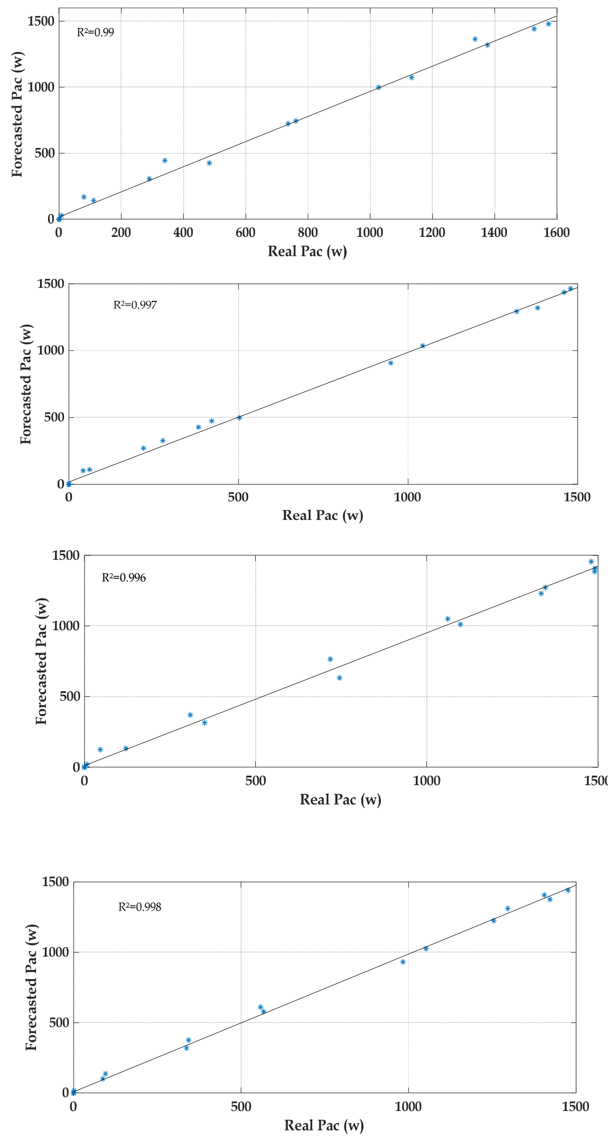

Figure11: Scatter plot 1 day ahead forecasting during sunny days

Tableau 3:Correlation of different parameters to (P_{AC})

Variables	Correlation to (P_{AC})
Solar irradiation	0.93
Ambient temperature	0.29

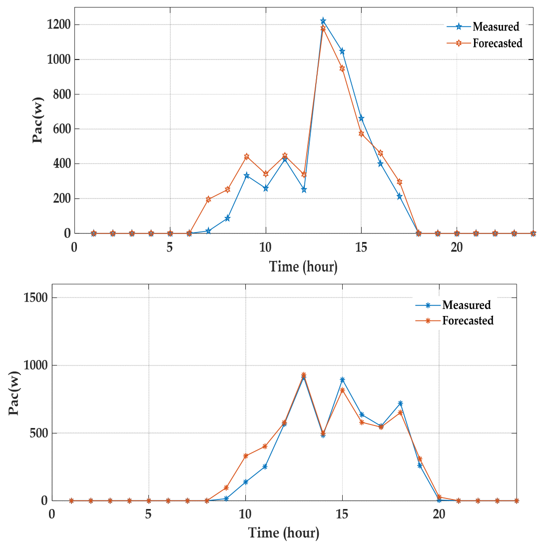

Figure 12: Predicted and measured output PV power(P_{AC}) as a function of time for cloudy days

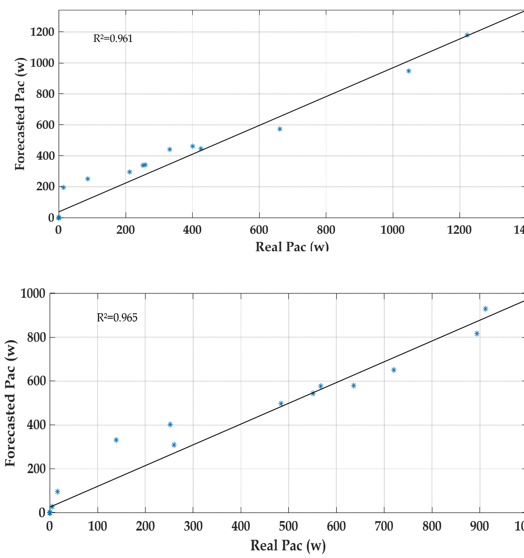

Figure 13: Scatter plot 1 day ahead forecasting during cloudy days

To justify this choice, the table 3 shows the correlation of input parameters (solar irradiance and ambient temperature) with the PV power produced. In this table, it is clear that there is a strong correlation between the solar irradiance and the PV power produced, with a correlation coefficient R of 0.93 Therefore, it can be said that the solar irradiation is a potential vector for the establishment of a prediction model of the PV power produced. On the other hand, regarding the parameter of the ambient temperature, it is noticeable that the correlation is relatively strong [28-29]. Thus, ambient temperature can be considered as an important parameter for predicting PV power.

To evaluate the precision of prediction by FFNN, a comparison between the predicted values of the generated PV power produced for 24 hours and the actual values for some typical days (sunny, cloudy and rainy) is shown.

On the fig 10, a comparison in the case of sunny days is represented. It appears on the figure that the measured PV power is totally in agreement with the measured values, which can be justified by the regression figures 11 which show that most of the points fall along the diagonal, with coefficients of determination (R^2) between (0.99 and 0.998).

In the second case of cloudy days, it is clear that the results between the measured PV power and the predicted PV power values (figs 12) are acceptable. Concerning the dispersion figures13, some fluctuations can be found with coefficients of (R^2) arranged between (0.961 and 0.965).

Finally, for rainy days represented by figs (14), which show that the measured PV power is only in partial agreement with the predicted values, whereas the dispersion figures 15 show some fluctuations, so that the coefficients of determination (R^2) include between (0.887 and 0.93).

To discuss the validity of these results, a thorough evaluation of the three cases using statistical parameters (RMSE, MAE, MBE, nMAE, nRMSE) is presented in Table 4. According to the results presented in table x, we note that the the RMSE varies between 24.25 Wh and 53 Wh, the nRMSE is between 1.64% and 3.62%, the MAE between 16.2wh and 35.37Wh, the nMAE is arranged between 4% and 7% and the MBE varies between -1.12Wh and 18Wh, for sunny days.

As for cloudy days, it is obvious that the RMSE varies between 24.25Wh and 53Wh, the nRMSE is between 1.64% and 3.62%, the MAE between 16.2wh and 35.37 Wh, the nMAE is arranged

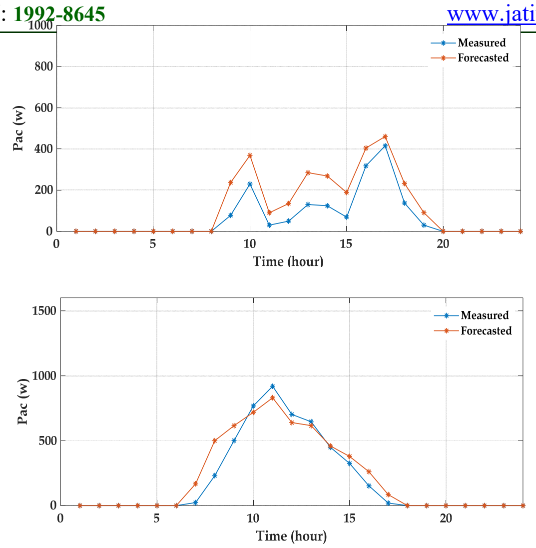

Figure 14: Predicted and measured output PV power(P_{AC}) as a function of time for rainy days

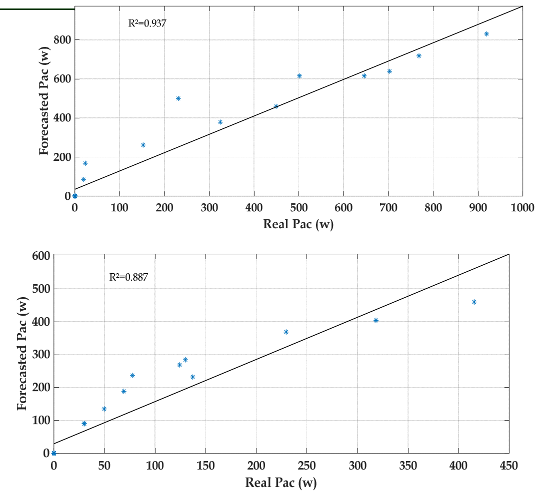

Figure15: Scatter plot 1 day ahead forecasting during rainy days

between 4% and 7%, the MBE varies between -1.12Wh and 18Wh. And for rainy days, the RMSE varies between 24.25Wh and 53Wh, the nRMSE is between 1.64% and 3.62%, the MAE between 16.2Wh and 35.37Wh, the nMAE is arranged at 4% and 7%, the MBE varies between -1.12Wh and 18Wh.

In the three cases presented, we can conclude that the most important errors occur mainly during rainy days, and on the other hand are acceptable for cloudy days and very interesting for sunny days. Finally, to show the effectiveness of the proposed model, the cumulative distribution function of the measured and predicted series was plotted.
As we can see, the predicted PV power is almost mingled with the measured PV power (see figs 16).

Tableau 4: *Error metrics in testing days*

Days	Weather condition	RMSE	nRMSE	MAE	nMAE	MBE
day1	sunny	45	2,86	29,1	6%	-5,36
day2	sunny	24,25	1,64	16,21	4%	-1,12
day3	sunny	30,85	2,08	20,33	5%	4,91
day4	sunny	53,70	3,63	35,37	7%	-18,06
day5	cloudy	70,023	5,73	42,67	21%	23,41
day6	cloudy	59,01	6,47	31,07	14%	13,58
day7	rainy	75,44	18,16	47,83	71%	47,83
day8	rainy	76,60	8,33	41,62	21%	22,31

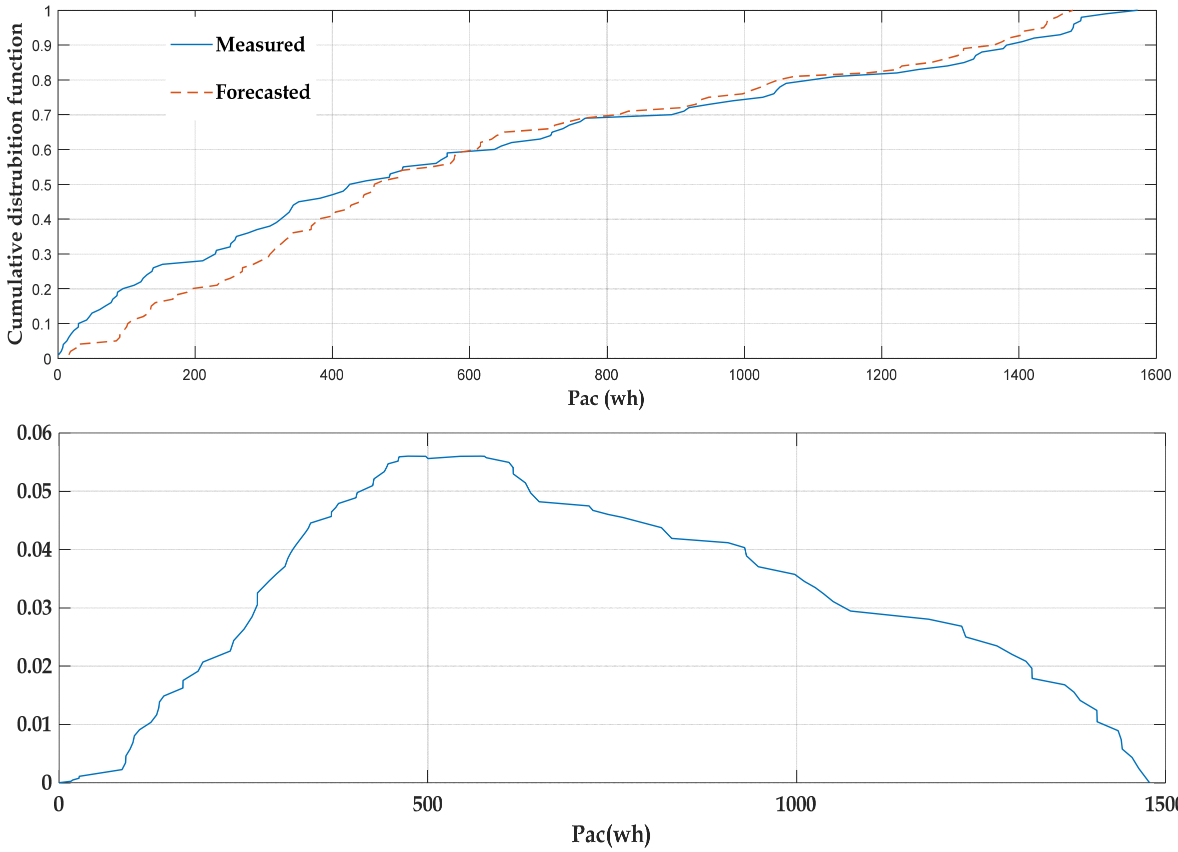

Figure 16 : Cumulative distribution fonctions curves

6. CONCLUSION:

In this paper, a prediction model of PV power produced by a photovoltaic system installed on the roof of the research building of the Faculty of Sciences and Technologies of Mohammedia, based on artificial neural networks of type (FFNN) is presented. The input parameters of the proposed neural model are the solar irradiance and the ambient temperature, while the output is represented by the 24 hours ahead of the PV AC power output. After several trials, the best configuration corresponds to a network of a single layer with two neurons (G_I, T_{am}) and a hidden layer of 5 neurons. The model was evaluated using several statistic parameters such as (RMSE,nRMSE ,MAE R^2). Results during unknown days of the year showed that the accuracy over sunny days is higher than the one over cloudy and rainy days, with determination coefficients of (0.99 ,0.96, and 0.93) for sunny, cloudy days and rainy days, respectively.

we plan to apply this method in other studies using data from other places and with other PV technologies in order to develop a model that represents all of Morocco

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