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Optimization numerical the neural architectures by performance indicator with LM learning algorithms

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Abstract
The objective of this study is to develop a mathematical model based on the MLP Artificial Neural Networks (ANN) to predict meteorological parameters in general and moisture in Particular. For this purpose, we used a time series of moisture, Measured in the area of Chefchaouen in Morocco, which depends on the air temperature, dew point temperature, atmospheric pressure, visibility, cloud cover, wind speed and precipitation. Furthermore, to choose the best architecture of the MLP neural network, we used several statistical Criteria such as: Root Mean Squared Error, Mean Absolute Percentage Error, Akaike Information Criterion, Bayesian Information Criterion, Mean Absolute Error and correlation coefficient. The obtained results of the MLP artificial neural network are discussed and compared to the MLR traditional method. Consequently, MLP method presents a very powerful ability to predict relative moisture. We have shown also that the structure of the MLP neural network {7-5-1} using the Levenberg-Marquart algorithm, and hyperbolic tangent functions and purelin as transfer function torque is the model the most efficient for predict the moisture in the region Chefchaouen.

Keywords: Criteria Information, ANN, Prediction, Moisture spleen, MLP, MLR.

1. Introduction
The Meteorology is a branch of physics that studies the atmosphic phenomena laws, allowing to predict the evolution of time for a short time (a few days) according to well-defined initial conditions. Among the weather parameters, moisture is the most important because of its direct impact on the environment, and consequently on the human health.

On the other hand, the mathematical models of the weather that are powerful instruments by their spatial coverage, their physical basis and they provide a modernized comprehension of the meteorological condition. These models are remarkable for their ability to deliver not directly measurable or difficult data to be interpolated that moisture.

These models are very complex, requiring unmeasured inputs, and thus with many parameters giving rise to many settings.

In the literature, artificial neural networks have found a great success in the simulation and prediction of environmental parameters and in the development of meteorological mathematical models.

Perez and *al*. [1] have predicted to predict the concentration of NO_2 and nitrogen oxide NO in Santiago based on climatic variables by using the linear regression and neural network. The results showed that the neural network was the method which performs the lowest error of the prediction.

Nohair and *al*. [2] have used neuronal statistical model to predict the variations of temperature, a watercourse in function the climatic variables, such as the temperature of the ambient air and the flow of water received by the watercourse. Two methods were used: the first iterative type, which uses the estimated value of the day j to predict the water temperature value of the day j + 1. The second method was much simpler to implement, is to estimate the temperature of daily considered once.

Lek and *al*. [3] have developed a method for modeling the rain and speed relationship, based on the use of neural networks. In their study, they have used the algorithm of the back propagation of errors with a three-layer network.

Fock and *al*. [4] have developed a neural model for a thermal simulation of buildings. This approach, based on the prediction of the temperature of inner surface of a wall, shows the feasibility and the possible implementation of the network in a code. The advantage of this network is to provide a simulation model for a component from the experimental data. This approach was intended to have a first estimate of the performance of new components.

This work present the techniques used for the development of neural mathematical models for predicting the humidity of the zone of Chefchaouen. The main objective is to study the variation of robustness tests (statistical indicators) as well as the effect of the number of neurons in the hidden layer, on the performance of network models of MLP type neurons, for time series prediction of humidity.

2. Materials and methods

2.1. *Database*

As part of this work, we used a database that consists of 1856 days and eight meteorological variables of Chefchaouen zone (Fig.1). These variables are summarized in table 1. The values of these variables were taken every four hours during 1856 days between 2008 and 2013. They were converted to daily averages for all variables, except for precipitation (amount of rain) which has been transformed into a cumulative value of all day [5]. Some statistical parameters of these data are shown in table 1.

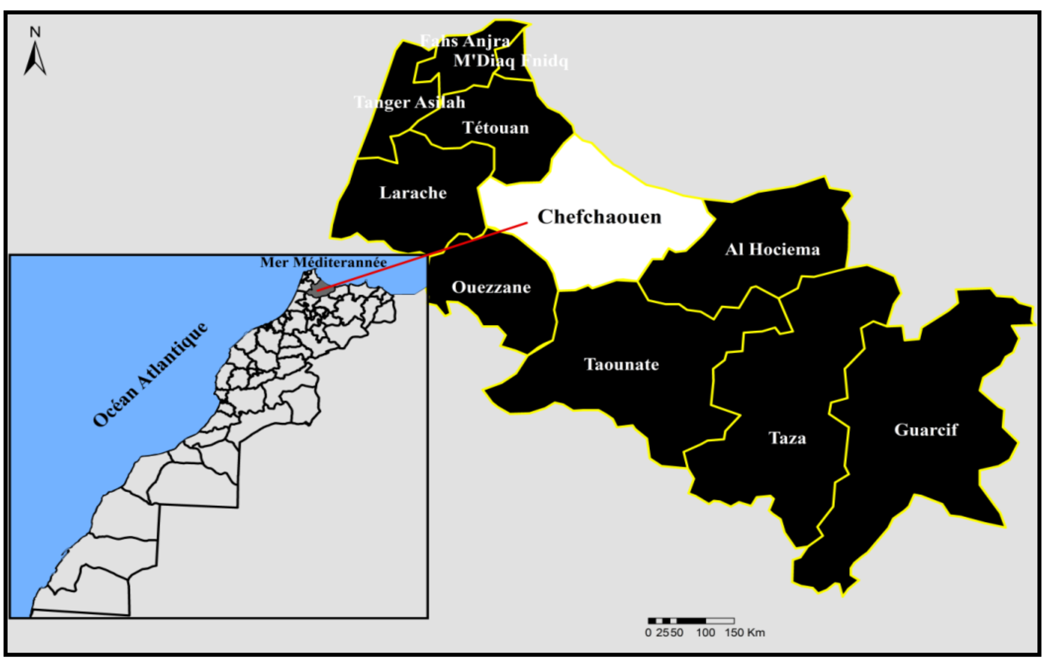

Figure 1: Geographical situation of the Chefchaouen zone.

Table 1: Meteorological variables used in this study and their statistical parameters.

Variable Types	Variables	Units	Minimum	Mean	Maximum	Standard deviation
Independent variables (predictors)	T_A : Air temperature	°C	1.7	18.8	43.8	0.054
	T_D : Dew point temperature	°C	-5.8	11.8	25.4	0.061
	P_A : Atmospheric pressure	hPa	679.5	1016.57	1036.10	0.033
	V_{is} : Visibility	km	5	13.6	16	0.147
	N_{eb} : Nebulosity	Octas	0	3.12	22.33	0.137
	P_r : Precipitation	mm	0	2300	299	0.102
	W_i : Wind speed	km/h	0	10.5	65.0	0.034
Dependent variable (explain)	H : Humidity	%	14.0	68.3	95.0	15.200

The evolution of the humidity during the period under is presented in fig. 2. It shows the evolution of the relative humidity during the studied period. During 2009, we observe that this parameter exceeds 60% in all months except May, June, July and August. For 2010 and 2011, the humidity exceeds this value during every month except June and August 2010 and July and August 2011. On the contrary, 2012 is characterized by a high value (> 70%) for most of the month except June, July and August. In general, in the Chefchaouen zone the humidity is important because of the proximity of this region to the Mediterranean. It is a seasonal evolution that is closely linked to the continentalization effect observed in the spatial distribution of rainfall.

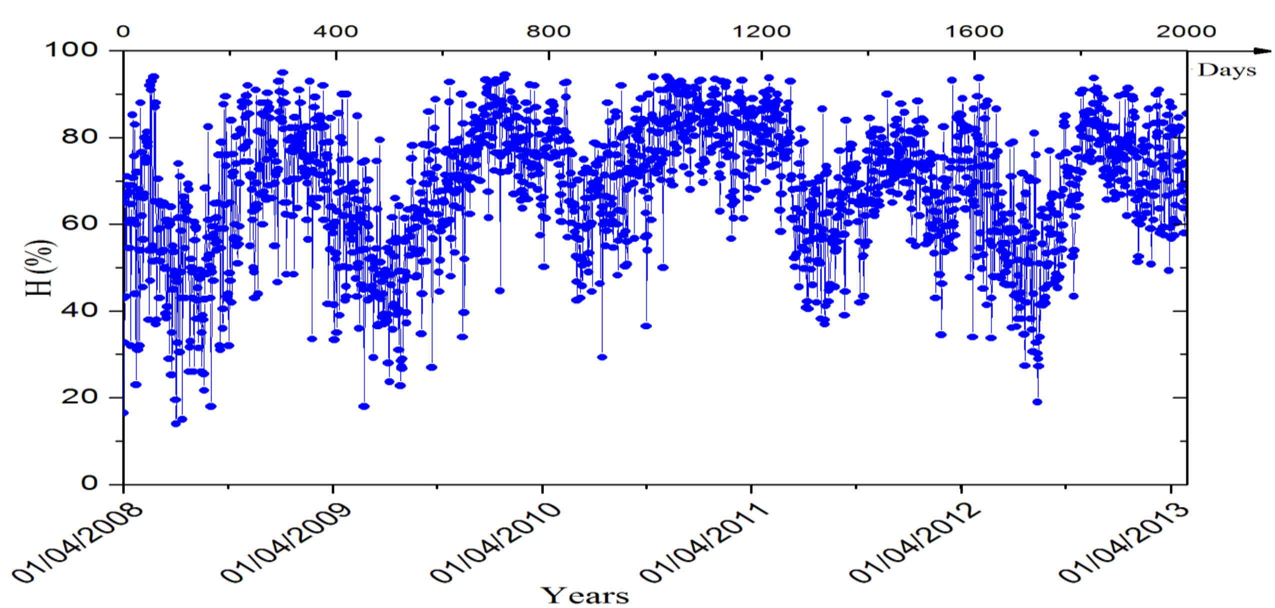

Figure 2: Variation in humidity during the study period.

Humidity is depending on the seasons; the dry season is not only usually marked by an absence or weakness of precipitation and dewatering in rivers, but also in the air. This explains why the regression of moisture is noticed in dry months including: June, July, August and September for all years. This humidity value of will be changed in the rainy season, during which the highest values are observed from January to April for the years 2009, 2010, 2011 and 2012.

2.2. *Data normalization*

In our study, the database has undergone a pretreatment, which comprises performing an appropriate normalization into account the amplitude of the values accepted by the network [6], prior to their use for training neurons network, in order to ensure homogenization of values propagated in the network. The inputs and the outputs are normalized between -1 and 1, for adapted to the requirements of the transfer function used by the neural network (Tansig function and Purelin function), with respect to their minimum and maximum values, using equation (1) of the following normalization [7;8;9;10]:

$$\overline{I_i} = \frac{2(I_i - I_{i(min)})}{(I_{i(max)} - I_{i(min)})} - 1 \quad (1)$$

$\overline{I_i}$: Normalized values;

I_i : Gross values, not normalized;

$I_{i(min)}$: Minimum values;

$I_{i(max)}$: Maximum values.

2.3. *Artificial Neural Network*

The neuron is the fundamental unit of a artificial neural network, strongly assembled with elementary processors operating in parallel. An artificial neuron is a calculation unit which receives a number of inputs (I_n) coming directly either from the environment or the situated upstream neurons [11;12]. When information comes from a neuron, we associate a weight W, which represents the ability of the upstream neuron to excite or inhibit the neuron situated downstream. Each neuron has a single output, which then branches to supply a variable number of downstream neurons. Figure 3 shows the structure of an artificial neuron.

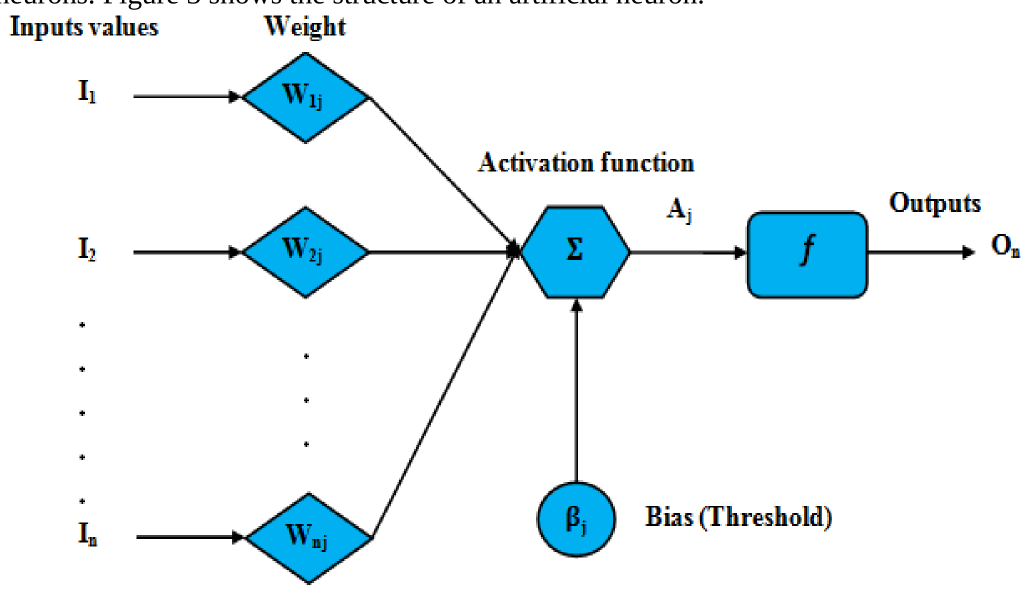

Figure 3: Structure of an artificial neuron.

Regarding artificial neuron behavior, there are two phases:

- The first is usually the calculation of the weighted sum of the inputs (Aj) by the following expression:

$$A_j = \sum_{j,i=1}^{n} W_{jn} I_i \quad (2)$$

Where the synaptic weight W_{jn} and I_i are the input values. It is the sum balanced activation which converges to the neuron [13].

- The second phase is that from this An value, the transfer function f calculates the value of the state of the neuron, called activation, which will be transmitted to the situated downstream neurons [14]:

$$O_n = f\left(\sum_{i=1}^{n} W_{in} I_i + \beta_j\right) \quad (3)$$

With β_j is bias of neuron j.

The bias allows add flexibility to networks for varying the threshold of the neuron by adjusting the weights during training. It is used in several types of activation functions.

3. Results and discussion

3.1. *Multiple Linear Regression (MLR)*

Multiple Linear Regression is used to establish a linear equation to estimate the values of a dependent variable (humidity) from the explanatory variables (weather parameters). For our database with Multiple Linear Regression, we have established the following equation:

$$H(\%) = 71.18 - 1.99xT_A + 1.71xT_D + 1.91xP_A - 0.56xV_{is} + 0.92xN_{eb} + 0.02x\,P_r - 0.04xW_i \quad (4)$$

N=1856 days; R= 0.86; MSE = 0.026

The R correlation coefficient obtained by this model (MLR) is R = 0.86, this shows that the relative humidity does not correlate linearly with the other meteorological parameters the table 2 shows the partial coefficients of the linear regression, the standard deviation of each coefficient, Student's test and the values of critical test probabilities for each coefficient.

Table 2: Partial coefficients of the model (MLR), Student test (t) and critical probability (Pr) the test for each coefficient.

Variable	Partial coefficients	Standard deviation	t	Pr>|t|
Constant	71.187	33.857	2.103	0.036
T_A (°C)	-1.995	0.054	-37.155	< 0.0001
T_D (°C)	1.719	0.061	28.366	< 0.0001
P_a (hPa)	0,019	0.033	0.577	0.564
V_{is} (km)	-0.564	0.147	-3.83	< 0.0001
N_{eb} (Octas)	0.927	0.137	6.772	< 0.0001
P_r (mm)	0.022	0.102	0.221	0.825
W_i (km/h)	-0.024	0.034	-0.699	0.485

From this table, we find the existence a relationship between the relative humidity and the variables: dew temperature, visibility, cloud cover and the temperature of the air; as for the coefficients of these variables, the Student test t gave very low probability values (less than 0.0001%). This means that these variables have a significant contribution. However, other variables seem to have effects, less important in explaining the relative humidity.

The linear equation developed by using the multiple linear regression discussed above, presents 86% of humidity explanation. We judged that this rate of explanation linearly connects the moisture in the Chefchaouen area with weather-independent parameters is not very significant. With this model, we believe that it is difficult to imagine that we can establish a fully deterministic model that would provide a truly accurate prediction of moisture. To overcome these difficulties and to improve the quality of predictive performance, we have developed mathematical models of type "black box" based on artificial neural networks (ANN) of MLP type.

3.2. *Information criteria and performance of neural statistical models*

The neural network configuration selection is a well known problem in the predictions domain. When the model is fixed, the method of information provides an essential framework for the development of suitable estimators. But in many situations, knowledge of the data does not allow to determine a single neural network architecture, in which he placed to perform a prediction of the humidity.

However, to choose the "best" neural network architecture, several statistical indicators (information criteria) are generally used to evaluate the performance of moisture estimation models and to facilitate the selection of the statistical model representing the best reality.

These statistical indicators are used to select the adequate model. The idea is to penalize the likelihood parameter estimates associated with the data, reflecting the predictive quality of the model or the number of independent variables in the model, or by the number of independent variables in the model and size of the database.

For this study, we chose to study the most popular statistical indicators and most used [15]. For this we randomly divided our database into three parts: 60% for training and 20% for the test and 20% for validation. These indicators are defined as follows:

- **RMSE (Root Mean Squared Error)**

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(H_t(i) - H_p(i)\right)^2} \qquad (5)$$

With H_t and H_p are the humidity respectively the values of the target vector and prediction vector the neuron output of network developed.

RMSE is a measure the variation between the predicted values and the measured values. The more its value is small, the greater the model is best.

- **MAPE (Mean Absolute Percentage Error):**

$$\mathrm{MAPE} = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|H_t(i) - H_p(i)\right|}{H_t(i)}\right).100 \qquad (6)$$

MAPE is a measure of the accuracy of the forecast. It measures the size of the error in percentage terms. It is calculated as the average error of the unsigned percentage. On a point close to zero the error can be infinitely large, causing a distortion of the overall error rate.

- **AIC (Akaike Information Criterion):**

$$AIC = \ln\left(\frac{N}{2}.Var(t)\right) + 2.\frac{N_W}{N} \quad (7)$$

With N is the number of samples tests studied and N_W represents all weights and biases used for each architecture.
AIC is a measure of the predictive quality regarding a statistical model for a data set. When estimating a statistical model, it is possible to increase the probability of the model by adding a parameter. The Akaike information criterion, as the Bayesian Information Criterion, allows penalizing models depending on the number of parameters. We choose the model with the Akaike information criterion the lowest.

- **BIC (Bayesian Information Criterion) :**

$$BIC = \ln\left(\frac{MSE}{N}\right) + N_W\left(\frac{\ln(N)}{N}\right) \quad (8)$$

MSE: Mean Squared Error;
N_W: Number of adjustable parameters or weights W_i the different connections.
This criterion of goodness fit represents the natural logarithm of the mean squared error, penalized by a function between the estimated number of parameters and the data number.

- **MAE (Mean Absolute Error) [16] :**

$$MAE = \sum_{i=1}^{N}\left|H_t(i) - H_p(i)\right| \quad (9)$$

H_t H_t and H_p are the humidity values of the target vector and prediction vector the neuron of output our network. The MAE is a quantity used to measure the average magnitude of the errors in a set of forecasts, regardless of their direction. It measures the accuracy for continuous variables [17;18;19;20].

In this work, we chose the Levenberg-Marquart algorithm network, which possesses only one hidden layer. For the first two layers (input layer, hidden layer), the chosen transfer function is the hyperbolic tangent, whereas for the neurons in the output layer, we chose to use a linear function of purelin type. This function combination permits to minimize although the mean squared error of the MLP type model [21;22;23;24;25].

Furthermore, to study the effect of the number of neurons in the hidden layer and to seek the optimal architecture of the neural network, we varied the number from 1 to 30. And for every number we calculated the values of Information Criteria: RMSE, MAPE, AIC, BIC, MAE. The Figures 4, 5, 6, 7 and 8 show the evolution of these performance indicators as a function the number of neurons in the hidden layer. These indicators are evaluated on the data set.

The Simulation performed in order to determine the number of neurons is necessary to predict moisture time series, have shown that the error can be optimized by choosing the network neural configuration. The absolute average error and the root mean squared error can be used in conjunction for diagnose the errors variation in a set of predictions. The mean squared error is always greater than or equal to the absolute average error. These two statistical indicators almost change in the same way according to the number of neuron in the hidden layer (Fig. 4 and 8). Furthermore, the simulations performed have shown that the studied statistical indicators present more or less irregular fluctuations, when the number of neuron in the hidden layer increases from 1 to 30. However, for all indicators, and without exception, the low value of error was recorded when the number of hidden neuron is 5.

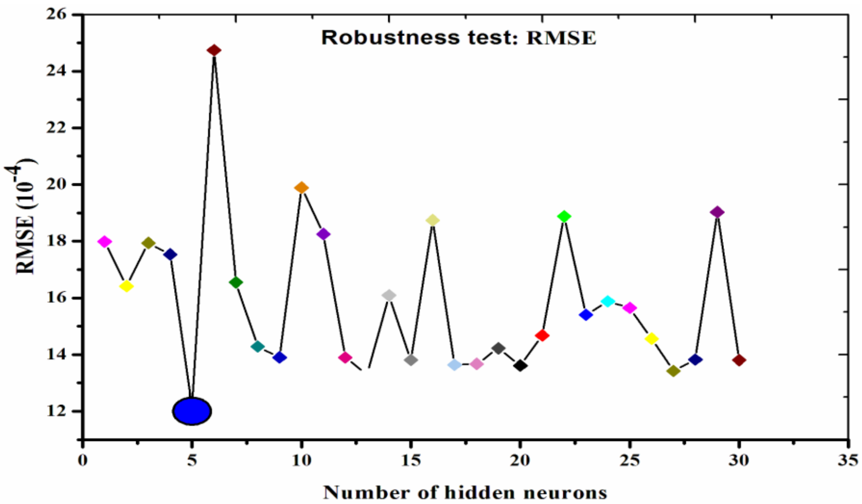

Figure 4: Variation of the root mean squared error as a function of number of neurons in the hidden layer.

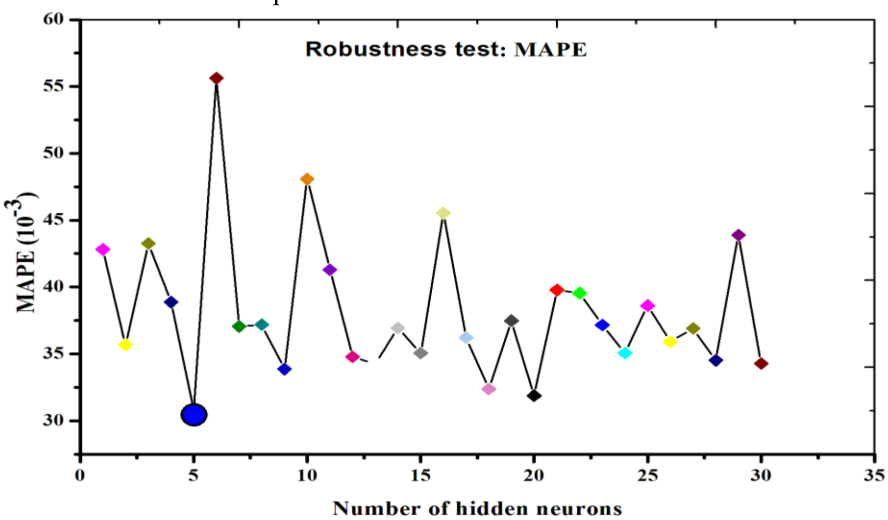

Figure 5: Variation of the average error absolute percentage as a function of the number of neurons in the hidden layer.

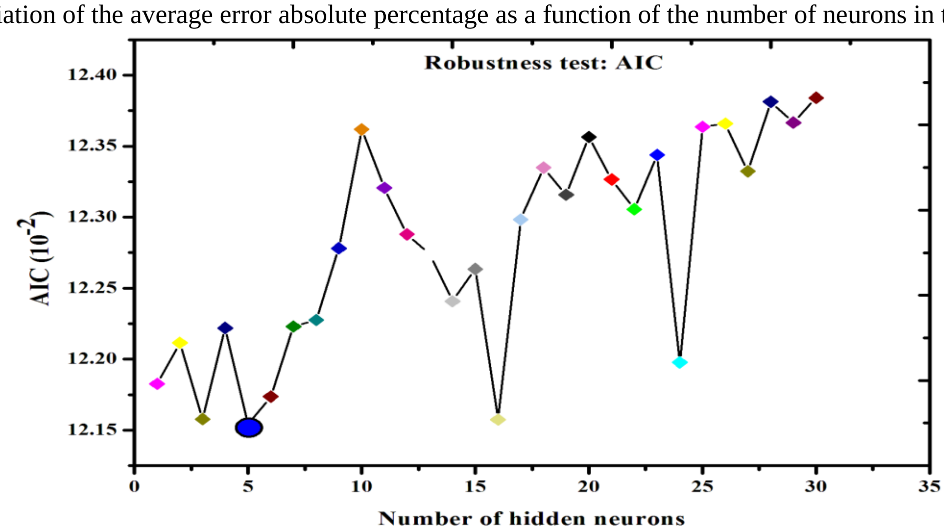

Figure 6: Variation of the Information Criterion Akaike as a function of the number of neurons in the hidden layer.

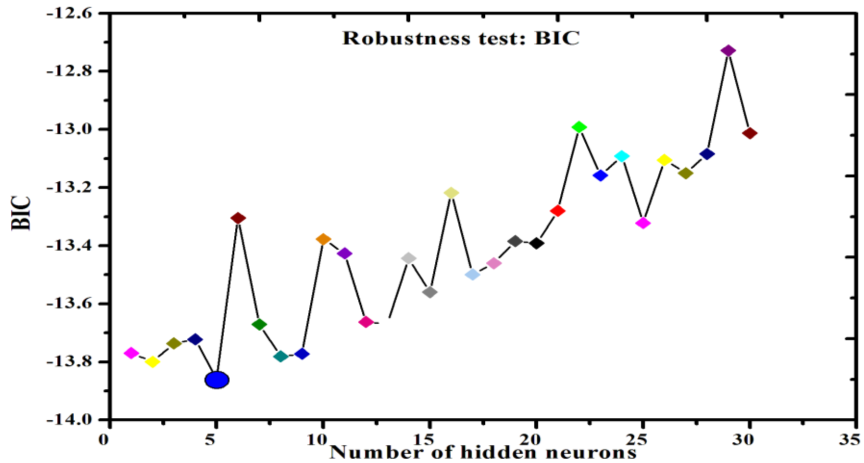

Figure 7: Variation of the Information Criterion Bayes as a function of the number of neurons in the hidden layer.

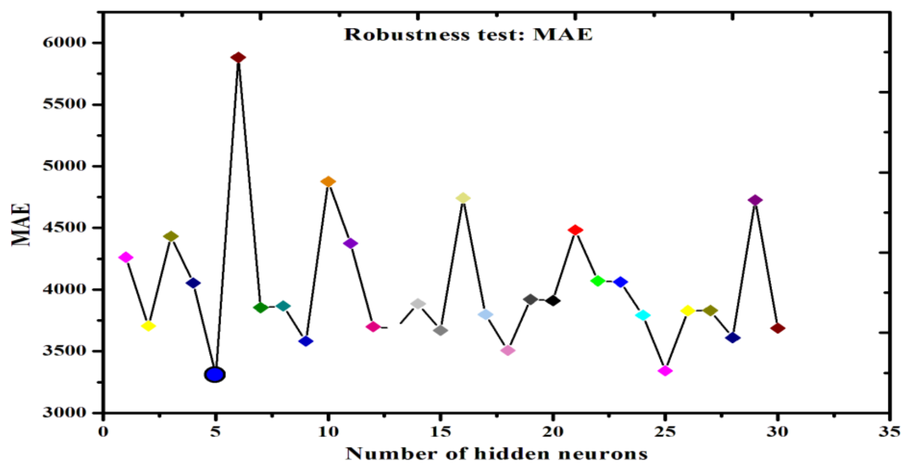

Figure 8: Variation of the mean absolute error as a function of the number of neurons in the hidden layer.

This shows that the best performing neural model configuration consists of 5 neurons in the hidden layer. Figure 9 shows the architecture of neural network the most efficient for predicting the humidity of the Chefchaouen zone.

This network configuration {7-5-1}, which contains three layers:

- Seven neurons in the input layer, representing the independent weather variables.
- Five neurons in the hidden layer. These are the neurons that we have chosen for the study of statistical indicators; and chosen therefore for optimizing results and avoid the phenomena of over-learning.
- One neuron of the output layer, representing the humidity.

3.3. *Comparison of different methodologies*

The purpose of this study allowed comparing the performance of the neural network model and the model of multiple linear regression for the prediction of moisture in the area of Chefchaouen.

The statistical indicators calculated related the methods established by the ANN model are significantly different from that of MLR. The correlation coefficient calculated by the ANN was significantly higher (0.98) by against the one calculated by using MLR model is averagely lower (0.86). From Table 3, the best estimates are obtained using the template ANN, because it presents the lowest values of statistical indicators RMSE, MAPE, AIC and MAE, and the best correlation coefficient.

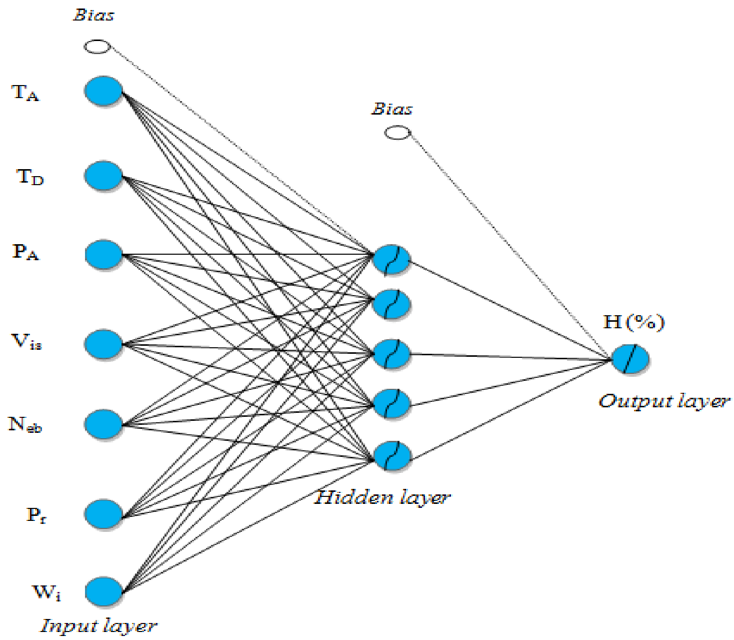

Figure 9: Architecture of the neural network to three layers of configuration {7-5-1} developed in this study.

This shows that the method based on the principle of artificial neural networks is more efficient compared with the method based on multiple linear regression, which is commonly used in the development of linear predictive models. This performance has been also reported in many studies, concerning studies the relations of heavy metals and physicochemical parameters of river sediments [7;8;9] and the study of prediction of organic carbon up from the physicochemical parameters of marine sediments.

Table 3: Comparison of performance of ANN and MLR models

Models	Correlation coefficient	Statistical Indicators			
	R	RMSE	MAPE	AIC	MAE
MLR	0.865	0.0260	0.053	60.546	5983
ANN	0.984	0.0012	0.030	0.121	3309

Conclusions

The performance of neural networks demonstrates the existence of a non-linear relationship between the humidity and the other meteorological parameters in the Chefchaouen area during 1856 days between 2008 and 2013. Also, there is no explicit an form explaining and analyzing the relationship between inputs and outputs. This causes difficulties in interpreting the results obtained by the neural networks. In addition, there is no well-defined method to determine the best structure of a neural network. The most common method is to perform tests and compare studying the statistical indicators of robustness especially the error obtained. In our study we have shown that the structure of the neural network {7-5-1} using the Levenberg-Marquart algorithm, and hyperbolic tangent functions and purelin as transfer function torque is the model the most efficient for predict the moisture in the region Chefchaouen.

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