ALGORITHM OF TEMPERATURE PREDICTION FOR 2017 YEAR IN THE MUNICIPALITY OF CAJICÁ

PAULA ANDREA TORRES AMAYA

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Darío Amaya Hurtado

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Algorithm of temperature prediction for 2017 year in the municipality of Cajicá

Paula Torres, Luisa Amaya, Olga Ramos

Nueva Granada Military University

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Address For Correspondence:
Paula Torres, Nueva Granada Military University

BACKGROUND
Climatic factors are decisive for human being, because with the passing of the years they show greater variation and drastically affect the behavior of the environment. One of the most important factors is the temperature, which is constantly analyzed in agriculture, to predict if the weather will be favorable in all types of crops, and if the conditions are not adequate.

OBJECTIVE
Design and implement a system for temperature prediction for 2017 year and some part of 2018 year in Cajicá, Colombia.

RESULTS
The ANN reached at least a data adjustment of 95%, was validated by a six validations, and got in 73 epochs in 1.23 min. The final neural network, with their respective regression, was able to obtain reliable predictions of temperature for a period of 18 months.

CONCLUSION
The forecast of a meteorological variables needs a relevant measured data to training properly the ANN and get a similar behavior of the meteorological variables predicted. In this case the forecasting using artificial neural networks showed the same pattern during the sample period but had a 37% difference in the data.

KEYWORDS: Temperature prediction, neural network, regression, climatological variables.

INTRODUCTION

After the industrial revolution, the world had a breakthrough in energy terms, changing animal traction systems by systems based on coal and oil, also mechanically operated systems were replaced by automated systems, which started the current environmental decline, causing the extinction of some species of fauna, flora and even complete ecosystems.[1] That is why after more than 100 years the deterioration began to affect the climate, conditions and meteorological phenomena, for this reason the human being is looking for mechanisms for the prediction and control of these variables such as neural nets and other artificial intelligence methodologies. [2]

Temperature is one of the variables that most affect our climate, based on the fact that it is one of the fundamental variables for different meteorological phenomena, many works have been developed such as the one presented in [3], where a model with neural networks were used to predict the temperature of the wind in an interval of 12 hours The predictions of the final models are available all year via the internet. In the same way the work presented in [4] uses artificial neural networks to predict the maximum and minimum temperature throughout the year, the temperature in June, July and August has been forecast with the data for the months of January to May and in the majority of cases the prediction error is kept below 5%.

Another similar work is presented in [5], where is performed the training of an artificial neural network with the climatic database of the State of Georgia, in order to predict the temperature of the dew point with 12 hours in advance. The developed system operates throughout the State of Georgia.

In the case of Colombia, in [6] was developed a univariate model of neural network in order to generate predictions of nowcasting type in Mosquera, Cundinamarca, in order to provide fundamental data for sustainability in the agricultural production of corn, potatoes and flowers in the different climates, in the same way as the near areas to Bogotá.

In [7] applies an algorithm of artificial intelligence for temperature prediction, were applied different methods of training and learning, in order to compare and select the best results generated, analyzing the pros and cons of each one. The final results are compared with the practical work of the Department of meteorology, confirming that the proposed model has the potential for predicting temperature reliably. The study presented in [8] is similar to previous work, they use a neural network trained by back propagation for the prediction of temperature, which is compared with a real database, adding that soft computing techniques were used for improving the response of the model.

Keeping in mind the previous works, was designed and implemented a system for temperature prediction for 2017 year and some part of 2018 year in Cajicá, Colombia. A neural network was trained with the aim of establish the behavior of temperature, by measuring it since August of 2016. As a principal result was obtained the representation of future variations of temperature, for helping in the decision-making about the different crops in the zone, and achieving a better productivity.

Methodology:

For the prediction of temperature in Cajicá was used the methodology shown in Figure 1, which is based on the collection of data from solar radiation of the meteorological station located in Cajicá, subsequently was performed the training of the neural networks for obtaining the necessary data to calculate solar radiation by using the mathematical method of Redd.

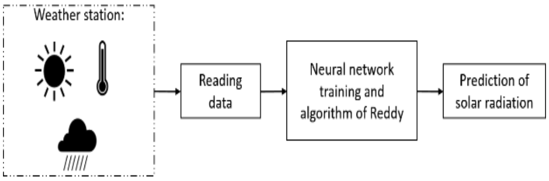

Fig. 1: Methodology used for the prediction of solar radiation.

To adequately predict temperature changes, were used data from two weather stations located in Cajica, the first station is located at latitude: 4 ° 56' 705 ' N and longitude: 74 ° 0'704 ' W. The second station is located at latitude: 4 ° 56'42 198 "N and longitude: 74 ° 0' 50.872" W, as shown in figure 2.

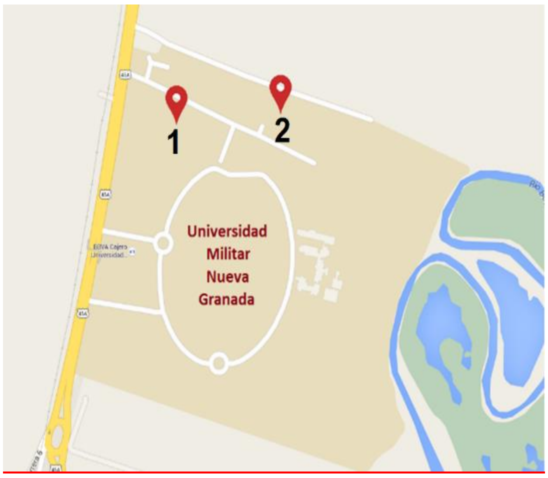

Fig. 2: Weather station located in Cajicá.

From each station were analyzed meteorological factors of average, maximum and minimum temperature and relative humidity and sunshine hours. This information was registered every hour since the 1 August 2015 until 16 July 2016, a 24 hours of registered data is shown in table 1, ordered as hour, day, month, year, radiation, minimum temperature and maximum temperature.

Table 1: Extract of the sample data for 24 hours.

H	D	M	Y	Rad	T. Min	T. Max
13	2	8	2015	716	15,9	19,1
14	2	8	2015	409	16,5	19,5
15	2	8	2015	568	15,5	18,8
16	2	8	2015	176	16,9	18,3
17	2	8	2015	288	16,6	18,4
18	2	8	2015	61	15,0	17,9
19	2	8	2015	0	13,4	14,8
20	2	8	2015	0	11,8	13,2
21	2	8	2015	0	10,6	11,6
22	2	8	2015	0	9,8	10,6
23	2	8	2015	0	9,7	10,4
24	2	8	2015	0	8,8	9,3
1	3	8	2015	0	9,1	9,6
2	3	8	2015	0	8,0	8,9
3	3	8	2015	0	8,1	8,7
4	3	8	2015	0	8,7	9,2
5	3	8	2015	0	8,9	9,4
6	3	8	2015	0	9,3	9,7
7	3	8	2015	12	9,7	10,0
8	3	8	2015	83	10,1	12,1
9	3	8	2015	343	12,3	15,3
10	3	8	2015	533	16,1	16,9
11	3	8	2015	449	15,8	17,5
12	3	8	2015	858	15,7	19,8

Once the registered data are normalized, the next step is to train the neural networks, defining as inputs the day, month and time radiation average and as a targets are defined the min and max temperature.

This neural network is composed of 3 inputs, 2 outputs, where the hidden layer has 150 neurons in the hidden layer and the outputs are the maximum and minimum temperature.

The equation 1 represents the adjustment of the weights for a minimum mean squared error T_{tot} between the desired output and the fd_i (discriminant function), where $i = 1, \dots, c,$ represents the real output for the number of training samples n, being c the classes number, x the samples of data and w is the weight vector.

$$E_{tot} = \sum_{i=1}^{n} (w^t X_i - fd_i)^2 \quad (1)$$

In the training of the ANN, in the moment of analyze the square error in the output layer Q, the responses of the output layer (rq) are related with the actual responses of the nodes (Oq). This relationship is represented by equation 2, which seeks reach adjust of minimum 95% of the data.

$$E_Q = \frac{1}{2} \sum_{q=1}^{N_Q} (r_q - O_q)^2 \quad (2)$$

Where N_Q is the number of nodes from the output layer Q and the factor $\frac{1}{2}$ is used as a quote, which represents the posterior derivation of the equation.

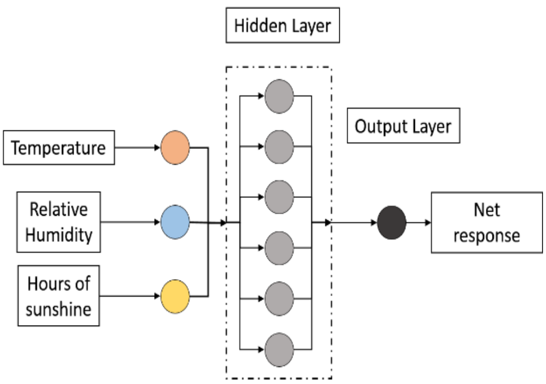

Fig. 3: Ilustración de la red neuronal utilizada.

For hidden layer, as well as the output layer, the activation function is the hyperbolic tangent sigmoid, represented by the equation number 1. This function allows to process data between -1 and 1, which is suitable for the data that we need to adjust.

$$P(t) = \frac{1}{1 + e^{-t}} \quad (1)$$

Once is obtained a regression greater than 95%, in the training data set of neural net in MATLAB, is possible to compute the average temperature by using the forecasting data.

Finally, with the prediction of average temperature, we made a comparison with the international database Meteonorm, with the aim of finding the average error of the predicted data.

Results:

The training of the artificial neural network that can predict the average temperature required different retrains, due to the amount of data. Once an ANN shows a good performance and regression, this mean that is possible predict the variables according with the data adjustment.

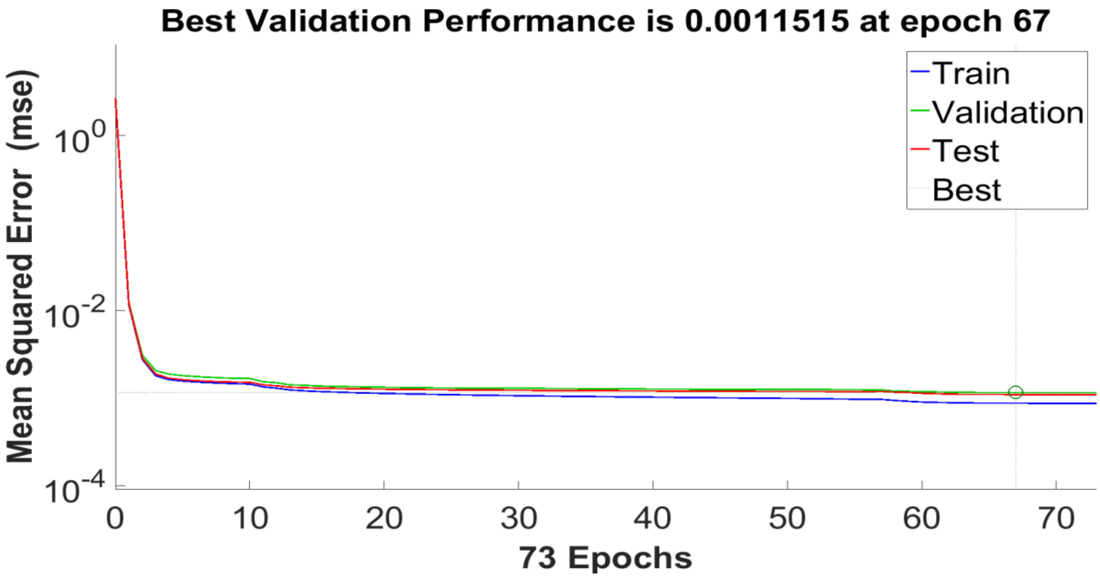

Fig. 4: Performance of the trained artificial neural network.

The figure 4 shows the performance reach by a trained artificial neural network, where it is evidence of that the training had a similar performance to the data used for validation and test. This mean that the ANN reached at least a data adjustment of 95%.

Once define de ANN for forecasting the average temperature at Cajicá, the ANN's features are evaluated, where in the training the ANN was validated by a six validations, got in 73 epochs in 1.23 min, these features are shown in table 2.

Table 2: Features of the trained artificial neural network.

Feature	Value
Epochs	73
Time	0:01:23
Performance	2.59/0.00
Gradient	3.73/1.00e-7
Mu	0.00100/1.00e+10
Validation checks	6/6

Once obtained the neural networks suitable for prediction of maximum and minimum temperature in Cajica, the information of 13 days was taken to validate the data, as shown in figure 4

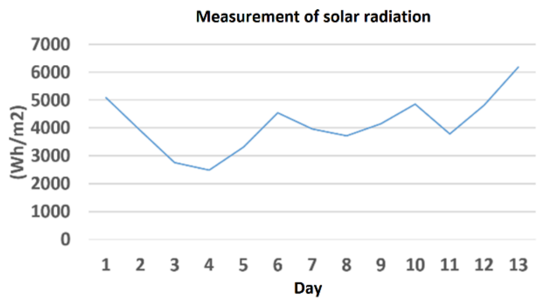

Fig. 4: Data from Meteonorm software for solar radiation from 14 to 26 July.

In Figure 4 can be seen the behavior of solar radiation at Cajicá since July 14 from until July 26, measured from different meteorological stations around the city. This data had an average of 4119 Wh/m2 radiation during the period.

On the other hand, with the artificial neural network was forecasted the minimum and maximum temperature for Cajicá during the same period. As is shown in figure 5, the behavior of solar radiation had the same three decreases but with less variation with the others values.

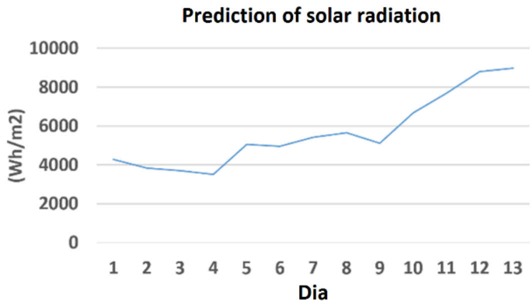

Fig. 5: Data of Meteonorm Software for solar radiation from 14 to 26 July.

In the same way that occurred with the forecast data, the ANN prediction has a similar behavior but unlike the Meteonorm data, the average solar radiation was 5665Wh/m2.

Conclusions:

The forecast of a meteorological variables needs a relevant measured data to training properly the ANN and get a similar behavior of the meteorological variables predicted. In this case the forecasting using artificial neural networks showed the same pattern during the sample period but had a 37% difference in the data.

Additionally, taking into account the unpredictable that is forecast meteorological, get the behavior is a beginning to try improve the algorithm using different compositions in the data and in the training methods of the ANN for getting a best performance in the results.

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