A Neofuzzy neuron approach for climatic variables forecast

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Abstract: - In this work it was created climatic variables prediction models based on a modified neofuzzy neuron approach. This neofuzzy neuron approach is a simple and accurate method for obtaining climatic variables forecasting results using climatic measurements from previous days. The variables used for building the model are Temperature, Humidity, Dew Point, Wind speed, Pressure, Rain and Solar Radiation. It's also presented as example the obtained results for temperature forecast in Ibarra, Ecuador using data from years 2012-2015.

Key-Words: - Neofuzzy Neuron, climatic variables prediction, forecast, neofuzzy neurons, Artificial Intelligence.

1 Introduction

Artificial intelligence [2] and its diverse techniques have been widely used for creating diverse prediction models [4] including virtual sensors [10], formal prediction model for identification and control systems [17], among others. Weather forecast is a very important area for building prediction models, because its related with security, environmental behavior and its impacts in basic activities as agronomy, engineering, tourism, constructions, social development, among others [12].

Some interesting contributions in the area of utilization of artificial intelligence for the prediction of weather variables can be found in [6, 14, 15].

Neofuzzy neurons approach was presented by Takeshi Yamakawa [18, 19] and tries to combine the best characteristics and capabilities of Artificial Neural Networks [8] and fuzzy logic [20]. Some applications of this neofuzzy neurons have been done in areas as Time series Forecasting [5], virtual sensors design for oil production processes [7], identification of nonlinear dynamic systems [9], fault detection and isolation [11] and operational condition prediction in mechanical systems [16].

In this paper it will be presented a proposal for building a forecasting model for climatic variables using the neofuzzy neuron approach and making some changes to the original algorithm in order to improve the convergence time and the accuracy of the prediction models.

This paper is organized as follows: Section 2 contains the Neofuzzy neuron description and characteristics. In section 3 it will be presented the proposal for climatic variables forecast using the Neofuzzy neuron-based approach. In section 4 it will be presented an example of the neofuzzy neuron-based forecasting approach for creating a prediction model for temperature in Ibarra city in Ecuador. In Section 5 it will be presented the appropriate conclusions, recommendations and further works.

2 Neofuzzy neuron description

Neofuzzy neuron [18, 19] is a very simple structure that uses the capabilities of artificial neural networks and fuzzy logic and is a great tool for modeling complex systems because of the simplicity of its structure, composed by a single neuron that in its weights are defined some fuzzy partitions in order to model the complexity and nonlinearities of the systems, being only necessary to change the number of fuzzy partitions in the input variables, allowing this way to find the most suitable structure. While in artificial neural networks it is necessary to change the number of layers, the number of neurons in each layer and the activation function to find the appropriate structure for obtaining good fitness, in the neofuzzy neuron there is only one structure and the only parameter that have to be changed is the number of fuzzy segments.

In Figure 1 it can be seen the structure of a Neofuzzy Neuron, where the interconnecting weights (synapse) are replaced by a set of nonlinear functions *fi*, and the cellular body perform the sum of the synaptic signals.

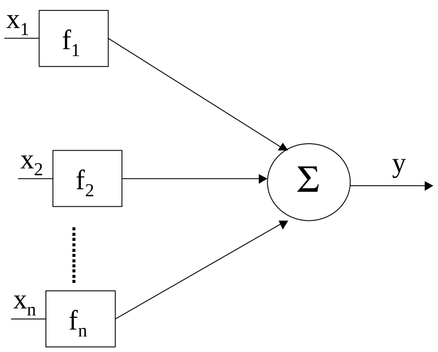

Figure 1: Structure of a Neofuzzy Neuron

In Figure 2 it's depicted the structure of each of the nonlinear functions *fi*. These functions are composed of IF <condition>-THEN <action> rules, using as <condition> the membership's function value of the input signals that are included in each of the complementary fuzzy segments defined in Figure 3. The <action> is a singleton with *wij* as corresponding value.

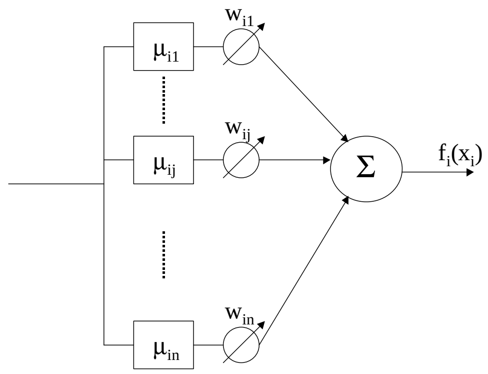

Figure 2. Structure of the Nonlinear Function (synapse)

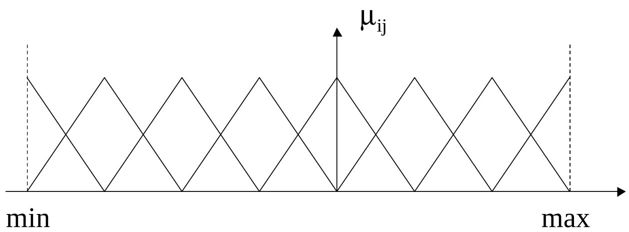

Figure 3. Complementary fuzzy segments

For obtaining the corresponding *fi(xi) (*output value of the synapse) it's used a defuzzification process that consider the complementary structure of the segments (the sum of the two activated membership functions should be equal to 1). So, the neofuzzy neuron output may be given as follows:

$$f_i(x_i) = \mu_{ik}(x_i)w_{ik} + \mu_{i,k+1}(x_i)w_{i,k+1} \qquad (1)$$

Where:

$\mu_{ik}(x_i)$ is the membership value obtained for the input signal *xi*.

w_{ik} are the interconnecting weights.

The incremental updating (Stepwise Training) learning algorithm used for updating the weights, is as follows:

$$\Delta w_{ij} = -\alpha(y_k - t_k)\mu_{ij}(x_{ik}) \qquad (2)$$

where:

y_k is the neofuzzy neuron output.

t_k is the desired output.

α is the learning rate.

In this particular work it has been used two different learning rate values: It was used a bigger value for the beginning of the algorithm in order to find a faster convergence and then it was uses a smaller value in order to have a better fitting and more accurate predictions.

3 Climatic variables forecast using the Neofuzzy neuron-based approach

For building forecasting models using the neofuzzy neuron-based approach for predicting climatic variables it´s very important to have a methodological framework considering issues related to the measurements, statistical analysis, kind of data to be used and the relationship between climatic variables. Next it will be presented the proposed methodology.

3.1. Methodological approach for climatic variables forecast using Neofuzzy neurons

A general methodology for climatic variables prediction using artificial neural network was presented in [12] and the main stages, phases and steps can be adapted for using it with a Neofuzzy neurons approach. Next, it will be presented the adaptation of the methodology proposed in [12] for the particular Neofuzzy neurons approach:

Stage 1. Analysis and Description of the climatic prediction Problem: In this stage it should be well studied the climatic conditions in the place where is going to be created the model, including the variables characteristics and behavior, the measurement devices used (meteorological stations, sensors, components, among others). Also is important to know the complete list of available information and the historical databases that will be used for creating the model.

Stage 2. Feasibility analysis for climatic variables prediction using Statistical Data Analysis and Neofuzzy neurons: According to the information collected in the previous stage it will be studied the feasibility of constructing a neufuzzy neuron-based model for predicting the climatic variables. It will depend on the quality of the available data, the collected historical data and the diverse measured variables and its relationship with the variables wanted to be predicted.

Stage 3. Statistical data analysis of the Variables that will be used for creating the climatic prediction model: Because the model will be created using a Neofuzzy neuron approach, it will highly depend on the quality of the data and the relationship between the variables that will be used for creating the model. It will be used statistical data analysis tools in order to take appropriate decisions concerning the variables and patterns that will be used and to evaluate and complete the data sets for making them useful for building the Neofuzzy neuron-based model. It will be used statistical techniques oriented to the detection of atypical observations, variables transformations if it is required, relationship between variables, data imputation, and data sets selection, among others. This stage contains four phases: *Available Data Description, Exploratory Data Analysis, Data processing and imputation and Training and testing sets Selection.*

Stage 4. Neofuzzy neuron-based prediction model construction: In this stage is given the building of the forecast model based on Neofuzzy neurons approach, using the arranged data set, the selected inputs and the defined training set. It´s also selected the diverse parameters needed for creating Neofuzzy neurons models. It should be decided if there is going to be used some time delay´s models in order to give temporal evolution information to the model. It will be evaluated the results found with diverse models and which of them presents a better fitting to the original data, and finally the same evaluation process should be done with the testing data set for determining the adjustment of the model to non-previously shown data set and the generalization capabilities. All these activities can be reduced in two phases: *Prediction Model Adjustment and Prediction Model Evaluation.*

Stage 5. Neofuzzy neuron-based forecasting model implantation: In this stage it will be created the operational model that will be used for continuously predicting the climatic variables. It will depend on the characteristics of the systems where the model will be running and the periodicity for having a new on-line prediction.

3.2. Creating climatic variables forecasting model using Neofuzzy neurons approach

Following the previously presented methodology and the results presented in [12, 13], it was first studied the typical climatic variables that usually are measured by the meteorological stations. After that, it was studied the relationship between the variables and it was selected next variables for creating the climatic variable forecasting model: Temperature, Humidity, Dew Point, Wind speed, Pressure, Rain and Solar Radiation.

For predicting any of the climatic variables for one day in the future, it´s important to use information concerning the measurements from one day before and also with information from previous days. The general structure of the neofuzzy neurons-based approach model can be seen in figure 4, where x_1, x_2, x_3, x_4 and x_5 correspond respectively to the day, month, year, hour and minute to be predicted. x_6 is the previous day temperature, x_7 the previous day humidity, x_8 the previous day Dew point, x_9 the previous day wind speed, x_{10} the previous day pressure, x_{11} the previous day rain and x_{12} is the previous day solar radiation. For a more general model, where it's desired to make the prediction using more previous days, it will be used 5+7*k (where k is the previous days inputs), because the first 5 inputs variables will correspond to the day, month, year, hour and minute to be predicted and it will be required 7 variables (Temperature, Humidity, Dew Point, Wind speed, Pressure, Rain and Solar Radiation) for each or the previous days used for the prediction model. This model can be seen in figure 5 as a general scheme and in figure 6 detailing the Neofuzzy neuron structure.

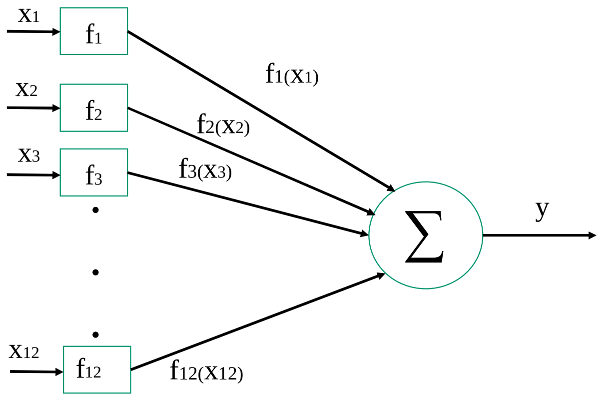

Figure 4. Structure of the neofuzzy neuron-based approach for climatic variable forecast using one time delay

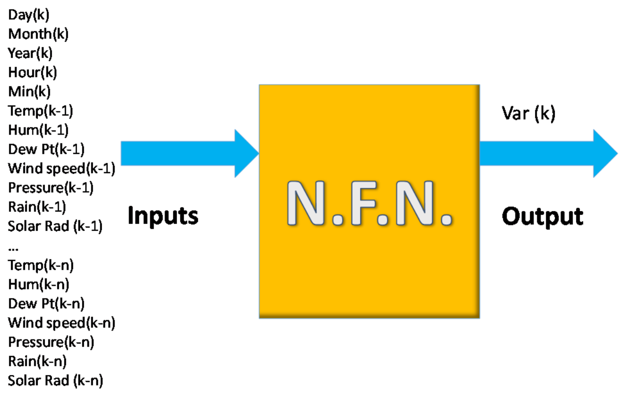

Figure 5. General scheme based on neofuzzy neuron-approach for climatic variable forecast using diverse time delay basis

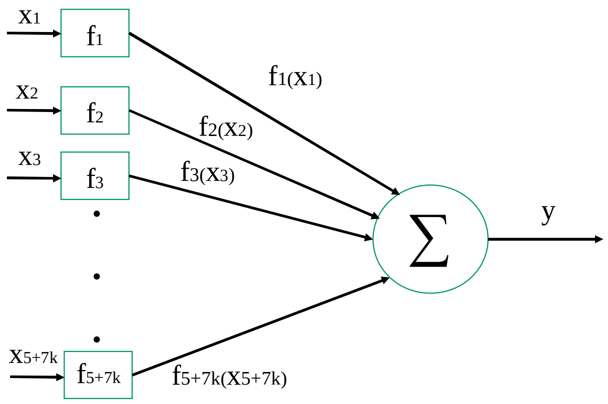

Figure 6. General structure of the neofuzzy neuron-based approach for climatic variable forecast using diverse time delay basis

4. Example of temperature forecast using the neofuzzy neuron approach

Following the previously presented methodology and the results presented in [12, 13], it was first studied the climatic station and the variables that have been measured during more than seven year. After that, it was considered the relationship between the variables and it was used the recommended climatic variables for creating the forecasting model: Temperature, Humidity, Dew Point, Wind speed, Pressure, Rain and Solar Radiation.

For building the forecast model it used the data collected and described in [12, 13]. It was analyzed the data taken every five minutes from January 1st 2012 until May 15th 2015 [12, 13] in Ibarra City [21]. It was made statistical analysis [3] concerning outliers, data imputations [1] and data sets selection for training and testing the model.

It was selected the data set that was going to be used for creating the neo-fuzzy neuron-based model (240.000 patterns) and the data set used for testing the model (116.640 patterns).

It was build models using diverse learning initial and final learning rate and diverse inputs from one previous day until five previous days and the model that gave the better results for training and testing phases was the one that uses the information concerning 4 previous days and the results can be seen in figure

The model that gave better result was the one created using nineteen (19) inputs variables, which means that it was used the information from two previous days from the moment wanted to be predicted. Figures 7 and 8 depict the scheme and the Neofuzzy neuron structure for this particular architecture. It was used as initial learning rate α=0.0001 and final learning rate (after 1000 iterations) of α=0.00001. The results can be seen in figures 9 and 10. In both cases (training and testing data sets) the error found between the real data and the predicted data is 10.37% and 9.08% respectively.

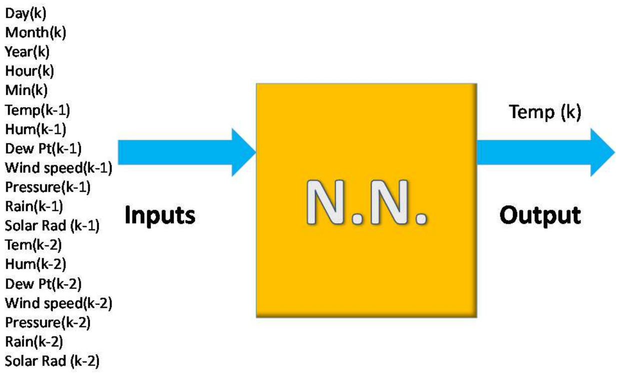

Figure 7. Structure of the neofuzzy neuron-based approach for climatic variable forecast using two time delay

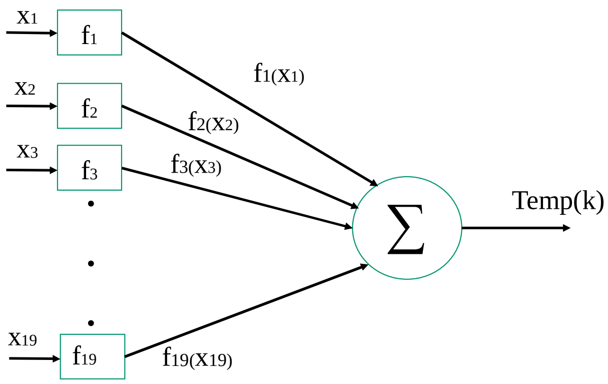

Figure 8. Structure of the neofuzzy neuron-based approach for temperature forecast using two time delay

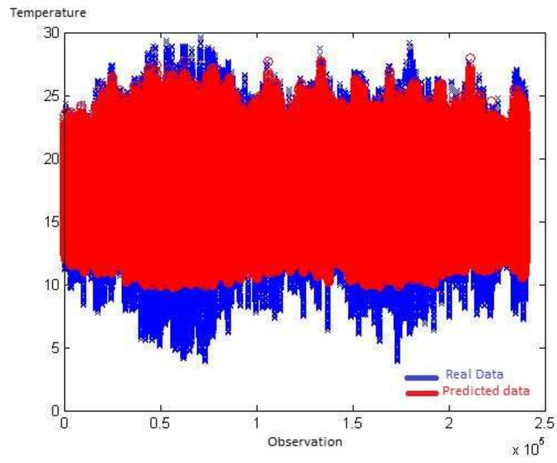

Figure 9. Result for the training data set using temperature prediction model

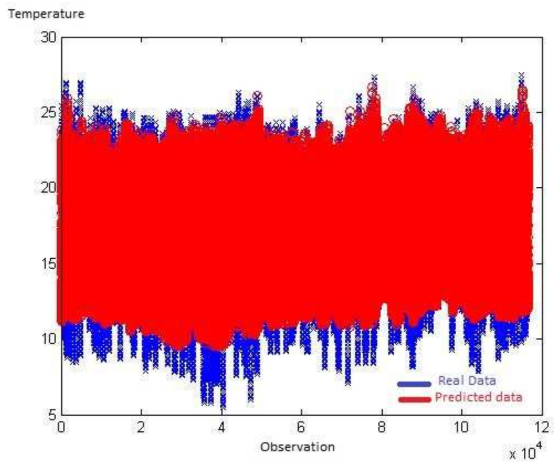

Figure 10. Result for the testing data set using temperature prediction model

5 Conclusion

In this work it was presented a proposal for creating climatic variables forecasting models using a neo fuzzy neuron approach.

This model was created using some modifications to the typical neofuzzy neurons approach, changing the training rate, having one with bigger value for obtaining a faster convergence and a smaller one after some iterations in order to have a more accurate values.

This climatic variables forecasting model proposed was used for modeling the temperature in the Ibarra city in Ecuador and it was found good results with a particular selected structure.

It will be continued this research, comparing these models with other neuronal and intelligent or hybrid systems models in order to try to improve the found results.

Acknowledgment: Authors want to thanks the support given to this project by the Secretaría de Educación Superior, Ciencia, Tecnología e Innovación of Ecuador and Prometeo Program.

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