Prediction of Solar Irradiance by Artificial Neuron Networks

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ResearchPaper

PREDICTION OF SOLAR IRRADIANCE BY ARTIFICIAL NEURON NETWORKS

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ABSTRACT

Accurate forecasting of solar irradiance is essential to minimize operating costs for solar photovoltaic (PV) generation, as it is often used to predict power output. This work aims at the prediction of daily solar irradiation for a photovoltaic power plant using artificial neural networks. By adopting the multilayer perceptron (MLP) in the Matlab environment, three neuronal structures are studied and compared to the naive model (known as the persistence model). In order to be able to evaluate the performance of the proposed forecasting system, two years of meteorological data (2019-2020) are collected from the Oued Kebrit photovoltaic plant in S/Ahras, and the RMSE and the MAE are used as error indices. For a one day ahead solar irradiance forecasting, the neural network of one hidden layer with 6 neurons and a 5-day prediction lag has shown the best performance.

1 Introduction

The planet's reserves of minerals and fossil fuels are limited, and the mining of coal, oil, gas and uranium are not viable in the long term. Fortunately, renewable energies from the regenerative flows of nature are inexhaustible and do not have a long-term negative effect on the environment.

It is clear that Algeria, through its new energy policy, tends to promote the development of renewable energies, particularly solar energy, due to its geographical location which has one of the highest solar deposits in the world. However, exploiting this solar energy stock raises certain technical challenges because of its intermittent and random character such as the prediction in order to size detectors or to estimate the potential of power plants.

In this context, our work consists of the proposal of a system for predicting daily solar irradiation, which could be of interest to electricity suppliers. In this way, we will investigate time series forecasting, which is a challenge in many fields. The current interest of researchers is to develop predictive models that achieve good performance by significantly reducing the error rate with respect to different time scales (minute, hour, daily or monthly)[1 2].

The objective therefore aimed by this work is to propose a sunshine prediction algorithm based on the use of artificial neural networks and to compare it with a naive model according to the prediction error. Using the data of the daily sunshine measured and taken from a meteorological station of the photovoltaic power plant of Oued Kebrit, the considered

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prediction system will be used to forecast the daily solar radiation for the following day.

2 Description of the system to be studied

The plant was commissioned on 24/04/2014 with a production capacity of 15MW which is injected directly into the electrical transformer station of LAOUINET wilaya of TEBESSA , was carried out by a foreign company.

The PV plant consists of the following main elements:

- PV solar fields: The photovoltaic plant is made up of 60,066 250W polycrystalline silicon solar panels of the YL250b-29p type. These panels divided into 15 subfields for a real installation power of 15 MW. Each subfield consists of 4004 photovoltaic modules whose installed power is equal to 1 MW. Each subfield divided into 182 strings, the latter consists of 22 panels in series (figure 1.21) and each panel has 60 photovoltaic cells (figure 1.22). The 182 strings connected in parallel are divided into two groups, each feeding an inverter with a maximum input voltage of 1000 V and a maximum input current of 1236 A. 01-15:
- Step-up three-phase transformer room (1250 KVA- 2x315/30000 V- 2x1146/ 24.1A).
- 2x500 V inverter room.
- A: MV block (01 36 KV outgoing cell - 04 Arrival cell - SSAA cell - 30 Kv/400v transformer).
- B: Control room.
- C: Emergency source (generator).
- D: 30/60KV transformer (Projected).
- E: Meteorological Station.
- F: Guard post + Administration.

3 Predictive techniques of solar irradiation

Recently, several sun irradiation prediction techniques for different time scales, including naive, physical, statistical, artificial intelligence and hybrid methods [1].

Naive approaches are also known as “naive predictor”. It is assumed that the sun irradiation at time “t+Δt” will be the same as at time “t”.

Physical forecasting approaches use numerical weather prediction to model on-site conditions at the location of interest. Even though these techniques are effective in forecasting, they involve a large amount of numerical weather forecast data such as temperature, humidity, pressure and topological parameters. Therefore, these methods are more appropriate for medium and long-term forecast horizons than for short-term forecast horizons [2 3].

Statistical approaches, quite simple compared to physical methods, use historical time series data, at a given location, for prediction purposes. These approaches, based on probability, random process theory and statistics, generally use recursive linear models such as autoregressive (AR) models, autoregressive moving averages (ARMA), autoregressive integrated moving averages (ARIMA) as well as nonlinear models such as NAR and NARMA, etc. [3].

Although statistical techniques outperform physical approaches for prediction of very short and short time horizon solar irradiance, their goodness of fit to nonlinear time series data could be further improved.

Artificial intelligence (AI)-based techniques, such as artificial neural networks (ANN), fuzzy logic, support vector machines (SVM), wavelet transformation, and evolutionary computing such as genetic algorithms (GA) and Particle Swarm Optimization (PSO), are commonly known for their efficiency and ability to handle nonlinear problems [1]. Although computationally expensive, these methods

Machine learning techniques, practically independent of time-series data, have recently attracted a lot of attention in prediction problems and sun irradiation forecasting problems [4].

Hybrid methods, they can combine physical techniques with statistical techniques or use a combination of different intelligent approaches, etc. Moreover, and with regard to smart and hybrid methods, several techniques have been proposed recently [5]. Combinations of two or more machine learning techniques can be used to improve the accuracy of forecasts and predictions.

4 Artificial neural networks

Artificial Neural Networks (ANN), based on biological neurons, are complex intelligent structures known to be a powerful tool providing good solutions to problems that cannot be solved analytically and represent an attractive technique for dealing with nonlinear problems. such as time series forecasting. It is made up of a number of interconnected simple processing elements, called neurons, designed to model the way the human brain thinks to perform a specific task. Generally, ANN is composed of an input layer, hidden layers and an output layer. Figure 1 describes the adopted architecture of ANN [1].

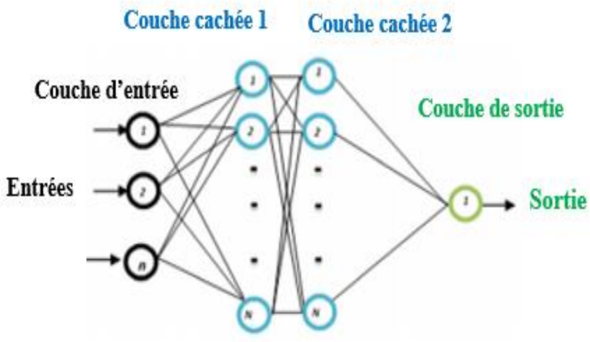

Fig. 1- Structure of the neural network [5].

A multilayer perceptron (MLP) neural network composed of one, two, or three hidden layers, implemented in MATLAB and trained using the Levenberg-Marquardt algorithm (trainlm) is used (see figure 2) , where past values of solar insolation are used to predict the next day's value. The transfer functions used for the hidden and output layers are respectively the tangent sigmoid “tansig” and the log sigmoid “logsig”.

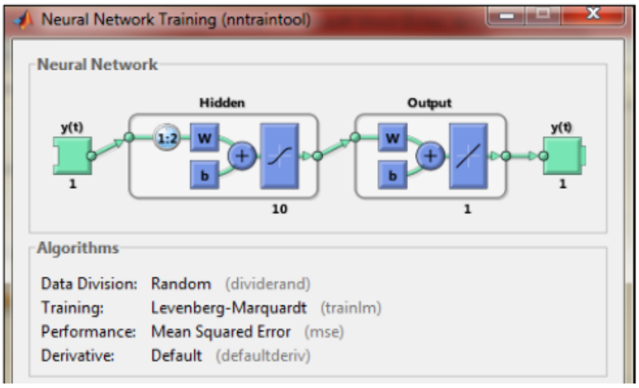

Fig. 2- Neural network implemented in MATLAB.

5 Overview of the prediction process

To test the daily insolation forecasting procedure, daily solar insolation data covering the two years 2019-2020 for the Souk Ahras region were obtained from the Oued Kebrit photovoltaic power plant, The values of Sunshine is recorded every fifteen minutes by dataloggers using ECXEL software.

Generally, data pre-processing is very important to improve the accuracy of the forecast. In this work, the daily insolation time series data is preprocessed as follows:

- From the collected sunshine data, the cumulative daily sunshine is calculated. It should be noted that the values of temperature, wind speed and humidity represent the average daily value, while the global daily irradiation is the insolation received during a day. Figures 3 illustrate the four meteorological parameters, namely daily sunshine, temperature, wind speed and humidity respectively from January 1, 2019 to December 31, 2020 at the Oued Kebrit power plant, Souk Ahras.
- Outliers are detected and removed for better learning of the neural network and hence high prediction accuracy.

The correlation coefficient denoted R is the specific measure that quantifies the strength of the linear relationship between two variables in a correlation analysis. We estimate the correlation coefficient using the following formula [1]:

$$R = \frac{\sum_{i=1}^{N}(X_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \times \sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{1}$$

The correlation coefficient serves above all to characterize a positive or negative linear relationship. This is a symmetrical measurement. The closer it is to 1 (in absolute value), the stronger the relationship, R= 0 indicates the absence of correlation.

Table 1- Correlation coefficient between solar irradiation and meteorological parameters of the Oued Kebrit power plant

	Temperature (°C)	**Wind speed (m/s)**	**Humidity**
Irradiation (W/m2)	0.76	- 0.25	- 0.54

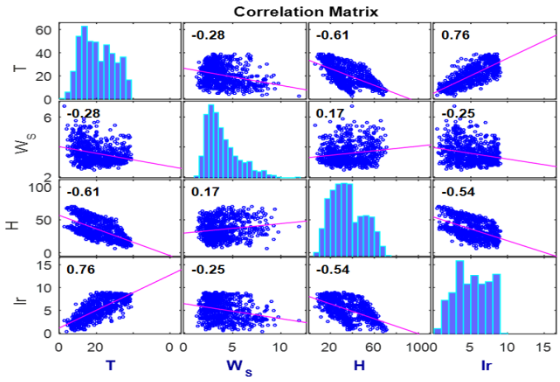

Fig. 3- Correlation between solar irradiation and meteorological parameters of Oued kebrit.

From table 1 and figure 3, we notice that the temperature increases proportionally with sunshine R>0 (positive correlation), is inversely proportional to wind speed and humidity R<0 (negative correlation). Also, it should be noted that there is a fairly strong correlation between sunshine and temperature with $R = 0.76$.

6 Prediction scheme

The ANN predictor, proposed in this work, accomplishes the prediction using a sliding window of size $n_{steps} = l$, representing the number of daily average solar irradiances of the previous days (jours: $j, j-1, j-2, \ldots, j-l$)used to predict the average solar irradiance of the next day ($j+1$). Thus, it is the Window size that dictates the number of neural network inputs as shown in Figure 4.

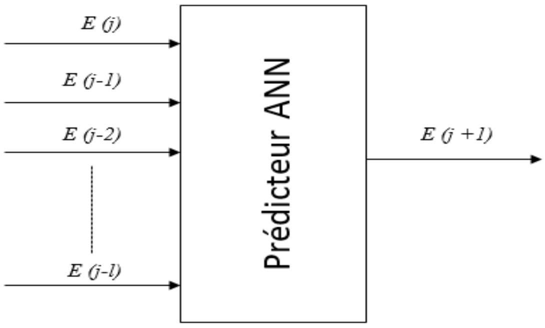

Fig. 4 - Structure ANN pour la prédiction de l'ensoleillement moyen du jour j+1

7 ANN structures examined

To determine the optimal prediction structure based on neural networks, we opted for three structures:

- Hidden single layer structure.
- Hidden two-layer structure.
- Hidden three-layer structure.

For each structure, the number of neurons per hidden layer is fixed and varies from 2 to 12. Moreover, the prediction step n_steps varies from 1 to 8 days. Thus, our job is to determine the optimal neural predictor minimizing the RMSE error. In other words, we need to look for:

- The structure with 1, 2 or even 3 hidden layers.
- The number of neurons per hidden layer.
- The prediction step n_steps days.

8 Simulations Results and discussion

To substantiate the accuracy and performance of any predictive model, several error measures are used

- the root mean square error (MSE) given by equation (2) is often used in the evaluation of prediction models.

$$\mathrm{MSE} = \frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N} \tag{2}$$

- The root mean square error (RMSE) and the mean absolute error (MAE) described by equations (3) and (4) respectively to measure the prediction performance of the scheme used [6]:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - \hat{x}_i)^2}{N}} \tag{3}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|x_i - \hat{x}_i| \tag{4}$$

Where $x_i$and $\hat{x}_i$represent measured and estimated solar irradiance data respectively.

Furthermore, to calculate the error difference e_{diff}between the used ANN structure and the persistent model, we used the following formula [1]:

$$e_{diff} = \frac{(\mathrm{erreur}_{persistant} - \mathrm{erreur}_{ANN})}{\mathrm{erreur}_{persistant}} \mathrm{x}100\% \tag{5}$$

Regarding the phenomenon of implicit random initialization in artificial neural networks, the Matlab program is executed 50 times and the average values of the RMSE and MAE errors are calculated.

8.1. Hidden single layer structure

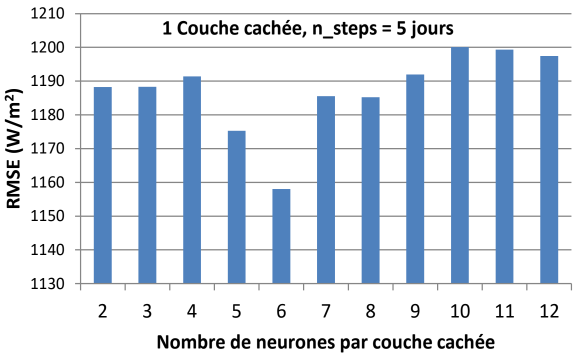

Fig. 5 - RMSE according to the numbers of neurons per hidden layer and n_steps=5jours.

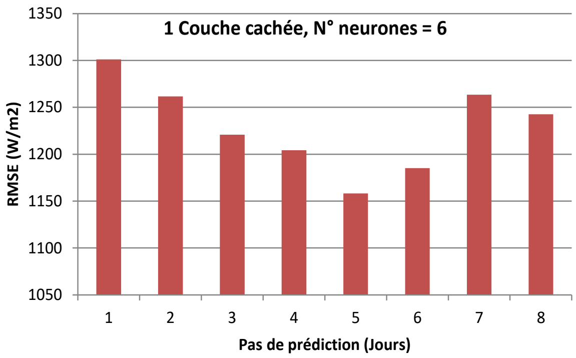

Fig. 6 - RMSE according to the prédiction step n_staps for the single-layer structure with 6 neurons.

8.2. Structure with two hidden covers

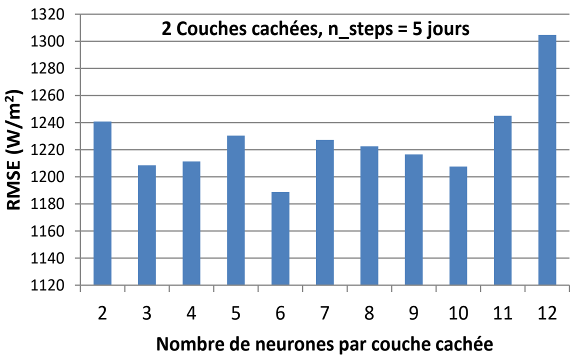

Fig. 6 – RMSE according to the numbers of neurons for the structure with two hidden layers and n_steps=5days.

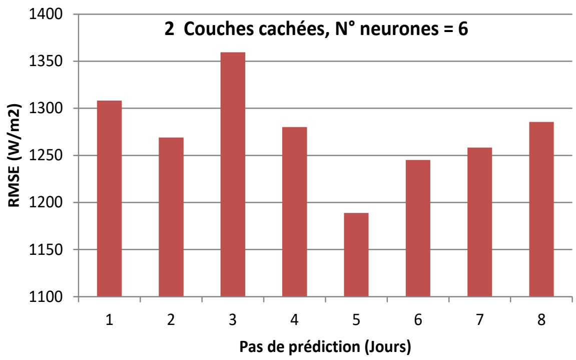

Fig. 5 - RMSE as a function of prediction step n_steps for the two hidden layers with 6 neurons.

8.3. Structure with three hidden layers

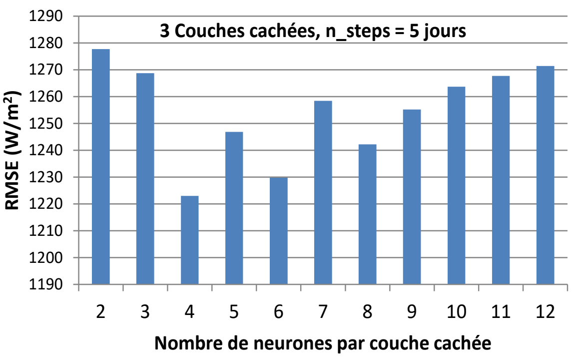

Fig. 9- RMSE as a function of the numbes of neurons for the structure with three hidden layers and n_steps=5days.

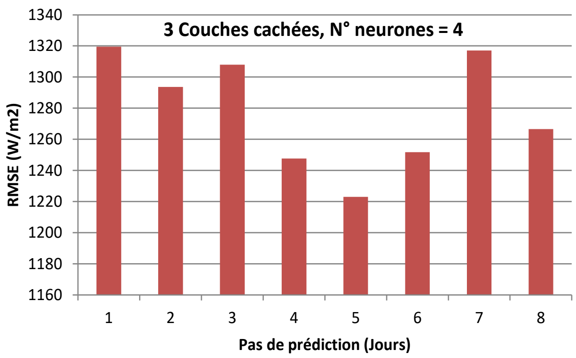

Fig.10 - RMSE as a function of prediction step n_steps for the hidden three-layers 4 neurons.

9 Comparison between the ANN predictor and the 'Persistence' model

By using these three structures, the Matlab code is executed 50 times and the ANN structures with the minimum RMSE are saved and compared with a very simple so-called naive predictor ('persistence model'), which serves as a gauge. From the results in terms of RMSE and MAE presented in Figures 11 and 12, it is clear that the ANN predictor outperforms the "persistence model" in terms of prediction accuracy. Moreover, according to FIG. 13, the ANN predictor presents an average gain in error, compared to the persistent model, of the order of 21% and 11% in terms of RMSE and MAE respectively.

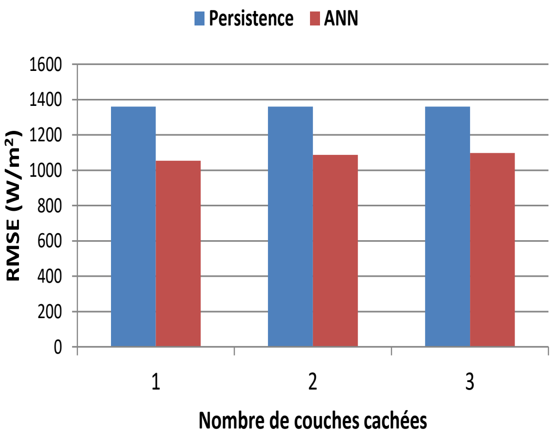

Fig. 8 – Comparison between the ANN predictor and the 'Persistance' model in terms of RMSE error.

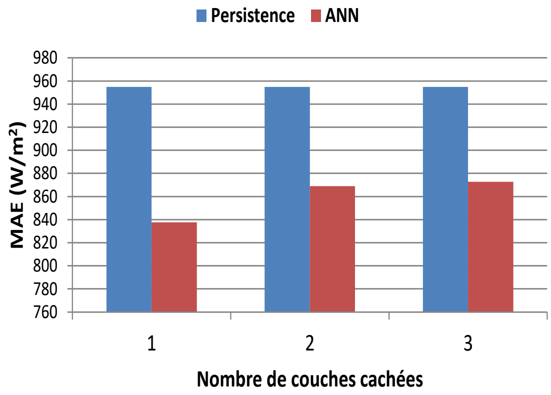

Fig. 7 - Comparison between the ANN predictor and 'Persistance' model in terms of MAE error.

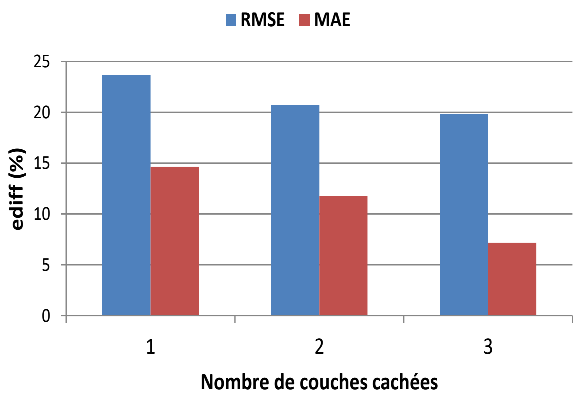

Fig. 9 - Difference in error betwwen the ANN predictor and 'persistance' model.

10 The optimal ANN structure

Summing up, the optimal neural predictor of sunshine, at the Oued Kebrit solar power plant, is the single hidden layer ANN structure (see figure 14) with 6 neurons and a prediction step n_steps = 5 days. .

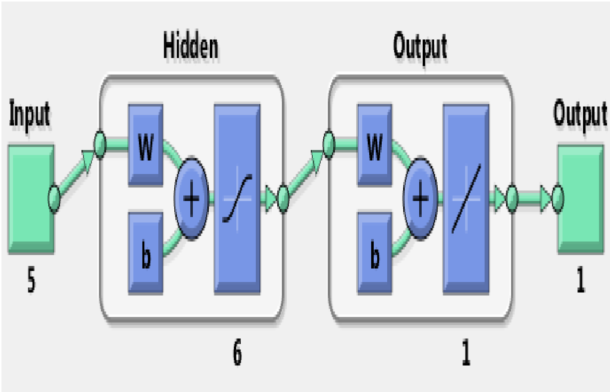

Figure 10 - Structure ANN optimal.

11 Conclusion

In this work, we have presented the simulation results of the prediction of the solar insolation of the next day using artificial neural networks. Based on the ANNs, three schemes were examined: one hidden layer, two layers and three hidden layers. By using the error indices of the RMSE and the MAE, the results obtained showed that the optimal neural structure for the prediction of sunshine, at the level of the solar power plant of Oued Kebrit, is the single-layer ANN structure. hidden with 6 neurons and a prediction step n_steps = 5 days.

References

[1] Khelil, K., Berrezzek, F., & Bouadjila, T. (2021). GA-based design of optimal discrete wavelet filters for efficient wind speed forecasting. *Neural Computing and Applications* , *33* (9), 4373-4386.

[2] Wang, H., Lei, Z., Zhang, X., Zhou, B., & Peng, J. (2019). A review of deep learning for renewable energy forecasting. *Energy Conversion and Management* , *198* , 111799.

[3] Singh, SN, & Mohapatra, A. (2019). Repeated wavelet transform based ARIMA model for very short-term wind speed forecasting. *Renewable energy* , *136* , 758-768.

[4]Liu, H., Chen, C., Lv, X., Wu, X., & Liu, M. (2019). Deterministic wind energy forecasting: A review of intelligent predictors and auxiliary methods. *Energy Conversion and Management* , *195* , 328-345.

[5] Berrezzek, F., Khelil, K., & Bouadjila, T. (2019). Efficient wind speed forecasting using discrete wavelet transform and artificial neural networks. *Artificial Intelligence Review* , *33* (December, 2019,).

[6] Obiora, CN, Hasan, AN, Ali, A., & Alajarmeh, N. (2021). Forecasting hourly solar radiation using artificial intelligence techniques. *IEEE Canadian Journal of Electrical and Computer Engineering* , *44* (4), 497-508.