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New method of prediction of climatic conditions by artificial neural networks (case of the province of Médéa)

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ABSTRACT/RESUME

Abstract: *The predictions of climate conditions have important impacts on people's lives through agriculture, food security, water resources management, health, natural disasters and environmental degradation, etc.*
The main focus of this paper is to develop an accurate mathematical model using the artificial neural network (ANN) method, to predict weather conditions such as: precipitation, wind speed, humidity and average temperature, based on a database composed of: the earth-sun distance, the annual evolution (time), the sunshine duration and the conversion factor, measured over a period from January 01, 2001 to December 31, 2010 for the city of Médéa (Algeria), the said data are normalized between 0 and 1, the number of neurons in the hidden layer of ANN, single layer MLP type is10 neurons. The architecture of the ANN is of MLP type with a single layer of 10 neurons with a tangential sigmoid function as activation function, and a learning algorithm of Levenberg-Marquardt type, with a mean square error RMSE = 0.1202 and a correlation coefficient R^2 *=0.8289. In addition, a graphical interface was developed by the Guide function programmed in Matlab in order to facilitate the use of the mathematical model established for the user.*

I. Introduction

Unique providers of predictions for the coming centuries, worrying heralds of climate change, numerical climate models are not huge mathematical edifices delivering oracles in a virtual and ethereal universe. On the contrary, they are constantly linked to observational data, through complex and varied links. Climatologists spend a great deal of their time testing these models, confronting them in many ways with measurements of the real climate. It is these evaluations, and more generally the circulations between observations and simulations, that put the models to the test of reality and constitute, in the eyes of the modelers, the main guarantors of the scientific validity and reliability of future climate projections. Yet the relationship between models and observations has remained virtually ignored by researchers in some disciplines such as social scientists and philosophers of science. In the last decades, the role of numerical analysis and scientific computation has been growing, especially for solving real-world problems. Work on models has long focused on their relationship to physical theories [1].

In the past few years, there has been a revival of reflections on computer modeling[2] criticizing the "cult of theory" [3] and a few studies are interested in numerical experiments [4].Artificial intelligence techniques, such as artificial neural networks (ANNs), genetic algorithms (GAs) and fuzzy and chaos theory, are alternative methods increasingly used in weather events. In the last two decades, several authors have developed ANNs models to predict climate factors in many countries. In a previous study, they proposed a model using multilayer back-propagation interaction neural networks to estimate air temperatures in southern Quebec, Canada [5].In Iran, in a study developed by [6], the capabilities of the artificial neural network system were evaluated to predict long-term

monthly air temperature values in 30 Iranian meteorological stations. Other ANNs models for air temperature prediction have been developed in Turkey [7], Japan [8], Saudi Arabia [9], and Spain [10].
In Algeria, several studies have been done in this field, especially for the prediction of solar irradiation, we cite as examples: [11], [12], [13] and [14]. No study in the literature has predicted four weather conditions mentioned in this study (precipitation, wind speed, humidity, and average temperature) at the same time.

II. Materials and methods

II.1. Study area and climatic data

The study area is the city of Médéa (Figure 1), with an area of 63.50 km², located about 84 km from the capital Algiers, latitude 36°15′51″ North, longitude 2°45′14″ East, altitude from sea level 910 m, its climate is classified as warm and temperate with significant rainfall throughout the year (more than 750 mm) [15].

Figure 1.*Geographical location of Médéa, Algeria.*

The data (temperature, humidity, wind speed, sunshine duration and precipitation) used in this study are provided by the National Office of Meteorology of Algeria in the province of Médéa, for a 10-year period from January 2001 to December 2010. Instead of working with annual numbers from 1 to 12 for the specification of the months, it would be better to work with more specific phenomenological parameters such as the monthly earth-sun distance [16] : (DT-S)1, (DT-S)2, ..., (DT-S)12for each season by the references as follows: spring (DT-S)3 = 149.106 km, summer(DT-S)7 = 152.106 km, autumn(DT-S)9 = 151.106 km and winter(DT-S)1 = 148.106 km. Figure 2 represents the interpolated variation of the distance between the earth and the sun for each month.

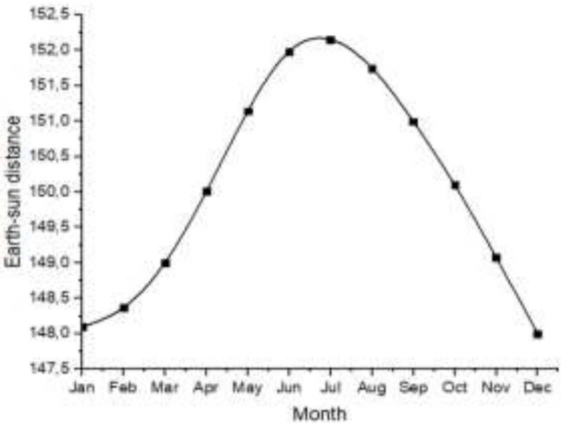

Figure 2. *Distance between earth and sun for each month.*

III. Neural modeling

III.1. Artificial neural network (ANN)

An artificial neural network (ANN) is a mathematical model used in artificial intelligence, the design of which is inspired by the functioning of the biological neuron, to take actions based on perception rather than reasoning. The neural approach is very fashionable and is used today for all sorts of applications in several fields. Neural networks are used in various disciplines and have today an important impact, and it is likely that their importance will grow in the future especially in the fields of engineering such as adsorption [17], extraction [18], solar energy [19], process engineering [20], drying [21], maintenance strategy [22] and others. The modeling consists in implementing a system of neural networks in an artificial way, this assumes that according to the biological principle we will have a correspondence for each element composing the biological neuron, so a modeling for each one of them (Figure 3) [23].

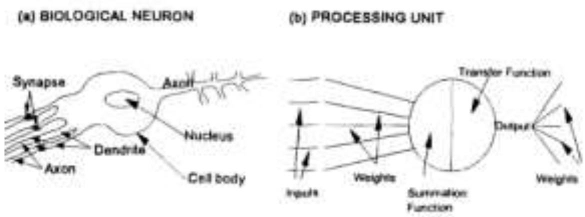

Figure 3. *Mapping biological neuron / artificial neuron [23].*

An artificial or formal neuron is a very simple mathematical operator, a neuron has inputs that can be outputs of other neurons, or inputs of external signals plus one or more outputs. The value of the output results from the calculation of the sum of the inputs weighted by coefficients (called connection weights or synaptic weights) and the calculation of a non-linear function (called activation function) of this weighted sum, a formal neuron can be defined by the following five elements (Figure 4) [24].

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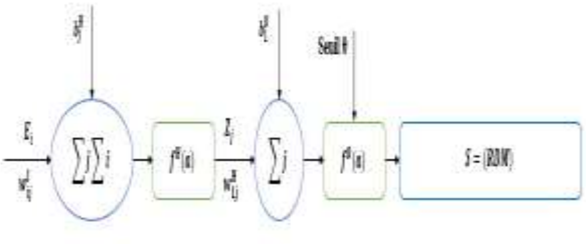

Figure 4. *Formal neuron [23]*

The input values (**Ei**) are external stimuli from the environment or outputs from other artificial neurons, they can be: Binary (0, 1), Boolean, or bipolar (-1, 1). The parameters (**Wij**) are often referred to as "weights" or, due to the biological inspiration of neural networks, "synaptic weights", They are real values that determine the contribution of each input. A learning algorithm is used to determine the best set of weights for the problem at hand. Finding the optimal set is often a compromise between minimizing the error as well as the computation time and preserving the generalization capacity of the network. The first thing a formal neuron does is to compute the weighted sum of weights and inputs. According to the usual usage (also inspired by biology), this weighted sum is called potential (activation level) [eq.1], from which a constant term b called bias (activation threshold) is often subtracted [24].

$$P = \sum_{j=1}^{n-1} w_{1j}\, x_j - b \qquad (1)$$

The N inputs of the neuron correspond to the vector X = [x1, x2,..., xn]T, while w = [w1,1w1,2 ---w1,n]T represents the vector of weights of the neuron. The output P of the integrator is given by [eq.2] which can also be written in the following matrix form:

$$P = W^T X - b \qquad (2)$$

The activation or transfer function (F) calculates the value of the neuron's state, and it is this value that will be transmitted to the downstream neurons. There are many possible forms for the activation function. Most transfer functions are continuous, offering an infinite number of possible values in the interval [0, +1] or [-1, +1]. The three most commonly used are the "hard limit", "linear" and "sigmoid" functions, the application of the transfer function to the weighted sum of these inputs is according to the following equation [eq.3]:

$$S = F\left(\sum_{j=1}^{n-1} w_{1j}\, x_j - b\right) \qquad (3)$$

The calculated output (S), which can be discrete or real depending on the activation function used, is passed to other neurons or directly to the external environment.

III.2. Neural modeling procedure

The black box model is the most primitive form of mathematical model: it is realized only from experimental, observational and/or generated data, it can have a predictive value in a certain domain of validity, but it has no explanatory value. The objective of black box modeling is to find, from the available data or measurements, a deterministic relationship, if it exists, between the input variables of the model (Ei) and the quantity to be modeled (S). The methodology adopted for the calculation of meteorological conditions by the neural technique can be summarized in figure 5:

III.3. Computational methodologies

Artificial neural networks are endowed with properties which, like learning from examples, seem promising in certain application domains. In fact, any problem that can be represented as a mapping function between an input space and an output space is considered eligible, as long as we only have examples of the behavior of this function [24].

III.4. Data base

The elaboration of a database, starting from the experimental database, is a decisive phase in the design of a neural
model,it must be executed with the utmost care because any error at this stage will have important influences both on the convergence of the model and on the generalization.
In order to build a reliable and representative database, we have followed a methodology that includes the following 4 steps: selection of the neural model inputs, data collection, data formatting, and data normalization. The database consists of 480 experimental values for the prediction of the variation of the weather conditions; it is constructed of 4 inputs such as: the distance between the earth and the sun for each month, the annual evolution, the sunshine rate, the conversion factor. With: the distance between the earth and the sun normalized = (the distance between the earth and the sun /152. 106) = (the distance between the earth and the sun / the maximum distance between the earth and the sun); the normalized annual evolution = (the annual evolution / 10) = (the annual evolution / the maximum annual evolution), the normalized monthly sunshine rate = (the monthly sunshine rate / 379) = (the monthly sunshine rate / the maximum monthly sunshine rate), and the normalized conversion factor "δ"= (the conversion factor /4) = (the conversion

factor / the maximum conversion factor); with: δ= 0. 25 for cumulative precipitation, δ= 0.5 for wind speed, δ= 0.75 for humidity, and δ = 1 for mean temperature.
The normalized weather variation = (weather variation for each parameter/ weather variation for each parameter maximum).From the vertical projection on the curve of the distance between Earth-Sun for each season according to each month, we can find the distance between the earth and the sun monthly (see figure2).

III.4.1. Data collection

Once the relevant model inputs are selected, the objective of this step is to collect them. The database thus constituted must meet two requirements: it must contain the maximum number of samples or examples (experimental and/or generic), and it must be representative of the data likely to be used during the use of the neural model (Tables 1.1 and 1.2).

Table1.1. *Statistical analysis of normalized inputs and outputs data for 4 outputs RNA.*

		Min	Mean	Max	STD
Inputs	Earth-Sun (-) Distance	0.9727	0.9861	1.0000	0.0097
	Year	0.1000	0.5500	1.0000	0.2875
	Sunshine rate	0.0765	0.6291	1.0000	0.2100
Outputs	Cumulated precipitation	0.0000	0.2585	1.0000	0.2407
	Wind speed	0.3409	0.6587	1.0000	0.1351
	Humidity	0.4494	0.7581	1.0000	0.1509
	Mean temperature	0.8835	0.9222	1.0000	0.0234

Table 1.2. *Statistical analysis of normalized inputs and output data for single output (weather condition) RNA.*

		Min	Mean	Max	STD
Inputs	Earth-Sun (-) Distance	0.9727	0.9861	1.0000	0.0097
	Year	0.1000	0.5500	1.0000	0.2875
	Sunshine rate	0.0765	0.6291	1.0000	0.2100
	Conversion factor"δ"	0.2500	0.6250	1.0000	0.2798
Output	Weather condition	0.0000	0.6493	1.0000	0.2909

III.4.2. Shaping of the data

In this step, the database is first divided, into three subsets, one set for training, one set for testing and the rest is reserved for validation. The sampling of the three sets is done in such a way that they perfectly reflect the starting database, i.e., we always choose, from the data table, two rows for learning and the third for validation and so on until the end, that is 67% of the total database for learning, and 17% for the test phase and the remaining 16% for the validation phase. Then, the whole data set is written in matrix form. As this is a supervised learning, we have matrices representing the input of the model and matrices representing the desired outputs, depending on the case.

III.4.3 Data normalization

Normalization is an important step in the process of data elaboration, it becomes, in most cases, a requirement for the input matrices, due to the fact that bounded transfer functions of sigmoid type are often used in static modeling.
In our work, we normalized the set of inputs and outputs that includes several parameters by the instruction "premnmx", programming the equation (4) shown below, in Matlab language, which performs a normalization of the maximum and minimum value of each row [25].

$$y_n = \frac{2*(y-y_{min})}{(y_{max}-y_{min})-1} \quad (4)$$

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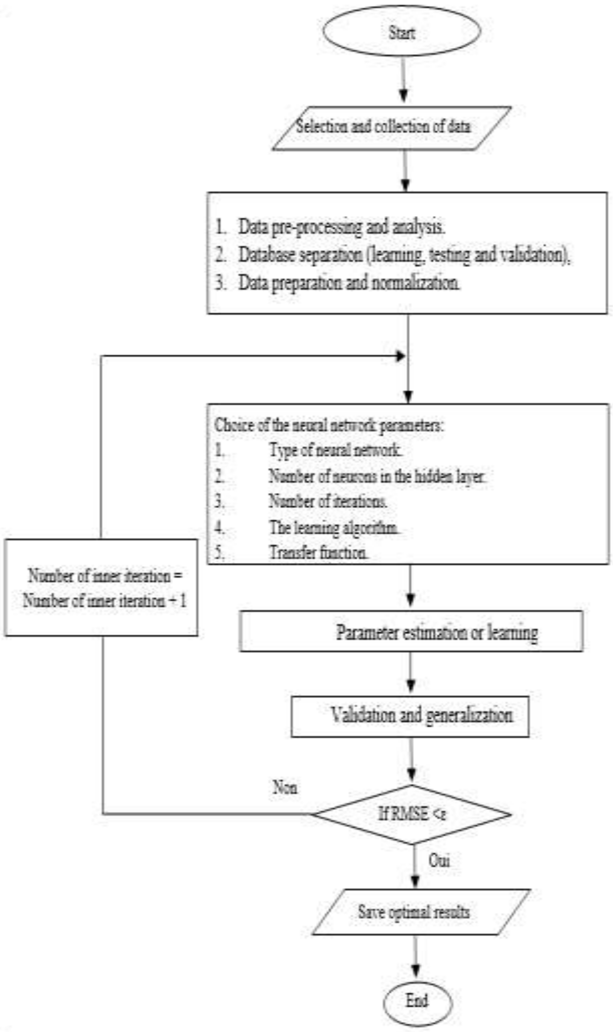

Figure 5. *Proposed algorithm to find the optimal neural network*

III.5. Network design

The design of a neural model consists of an evaluation study of the network's constituent elements according to the desired modeling performance it aims to fix the following: the type of network, the number of hidden layers, the number of neurons in the layers, the transfer function, the learning algorithm and the number of iterations [25].

In our case, it is a question of approximating the weather conditions which is a sufficiently regular function, by a neural network, it is thus a question of making a static modeling independently of the time, the adequate network with the sight of the consulted monograph, can be in general only one network not looped type MLP (Multi Layer Perceptron), the fundamental property of these networks is the universal approximation, which is expressed in the following way: Any sufficiently regular bounded function can be approximated uniformly, with arbitrary precision, in a finite domain of the space of its variables, by a neural network with a layer of hidden neurons in finite number, all having the same activation function and a linear output neuron. It is this property, also called the existence theorem, which justified our choice of neural network architecture with one hidden layer, MLP type, with sigmoid tangents as transfer functions of the hidden neurons and a linear function (identity) for the output neuron. The best suited learning algorithm, according to the bibliography and after confirmation by an evaluative study, is the Levenberg-Marquardt algorithm [25].

Learning is probably the most interesting property of neural networks. Learning is a phase in the development of a neural network during which the behavior of the network is modified until the desired behavior is obtained, learning uses examples of the behavior of the process to be modeled, learning can be considered as the problem of updating the weights of the connections within the network, in order to succeed in the task that is asked of it. Learning is the main characteristic of artificial neural networks and it can be done in different ways and according to different rules: Hebb's learning rule, F. Rosenblatt's perception learning rule, Windrow-Hoff's learning rule (ADALINE), Gradient backpropagation algorithm (Newton's method, quasi-Newton's method, Levenberg-Marquardt's method), in our case we have retained the Levenberg-Marquardt's method [26].

Generalization concerns the task performed by the network once it has been trained, it can be evaluated by testing the network on data that have not been used for training, it is essentially influenced by four factors: the complexity of the problem, the learning algorithm, the complexity of the sample (the number of examples and the way they represent the problem), and finally, the complexity of the network (number of weights). The complexity of the problem is partly determined by its very nature: we can speak of "intrinsic complexity". Moreover, the learning algorithm influences the generalization by its ability to find a deep enough local minimum, if not the global minimum. However, one way to evaluate the ability to generalize the representation built by the neural network to all the data, including those not belonging to the training set, is to measure the performance of the network on data representative of the unlearned problem. This is an evaluation of the generalization error. The difference between the learning error and the generalization error represents a measure of the quality of the learning performed [26].

Stopping criterion for learning, one of the methods to control the capacity of a neural network is to stop the learning "in time", so different criteria to decide when to stop the learning algorithm have been developed: when the learning error reaches a fixed threshold; after a fixed number of learning cycles; when an estimate of the generalization error is minimum [27].

III.6. Synoptic diagram of the model

The simplified diagram of the neural network architecture is shown in Figure 6.

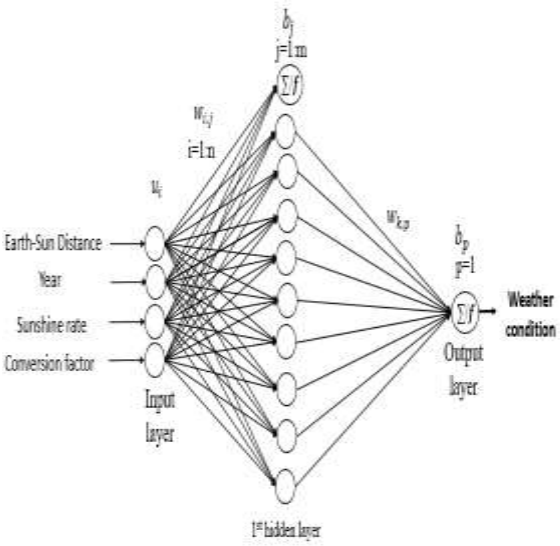

Figure 6. *Simplified diagram of the neural network architecture*

Statistical performance criteria

The accuracy and reliability of model, developed from artificial intelligence methods, rely on various statistical quantities [27] :

- Square correlation coefficient R^2 :

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{n}((Y - Y_{cal})^2)}{\sum_{i=1}^{n}((Y - \bar{Y})^2)}\right) \tag{5}$$

Where $\bar{Y}$ is the arithmetic mean of the observed data given by (Eq.6):

$$\bar{Y} = \frac{1}{n}\sum_{i=1}^{n} Y \tag{6}$$

- Correlation coefficient R :

$$R = \frac{\sum_{i=1}^{n}((Y-\bar{Y})*(Y_{cal}-\bar{Y}_{cal}))}{\sqrt{\sum_{i=1}^{n}(Y-\bar{Y})^2 * \sum_{i=1}^{n}(Y_{cal}-\bar{Y}_{cal})^2}} \tag{7}$$

- Mean square error MSE:

$$MSE = \frac{1}{n} * \sum_{i=1}^{n}(Y - Y_{cal})^2 \tag{8}$$

- Root mean square error RMSE:

$$RMSE = \sqrt{\frac{1}{n} * \sum_{i=1}^{n}(Y_{cal} - Y)^2} \tag{9}$$

- Root of the normalized mean squared error:

$$NRMSE = \sqrt{\frac{n\sum_{i=1}^{n}(Y-Y_{cal})^2}{\left(\sum_{i=1}^{n} Y\right)^2}} \tag{10}$$

- Absolute mean error MAE:

$$MAE = \frac{1}{n} * \sum_{i=1}^{n}|Y_{cal} - Y| \tag{11}$$

Where Y is the observed data, Y_{cal} is the calculated value and "n" is the number of data.

IV. Results and discussion

IV.1. Neural modeling

IV.1.1. Development of an ANN model

The main objective of this modeling is to develop an optimized artificial neural model (ANNO) to predict the output which is a variation of the weather conditions, using four input parameters: the distance between the sun and the earth for each month; the annual change; the sunshine rate and the conversion factor (Figure 7).

The table 2 summarize the architecture of the network developed to predict weather conditions.

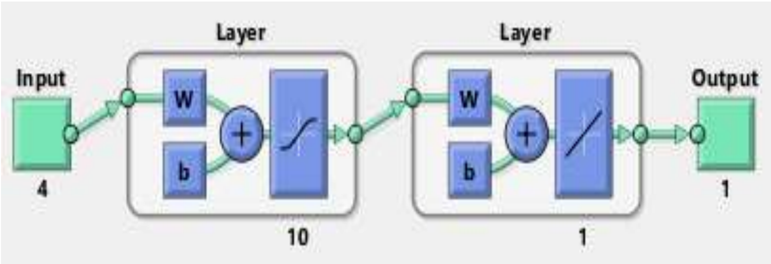

Figure 7. *Block diagram of the model*

The table 2 summarize the architecture of the network developed to predict weather conditions.

Table 2. *Architecture of the network developed to predict weather conditions.*

Network type	Number of neurons in the hidden layer	Transfer function of the hidden layer neurons	Transfer function of the output neuron	Learning algorithm	Number of iterations or cycles
Single layer MLP	10 Neurons	Sigmoidaltangential	Purelin	Levenberg-Marquardt	$1.5*10^6$

For the presentation of the results, we first start with the results obtained during the design phase of the neural model, i.e. the learning and generalization phase. The figures from 8 to 10 as well as table 3 present these results, we notice for the weather conditions that the average value of the absolute error with respect to the data used is less than 0.074% for the learning and 0.1% for the generalization phase. The correlation coefficient R^2 of the linearization curve (the values of the weather conditions estimated from the ANN model according to the experimental values of the weather conditions of the database or reference) is equal to 0.8289. It is important to remember, that the size of the raster data used to perform the learning phase is 67% of the overall base, the validation is 16% and for the generalization of 17% data. We also notice in this phase that the neural model perfectly reproduces the data that were used for learning and validation.

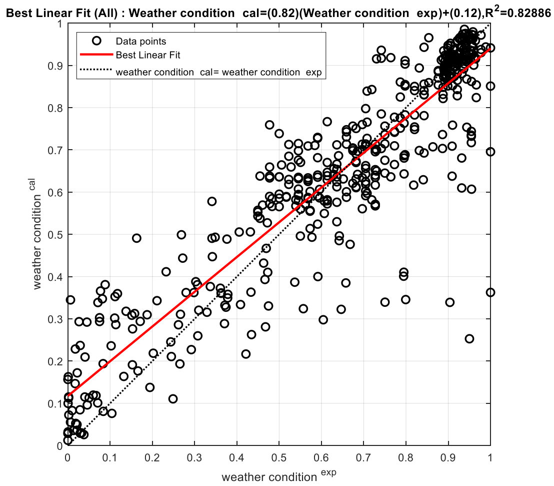

Figure 8. *Linear regression curve of the experimental of weather condition with the calculated weather condition by the ANN optimized for the overall phase (learning, testing, and validation).*

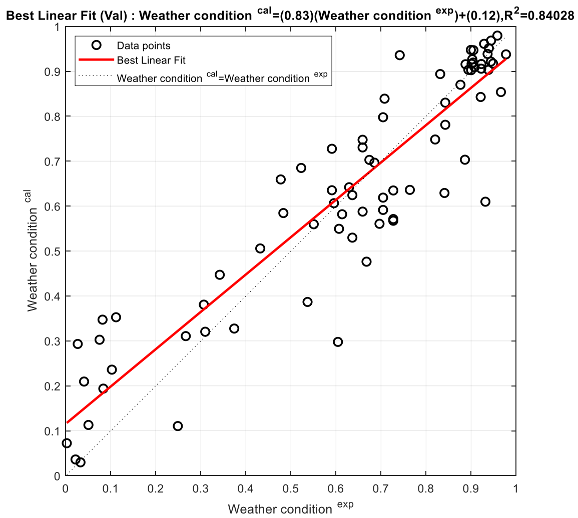

Figure 9. *Linear regression curve of the experimental of weather condition with the calculated of weather condition by the ANN optimized for the validation phase.*

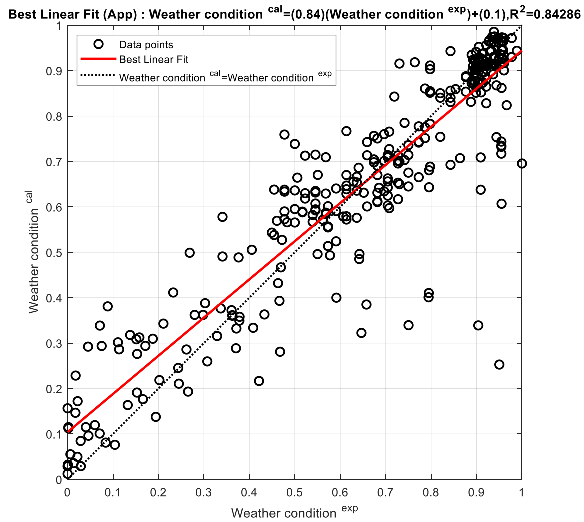

Figure 10. *Linear regression curve of the experimental weather condition with the calculated weather condition by the ANN optimized for the learning phase.*

Table 3. *Statistical performance of the network (ANNO).*

Type of error	Phase (Learning)	Phase (Test)	Phase (Val)	Phase (All)
MSE	$2.1574*10^{-5}$	0.0017	0.0043	0.0023
RMSE	0.1136	0.1456	0.1178	0.1202
NRMSE	0.0071	0.0635	0.1027	0.0732
MAE	0.0731	0.0983	0.0873	0.0797
R	0.9180	0.8762	0.9170	0.9104
R^2	0.8429	0.7672	0.8403	0.8289

IV.2. Global sensitivity analysis

The importance of ANN's input parameters for weather prediction is illustrated in Figure 11. As an observation, all parameters have approximately the same effects. The results prove that all the input parameters designated in this study have decisive effects on the weather conditions; therefore, they were selected appropriately and relevantly.ANNO provided a matrix of connection weights, the weights are coefficients related to artificial neurons, are analogous to the synaptic forces between axons and dendrites in real biological neurons. The matrix of weights from ANNO can be used to analyze the sensitivity of the inputs to the desired output, for this we use an equation (Eq.12) based on the partitioning of connection weights [28]:

$$I_j = \frac{\sum_{m=1}^{m=N_h}\left(\left(\frac{abs(W_{jm}^{ih})}{\sum_{k=1}^{N_i} abs(W_{km}^{ih})}\right)*abs(W_{mn}^{ho})\right)}{\sum_{k=1}^{k=N_i}\left(\sum_{m=1}^{m=N_h}\left(\frac{abs(W_{km}^{ih})}{\sum_{k=1}^{N_i} abs(W_{km}^{ih})}\right)*(abs(W_{mn}^{ho}))\right)} \quad (12)$$

Where: **Ij** is the relative sensitivity of the j-th input variable on the output variable; N_i and N_h represent the number of input and hidden neurons, respectively; Ws are connection weights, the superscript i, h and o refer to the input, hidden and output layer respectively, and the subscripts k, m, n and refer to the input, hidden and output layer respectively. The relative sensitivity of the different variables calculated by (Eq.11) is shown in Figure 11. As can be seen, all variables have significant effects on the weather conditions. Therefore, it can be observed that the highest contribution was obtained with the value of annual change (38%). The distance between the earth and the sun for each month and the sunshine rate have almost the same influence on the variation of weather conditions with (12%) and (15%) respectively as well as the conversion factor has a rate of (35%).

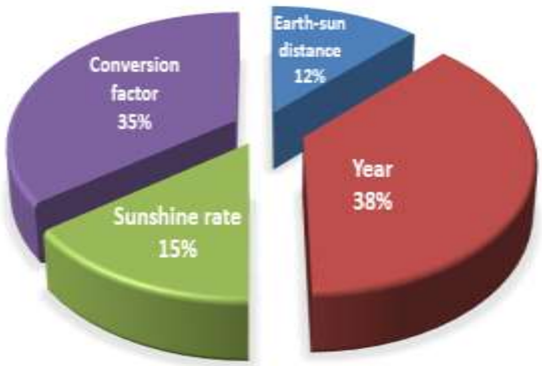

Figure 11. *Relative importance of input variables on weather prediction.*

IV.3. Graphical interface for weather prediction

The best ANNO model was implemented in a user-friendly graphical user interface designed using Matlab software and shown in Figure 12. This interface can compute the desired compound output knowing only the selected inputs. This was done in order to bring more flexibility to the use of the developed neural model. The program will therefore allow a simple and fast calculation of the weather conditions. The methodology of the steps to follow for the development of the graphical interface of ANNO by Matlab can be summarized as follows:

- Creation of a graphical interface using the guide function of Matlab
- Programming of the mathematical function obtained from the direct ANNs modeling that links the weather conditions with the four input parameters in MatLab® taking into account the weights and biases matrix, the normalization and de-normalization function.
- The input to predict the weather conditions (Figure 12)

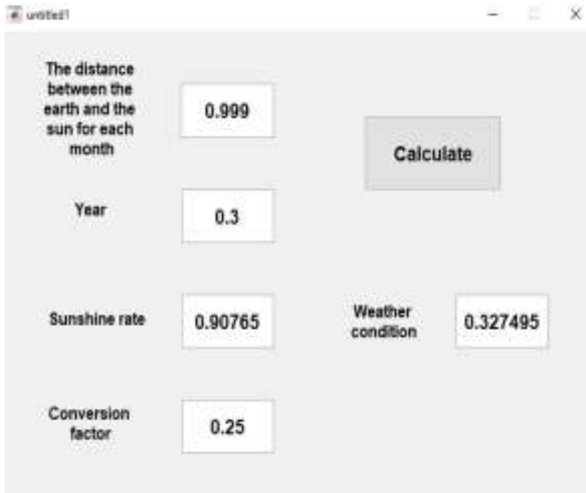

Figure 12. *MatLab graphical interface for weather prediction via ANNO.*

V. Conclusion

In this work, we were interested in developing an ANN neural network model for the prediction of four weather conditions (precipitation, average temperature, humidity and wind speed) as a function of four variables (land-sun distance, annual change, sunshine and conversion factor), recall that each value of the conversion factor "δ" indicates the desirable weather condition to be predicted: δ = 0.25 for cumulative precipitation, δ = 0.5 for wind speed, δ = 0.75 for humidity, and δ = 1 for average temperature. A total of 480 experimental data points were used and divided into three phases: learning, testing and validation. The architecture of the proposed model, includes a hidden layer of 10 neurons with a tangential sigmoid transfer function, a Levenberg-Marquardt type learning algorithm and $1.5\text{x}10^6$ iterations. Sensitivity analysis, confirmed that all input variables have a significant and large effect, and therefore the model developed in this work is reliable and can be successfully used to provide a good weather prediction.

VI. Acknowledgements

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