PAN POLSKA AKADEMIA NAUK

JOURNAL OF WATER AND LAND DEVELOPMENT

e-ISSN 2083-4535

ITP-PIB

Polish Academy of Sciences (PAN) Institute of Technology and Life Sciences – National Research Institute (ITP – PIB)

JOURNAL OF WATER AND LAND DEVELOPMENT
DOI: 10.24425/jwld.2022.141550
2022, No. 54 (VII–IX): 13–20

Development of a neural statistical model for the prediction of relative humidity levels in the region of Rabat-Kenitra, North West Morocco

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RECEIVED 01.04.2021 ACCEPTED 30.03.2022 AVAILABLE ONLINE 28.09.2022

Abstract: This article accounts for the development of a powerful artificial neural network (ANN) model, designed for the prediction of relative humidity levels, using other meteorological parameters such as the maximum temperature, minimum temperature, precipitation, wind speed, and intensity of solar radiation in the Rabat-Kenitra region (a coastal area where relative humidity is a real concern). The model was applied to a database containing a daily history of five meteorological parameters collected by nine stations covering this region from 1979 to mid-2014.

It has been demonstrated that the best performing three-layer (input, hidden, and output) ANN mathematical model for the prediction of relative humidity in this region is the multi-layer perceptron (MLP) model. This neural model using the Levenberg–Marquard algorithm, with an architecture of [5-11-1] and the transfer functions Tansig in the hidden layer and Purelin in the output layer, was able to estimate relative humidity values that were very close to those observed. This was affirmed by a low mean squared error (*MSE*) and a high correlation coefficient (*R*), compared to the statistical indicators relating to the other models developed as part of this study.

Keywords: artificial neural network (ANN), learning algorithm, multi-layer perceptron (MLP), modelling, Rabat-Kenitra, relative humidity

INTRODUCTION

The problem of excessive humidity is a constant concern in a coastal zone, especially for vulnerable people, and for industries such as the building industry, the pharmaceutical sector, etc. In fact, excessive moisture causes several types of allergic reactions, building deterioration, mould formation, rapid corrosion, and mechanical damage. The limit value for excessive humidity is set at 75% of relative humidity. The need to control and predict variations in this environmental parameter is considered to be a major challenge.

Different scientific studies affirmed the effectiveness of artificial neural networks (ANN) in the data processing, simulation, and modelling of the relations between environmental parameters [Abdallaoui, El Badaoui 2016]. These neural networks have been used successfully in several domains, such as image processing, optimisation, forecasting, and prediction in general. In fact, they are considered to be information processing techniques, established by algorithms involving concepts of learning.

In the bibliography, we cite examples including some prediction work using, among others, Multi-layer perceptron (MLP) artificial neural network type.

Parishwad *et al.* [1998] developed mathematical models to predict meteorological parameters at different locations in India, for example by estimating the outdoor ambient temperature from relative humidity and wind speed.

Imran *et al.* [2002] used artificial neuron networks to develop a mathematical model to predict the mean values of outside ambient temperature 24 h in advance. The neural network formed was successfully applied to estimate temperatures for years.

KEMAJOU *et al.* [2012] developed a neural model to predict the hourly indoor air temperature in modern buildings and in hot and humid climate 7 h in advance.

ÖZBALTA *et al.* [2012] predicted the average daily temperature and average relative humidity in a teaching building located in a hot and humid city in Turkey by applying artificial neural networks. The authors considered the values of the correlation coefficient between the predicted values and the actual values to be significantly important.

EL BADAOUI *et al.* [2014a, b] considered a time series of meteorological data and showed the robustness of artificial neural networks of the multilayer perceptron type by developing neural statistical models of the multilayer perceptron type and the radial basis function type for the prediction of the humidity level in the city of Chefchaoun in Morocco.

BEN EL HOUARI *et al.* [2014; 2015; 2016a, b, c] recently developed mathematical neural models for the prediction of air temperature and precipitation in the city of Meknes in Morocco. They used several indices and statistical indicators to evaluate the performance of their models and to justify the choice of learning algorithms, numbers of hidden layers and neurons, and activation functions.

Meanwhile, BEN EL HOUARI *et al.* [2016a] used the self-organising maps based on artificial neural networks to identify classes of similar objects in a database containing meteorological parameters of Meknes city (Morocco). The results they obtained allowed them to classify the 216 months corresponding to the period of their study into three classes, according to the meteorological parameters: Class 1: consisting of 76 months, characterised by fairly high average temperature, relative humidity, and wind speed. Class 2: consisting of 56 months, characterised by low average temperature, heavy rainfall, and relative humidity. Class 3: consisting of 84 months characterised by very high temperatures and low values of relative humidity, precipitation, and wind speed.

Furthermore, relative humidity depends on many meteorological parameters [BIMAL, SUSANTA 2011], especially temperature: the higher the temperature of the air, the more water vapour it can contain.

In the present study, our objective is to establish an efficient model based on artificial neural networks to predict relative humidity in the region of Rabat-Kenitra (north-west of Morocco). This prediction will take as inputs other meteorological parameters such as the maximum temperature, minimum temperature, precipitation, wind speed, and intensity of solar radiation.

MATERIALS AND METHODS

DATABASE DESCRIPTION

The database used for this study consists of the daily values of six meteorological variables, recorded between 1st Jan 1979 and 21st Jul 2014, in nine stations installed in three parallel rows in the region of Rabat-Kenitra (Morocco) – Figure 1. Hence, data was collected on 12,986 days in each station.

Table 1 presents the six meteorological variables, their types, their symbols, and their units. It is reported that daily values of these variables were converted into monthly averages (i.e. 427 observations) for all variables except for precipitation, which was converted to a monthly cumulative value, as indicated by several authors [BISHOP 1995; DEDECKER *et al.* 2002].

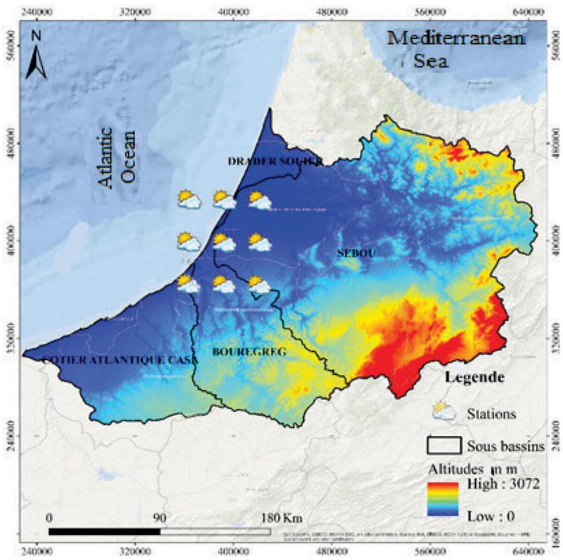

Fig. 1. Map of meteorological stations located in the Rabat-Kenitra region (Morocco); source: own elaboration

Table 1. Meteorological parameters, their symbols, their units of measurement, the notation, and type of each variable

Variable type	Meteorological parameter	Symbol	Unit
Independent variables	maximum temperature	T_{max}	°C
	minimum temperature	T_{min}	°C
	precipitation	P	mm
	wind speed	v	$m \cdot h^{-1}$
	intensity of solar radiation	S	$MJ \cdot m^{-2}$
Dependent variable	relative humidity	RH	%

Source: own elaboration.

NORMALISATION AND DISTRIBUTION OF THE DATABASE

The incompatibility of the units of measurement between the variables can affect the results. Moreover, the amplitudes of the values of the variables in the database are very different. For a good homogenisation of these values, which will be propagated in the artificial neural network, the database has undergone pre-processing, which consists in carrying out an appropriate normalisation, taking into account the amplitude of the values accepted by the network [DOMBAYCI, GOLCU 2009].

So, the values of the independent variables and those of the dependent variable were normalised in the interval [–1; 1], relative to their minimum and maximum values, applying the following normalisation equation [ABDALLAOUI, EL BADAOUI 2011]:

$$\bar{X}_i = \frac{2\left(X_i - X_{i(\min)}\right)}{\left(X_{i(\max)} - X_{i(\min)}\right)} - 1 \tag{1}$$

where: $\bar{X}_i$ = normalised values of the variable i; X_i = gross values, non-normalised values of variable i; $X_{i(\min)}$ = minimum values of variable i; $X_{i(\max)}$ = maximum values of variable i.

Furthermore, in order to develop an application based on neural networks, it is necessary to divide the database into two groups, with one group intended for training and another for testing the trained network and for assessing its performance.

To do this, we randomly divided our database into two groups according to specific percentages. Table 2 presents the values of the correlation coefficients and the mean square errors for each distribution of the database and for three different tests.

Table 2. Correlation coefficients (R) and mean squared errors (MSE) for each database distribution

Training group		90%	80%	70%
Validation and test group		10%	20%	30%
Test 1	R (learning)	0.82	0.83	**0.92**
	$MSE{\cdot}10^{-4}$	0.12	0.93	**0.01**
Test 2	R (learning)	0.81	0.83	**0.90**
	$MSE{\cdot}10^{-4}$	0.74	0.15	**0.09**
Test 3	R (learning)	0.73	0.90	**0.93**
	$MSE{\cdot}10^{-4}$	0.41	0.67	**0.08**
Average of the 3 tests	R (learning)	0.79	0.85	**0.92**
	$MSE{\cdot}10^{-4}$	0.42	0.58	**0.06**

Source: own elaboration.

Table results analysis indicates that the best distribution of the database is that which includes 70% of the database for the training base (learning) and 30% for the validation and test base. In fact, with this distribution, we obtained the most significant correlation coefficient, which was closest to 1 (R = 0.92 – average of three tests), and the lowest mean squared error (MSE = $0.06{\cdot}10^{-4}$ – average of three tests) during the study.

ARTIFICIAL NEURAL NETWORKS

Presentation

Through their performance in environmental modelling and simulation, artificial neural networks are generally used in solving mathematical problems, specifically in statistical problems where variables are linked by non-linear relationships [EL AZHARI *et al.* 2017; EL BADAOUI *et al.* 2014a, b]. These neural networks, whose design is schematically inspired by the functioning of biological neurons, have found many applications in several fields, such as optimisation [FRENCH *et al.* 1992; GARDNER, DORLING 1998], estimation [HSU *et al.* 1997; HUBBARD *et al.* 2003; IMRAN *et al.* 2002], data simulation [KIMAJOU *et al.* 2012; LAAFOU *et al.* 2016], environmental parameters analysis [LUK *et al.* 2000; MAHMOOD, HUBBARD 2005; OMARI *et al.* 2016], and also in the fields of forecasting and prediction [PARISHWAD *et al.* 1998; RADHIKA, SHASHI 2009; ROJAS 1996; SANTHOSH BABOO, SHEREEF 2010; SMITH *et al.* 2006].

A neuron performs a non-linear transformation between the inputs and the output. In other words, a neuron performs a non-linear function of a combination of parameter-weighted X_i inputs (where w_i denotes the weights). The linear combination is called potential (n), to which is added a constant term w_0 or "bias". These networks are all composed of artificial neurons connected to each other [EL AZHARI *et al.* 2017; EL BADAOUI *et al.* 2014a, b].

A neural network typically consists of three layers of neurons (Fig. 2):
– a layer responsible for coding the information relating to the independent input variables; no calculation is done in this layer;
– one or more intermediate or hidden layers, where all optimisation calculations of neural network parameters are performed; the number of units in the middle layer is determined by the user based on the reliability of the expected results;
– an output layer loaded to estimate (calculate), the dependent variable (s) that are to be predicted [GARDNER, DORLING 1998].

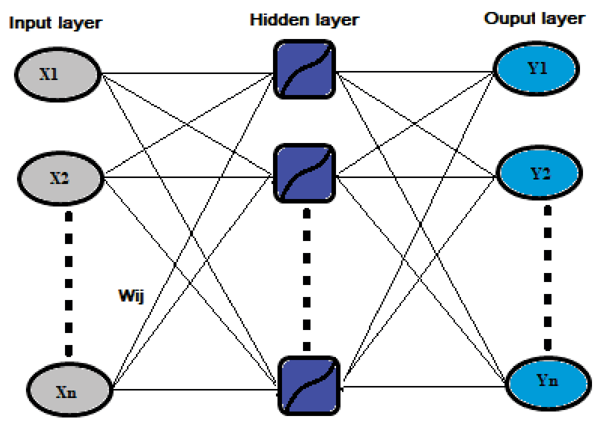

Fig. 2. Architecture of a neural network with three layers; source: own elaboration

Multilayer perceptron (MLP)

The multi-layered perceptron consists of an assembly of neurons distributed over several successive layers: an input layer, one or more hidden layers, and an output layer. Its neurons are characterised by the following features:
– each neuron of a layer receives signals from the previous layer and transmits the result to the next one if it exists;
– neurons of the same layer are not interconnected;
– a neuron can only send its result to a neuron located in a next layer;

For a multi-layered perceptron, all or some of the neurons in a layer are connected with all or some of the neurons in the adjacent layers. However, the number of hidden layers and the number of neurons per layer have a significant impact on model performance.

Statistical indices calculated

To assess the performance of the different types of ANN studied, two statistical indices were calculated for each type of ANN:
- The Pearson correlation coefficient (R), which is the square root of the coefficient of determination (R^2). It measures the intensity of the linear link between two variables, and is calculated with the equation:

$$R = \sqrt{1 - \frac{\sum_{j=1}^{N} \left(\hat{Y}_j - Y_j\right)^2}{\sum_{j=1}^{N} \left(\hat{Y}_j - Y_{\mathrm{avr}}\right)^2}} \tag{2}$$

where: $\hat{Y}_j$ = estimated value j for the variable Y; Y_j = observed j value of variable Y; j = varies from 1 to N; N = number of observations; Y_{avr} = average value of the variable Y calculated from the N observed values.

- The mean squared error (*MSE*), also called squared risk, which represents the arithmetic mean of the squares of the deviations between the observed values and the values estimated by a model.

The *MSE* is a measure of the quality of a model; it is always positive, and values closer to zero are considered better.

It is very useful for comparing several models. The most efficient model is simply the one with the smallest mean square error.

$$MSE = \frac{1}{N}\sum_{j=1}^{N}\left(\hat{Y}_j - Y_j\right)^2 \tag{3}$$

RESULTS AND DISCUSSION

EFFECT OF ARTIFICIAL NEURAL NETWORK TYPE

Referring essentially to the literature review, we have limited trials to six types of neural networks that have been shown to be effective in similar studies (Tab. 3). It presents the obtained values of the correlation coefficient and the mean square errors for six types of neural networks tested.

Table 3. Values of the performance indicators according to the type of artificial neural network (ANN)

ANN type	*R* (learning)	*MSE*·10^{-4}	Iteration
Multilayer perceptron (MLP)	**0.99**	**4.51**	**19**
Feed forward back propagation (FFBP)	0.89	8.31	33
Cascade forward backprop (CFB)	0.99	4.57	21
Elman backprop (EB)	0.83	4.90	28
Layer recurrent (LR)	0.62	5.77	25
Nonlinear autoregressive exogenous (NARX)	0.49	1.42	44

Explanations: *R* (learning) = Pearson correlation coefficient, *MSE* = mean squared error.
Source: own study.

Table 3 shows that the most effective model for predicting air humidity in the Rabat-Kenitra region is the multilayer perceptron network (MLP). Indeed, this network has a remarkably higher correlation coefficient, a lower *MSE*, and a lower number of iterations, compared to the other types of neural networks tested.

NUMBER OF NEURONS IN THE HIDDEN LAYER EFFECT

A network with only one intermediate layer is used to limit the calculation time, in particular when the expected results are satisfactory. Therefore, we tested the effect of the number of hidden neurons by varying their number from 1 to 20 neurons in the hidden layer according to the bibliography, and by remaining attentive to the general trend of performance.

Table 4 shows all the results relating to the values of the performance indicators depending on the number of neurons in the hidden layer (*HLN*).

Table 4. Values of performance indicators as a function of the number of neurons in the hidden layer (*HLN*)

HLN	*MSE*·10^{-4}	*R* (learning)	Iteration
1	3.20	0.84	154
2	2.01	0.85	209
3	0.83	0.85	31
4	1.75	0.86	19
5	2.71	0.89	86
6	7.68	0.87	121
7	1.02	0.90	22
8	6.06	0.91	209
9	1.53	0.90	8
10	5.03	0.93	22
11	**0.11**	**0.96**	**4**
12	0.54	0.92	18
13	4.14	0.93	29
14	0.27	0.89	14
15	0.16	0.92	65
16	1.36	0.91	143
17	0.66	0.91	15
18	3.16	0.89	5
19	1.35	0.90	25
20	0.71	0.92	132

Explanations as in Tab. 3.
Source: own study.

It is clear that the error decreases significantly when the number of neurons in the hidden layer amounts to 11 (*HLN* = 11 neurons) since the correlation coefficient indicates a convergence towards a higher and optimal value when the number of neurons in the hidden layer is equal to 11. Similarly, for this number of hidden neurons, we recorded the highest correlation coefficient (0.96), compared to those for other hidden neuron numbers, ranging between 1 and 20. In addition, the number of iterations in the learning sequence noted in this case is optimised to 4.

Figure 3 describes the evolution of the mean squared error of the three phases of learning (training), validation, and testing with 11 neurons in the hidden layer.

It shows that for the three phases the curves converge correctly, towards the minimum *MSE*.

ACTIVATION FUNCTIONS EFFECT

The multilayer perceptron (PMC) uses nonlinear and linear activation functions; widely used functions have the following syntax in MATLAB:

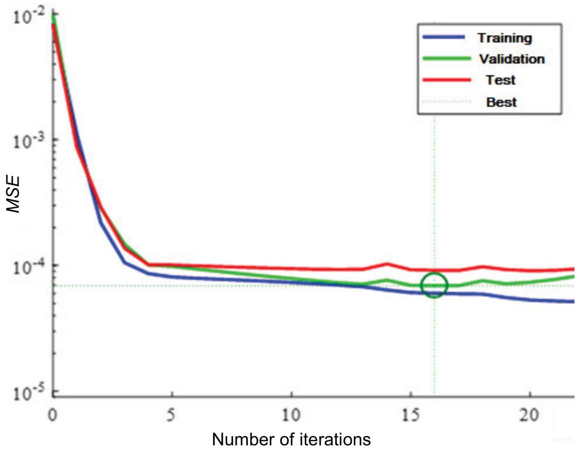

Fig. 3. Evolution of mean squared error with 11 neurons in the hidden layer; source: own study

– Hyperbolic tangent: Tansig;
– Sigmoid: Logsig;
– Linear: Purelin.

The results obtained by combining the different transfer functions in the hidden layer and the output layer for the MLP model are presented in Table 5.

Table 5. Values of the performance indicators of the models developed by the multi-layer perceptron-type neural network for different transfer functions in the hidden layer and the output layer

Hidden layer	Output layer	*R* (learning)	$MSE{\cdot}10^{-4}$
Tansig	Tansig	0.98	1.12
Tansig	Logsig	0.93	1.18
Tansig	**Purelin**	**0.98**	**0.96**
Logsig	Logsig	0.93	10.65
Logsig	Tansig	0.68	0.94
Logsig	Purelin	0.92	1.21
Purelin	Purelin	0.96	3.55
Purelin	Logsig	0.96	13.02
Purelin	Tansig	0.96	3.11

Explanations as in Tab. 3.
Source: own study.

From the analysis of the results presented in this table, the best performance emerges for the pair of Tansig-Purelin transfer functions; that is to say, with a Tansig function in the hidden layer and the Purelin function in the output layer. Indeed, for this pair of functions, we recorded the highest correlation coefficient and the lowest mean squared error.

LEARNING ALGORITHM EFFECT

The performances of approximately ten of the most efficient algorithms in the field of meteorological modelling were compared for the training of predictive models.

- **One step secant (OSS) algorithm**

This is a quasi-Newtonian method with the advantage of not storing the complete Hessian matrix. To avoid the calculation of the inverse matrix, this one step secant algorithm assumes that at each iteration, the preceding Hessian is the identity matrix.

- **Batch gradient descent with inertial term (momentum)**

In most cases, if the error function has more than one local minimum, the network will be stuck in one of them or in a region where the error surface is flat. To do this, researchers introduced a momentum term α in the back propagation learning rule which acts as a low pass filter, and which eliminates tiny variations on the error surface to prevent the network from being arrested at a local minimum.

- **Conjugate gradient algorithms**

The search in the methods of conjugate algorithms is done in conjugate directions instead of the direction opposite to that of the gradient of the cost function. These algorithms are characterised by their convergence speeds, which are much higher than that of conventional gradient algorithms [El Badaoui *et al.* 2014a, b; Laafou *et al.* 2016]. According to El Badaoui *et al.* [2014a, b], there are many types of conjugate gradient algorithms that can be used for training, such as:

– conjugate scalar gradient (CSG);
– gradient conjugated with Fletcher-updates Reeves (FR);
– gradient combined with Polak–Ribière (PR).

- **Resilient back propagation**

The resilient back propagation algorithm is used to eliminate the harmful effects of the moduli of partial derivatives, especially for neural networks using the sigmoid function as transfer functions.

- **Bayesian regularisation-backpropagation (BR-BPNN)**

This learning algorithm is used to predict some aspects of the gecko spatula detachment, such as the variation of the maximum normal and tangential withdrawal forces and the force angle resulting in the detachment with the peel angle.

- **Random weight/bias rule (NR)**

It generally uses some form of gradient descent method, which are known to be long, sensitive to initial parameter values, and converging to local minima.

- **Levenberg–Maquardt (LM)**

It is an improvement of the classical Gauss–Newton numerical method in solving optimisation and nonlinear least squares regression problems. The LM is the recommended method for nonlinear least squares regression problems because it is the most efficient compared to optimisation algorithms.

We tested the performance of these algorithms. In Table 6, we presented the summary of these tests. It displays the values of the performance indicators of the models developed by the PMC type neuron network according to the learning algorithms studied.

The results clearly show that the Levenberg–Marquardt learning algorithm delivers the best performance. With this algorithm, we obtained the best correlation coefficient and the lowest mean squared error, in comparison with the other algorithms studied.

SUMMARY OF THE BEST PERFORMANCE OF THE NEURAL MODEL

The results compared in Table 7 show that the models established by the RNAs are clearly efficient, whether it is for the learning or testing phase.

Correlation coefficients obtained by testing the validity of the models established by the ANNs are clearly close to those

Table 6. Values of the performance indicators of the models developed by the multi-layer perceptron-type neural network according to the learning algorithms studied

Learning algorithm	*R* (learning)	$MSE{\cdot}10^{-4}$
One step secant (OSS)	0.94	0.74
Batch gradient descent with inertial term (momentum)	0.87	3.11
Gradient conjugate scalar (GCS)	0.97	2.08
Gradient conjugated with Fletcher-up-dates Reeves (FR)	0.96	0.35
Gradient combined with Polak–Ribière (PR)	0.97	0.20
Backpropagation (RProp)	0.97	0.22
Gradient descent (GD)	0.88	10.35
Bayesian regularisation-backpropagation (BR-BPNN)	0.96	10.16
Random weight/bias rule (NR)	0.95	0.54
Levenberg–Marquardt (LM)	**0.98**	**0.08**

Explanations as in Tab. 3.
Source: own study.

Table 7. Performance indices obtained by multiple regression for the phases

Phase	*R*	$MSE{\cdot}10^{-4}$
Learning	0.98	0.08
Test	0.96	0.21

Explanations as in Tab. 3.
Source: own study.

related to learning. This shows a very good correlation between the simulated and observed values with very good statistical indicators, as well as the predictive advantage of these models established by artificial neural networks in predicting relative humidity levels in the Rabat-Kenitra region.

ARCHITECTURE AND EQUATION OF THE ANN MODEL

- **Architecture of the RNA model**

The most efficient network, developed for the prediction of the relative humidity of the Rabat-Kénitra region from meteorological parameters, has a [5-11-1] configuration and therefore contains (Fig. 4):

– 5 neurons in the input layer which correspond to the meteorological parameters;
– 11 neurons in the hidden layer;
– 1 neuron in the output layer which corresponds to the rate of relative humidity.

- **Equation obtained with the ANN model**

Then, the equation obtained by the most efficient PMC type RNA model of configuration [5-11-1] is:

$$Y = \mathrm{Purelin}\left(\mathrm{LW}_{2,1}\left(\mathrm{Tansig}\ \left(\mathrm{IW}_{1,1}\ X + \theta_1\right)\right) + \theta_2\right) \qquad (4)$$

where: Y = relative humidity value, calculated by the network (estimated value); X = row vector representing the row of inputs

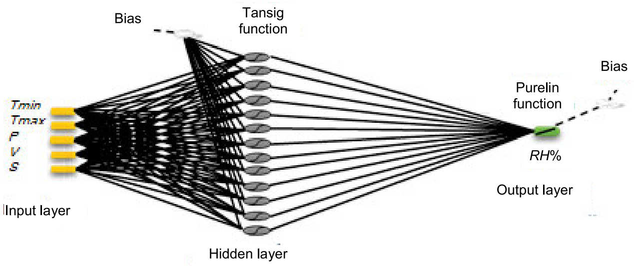

Fig. 4. Architecture of the neural network with three configuration layers [5-11-1] developed for the prediction of relative humidity (*RH*) in the region of Rabat-Kenitra; source: own study

received by the network; it is the vector representing the independent variables (meteorological parameters); $\mathrm{LW}_{2,1}$ = matrix of connection weights linking the hidden layer to the output layer; $\mathrm{IW}_{1,1}$ = matrix of connection weights linking the input layer to the hidden layer; Tansig = hidden layer activation function; Purelin = output layer activation function; θ_1 = bias of the hidden layer; θ_2 = bias of the output layer.

The determination of the parameters of the model is performed according to a calculation algorithm. The purpose of this calculation is the minimisation of the error function (*MSE*) between the desired (observed) values and the responses to the output of the model (estimated).

PERFORMANCE EVALUATION OF THE ESTABLISHED MODEL

We tested the performance of our network with another performance indicator, which is the schematic presentation of the values observed as a function of the estimated values. Figure 5 represents the relationship between the estimated values using an MLP type neural model of configuration [5-11-1] and the values observed in the Rabat-Kenitra region.

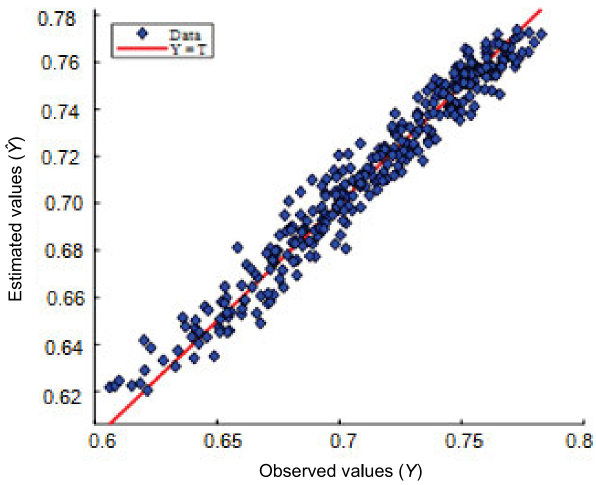

Fig. 5. Relationship between the estimated values ($\hat{Y}$) and the observed values (Y) using a neural configuration model [5-11-1] in the Rabat-Kénitra region; source: own study

It clearly shows the predictive power of this model in predicting humidity levels in this region. This performance is evaluated by a correlation coefficient (R = 0.98) for all the total data. This predictive power developed by PMC type ANNs is in perfect agreement with the results obtained by SMITH *et al.* in [2006] for the prediction of air temperature, and those obtained by El Badaoui *et al.* [2014 a, b], to predict the humidity rate in the Chefchaouen region (Morocco), as well as those obtained by Ben El Houari [2015], concerning the forecast of the air temperature of the city of Meknes (Morocco). These mathematical models developed by these authors, as well as our relevant model, use a Levenberg–Marquardt type learning algorithm.

In addition, the correlation coefficient, obtained by testing the validity of our model established by the ANNs, is much closer to that linked to learning. This shows a very good correlation between the simulated and observed values with a very good correlation coefficient. This demonstrates the advantage of our predictive model established for the calculation of the relative humidity rate in the Rabat-Kenitra region.

CONCLUSIONS

As part of this study, we sought to develop an efficient mathematical model based on artificial neuron networks, for the prediction of relative humidity rates from meteorological parameters of the region of Rabat-Kenitra.

To determine the most efficient and effective model, we studied the effects of the type of artificial neural network, the number of neurons in the hidden layer, activation functions, and the learning algorithm on the efficiency of the developed mathematical model. This was done by calculating and comparing the correlation coefficients and the mean squared errors.

Thus, we have shown that the model based on artificial neuron networks of the multilayer perceptron (PMC) type, of configuration [5-11-1], using a Levenberg–Marquardt learning algorithm with a nonlinear activation function of the Tansig type in the hidden layer, and a linear activation function of the Purelin type in the output layer, is more efficient than the other models studied within the framework of this study.

The performance of this model can be considered an important tool, having high efficiency in the field of the prediction of relative humidity levels in the region of Rabat-Kenitra.

The robustness of our model consists in its performance in predicting the daily rate of relative humidity from five meteorological parameters with a 35-year learning process, which suggests that it can be relied on to predict this variable for periods of drought as well as for wet periods. Our model allows the prediction of daily relative humidity from climatological parameters over a long period thanks to the representativeness of our database that spans 35 years.

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