Development of a Neural Statistical Model for the Relative Humidity Levels Prediction in the Region of Rabat-Kenitra (Morocco)

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Development of a neural statistical model for the relative humidity levels prediction in the region of Rabat-Kenitra (Morocco)

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Abstract

This work provides the development of a powerful artificial neural network (ANN) model, for the prediction of relative humidity levels, using other meteorological parameters of the Rabat-Kenitra region. The treatment was applied to a database containing a daily history of five meteorological parameters of 9 stations covering this region for a period from 1979 to mid-2014.

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

Key words — Modeling; ANN; MLP, learning algorithm; Relative humidity; Rabat-Kenitra.

I. Introduction

For a coastal zone, the problem of excessive humidity is a constant concern, especially for vulnerable people, for industries such as the building industry, the pharmaceutical sector, etc. In fact, Excessive moisture causes several types of allergic reactions, deterioration, mold formation, rapid corrosion and mechanical damage. The limit value of humidity excessive is

set at 75% relative humidity. The need to control and predict variations in this environmental parameter is considered as a major challenge.

Different scientific studies affirmed the effectiveness of networks of artificial neurons (ANN) in the data processing, simulation and the modelling of the relations which control correlations between environmental parameters. These neural networks have been used successfully in several domains, such as the image processing, optimization, forecasting and prediction in general. In fact, they are considered as information processing techniques, which are established concretely by algorithms involving concepts associated with the nature of the brain for the notion of learning.

In bibliography, we cite as examples some prediction work using, among others, MLP (Multi-Layer Perceptron) artificial neural network type:

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

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

Kemajou and al. **[Kemajou et al., 2012]** developed a neural model to predict the hourly indoor air temperature seven hours in advance in modern buildings and in hot and humid climate.

Turkan and al. **[Turkan et al. 2016]** predicted the average daily temperature and average relative humidity in a teaching building in a hot and humid city in Turkey by applying artificial neural networks. The values of the correlation coefficient obtained between the predicted values and the actual values were considered by the authors to be significantly important.

In 2014, El Badaoui and his collaborators **[El Badaoui and al., 2014]**, treated 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 of the radial basis function type for the prediction of the humidity rate of the city of Chefchaoun in Morocco.

Ben El Houari and al. **[Ben El Houari and al. 2014; 2015; 2016]** 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 developed and to justify the choice of learning algorithms, numbers of hidden layers and neurons and activation functions.

Otherwise, Ben El Houari et al. **[Ben El Houari and al., 2016]** used the self-organizing maps based on artificial neural networks to identify classes of similar objects in a database containing meteorological parameters of Meknes city (Morocco). Acquired results allowed classifying the 216 months corresponding to the period of their study into three classes, according to the meteorological parameters: A class, made up of 76 months, characterized by fairly high averages of temperature, relative humidity and wind speed. A second class consisting of 56 months, categorized by low averages of temperature, heavy rainfall and relative humidity. A third class consisting of 84 months characterized by very high temperatures and low values of relative humidity, precipitation and wind speed.

Furthermore, and regarding relative humidity, it largely depends on many meteorological parameters **[Bimal and al., 2011]** especially temperature: the higher the air temperature, the more water vapor it can contain.

In the present work, 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 that the maximum of temperature, minimum of temperature, precipitation, wind speed and intensity of solar radiation.

II. Materials and methods

II. 1 Database description

The database used for this study consists of the daily values of six meteorological variables, recorded between 01/01/1979 and 07/21/2014, in 9 stations installed in three parallel rows in the region of Rabat-Kenitra (Morocco) (Fig. 1). Hence, 12,986 days for each station.

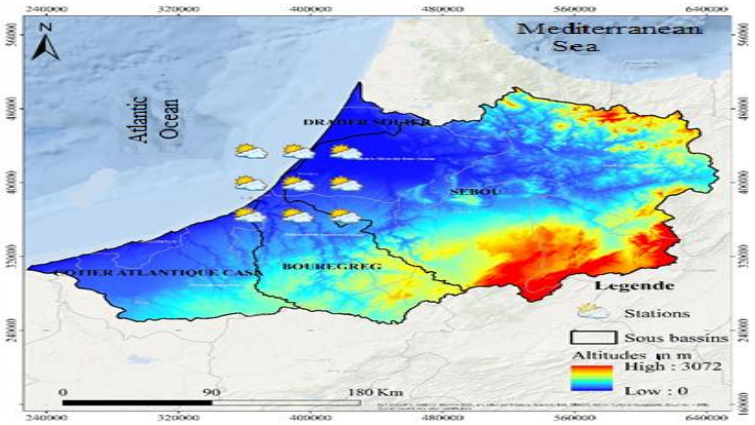

Fig. 1 : Map of meteorological stations location in the Rabat-Kenitra region (Morocco).

The six variables include:

- Five independent (explanatory) variables: maximum of temperature, minimum of temperature, precipitation, wind speed, intensity of solar radiation.
- A dependent variable (to be predicted): the humidity rate (the relative humidity).

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

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

Meteorological parameters	Symbol	Unit	Notation	Types of variable
Maximum of temperature	T_{max}	°C	X_1	Independent variables
Minimum of temperature	T_{min}	°C	X_2	
Precipitation	Pr	mm	X_3	
Wind speed	V	m/h	X_4	
Intensity of solar radiation	S	MJ/m^2	X_5	
Relative humidity	HR	%	Y	Dependent variable

II. 2 Normalization 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 homogenization of these values, which will be propagated in the artificial neuron

network, the database has undergone a pre-processing, which consists in carrying out an appropriate normalization taking into account the amplitude of the values accepted by the network **[Dombayc and al., 2009].**

So, the values of the independent variables and those of the dependent variable were normalized in the interval [-1; 1], relative to their minimum and maximum values, applying the following normalization equation: **[El Badaoui and al., 2014]**:

$$\overline{\mathbf{X}}_{\boldsymbol{i}} = \frac{2\left(X_{\boldsymbol{i}} - X_{i(min)}\right)}{\left(X_{i(max)} - X_{i(min)}\right)} - 1$$

Avec : $\overline{\mathrm{X}}_i$: Normalized values of the variable i;

$X_{\boldsymbol{i}}$: Gross values, non-normalized 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: one group for training and another to test the trained network and determine its performance.

For it, we randomly divided our database into two groups according to well-defined percentages. Table 2 presents the values of the correlation coefficients and the mean square errors obtained for each distribution of the database and this for three different tests.

Tab.2 : Correlation coefficients (R) and mean square errors (MSE) for each database distribution.

Training group		90%	80%	70%
Validation et test group		10%	20%	30%
Test 1	**R**	0,82	0,83	**0,92**
	MSE x 10^{+4}	0,12	0,93	**0,01**
Test 2	**R**	0,81	0,83	**0,90**
	MSE x 10^{+4}	0,74	0,15	**0,09**
Test 3	**R**	0,73	0,90	**0,93**
	MSE x 10^{+4}	0,41	0,67	**0,08**
Average of the 3 tests	**R**	0,79	0,85	**0,92**
	MSE x 10^{+4}	0,42	0,58	**0,06**

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 during the apprenticeship the most important correlation coefficient and the closest to 1 (R = 0.92 - average of 3 tests) and the lowest mean square error (MSE = $0{,}06 \times 10^{-4}$ - average of 3 tests).

II. 3 Artificial Neural Networks

II.3.1. Introduction :

Through their performance in environmental modeling and simulation, artificial neural networks are generally used in solving problems of a mathematical nature and precisely in statistical problems where variables are linked by non-linear relationships **[El Azhari and al. 2017; El Badaoui and al., 2014]**. These neural networks, whose design is schematically inspired by the functioning of biological neurons, have found many applications in several fields.: optimization **[French and al., 1992; Gardner and al., 1998]**, estimation **[Hsu and al., 1997; Hubbard and al., 2003; Imran and al., 2002]** data simulation **[Kemajou and al., 2012; Laafou and al., 2016],** environmental parameters analysis **[Luk and al., 2000; Mahmood and al., 2005; Omari and al., 2016]** , and also in the fields of forecasts and predictions **[Parishwad and al., 1998; Radhika and al., 2009; Rojas R., 1996; Santhosh and al., 2010; Smith and al., 2006; Turkan and al., 2012; Trahi, 2011].**

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 are 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 by connections **[El Azhari and al., 2017; El Badaoui and al., 2014]**.

A neural network typically consists of three layers of neurons. (Fig. 2):

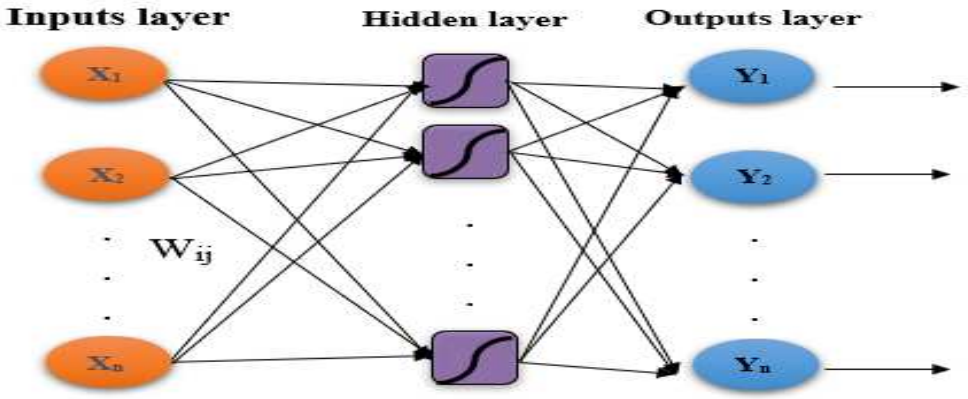

Fig. 2 : Architecture of a neural network with 3 layers.

- A layer responsible for coding the information relating to the independent input variables. In this layer no calculation is done.
- One or more intermediate or hidden layers, where all optimization 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) to predict **[Gardner and al., 1998]**.

II.3.2. 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 characterized by:

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

II.3.3. 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 correlation coefficient of Person (R), which is the square root of the coefficient of determination (R^2). It measures the intensity of the linear link between two variables, it is given by the relation:

$$R = \sqrt{1 - \frac{\sum_j (\hat{Y}_j - Y_j)^2}{\sum_j (Y_j - Y_{avr})^2}}$$

$\hat{Y}_j$ 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_{aver} : Average value of the variable Y calculated from the N observed values.

- ✓ The mean squared error also called squared risk, which we will denote by MSE: it represents the arithmetic mean of the squares of the deviations between the observed values and the values estimated by a model.
The mean square error is a measure of the quality of a model; it is always positive, and values closer to zero are better.
It is very useful for comparing several models. The most efficient model is simply the one with the smallest mean square error.

$$\mathbf{MSE} = \frac{\mathbf{1}}{\mathbf{N}} \sum_{\mathbf{j=1}}^{\mathbf{N}} (\hat{\boldsymbol{Y}}_{\boldsymbol{j}} - \boldsymbol{Y}_{\boldsymbol{j}})^{\mathbf{2}}$$

III. Results and Discussion

III. 1 ANN type effect

Referring essentially to the literature review, we have limited trials on six types of neural networks that have been shown to be effective in similar studies (Table 3). It presents the obtained values of the correlation coefficient and the mean square errors for 6 types of neural networks tested.

Tab.3 : Values of the performance indicators according to the type of ANN.

ANN type	R	MSE x 10^{+5}	Iteration
Multilayer Perceptron (MLP)	**0,99**	**4,51**	**19**
Feed-forward distribut time delay (FFDTD)	0,89	8,31	33
Cascade forward backprop (CFB)	0,99	4,57	21
Elman bacprop (EB)	0,83	4,90	28
Layer reccurent (LR)	0,62	5,77	25
NARX	0,49	1,42	44

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 type has a remarkably higher correlation coefficient, a lower MSE and a lower number of iterations, compared to those relating to the other types of neural networks tested.

III. 2 Number of neurons in the hidden layer effect

To limit the calculation time and in particular when the expected results are satisfactory, a network with only one intermediate layer is used. Therefore, we tested the effect of the number of hidden neurons by varying their number from 1 to 20 neurons in the hidden layer.

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

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

HLN	MSE $x10^{+4}$	R	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

It is clear that the error decreases significantly when the number of neurons in the hidden layer is 11 neurons (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 largest correlation coefficient (0.96), compared to those for other hidden neuron numbers, between 1 and 20. In addition, the learning duration (learning sequence) noted here number of iterations is optimized to 4.

In addition, Figure 3 describes the evolution of the average quadratic error of the three phases of learning (train), validation and testing with 11 neurons in the hidden layer.

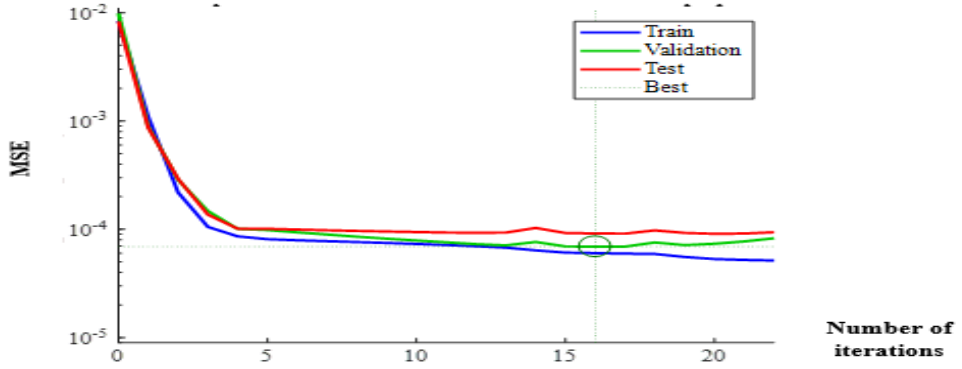

Fig. 3 : Evolution of average quadratic error with 11 neurons in the hidden layer.

It shows that for the three phases the curves converge correctly, towards the minimum mean square error (MSE).

III. 3 Activation functions effect

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

- ✓ 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 given in table 5.

Tab.5 : Values of the performance indicators of the models developed by the MLP-type neural network for different transfer functions in the hidden layer and the output layer.

Hidden layer	Output layer	R	MSE
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	0,98	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

From the analysis of the results of 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 largest correlation coefficient and the lowest mean squared error.

III. 4 Learning algorithm effect.

The performances about ten of the most efficient algorithms in the field of meteorological modeling were compared for the training of predictive models. These algorithms are:

III.4.1. 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.

III.4.2. Batch gradient descent with inertial term (momentum):

In most cases, if the error function has more than one local minima 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 avoid imprisonment in a local minimum.

III.4.3. 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 characterized by their convergence speeds much higher than that of conventional gradient algorithms **[El Badaoui and al., 2014], [Laafou and al., 2016].** There are many types of conjugate gradient algorithms that can be used for training such us: **[El Badaoui and al., 2014]**:

- ✓ **Conjugate Scalar Gradient (CSG) ;**
- ✓ **Gradient conjugated with Fletcher-updates Reeves (FR) ;**
- ✓ **Gradient combined with Polak-Ribière (PR).**

III.4.4. 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.

III.4.5. Bayesian regularization-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.

III.4.6. 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.

III.4.7. Levenberg-Maquardt (LM)

It is an improvement of the classical Gauss-Newton numerical method in solving optimization and nonlinear least squares regression problems. The method is presented in detail by Moré in 1977. It is the recommended method for nonlinear least squares regression problems, because it is the most efficient compared to optimization algorithms.

We tested the performance of these algorithms. In table 6, we present 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.

Tab.6 : Values of the performance indicators of the models developed by the MLP type neural network according to the learning algorithms studied.

Learning algorithme	**R**	**MSE** x 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-updates 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 regularization-backpropagation (BR-BPNN)	0,96	10,16
Random Weight/Bias Rule (NR)	0,95	0,54
Levenberg-Marquardt (LM)	**0,98**	**0,08**

From the results, it is clear that the Levenberg Marquardt learning algorithm has 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.

III. 5 Summary of the best performance of the neural model

The results compared in Table III.9, show that the models established by the RNAs are clearly efficient whether it is for the learning or testing phase.

Tab.7 : Indices de performances obtenues par RLM pour les phases

Phases	R	MSE x 10^{+4}
Learning	0.98	0.08
Test	0.96	0.21

Correlation coefficients obtained by testing the validity of the models established by the ANNs are clearly close to those relating to learning. This shows a very good correlation between the simulated and observed values with a very good statistical indicators. This shows, the predictive advantage of these models established by artificial neural networks in predicting relative humidity levels in Rabat-Kenitra region.

III. 6 Architecture and equation of the ANN model.

III.6.1 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 configuration [5-11-1] 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.

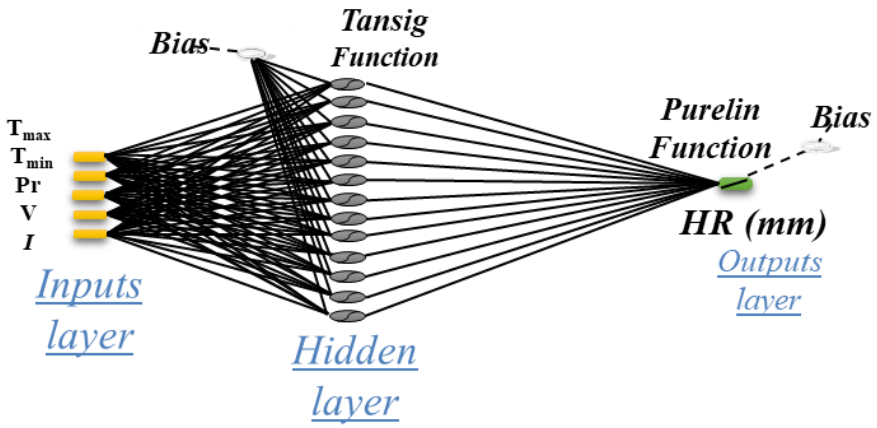

Fig. 4 : Architecture of the neural network with three configuration layers [5-11-1] developed for the prediction of relative humidity in the region of Rabat-Kenitra.

III.6.2 Equation obtained with the ANN model:

Then, the equation obtained by the most efficient PMC type RNA model of configuration

[5-11-1] is:

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

- Y : Relative humidity value, calculated by the network (estimated value);
- X : Row vector representing the row of inputs received by the network; it is the vector representing the independent variables (meteorological parameters) ;
- $\text{IW}_{1,1}$: Matrix of connection weights linking the input layer to the hidden layer;
- $\text{LW}_{2,1}$: Matrix of connection weights linking the hidden layer to the output layer;
- Tansig : Hidden Layer Activation Function;
- Purelin : Output layer activation function;
- $\boldsymbol{\theta}_1$: Bias of the hidden layer;
- $\boldsymbol{\theta}_2$: Bias of the output layer.

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

III. 7 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 a MLP type neural model of configuration [5-11-1] and the values observed in the Rabat-Kenitra region.

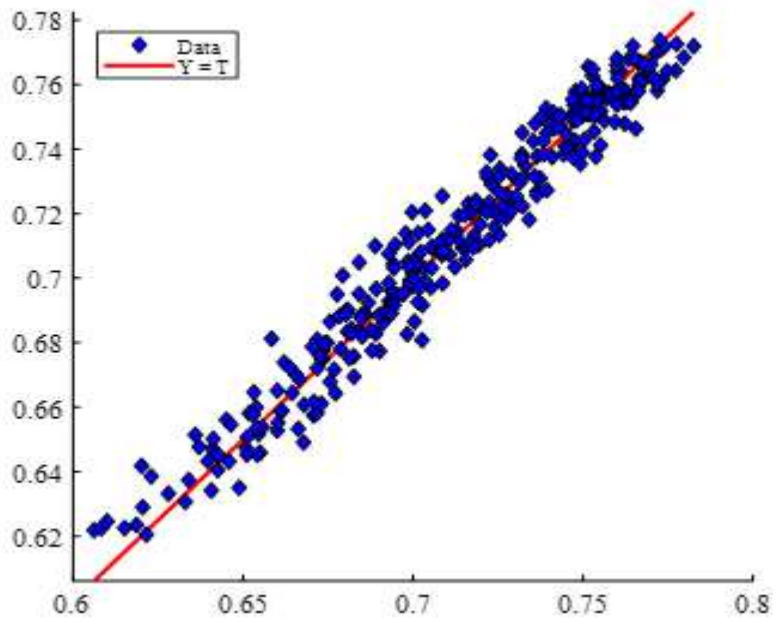

Fig. 5 : Relationship between the estimated values ($\hat{Y}$) using a neural configuration model [5-11-1] and the observed values (Y) in the Rabat-Kénitra region.

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 found by Smith and al. in 2006 for the prediction of air temperature **[Vassiliki and al., 2013]**, and those found in 2014 by El Badaoui and al., to predict the humidity rate in the Chefchaouen region (Morocco) **[Ben El Houari and al., 2014]**, as well as those found in 2015 by Ben El Houari et al. **[Ben El Houari and al., 2016]**, 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 proves the advantage of our predictive model established for the calculation of the relative humidity rate in the Rabat-Kenitra region.

IV. CONCLUSION

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, the learning algorithm on the efficiency of the developed mathematical model; and this 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 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 the more efficient than the other models studied within the framework of this study.

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

-Ethical Approval: We do not need research data support or it is not applicable;

-Consent to Participate: All participants provided informed consent to participate and to have the results disseminated in a variety of ways;

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  - C - statistical analysis

- D - data interpretation
- E - manuscript preparation
- F - literature search

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- B - data interpretation
- C-manuscript preparetion

☞ Ali DEHBI1:

- A - study design
- B - manuscript preparation
- C- literature search

☞ Abdelaziz ABDALLAOUI:

- A - study design
- B - data collection
- C - statistical analysis
- D - data interpretation
- E - manuscript preparation
- F- literature search

☞ Hamid ZINEDDINE:

- A - study design
- B - data interpretation
- C - manuscript preparation
- D- literature search

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-Availability of data and materials: Available.

Références

- Abdallaoui A. & El Badaoui H., 2011. Intelligences artificielles pour modéliser les données météorologiques. Éditions Universitaires Européennes. 216 p.
- Abhishek K., Singh M. P., Ghosh S., Anand A., 2012. Weather forecasting model using Artificial Neural Network, Computer Science and Engineering Department, NIT Patna, Inde, Technology Process, vol. 4, 311 – 318.
- Alayat H., El Badaoui H., Abdallaoui A., Abrid D., El Hmaidi A., 2018. Development of mathematical models for predicting the iron concentrations of Lake Oubeira waters (NE ALGERIAN). J. Fundam. Appl. Sci., 2018, 10 (1), 83-96.
- Ben El Houari M., Zegaoui O., Abdallaoui A., 2014. Development of Mathematical Models to Forecasting The Monthly Precipitation, American Journal of Engineering Research (AJER), Volume 3, Issue 11, 38-45.
- Ben El Houari M., Abdallaoui A., Zegaoui O., 2016. Forecasting of the ambient air temperature using the artificial neural networks, International Journal of Multi-disciplinary Sciences (IJMS), Volume 3, Issue 2, 14-19.
- Ben El Houari M., Zegaoui O., Abdallaoui A., 2015. Prediction of air temperature using Multi-layer perceptrons with Levenberg-Marquardt training algorithm, International Research Journal of Engineering and Technology (IRJET), Volume 2, Issue 8, 26-32.
- Ben El Houari M., Zegaoui O., Abdallaoui A., 2016. The use of Kohonen self-organizing maps to study meteorogical parameters in Meknes city (Morocco), International Journal of Scientific & Engineering Research (IJSER), Volume 7, Issue 7, 608-612.
- Ben El Houari M., Zegaoui O., Abdallaoui A., 2016. Development of Multilayer Perceptron and Radial Basis Function Artificial Neural Network models for forecasting the monthly air temperature. Advances in Information Technology: Theory and Application, 1 (1), 147-152.
- Bimal D., Susanta M., 2011. Better Prediction of Humidity using Artificial Neural Network, Fourth International Conference on the Applications of Digital Information and Web Technologies. IEEE 59-64.
- Bishop C. M., 1995. Neural networks for pattern recognition," Oxford, Presse universitéaire, 498 p.
- Dedecker A., Peter L., Goethals M., Gabriels W., De Pauw N., 2002. Optimisation of Artificial Neural Network (ANN) model design for prediction of macroinvertebrate communities in the Zwalm river basin (Flanders, Belgium). The Scientific World Journal, 2, 96-104.
- Dombayc O. A., Golcu M., 2009. Daily means ambient temperature prediction using artificial: a case study of Turqy. Energie renevlable, 34, 1158-1161.
- El Badaoui H., Abdallaoui A., Chabaa S., 2014. Multilayer Perceptron and Radial Basis Function Grating for Moisture Prediction. International Journal of Innovation and Scientific Research, volume 5 (1), 55-67.

- El Azhari K., El Badaoui H., Abdallaoui A., Zineddine H., 2017. Optimization of neural architectures for prediction of heavy metal concentrations in Red Sea sediments. International Journal of Scientific & Engineering Research Volume 8, Issue 7, 906-912.
- El Badaoui H., Abdallaoui A., Chabaa S., 2014. Using MLP neural networks for predicting global solar radiation. The International Journal of Engineering and Science (IJES), volume 2 (12), 15-26.
- French, M. N., Krajewski, W. F., Cuykendal, R. R., 1992. Rainfall forecasting in space and time using a neural network. Journal d'Hydrologie, 137, 1–37.
- Gardner M. W., Dorling S. R., 1998. Artificial Neural Networks (the Multilayer Perceptron)—A Review of Applications in the Atmospheric Sciences. Environnement Atmosphérique, 32, 2627-2636.
- Hsu, K., Gao X., Sorooshain, S., Gupta, H. V., 1997. Precipitation estimation from remotely sensed information using artificial neural networks. Journal de metéorologie appliquée, 36(9), 1176–1190.
- Hubbard, K. G., Mahmood R., Carlson C., 2003. Estimation of daily dew point temperature in the northern Great Plains using maximum and minimum temperatures. Agron. J., 95, 323-328.
- Imran T., Shafiqur R., Khaled B., 2002. Application of neural networks for the prediction of hourly mean surface temperatures in Saudi Arabia. Renewable Energy. Vol 25, 545-554.
- Kemajou A., Léopold MBA, Meukam P., 2012. Application of artificial neural network for predicting the indoor air temperature in modern building in humid region. British Journal of Applied Science & Technology. Vol 2 (1), 23-34.
- Laafou S., Omari H., Abdallaoui A., 2016. Application of artificial neural networks with error back-propagation algorithm to predict nitrate levels in water. Advances in Information Technology: Theory and Application, 1 (1), 135-140.
- Lu T., Viljanen M., 2009. Prediction of indoor temperature and relative humidity using neural network models: model comparison. Journal de l'informatique neuronale et applications. Vol 18, 345–357.
- Luk, K. C., Ball J., Sharma A., 2000. A study of optimal model lag and spatial inputs to artificial neural network for rainfall forecasting. Journal d'Hydrologie, 227, 56-65.
- Mahmood, R., Hubbard K. G., 2005. Assessment of bias in estimates of evapotranspiration and soil moisture through the use of modeled solar radiation and dew point temperature data. Agriculture and forest Meteorology, 130, 71-84.
- Omari H., Abdallaoui A., Laafou S., 2016. Multilayer perceptron neural networks with error back-propagation algorithm for the prediction of nitrate concentrations in groundwater. The International Journal of Multi-disciplinary Sciences, 3 (2), 1–7.
- Parishwad G. V., Bhardwaj R. K., Nema V.K., 1998. Prediction of monthly-mean hourly relative humidity, ambient temperature, and wind velocity for India. Renew Energy. Vol 13(3), 363–380.
- Radhika Y., Shashi M., 2009. Atmospheric Temperature Prediction using Support Vector Machines," International Journal of Computer Theory and Engineering, Vol. 1, No. 1, 1793-8201.

- Rojas R., 1996. Neural Networks. A Systematic Introduction. Springer-Verlag, Berlin, 509 p.
- Santhosh Baboo S., Shereef I. K., 2010. An Efficient Weather Forecasting System using Artificial Neural Network. International Journal of Environmental Science and Development, Vol. 1, No. 4, ISSN: 2010-0264.
- Smith, B. A., McClendon R. W., Hoogenboom G., 2006. Improving air temperature prediction with artificial neural networks. Journal international d'intelligence computationnelle, 3, 179-186.
- Turkan G. Ö., Sezer A., Yıldız Y., 2012. Models for Prediction of Daily Mean Indoor Temperature and Relative Humidity: Education Building in Izmir, Turkey. Indoor Built Environ vol 21 (6), 772–781.
- Trahi F., 2011. Prédiction de l'irradiation solaire globale pour la région de Tizi-Ouzou par les réseaux de neurones artificiels. Application pour le dimensionnement d'une installation photovoltaïque pour l'animation du laboratoire de recherche LAMPA, Magister en électronique, Université de Tizi-Ouzou, 113 p.
- Vassiliki Mantzari H., Dimitrios Mantzaris H., 2013. Solar radiation: Cloudiness forecasting using a soft computing approach, Artificial Intelligence Research, volume 2, 69-80.

Figures

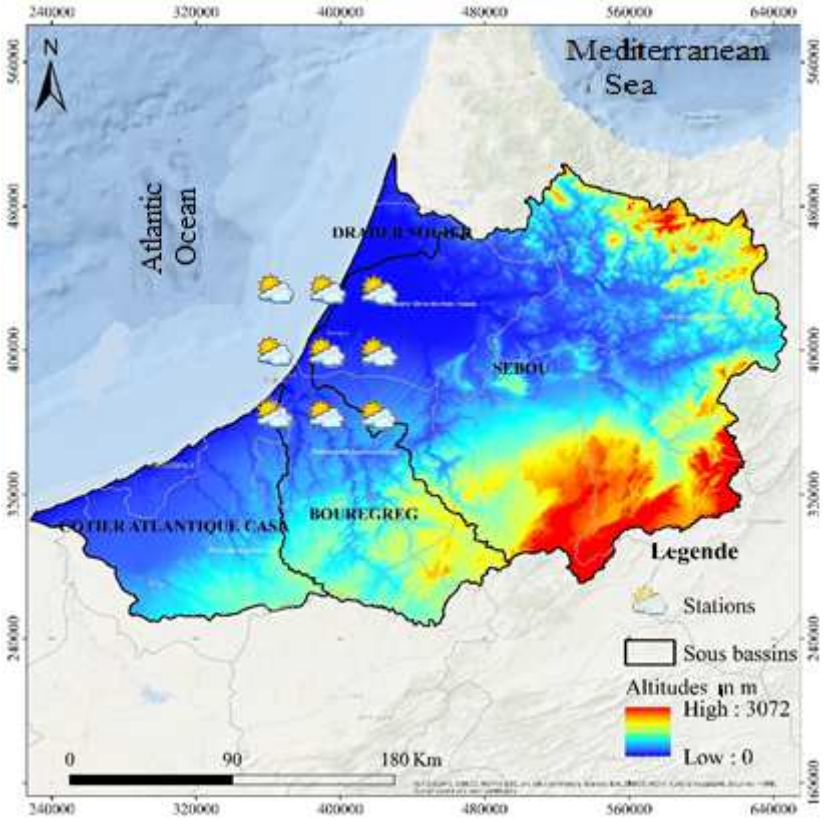

Figure 1

Map of meteorological stations location in the Rabat-Kenitra region (Morocco). Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

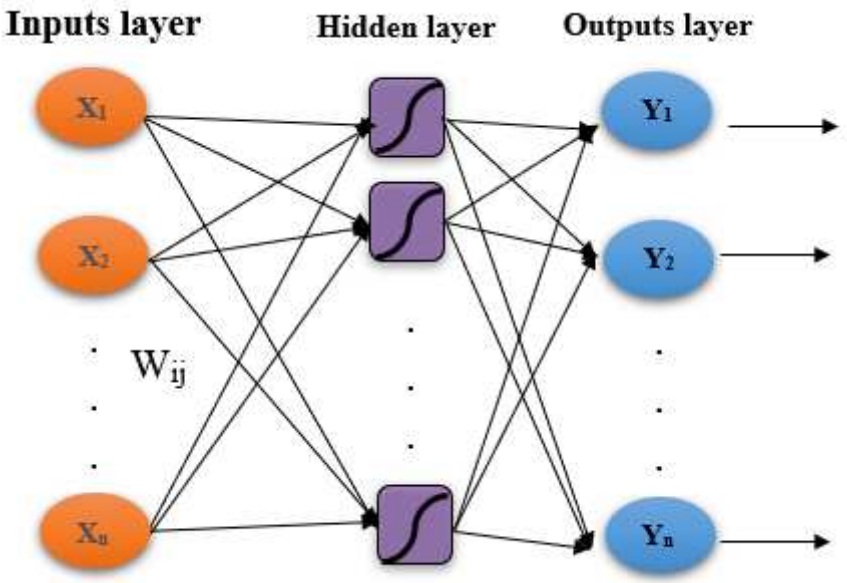

Figure 2

Architecture of a neural network with 3 layers.

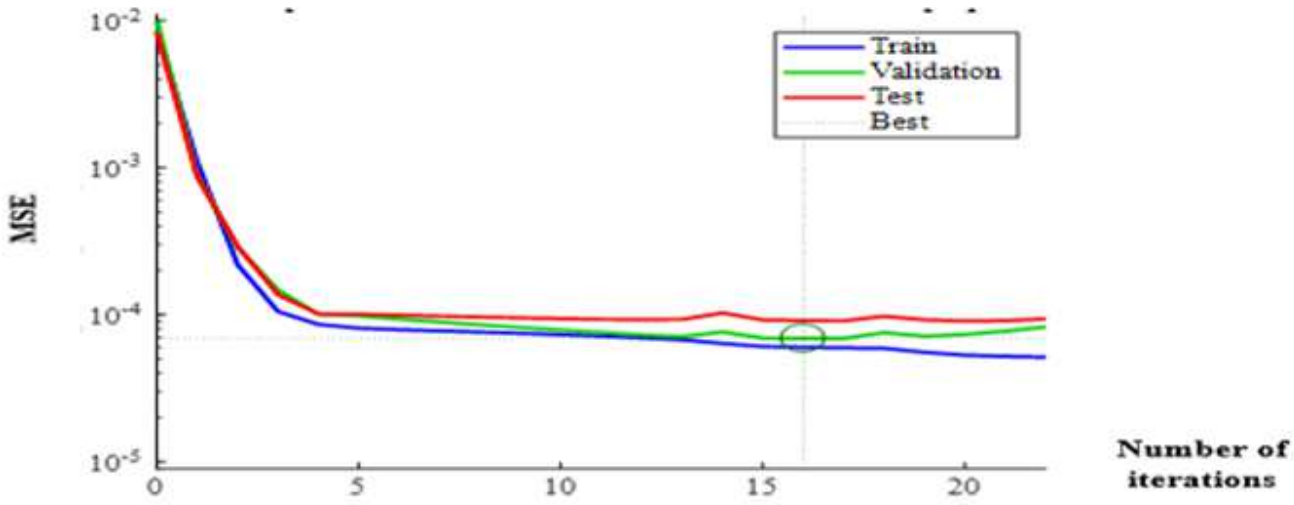

Figure 3

Evolution of average quadratic error with 11 neurons in the hidden layer.

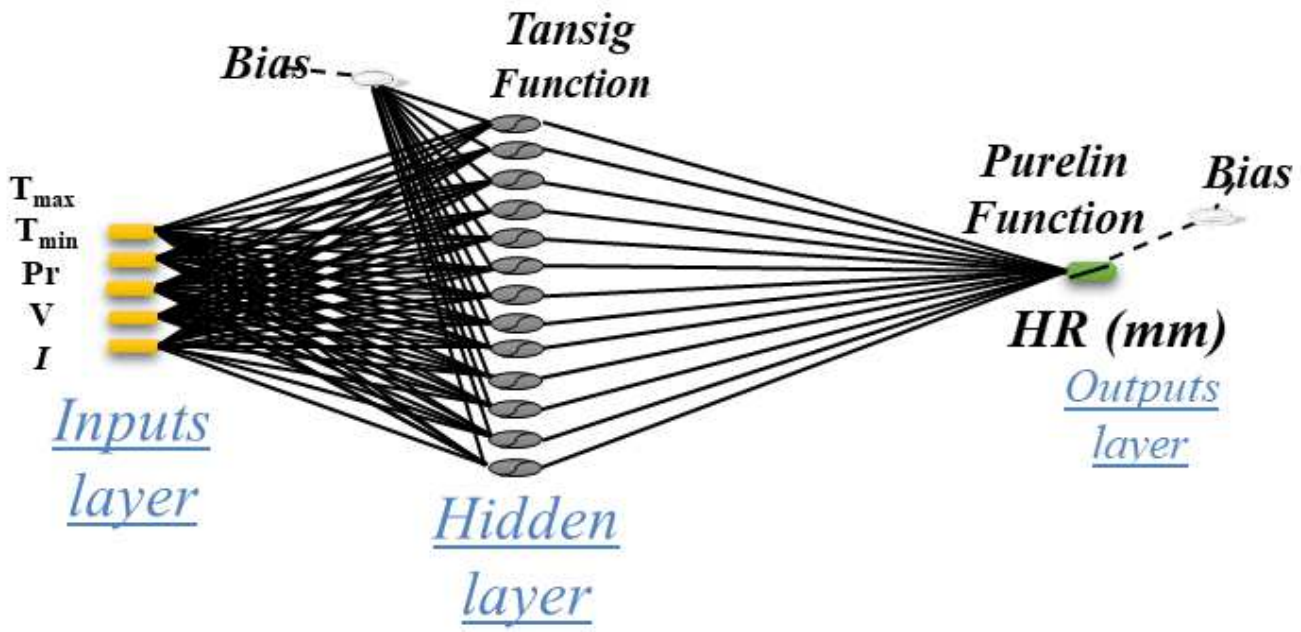

Figure 4

Architecture of the neural network with three configuration layers [5-11-1] developed for the prediction of relative humidity in the region of Rabat-Kenitra.

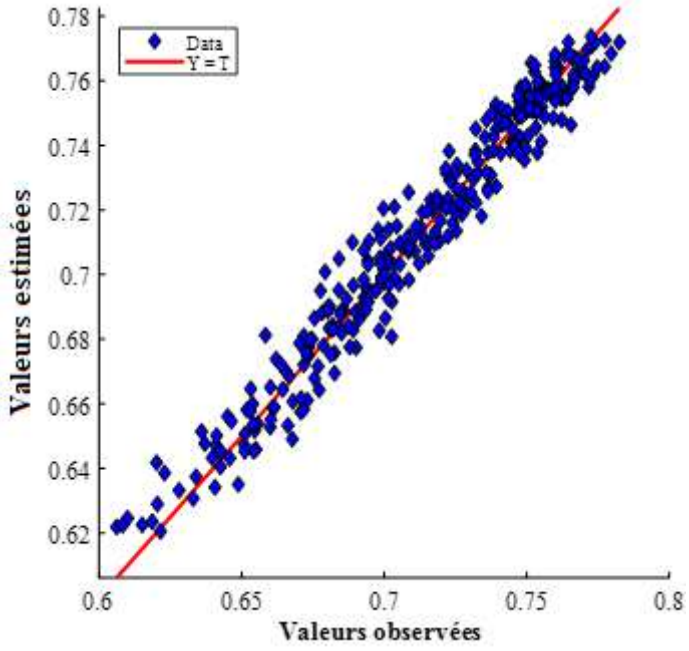

Figure 5

Relationship between the estimated values (Ŷ) using a neural configuration model [5-11-1] and the observed values (Y) in the Rabat-Kénitra region.