MODELING OF GLOBAL SOLAR RADIATION ON A HORIZONTAL SURFACE USING ARTIFICIAL NEURAL NETWORK: A CASE STUDY

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ABSTRACT

The present work investigates the potential of artificial neural network (ANN) model to predict the horizontal global solar radiation (HGSR). The ANN is developed and optimized using three years meteorological database from 2011 to 2013 available at the meteorological station of Blida (Blida 1 university, Algeria, Latitude 36.5°, Longitude 2.81° and 163 m above mean sea level). Optimal configuration of the ANN model has been determined by minimizing the Root Means Square Error (RMSE) and maximizing the correlation coefficient (R^2) between observed and predicted data with the ANN model. To select the best ANN architecture, we have conducted several tests by using different combinations of parameters. A two-layer ANN model with six hidden neurons has been found as an optimal topology with (RMSE=4.036 W/m²) and (R^2=0.999). A graphical user interface (GUI), was designed based on the best network structure and training algorithm, to enhance the users' friendliness application of the model.

Key Words: *Artificial neural network; global solar radiation; solar energy; prediction; Algeria.*

NOMENCLATURE

Symbols :

W Poids

T Bias

GUI Graphical user interface

GSR Global Solar Radiation, Wh/m²

HGSR Horizontal global solar radiation, Wh/m²

ANN Artoficial Neural Network

Y Year

SD Sunshine duration

DN Number of the day

t Time, h

$$Root\,Mean\ Squared\,Error : RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(HGSR^{\exp} - HGSR^{pred})^2}$$

T Temeprature, °C

R^2 Determination coefficient,

$$R^2 = 1 - \frac{\sum_{i=1}^{N}\left(GSR^{\exp} - GSR^{pred}\right)^2}{\sum_{i=1}^{N}\left(GSR^{\exp} - \bar{GSR}\right)^2}$$

RH Relative humidiy, %

In Input

Indices / Exponents :

in scaled value of the variable x in the psotion

i position of an element (i=1 to n)

exp exeprimental value

pred predicted value

s number of neurons in the hidden layer (s =

k number of neurons in the input layer (k=1

l number of neurons in output layer (l = 1)

1. INTRODUCTION

Solar potential is desirable for many areas of research and applications in different engineering fields. However, global solar radiation is not as readily available as other data due to the cost of pyranometers and difficulty in measurement. In spite of the existence of meteorological stations at many places, sometimes the measurements are not available continuously due to recording deficiencies.

Therefore, there is the need to develop alternative ways to generate these data. Many models have been developed to predict the solar radiation. Comparative studies of artificial neural networks (ANNs) and the traditional regression approaches in modeling global solar radiation (GRS) have been shown that ANN methodology offers a promising alternative to the traditional approach. The relationship between radiation and meteorological data is highly non-linear, and consequently an ANN can be a suitable alternative to model the underlying radiation properties.

A three-layer feedforward artificial neural network can approximate any nonlinear continuous function to an arbitrary accuracy [1-4]. The use of ANN to solve real problems always includes selecting the appropriate network models and network topology, as well as the efficient training [5].

In the recent years, ANN has been widely used to model global solar radiation in Algeria. Such as Mellit et al., [6], proposed a hybrid model based on ANN-MTM (Markov Transition Matrix) for generating sequences of direct GSR and the optimal model has been obtained with a correlation coefficient ranging from 90 to 92% and a RMSE error not exceeding 8% between the measured and predicted data. Yacef et al, [7] presents a comparative study between Bayesian Neural Network (BNN), classical Neural Network (NN) and empirical models for estimating the daily global solar irradiation (DGSR). Results show that the BNN performs better that other NN structures and empirical models. The experimental dataset used in this work is available by the National Renewable Energy Laboratory (NREL) in the north-eastern of Algeria in the city of Jijel. The optimal ANN is obtained with an RMSE of 8.4173 %. Estimating the global solar radiation (GSR) as a function of air temperature and relative humidity data using artificial neural network (ANN) in a in the south-western region of Algeria has been conducted by [8]. The RMSE and R^2 values of this network were 17.20 and 0.9999, respectively for the test.

A set of ANN models for global solar radiation prediction at Djelfa (Algeria) has been proposed by [8]. The obtained error performance was 11.69% for RMSE. Dahmani et al, [9] developed a MLP model of solar tilted global irradiation from horizontal ones. The optimal configuration has been obtained with relative root means square error around to 8%. The model is trained with an experimental database available at the Renewable Energies Development Centre (CDER) in Bouzareah near Algiers (latitude: 36.8°N; longitude: 3.17°E) at an altitude of 347 m.

Till now, no work have been conducted to model global solar radiation using ANN in the city of Blida, although this latter is an industrial city and has one of the biggest universities in Algeria where renewable energy is taught as an important subject.

In this study, the half-hourly values of global solar radiation on horizontal surface over the City of Blida (Algeria) will be modeled using artificial neural networks based on readily available meteorological data. The developed model in this study will enable the easy estimation of solar radiation which is essential in the design of solar devices, simulate its behavior and optimize its management.

1. GLOBAL SOLAR IRRADIATION MODELING WITH NEURAL NETWORK

In order to model horizontal global solar radiation by one ANN model, six variables have been selected as inputs: year of test, sunshine duration, day of the year, time, temperature and relative humidity. The choice of the input and output variables is motivated by their availability in meteorological station. The application of ANN modeling of HGSR was performed using MATLAB® (version R2013a) and the strategy proposed by Plumb [10]:

1. The experimental data should be divided into training (in this work: 1157 data), validation (in this work: 578 data) and test set (in this work: 578 data): the validation set is used in parallel with the training set. The connection weights of the neurons will be adjusted during the training in order to acquire the knowledge of the network. While, the validation set will be used for verifying the generalization ability of the network during the training process, it is used as a stop criterion for training. Then, the accuracy of the proposed ANN model was evaluated through a test data set not used in the training stage [11].
2. Since the variables of input‑output data have different physical units and range sizes and in order to improve the efficiency of network training and to prevent saturation of the transfer functions, data were normalized in order to fall in the range [−1, 1] by calculating the minimum and the maximum of each vector variable and scaling the data with respect to these limits. The normalization function used in this work is given by (eq.1) and programmed in Matlab as (mapminmax, [-1, +1]) [12]:

$$x_{in} = \frac{2\{x_i - \min(x_i)\}}{\{\max(x_i) - \min(x_i)\}} - 1 \tag{1}$$

3. The most widely used algorithm for prediction purpose is the feed-forward multilayered network commonly named "back-propagation, a typical architecture incorporating back-propagation has at least three layers. The first is the input layer that presents data into the network. This layer has as many neurons as the number of variables used in prediction. The output layer where each neuron receives input from each neuron in the hidden layer immediately proceeding. The number of neurons in the output layer will equal the number of variables to be predicted. The middle layer is designed for data processing [13]. A network may have more than one hidden layer depending on the complexity of the problem. For solar radiation forecasting, typically one hidden layer may be sufficient to map input data to output data.
4. In supervised training method, a network is trained by presenting it with a series of training cases (vectors) each with associated target output values. The weights are then adjusted based on the learning rule specified [13].
5. The neurons can be fully connected or partially connected. In the case of a fully connected network, all first layer neurons are connected to all hidden neurons in the next layer and all second layer neurons are connected to all third layer neurons. Finally, all neurons in the last hidden layer are connected to all neurons of the output layer.
6. The number of neurons in the hidden layer can be varied depending on the performance of the network during the training phase. In general neural networks are sensitive to the number of neurons in their hidden layers. Too few hidden neurons provide faster training and limit the ability of the neural network to model the process (under fitting). Too many neurons can contribute to over fitting and long training period. Despite the fact that there is a lot of methods proposed by various researchers such as [14] suggests hidden neurons between half the number of input variables and two times that number and according to the work done by [15], the selection of the neurons in the hidden layer usually has to be done by trial and error.
7. From among activation functions the sigmoid (logistic logarithmic) function is the most usually employed for the hidden layer in ANN applications [16-17] and the tansig transfer function, for the output layer which can satisfy the requirement of variety for different output result.
8. The optimal configuration of the optimal ANN model is obtained based on error analysis (RMSE) and the appropriate correlation coefficient (R^2) of test data set. The regression results are represented by values between 0 and 1 where a value of 1 indicates perfect correlation between the targets and the actual outputs of the networks and 0 indicates the opposite.
9. The above strategy has been implemented in a MATLAB program for ANN modelling of the HGSR. Initially, the program starts with the default feedforward backpropagation NN type (feedforwardnet), Bayesian Regularization backpropagation (trainbr) and one hidden layer. Once the topology is specified the starting and ending number(s) of neurons in the hidden layer(s) have to be specified. The number of neurons in a hidden layer is then modified by adding neurons one at a time. The procedure begins with the logarithmic sigmoid activation function for the hidden layers and the hyperbolic tangent sigmoid activation function for the output layer.

Based on this global strategy, detail of the different phases of the procedure used in this work is depicted in Figure 1.

2. RESULTS AND DISCUSSIONS

The best ANN algorithm obtained in this work was a multilayer feedforward back propagation network that consisted of a 6-6-1 topology. The optimized values of network for learning rate and momentum were 0.01 and 0.8, respectively. The learning was completed in RMSE = 4.036 W/m^2 and R^2= 0.999. The training process was activated to achieve a performance target of 1×10^{-3} for maximum training epochs of 2000. The values of these parameters were obtained after performing several trial and error runs. It was found that these values insure fast learning.

Table 1 shows the structure of the optimized NN model. The weight matrices and bias vectors of the NN model are listed in Table 2, where IW{6,6} is the input-hidden layer connection weight matrix (6 rows x 6 columns), LW{6,1} is the hidden-output layer connection weight matrix (6 rows x 1 column).

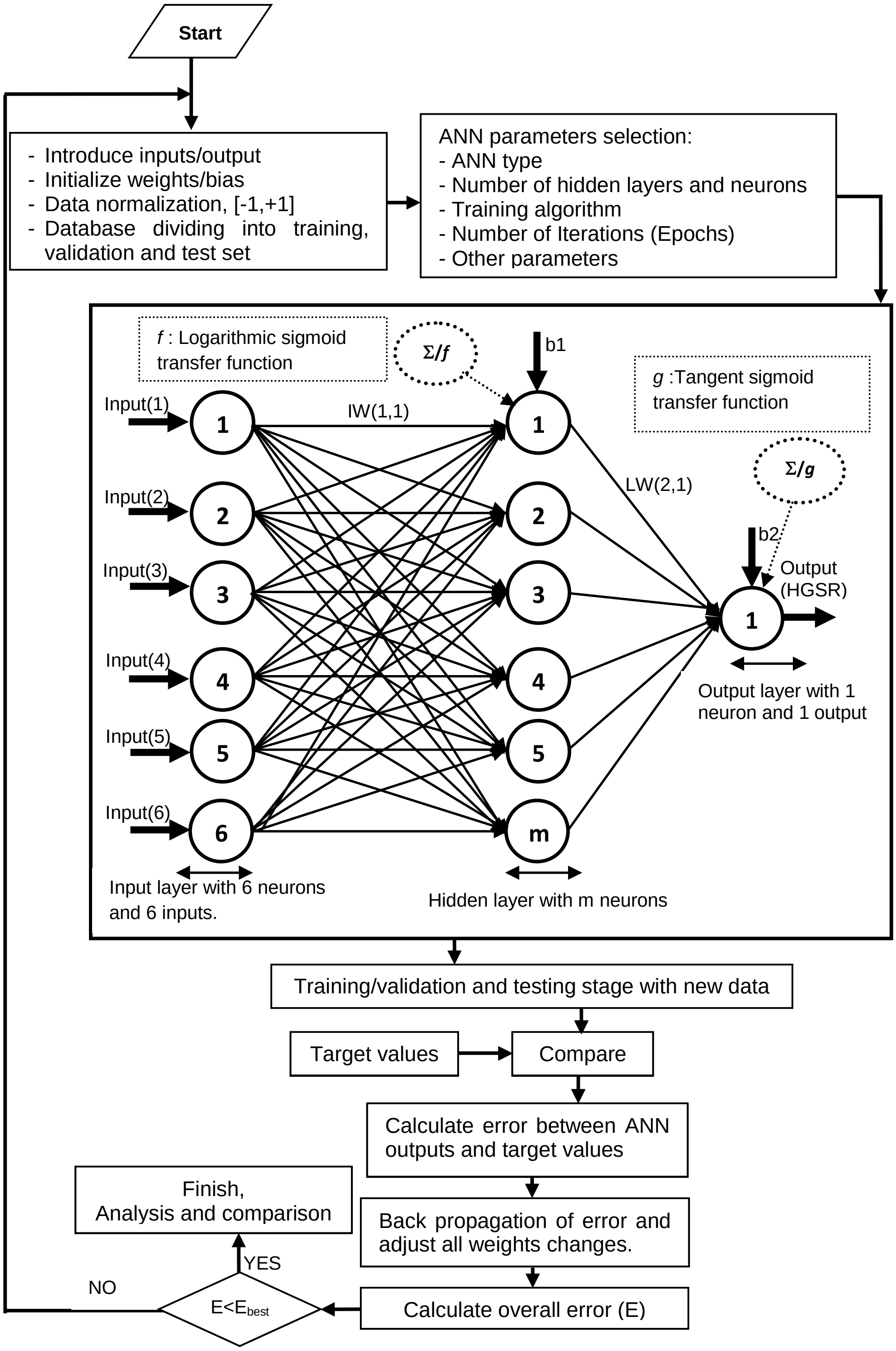

FIGURE 1. Flowchart of multilayer feed-forward neural network modeling.

TABLE 1. Structure of the optimized artificial neural networks model.

Type of network	Training Algorithm	**Input layer**	**Hidden layer**		**Output layer**	
		No. of neurons	Number of neurons	Activation function	Number of neurones	Activation function
FFBP NN (***feedforwardnet*** MATLAB function)	Bayesian Regularization backpropagation (***Trainbr*** MATLAB function)	6	6	Logarithmic sigmoid (***logsig*** MATLAB function)	1	Tangent Sigmoid (***tansig*** MATLAB function)

We randomly chose a periods of 4 days for which we plotted the experimental and estimated data in order to show the interpolating ability of the ANN model (Figure 2). This figure shows excellent agreement between experimental curve (shown as blue line) and the NN predicted results (shown as red-star markers), all points follow exactly the trend of the experimental data which suggests a good predictive ability of the NN model for HGSR within the range of inputs for which the model has been designed (Table 3). This result also means that the experimental data has been fitted with a high accuracy using the optimal ANN model.

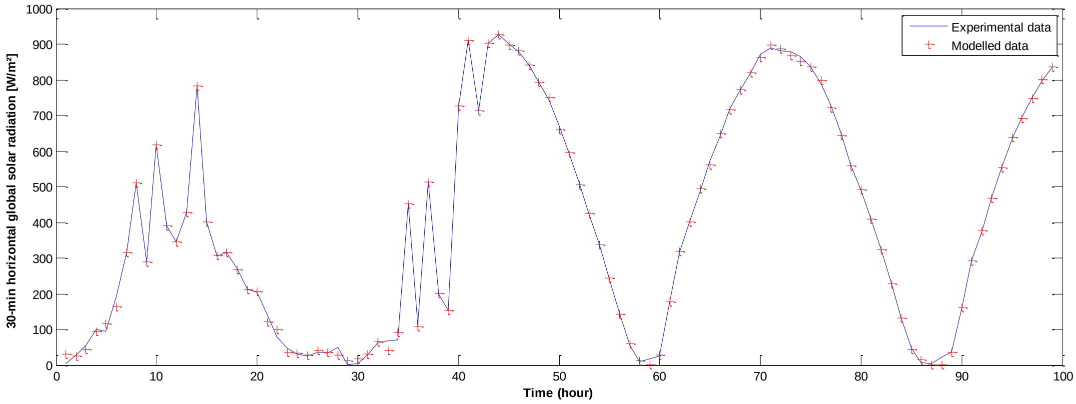

FIGURE 2. Validation of the Model on a 4 days period

TABLE 2. Weight and bias of the optimized ANN model during the training stage

Input-hidden layer connections							**Hidden-output layer connections**	
IW{1,1}						b(1)	LW{2,1}	b(2)
1,1511	0,7839	0,2512	-3,0193	-0,9991	-0,3799	3,0140	5,1376	
-0,2027	-0,2586	0,9084	4,4869	-1,5233	-0,2084	3,0579	5,1588	
3,0786	1,0063	-1,3776	-2,6283	-2,7958	1,9204	3,7276	-7,7930	-5.1461
-0,9502	1,7816	-5,1045	-1,2838	5,5163	-1,7528	3,1900	3,2007	
1,4085	4,5360	3,0091	-0,5884	-6,1431	2,6033	-2,8581	1,6305	
-0,1832	1,0829	3,4803	4,0157	0,9689	-1,7411	-3,1123	-6,8747	

Since the ANNs are poor in extrapolating, eq.4 is valid within the range of the input data during the training. Table 3 that follows represents the maximum and the minimum of each input.
The mathematical formula of the predicted output is given by the Eq. (4):

$$HGSR = \sum_{s=1}^{S}\left[W_{0(l,s)}\left(\frac{2}{1+\exp(-2(\sum_{k=1}^{K}(W_{i(s,k)}.In_{(k)})+b1_{(s)}))}-1\right)\right]+b2_{(l)} \qquad (2)$$

Where s is the number of neurons in the hidden layer (S = 6), k is the number of neurons in the input layer (K = 6), l is the number of neurons in output layer (l = 1), W_i (IW), W_o (LW) and $b1_{(s)}$, $b2_{(l)}$ are weights and bias between input-hidden layer and hidden-output layer respectively. The eq. (4) is not complex because is made up of a simple arithmetic operation. Therefore, it can be used for on-line estimation application for industrial processes.

TABLE 3. Input and output parameters used in model

Variable category	Parameters	Symbol	Unit	Minimum	Maximum
Inputs	Year	Y	(-)	2011	2013
	Sunshine duration	SD	(h)	-23,45	23,39
	number of the day	DN	(-)	1	365
	Time	t	(h)	6	20
	Temeprature	T	(°C)	19	41.2
	Relative humidiy	RH	(%)	24	86
Output	Global solar irradiation received on horizontal surface	HGSR	(W/m^2)	1	1074

3. CONCLUSIONS

In this paper, a suitable method for predicting horizontal global solar radiation using an artificial neural network is described.This model can predict HGSR using some commonly available parameters like, year, sunshine duration, and number of the day, time, temperature and relative humidity as input parameters. The validation of the model was performed with previous data, which has not been used in the training of the network. The network structure with [6-[6]-1] configuration trained with the Bayesian Regularization backpropagation 'trainbr' algorithm gave the best prediction performance with highest R^2 (0.999) and lowest RMSE (4.036%). This accuracy is within the acceptable level used by design engineers.

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