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Temporal global solar radiation forecasting using artificial neural network in Tunisian climate

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***Abstract*— The temporal prediction of the solar radiation is very important for the operation of any solar energy system technology and completing data set. Based on meteorological parameters, the artificial neural network (ANN) can bring a technical solution for the prediction problems. In this paper, we developed an ANN for the south Tunisian climate to predict global solar radiation. Five years of record from January 2008 to December 2012 and five zones were selected to train and test the neural networks. The root mean square error (rmse), the coefficient of correlation (r) and the mean absolute error (Mae) are used to evaluate our model. The results show that the errors for the temporal forecasting varies between: 0.952 ≤ r ≤ 0.988, 4.9% ≤ rmse ≤ 10.1% and 1847 ≤ mae (j/cm²) ≤ 4657.**

***Keywords*— temporal forecasting, solar energy, artificial neural network, ground station meteorological parameter, south Tunisia**

I. Introduction

Within decades the solar energy discussion begins to be more and more scatter in our entire globe. This is because the awareness of the actual situation and the futuristic situation in conventional energy resource's need and the climate change problem. Irradiation from the sun may be the most advanced alternative energy resources due to its abundance and its potential to spread over a big spectrum of application. And like any fuel, the knowledge of the availability and forecasted value is necessary to evaluate any solar technology system performance and the financial viability of the project. The North African region is considered like one of the major promoted region in the solar energy sector due to the solar deserts potential and its strategic location. "In theory, a fairly small area of the Sahara desert could be used to provide enough electricity to supply the whole of the world ". So quantifying this sentence needs, researches and works for a serious assessment of the solar radiation. The first step of developing any solar project is evaluating the solar potential at the local climate. This can provide a reliable policy -market entrance.

As reviewed by Inman [1], many researches were performed to provide solar radiation maps, and they are available for the whole of the world. But most of these models and skills behind these researches are based on mathematical equations and requires the knowledge of meteorological parameters not usually available at the northern African meteorological stations. Country like Tunisia, despite its Saharan desert climate in the south [2], still covered by satellite based models instead of ground station based models.

The problem with the global solar radiation retrieved from the ground station is that we have lack of data due to maintenance operations in the station or other issues. To complete the ground station data, we calculated global radiation using the ANN method which uses the local available meteorological data like input.

Authors in the literature have used the ANN model to tackle the geographic and temporal data forecasting problems. The temporal forecasting, especially, short term solar radiation prediction is very useful for planning the operation of renewable energy power plants.

This paper describes the reliability of the use of the ANN model for temporal solar radiation forecasting in the Tunisian desert climate. It will be organized as follows:

The following section deals with our case of studies, including the database description. The section 2 will exhibit the model implementation. In the last section we will show the results of ANN implemented model in Tunisian climate.

II. The actual case studies

1) *The data set*

The monthly values were chosen to train the neural network; again we are trying to resolve the market entrance and not the connecting greed problem by forecasting short time problem. Since the north African countries are still in the first step of developing energy system. The data are retrieved from the National Institute of meteorology with a cover of 5 years of measurement: from January 2008 to December 2012 in 5 stations located at the south of Tunisia (Djerba, Remada,

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Touzeur, Kebili and Sfax). Details for the locations are attached to the Table I, fig 1.

Fig 1. Selected region's data base

TABLE I. LOCATION OF THE METEOROLOGICAL STATION

Place	*Longitude*	*Latitude*	*Altitude (m)*
Djerba	10°46'(10.76)	33°52'(33.86)	3
Remada	10°24'(10.4)	32°19'(32.31)	300
Touzeur	8°06'(8.1)	33°55'(33.91)	87
Kebili	8°58'(8.96)	33°42'(33.7)	43
Sfax	10°41'(10.68)	34°43'(34.71)	21

2) *First analysis*

Due to the inter-annual variability of the solar radiation, we tried to analyse some of the captured ground station data to have a better view of the tunisian global solar radiation deviation. So, we calculate the correlation coefficient "r" for each couple of year at each location, the global solar radiation (GHI). The result is presented in table II.

TABLE II. TEMPORAL DEVIATION OF THE GLOBAL SOLAR RADIATION

Place	**Minimum correlate coefficient(r)**	**Average r**
Djerba	0.755	0.89
Remada	0.895	0.953
Touzeur	0.892	0.928
Kebili	0.731	0.882
Sfax	0.919	0.966

The minimum correlate coefficient indicate that we have a maximum interannual deviation of the global solar radiation and the average correlate coefficient gives us an idea about how meanly the GHI deviate. These information are very important for project developer because they must know exactly the maximum expected deviation over a long period of time for a viable financial analysis of any solar project.

Analysing the interannual deviation, the minimum correlate coefficient varies beteen 0.731 and 0.919. So, the highest deviation is recorded in Kebili which represent the most bothering region for project developer where the uncertainty is the highest. On the other hand, we have the most stable interannual GHI recorded in SFAX with r = 0.919. The average "r" for GHI varies between 0.88 and 0.966.

3) *ANN Implementation*

A two-layer feed-forward network with sigmoid hidden neurons and linear output neurons is used to build the neural network. It will be trained with Levenberg-Marquardt back-propagation algorithm (trainlm) within the Matlab software. Ten hidden neurons were used to train the neural network within the fitting toolbox in Matlab.

Prediction of solar radiation requires geographical and meteorological variables as input parameters to ANN models. Therefore, researcher has to choose the most relevant parameters which give less prediction error. Several authors like Rehman [3], Koka [4] and Tymvios [5], have identified relevant parameters for prediction by using different combinations of meteorological input for the ANN model.

Bearing the most commonly relevant parameters found in the literature with the availability of meteorological data in Tunisia, we used the monthly value of: Longitude, latitude, altitude, month, sunshine duration in hours, mean maximal humidity (%), mean temperature (°C) and cumulative evaporation (mm) as inputs to the ANN and the Global solar radiation (J/cm²) as the target (Fig 2).

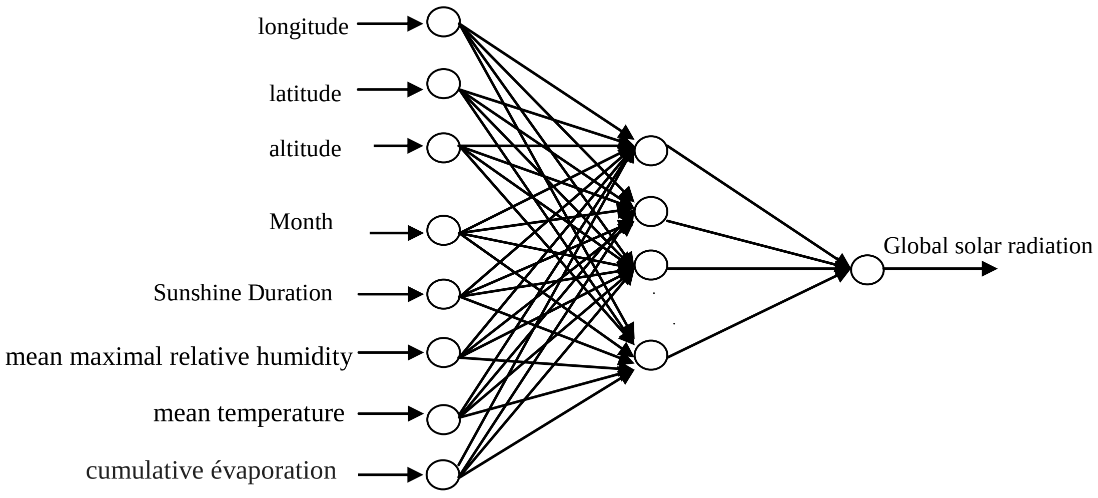

Fig 2. ANN implementation

III. Results and Discussions

1) Temporal forecasting

The concept of the temporal forecasting using the ANN model is: by the knowledge of the meteorological inputs for the actual month which are: sunshine duration in hours (SD), mean maximal humidity (MH %), mean temperature (MT°C) and cumulative evaporation (CEv mm) and the global solar radiation (GHI J/cm²) for the previous two months (for time t-1 and t-2), we can predict the global solar radiation (J/cm²) for the actual month :

$$GHI(t) = f(GHI(t-1), GHI(t-2), SD, MH, CEv)$$

In this case, the training ANN is performed in only one region, since the unique variable is the time "t" which represent the month interval time.

The database was used to train a neural network for the evaluation of time forecasting. The result of the global horizontal radiation (j/cm²) is compared with the measured value. Here we represent the result of five selected regions. So, in addition, of the meteorological input parameter shown in fig 2 we add two other important inputs which are the global solar radiation for the last two months GHI(t-1) and GHI(t-2). The results are represented in the fig 3,4,5,6,7 with the ANN predicted GHI vs. the measured one.

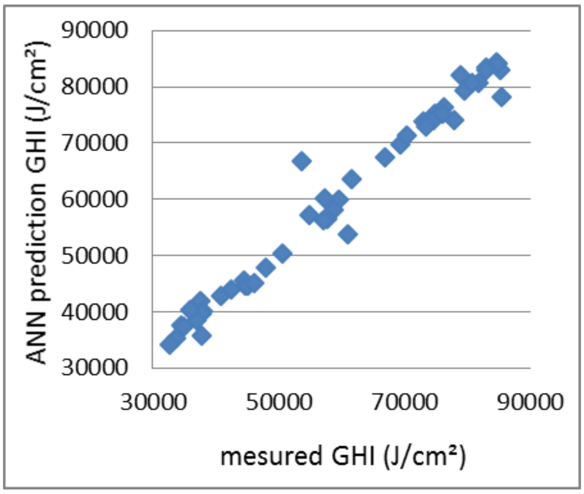

Fig 3. Temporal forecasting for Kebili region

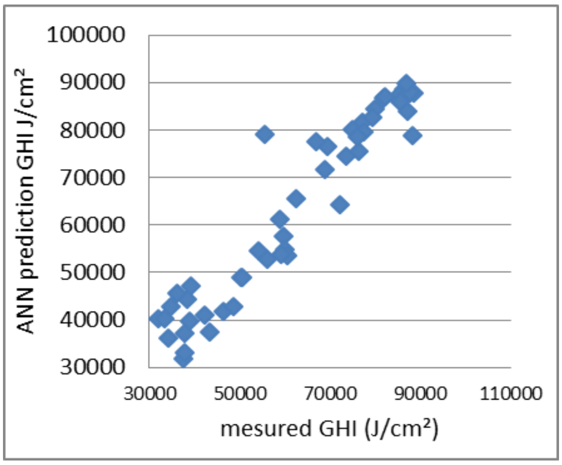

Fig 4. Temporal forecasting for tozeur region

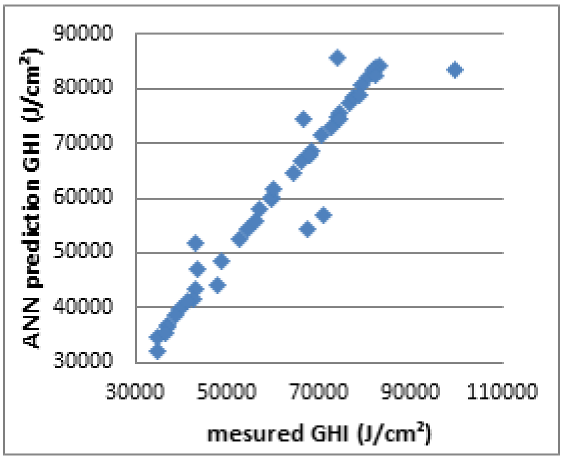

Fig 5. Temporal forecasting for Djerba region

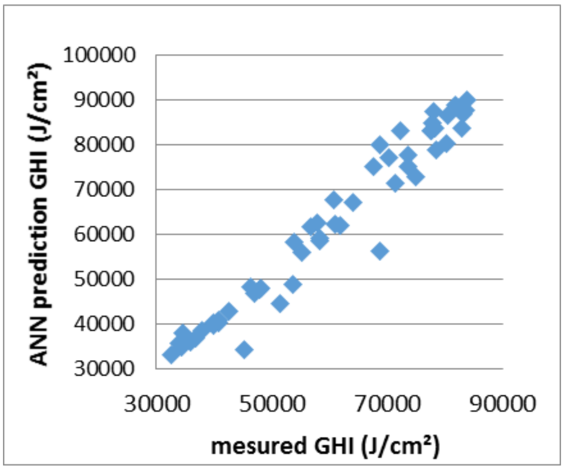

Fig 6. Temporal forecasting for Remada region

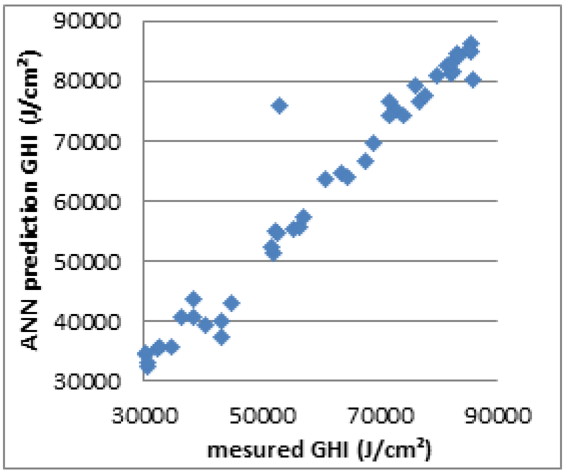

Fig 7. Temporal forecasting for sfax region

2) Statistical evaluation of the ANN model

Statistical error measures are used to evaluate the temporal forecasting. But first, we define the error of a single measurement:

$$\varepsilon_i = GHI_{i,\ predicted} - GHI_{i,\ mesured} \qquad (1)$$

$GHI_{i,\ predicted}$ represent the global solar radiation predicted by the ANN model, and $GHI_{i,\ measured}$ is the corresponding ground station captured value.

The root mean square error (rmse) and the bias (mbe) are used to evaluate the modelled solar radiation within the flowing expressions:

$$rmse = \frac{1}{\sqrt{N}} \sqrt{\sum_{i=1}^{N} \varepsilon_i{}^2} \qquad (2)$$

$$mbe = \frac{1}{N} \sum_{n=1}^{N} \varepsilon_i \qquad (3)$$

For each selected zone we evaluate the forecasted global solar radiation. It is represented in table III.

TABLE III. STATISTICAL EVALUATION OF THE ANN MODEL

	KEBILI	***TOZEUR***	***DJERBA***	***REMADA***	***SFAX***
R	0.988	0.952	0.96	0.974	0.98
rmse (%)	4.9	10.1	10	8.2	7.4
mbe (j/cm²)	1847	4657	3097	3792	2349

The ANN developed shows the following results:

- $0.952 \leq r \leq 0.988$
- $4.9 \leq rmse \leq 10.1\%$
- $1847 \leq mbe \leq 4657$ (j/cm²)

These results are in the same level of precision as the other solar forecasting works using ANN model done by different authors in other countries [6-10]. Kebili and Sfax seams responding very well with our ANN model since they have the least error recorded. However the other region are still in the accepted error zone. The average interregional rmse is equal to 8.12 which make our model relatively acceptable.

IV. CONCLUSIONS

Using the ground station meteorological data, we constructed an artificial neural network that predict the global solar radiation at a specific month. The main purpose of the model is to complete the lacks found in the ground station data set. Since the artificial neural networks prove its accuracy from different authors, we integrate an ANN model Tunisian climate to evaluate its accuracy in temporal prediction of the solar global radiation. Indeed, our model shows a great precision especially with Kebili and Sfax region. We note that the Kebili region, despite its highest temporal deviation, the ANN model showed the most accurate prediction for this region. These results mean that the artificial neural network can redress deviations and create a precise prediction.

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