Revue des Energies Renouvelables Vol. 19 N°1 (2016) 21 – 28

A direct normal irradiation forecasting model based on artificial neural networks

I. Belhaj, O. El Fatni, S. Barhmi and E.H. Saidi

Laboratory of High Energy Physics, Modelling and Simulations
Faculty of Sciences Rabat, Mohammed V University,
4 Avenue Ibn Battouta B.P. 1014 RP, Rabat, Morocco

(reçu le 10 Novembre 2015 – accepté le 29 Mars 2016)

Abstract - *We investigate the forecasting of the hourly Direct Normal Irradiation (DNI) using Artificial Neural Networks (ANN). The data used are hourly satellite data for the region of Ouarzazate in the South West Mediterranean basin region. The database is a total of 19 years. A feed-forward multilayer Perceptron is used with ten input parameters. The results show a very good accuracy for the four seasons of the years forecasted.*

Résumé - *Nous étudions la prédiction de l'irradiation horaire normale directe (DNI) en utilisant les réseaux de neurones artificiels (RNA). Les données utilisées sont les données satellitaires horaires pour la région de Ouarzazate dans la région Sud-Ouest du bassin méditerranéen. La base de données est un total de 19 ans. Un Perceptron multicouche feed-forward est utilisé avec dix paramètres d'entrée. Les résultats montrent une très bonne précision pour les quatre saisons des années prévues.*

Keywords: Forecasting - Artificial neural networks - Direct normal irradiation (DNI) – Backpropagation – Perceptron.

1. INTRODUCTION

Forecasting solar irradiation is of big importance due to applications in electricity generation, planning, dispatch and water heating energy. Variability of electricity produced from unstable renewable energy resources leads to fluctuations that affect the power grid and the limited storage hour's capacity; therefore forecasting of solar irradiation proves to be a very important solution.

Direct Normal Irradiation (DNI) is the main component of Concentrated Solar Power (CSP), Solar Thermal (ST) systems and Concentrated Photovoltaic's (CPV) and present a challenging task to foresee, since its high fluctuations caused by many parameters such as temperature, humidity and cloudiness that can affect it in a very effective manner; therefore, its forecasting is crucial.

Various energy demand forecasting models exist [1], such as time series [2-4], artificial neural networks [5-8] and Markal and Leap models. In general, forecasting methods can be divided into: statistical approaches, techniques based on cloud and satellite images [9], NWP models and hybrid models [10-12]. For example, an image processing methodology was elaborated to generate deterministic DNI forecasts for horizons ranging from 3 to 15 min ahead called the Sector-ladder method [13].

A hybrid model of a time delay neural network (TDNN) and Arma was used for predicting the hourly solar radiation which was then compared to ANN and Arma [14]. A univariate Dynamic Harmonic Regression (DHR) model was proposed for short-term (1-24h) solar irradiation forecasting using GHI and DNI from ground-based weather stations located in Spain [15].

A hybrid Arma/ANN model was tested to predict hourly global radiation using Numerical Weather Prediction (NWP) model database [16]. An exponential smoothing state space (ESSS) model was used to forecast high-resolution solar irradiance time series [17].

The solar forecasting methods are linked to the horizon of forecasting and its purpose [18]. For short-term and medium-term forecasting, Artificial Neural networks techniques are known to be the best method to give accurate results in comparison to conventional methods [18, 19].

In this paper, we study forecasting hourly Direct Normal Irradiation (DNI) using Artificial Neural Network (ANN). The data used are Ouarzazate's region in south-west Mediterranean basin, (south-east Morocco). The importance of Ouarzazate's platform for Africa is similar to the one of Almeria's platform for Europe since it has the same purpose for the Mediterranean region which is to exploit the high CSP potential with high solar incidence and proximity to Europe to export energy to region countries.

Ouarzazate is also part of the Moroccan solar plan of electrical energy production from renewable energy. The data are calculated from Meteosat MSG and MFG satellite data (EUMETSAT) and from atmospheric data (ECMWF and NOAA) by Solar GIS method. Since the forecasting accuracy of ANN models is dependent on input parameter combinations, training algorithm and architecture configurations [20], ten meteorological parameters are used as inputs based on a statistical test selection, namely: sun altitude angle, Sun azimuth angle, atmospheric pressure, relative humidity, air temperature at 2 m, wind speed at 10 m, wind direction, dew point temperature, wet bulb temperature and Direct Normal Irradiation (DNI) at a time t.

The forecasting model used is a Feed-forward Multilayer Perceptron (FFMLP) with a Back-Propagation Learning (BPL) algorithm. Ten ANN forecasting models are compared.

2. DATA

The Direct Normal Irradiation (DNI) and the meteorological data used are the hourly data provided by MASEN (Moroccan Agency for Solar ENergy) calculated from Meteosat MSG and MFG satellite data (Eumetsat) and from atmospheric data (ECMWF and NOAA) by Solar GIS method for the region of Ouarzazate. The spacial resolution for solar radiation data is 250 m × 250 m and for meteorological data is 1000 m × 1000 m, which reveals the quality of the data used. The region of Ouarzazate located in the latitude 31°:00’83’’ and longitude -06°:86’27’’ in South Morocco is a strategic region for the Moroccan Solar Plan (MSP) that aims to produce 2000 MW by 2020, making of Morocco one of the first countries in the world in terms of producing electricity from renewable energy resources. The entire hourly database used represents 19 years of data starting from 1st January 1994 to 31st December 2012.

3. METHODS

In this section, we present the methodology used for forecasting the hourly Direct Normal Irradiation (DNI). The data are pre-processed by excluding the 29th February day from each year to avoid the leap years and homogenize the data. The period between 07:30 AM to 17:30 is considered as it represents the daytime solar duration. The method used here is the artificial neural networks ANN; this is a method of artificial intelligence (AI) very used in finance, process analysis and solar forecasting.

It consists of three layers: the input layer, the hidden layer and the output layer. Each layer has a number of nodes called ‘neurons’. Every layer is connected to the following one by its nodes. Each connection is represented with the multiplication of the node by a random weight all summed with a bias in a transfer function given by the following equation,

$$y = f\left(\sum_{i=1}^{N} W_i x_i + b_i\right) \tag{1}$$

where f is the transfer function, W_i the random weights assigned to each input, N the number of the neurons and b_i the bias. First, the database is divided randomly into 3 parts: training data, test data and validation data as shown in **Table 1**.

Table 1: Partition of data

	Training	Test	Validation
Years	1994	1995	1996
	1997	1998	1999
	2000	2001	2002
	2003	2004	2005
	2006	2007	2008
	2009	2010	2011
	2012		

Ten meteorological data are used as inputs, namely: sun altitude angle, Sun azimuth angle, atmospheric pressure, relative humidity, air temperature at 2 m, wind speed at 10 m, wind direction, dew point temperature, wet bulb temperature and Direct Normal Irradiation (DNI) at a time t.

These inputs are then normalized in the range [0, 1] using the equation

$$x_{normalized} = \frac{x_{actual} - x_{min}}{x_{max} - x_{min}} \tag{2}$$

to reduce the discrepancies between the data since it's the domain of definition of the sigmoid function used as a transfer function in this work. The sigmoid function is given by the following equation

$$f(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

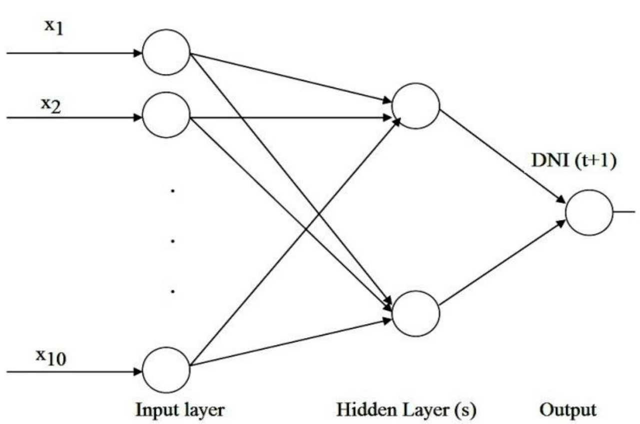


Fig. 1: ANN Architecture

Figure 1 shows the architecture of the feed-forward multilayer perceptron (MLP) used, which consists of one hidden layer with one neuron and a bias. The Back-propagation algorithm is used for training the forecasting model and the cross validation method is used for validation. DNI forecasts are then evaluated by computing the Root Mean Squared Error (RMSE) and Mean Squared Error (MSE) given by

$$\mathrm{RMSE} = \left(\frac{1}{n} \sum_{i=1}^{n} (t_i - y_i)^2 \right)^{\frac{1}{2}} \tag{4}$$

And

$$\mathrm{MSE} = \frac{1}{n} \sum_{i=1}^{n} (t_i - y_i)^2 \tag{5}$$

where n is the number of samples, t_i the targets and y_i the neural network outputs.

4. RESULTS

In this study, a feed-forward MLP is used with ten inputs to forecast the hourly normal irradiation (DNI). The database consists of 19 years of data where the period from 07:30 to 17:30 is considered to omit the period of darkness. As mentioned earlier, many studies have been conducted to forecast solar irradiation.

It was shown that ANN gave the best forecasting skill in one hour horizon for different regions [18]. In our work, the optimal ANN architecture selected in this study is 10-1-1, which consists of the least number of neurons and hidden layers possible.

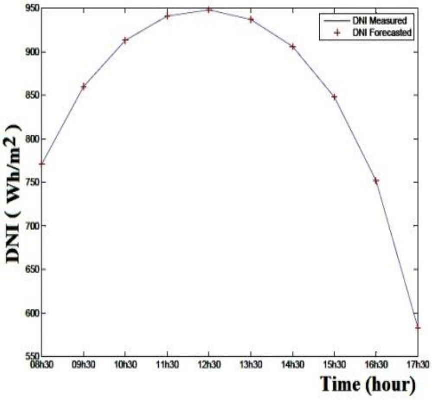


Fig. 2**a-** 15 April 2002

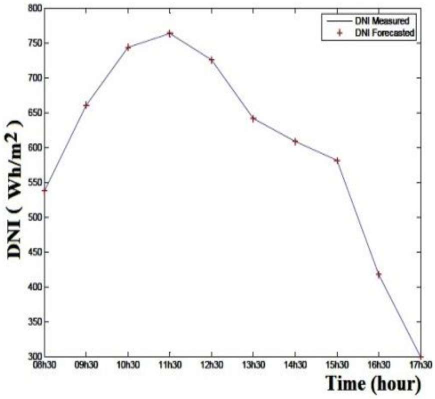


Fig. 2**b-** 15 July 2005

Table 2 shows the metric results of the validation set for the forecasting models tested. As can be seen from the table, the least error found is $\mathrm{RMSE} = 0.3317$ while we can notice that exceeding two hidden layers yields to a filter behaviour. The value of the error found shows the good accuracy of the model since the DNI in the validation set ranges from 0 to 1049 Wh/m^2. The determination coefficient R^2 is then computed by the following equation

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - t_i)^2}{\sum_{i=1}^{n}(t_i - \bar{t})^2} \tag{6}$$

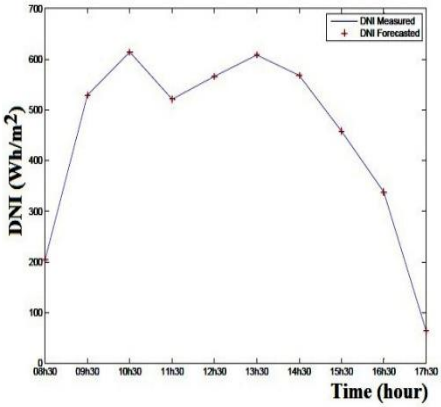


Fig. 2**c-** 15 October 2008

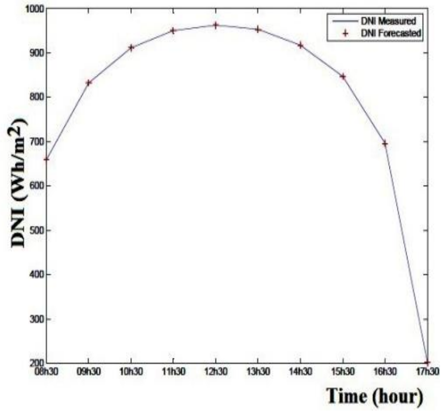


Fig. 2**d-** 15 January 2011

Fig. 2: Comparison between forecasted DNI
and actual DNI for four random days

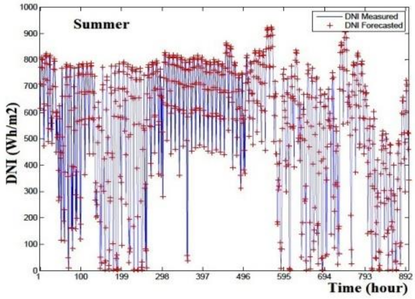
where y_i the forecasts from ANN, t_i measured values and $\bar{t}$ the average of DNI. The value shows a perfect description of the data with R^2 = 1:000. Figure 2 displays the results of four random days: 15th April 2002 Fig. 2**a-**, 15th July 2005 Fig. 2**b-**, 15th October 2008 Fig. 2**c-** and 15th January 2011 Fig. 2**d-**.

The nRMSE, normalized RMSE, is used to measure the error in each season to view the accuracy of the forecasting model used with the following equation

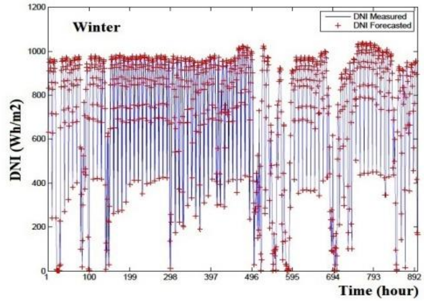
$$nRMSE = \frac{\frac{1}{N}\left(\sum_{i=1}^{N}(t_i - y_i)^2\right)^{1/2}}{\frac{1}{N}\sum_{i=1}^{N} y_i}$$

As listed in **Table 3**, the normalized root mean square errors for the four seasons don't exceed 1%. This could be explained by the fact that the hours of sunshine and sunset induce global errors in the database as a whole but when the error is normalized, their influence is negligible as predicted since most of these errors appear for values are less than 5 Wh/m^2.

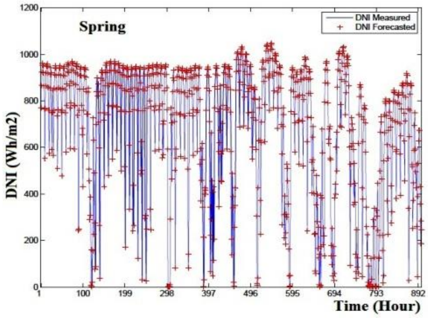
Figure 3 illustrates how the forecasts are in very good agreement with the actual DNI values for the four seasons: summer (Fig. 3**a-**), Winter (Fig. 3**b-**), Spring (Fig. 3**c-**) and Autumn (Fig. 3**d-**).



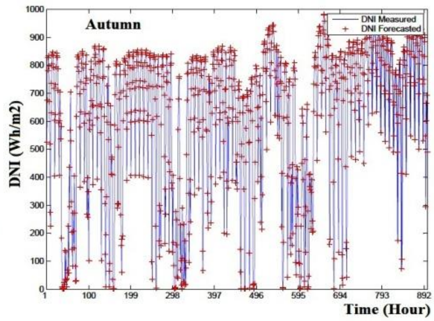
-a- Summer: 1st July to 15th July



-b- Winter: 1st February to 15th February



-c- Spring: 1st April to 15th April



-d- Autumn: 1st October to 15th October

Fig. 3: Comparison between forecasted DNI and actual DNI for four seasons

Table 2: Statistical metrics for the models tested
Bold values indicate the model selected using the validation dataset

Network N°	N° of hidden layers	N° of neurons	MSE	RMSE (Wh/m^2)
1	1	1	0.11000	0.3317
2	1	2	0.11000	0.3317
3	1	3	0.11000	0.3317
4	2	2	0.11000	0.3317
5	2	3	0.11000	0.3317
6	2	4	0.11000	0.3317
7	3	3	Filter	Filter
8	3	4	Filter	Filter
9	3	5	Filter	Filter
10	3	6	Filter	Filter

Table 3: Statistical metrics for seasons from the forescasting model chosen

Season	RMSE (Wh/m^2)	MSE (Wh/m^2)	nRMSE (%)
Winter	0.3009	0.0906	4.3058e-04
Spring	0.3364	0.1131	5.0385e-04
Summer	0.3156	0.0996	5.6977e-04
Autumn	0.3490	0.1218	5.8206e-04

5. CONCLUSION

Forecasting solar irradiation has known many improvements in terms of experimental methodologies and results accuracy. From time series, to artificial techniques to hybrid models, satellite imagery and cloud tracking, depending on the time-scale needed and the forecasting purposes, results differ.

However, the results of the basic methods can be further improved by exploring different new sets of independent variables that affect the dependent variable.

In this study, DNI forecasting using the artificial neural networks (ANN) is explored with a new different set of independent variables. Ten exogenous parameters were used based on a statistical P-value selection.

A feed-forward MLP is used with a back propagation algorithm. The results show that ANN gives very accurate results using these inputs demonstrated by the very low mean squared error. The model reveals also a good forecasting accuracy in each of the four seasons which can be shown by an MSE equal to 0.0906 Wh/m^2 in Winter, 0.1131 Wh/m^2 in Spring, 0.0996 Wh/m^2 in Summer and 0.1218 Wh/m^2 in Autumn.

Artificial neural networks prove to be a very good tool for forecasting although, the choice of independent variables and the huge database (69 350 data in our case) play an important role in the enhancement and achievement of good results which is still an ill-defined subject of matter in the artificial intelligence field.

Further improvement shall come up in next works by using optimizing algorithms, multiple regression and hybrid models with a comparison between these results using the same inputs.

ACKNOWLEDGEMENTS

The authors thank the Moroccan agency for solar energy for putting a disposal data.

REFERENCES

[1] L. Suganthi, Anand A. Samuel., '*Energy Models for Demand Forecasting- A Review*', Renewable & Sustainable Energy Reviews, Vol. 16, N°2, pp. 1223 - 1240, 2012.

[2] C. Voyant, P. Haurant, M. Muselli, C. Paoli, M.L. Nivet, '*Time Series Modelling and Large Scale Global Solar Radiation Forecasting From Geostationary Satellites Data*', Solar Energy, Vol. 102, pp. 131 - 142, 2014.

[3] G. Reikard, '*Predicting Solar Radiation at High Resolutions: A Comparison of Time Series Forecasts*', Solar Energy, Vol. 83, N°3, pp. 342 - 349, 2009.

[4] J.G. De Gooijer and R.J. Hyndman, '*25 Years of Time Series Forecasting*', International Journal of Forecasting, Vol. 22, pp. 443 – 473, 2006.

[5] C. Paoli, C. Voyant, M. Muselli and M.L. Nivet, '*Forecasting of Preprocessed Daily Solar Radiation Time Series Using Neural Networks*', Solar Energy, Vol. 84, N°12, pp. 2146 - 2160, 2010.

[6] Y. Kashyap, A. Bansal and A.K. Sao, '*Solar Radiation Forecasting with Multiple Parameters Neural Networks*', Renewable and Sustainable Energy Reviews, Vol. 49, pp. 825 - 835, 2015.

[7] H.N. Wang, Y.M. Cui, R. Li, L.Y. Zhang and H. Han, '*Solar Flare Forecasting Model Supported with Artificial Neural Networks Techniques*', Advances in Space Research, Vol. 42, N°9, pp. 1464 – 1468, 2008.

[8] S.X. Chen, H.B. Gooi and M.Q. Wang, 2013. '*Solar Radiation Forecast Based on Fuzzy Logic and Neural Networks*', Renewable Energy, Vol. 60, N°C, pp. 195 - 201, 2013.

[9] C. Rigollier, M. Lefèvre and L. Wald, '*The Method Heliosat-2 for Deriving Shortwave Solar Radiation from Satellite Images*', Solar Energy, Vol. 77, N°2, pp. 159 - 169, 2004.

[10] J.Z. Wang, H. Jiang, Y.J. Wu and Y. Dong, '*Forecasting Solar Radiation using an Optimized Hybrid Model by Cuckoo Search Algorithm*', Energy, Vol. 81, N°C, pp. 627 – 644, 2015.

[11] M. Diagne, M. David, Ph. Lauret, J. Boland and Nicolas Schmutz, '*Review of Solar Irradiance Forecasting Methods and a Proposition for Small-Scale Insular Grids*', Renewable & Sustainable Energy Reviews, Vol. 27, pp. 65 – 76, 2013.

[12] Y. Gala, A. Ferandez, J. Diaz and J.R. Dorronsoro, In press, '*Hybrid Machine Learning Forecasting of Solar Radiation Values*', Neurocomputing, Vol. 176, pp. 48 – 59, 2016.

[13] S. Quesada-Ruiz, Y. Chu, J. Tovar-Pescador, H.T.C. Pedro and C.F.M Coimbra, '*Cloud Tracking Methodology for Intra-Hour DNI Forecasting*', Solar Energy, Vol. 102, pp. 267 – 275, 2014.

[14] Ji Wu and Chee Keong Chan, '*Prediction of Hourly Solar Radiation Using a Novel Hybrid Model of ARMA and TDNN*', Solar Energy, Vol. 85, N°5, pp. 808 - 817, 2011.

[15] J.R. Trapero, N. Kourentzes and A. Martin, '*Short-Term Solar Irradiation Forecasting Based on Dynamic Harmonic Regression*', Energy, Vol. 84, N°2, pp. 289 – 295, 2015.

[16] C. Voyant, M. Muselli, Ch. Paoli and M.L. Nivet, '*Numerical Weather Prediction (NWP) and Hybrid ARMA/ANN Model to Predict Global Radiation*', Energy, Vol. 39, N°1, pp. 341 - 355, 2012.

[17] Z. Dong, D. Yang, T. Reindl and W.M. Walsh, '*Short-Term Solar Irradiance Forecasting using Exponential Smoothing State Space Model*', Energy, Vol. 55, Issue C, pp. 1104 – 1113, 2013.

[18] R.H. Inman, H.T.C. Pedro and Carlos F.M. Coimbra, '*Solar Forecasting Methods for Renewable Energy Integration-Review*', Progress in Energy and Combustion Science, Vol. 39, N°6, pp. 535 - 576, 2013.

[19] R. Marquez and Carlos F.M. Coimbra, '*Forecasting of Global and Direct Solar Irradiance using Stochastic Learning Methods, Ground Experiments and the NWS Database*', Solar Energy, Vol. 85, N°5, pp. 746 – 756, 2011.

[20] A.K. Yadav and S.S. Chandel, '*Solar Radiation Prediction using Artificial Neural Network Techniques: A Review*', Renewable and Sustainable Energy Reviews, Vol. 33, pp. 772 – 781, 2014.