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Water Level Prediction Using Artificial Neural Network Model

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Abstract

Due to its topographical characteristics and its particular hydrometerelogical regime, Colombia has long extensions susceptible of flooding; considering this situation, in this article a system based on artificial neural networks is proposed to model and predict the water level in the river system.

The variables used in this model include: historical water level data in different stations, rain season and La Niña or El Niño phenomenon. The results showed a good system performance.

Keywords: Artificial Neural Network, Water Level, Flood, Prediction.

INTRODUCTION

Due to its topographical characteristics and its particular hydrometereological regime, Colombia has long extensions susceptible of flooding, especially in the lower regions of the basins and the valleys of main rivers such as Magdalena, Cauca, Atrato and Putumayo [1]. According to DesInventar database information (OSSO and EAFIT Corporation, 2011) in most of the national territory the predominant historical losses are caused by floods [2].

Artificial Neural Networks (ANN) will be used as a base to create the predictive system; those are information processing systems whose structure and functioning are inspired in biological neural networks [3]. It is noteworthy that the ANN have been used in the last years in diverse fields with predictive purposes such as financial and economic modeling, market and customer profiles, medical applications, industrial process optimization and scientific research.

Consequently, a Neural Network Autoregressive with Exogenous Input (NN-ARX) will be implemented to model and predict the river system water level. The system could be useful for predicting floods that can affect productive activities like agronomy and livestock; as well as it could be used to avoid damaging in the energetic industry and transport infrastructure.

FRAMEWORK

Neural Networks

An agent is defined as entity that acts in an environment and it is described as intelligent when it makes appropriate actions to the circumstances and the goals set; other characteristics are its flexibility to changes in the environment, its learning from experience and its capability to make decisions based on its perceptive and computational limitations [4].

Artificial Neural Networks are defined as processing systems of information which functioning are inspired in biological neural networks; they are composed by a set of simple processing elements called nodes or neurons that have connections with a specific weight [5].

Figure 1 shows an artificial neural network that simulates the inputs, weights and output of an activation function [6] where each input is assigned a weight that is subsequently added to use the activation function; in this way the neurons have the ability for pattern recognition [7].

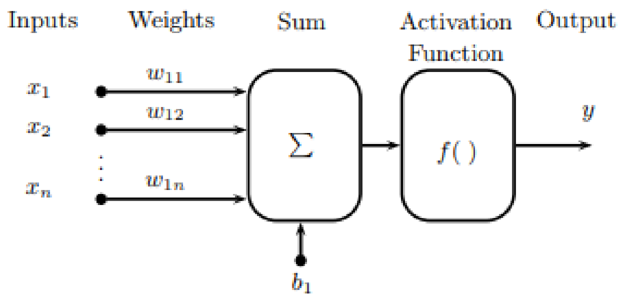

Figure 1. Artificial Neuron [8].

The multilayer perceptron is the simple perceptron generalization; in 1969, Minsky and Papert [9] demonstrated that the combination of some simple perceptrons, that is, the inclusion of hidden neurons, could be a suitable solution to solve non-linear problems.

In spite of Minsky and Papert research did not demonstrate how it was possible to adapt the weights from the input layer to the hidden layer, the idea of combining simple perceptrons worked as a base of the subsequent studies made by Rumelhart, Hinton and Williams in 1986 [10]. They presented a form of back-propagation of the errors measured in the output of the network to the hidden neurons, giving rise to the generalized delta rule.

The multilayer perceptron allows connecting the input and outputting variables of the network, this relation is obtained by the forward propagation of the input values. For this purpose, each neuron processes the information received and produces a response or activation that is propagated through the links to the neurons of the subsequent layer [11].

An example of a multilayer neural network is shown in Figure 2.

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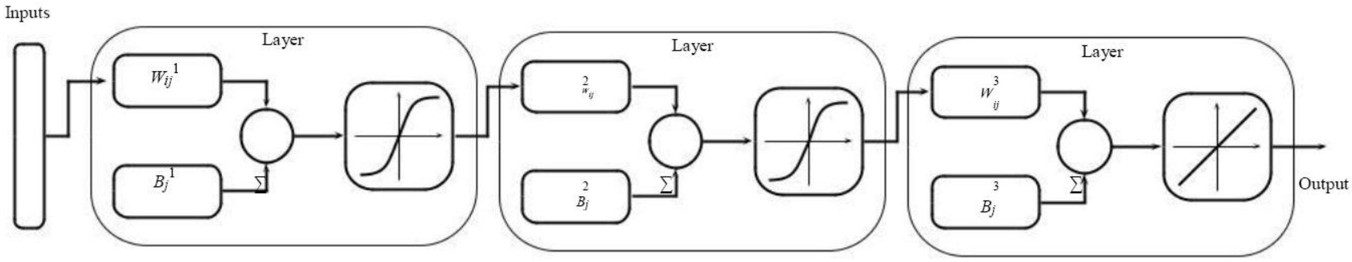

Figure 2. Multilayer Neural Network.

Recurrent Neural Networks (RNN) are networks that can process sequential data; this is possible due they have feedback paths between their elements. Therefore, a neuron is connected to all the previous and/or subsequent neurons through weights vectors that are altered in every epoch (time period to train the network) in order to reach the target values [12].

NATURE OF FLOODS

A flood occurs when the water reaches a piece of land that is normally dry. The most common way that this happens is a river flooding, which can happen when excessive rain makes that water exceeds the river bank and it extends through the adjacent called alluvial plain.

Most of floods take hours or even days to develop, giving the residents time to be prepared or to evacuate. Other type of floods are generated quickly and with few warning signs, these ones can be extremely dangerous because of their sudden nature, they can convert a stream in a water wall capable of destroying all within its way.

However, if it is known approximately how much rain falls in a specific zone and the moment in which changes the level river start is registered after the rainfall, an alert can be generated before the flood happens [13].

Measurement of the River Level

The monitoring of the rain measurements and the level of the rivers and ravines, through rain gauges and hydrometric scales, respectively, allows knowing the hydrological conditions which can unleash in a flood. The rain gauges provide information of water volume that is on the soil (fallen rain), while the hydro-metric scales provide information about the increase on the water level in the water bodies.

Rain Gauges The necessary amount of rain gauges depends on the local conditions of each minor basin. For example, mountainous areas require more rain gauges than at areas.

Limnimeters The limnimeters are rules that allow reading the height of water in the rivers and ravines. This rule has to be long enough to measure the river level even when it is very high [14].

PROPOSED SYSTEM

The data used in this study was taken from some stations of the Magdalena River for instance Aguadas, Barbosa and Palenquito, the samples were gathered between 01/01/1997 and 31/12/2015.

The chosen inputs for the proposed system are presented in the block diagram Figure 3.

- Signal delays: 2, 3 and 5 delays for time series were tested.

- Station coding: Depending on which data belong on which station, each one of the stations was coded with a weight of 1 when the data was associated with it and with a weight of 0 if it was not.

- Season of the year: The season in Colombia varies approximately in the following way:

Table 1. Seasons in Colombia.

Season	Months
Strong summer	December, January and February
Strong winter	March, April and May
Weak summer	June, July, August
Weak winter	September, October and November

Each one of the seasons has an associated weight, depending on the month that the data belongs to.

- El Niño or La Niña phenomenon: These phenomena affect the quantity of rain fallen in a period of time; therefore, it affects the river system water level.

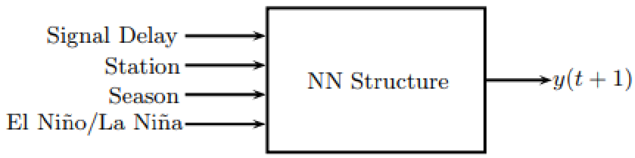

Figure 3. Neural Network inputs and output.

The output of the system is the river level (normalized) for the respective station.

The design of the neural network with the considered inputs and one output using two layers is shown in Figure 4.

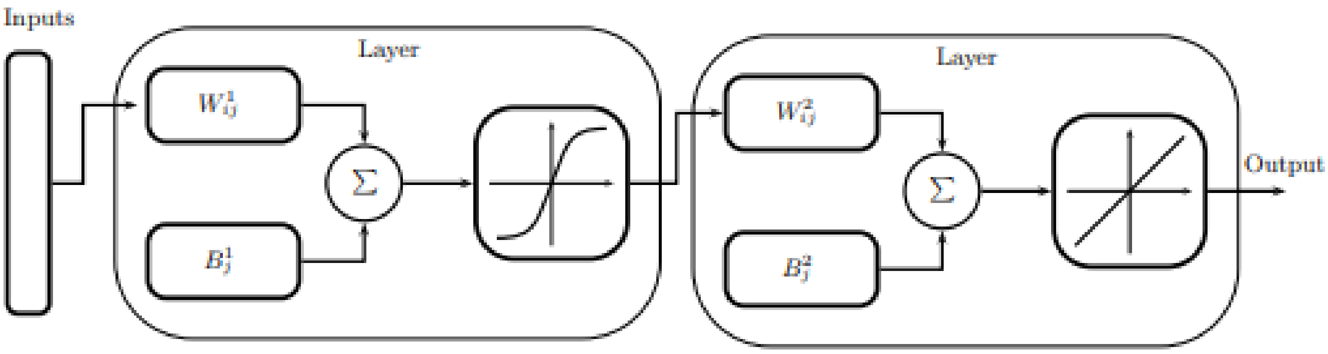

Figure 4. Neural Network Diagram.

RESULTS

The number of delays and neurons in the hidden layer were considered in order to design and train the neural network. The activation functions that were used are *logsig* for the hidden layer and *satlin* for the output layer. The configurations are shown in Table 2. 70% of data was used for training and 30% for testing.

Table 2. Configurations Considered.

	Delays		
Neurons	2	3	5
3	Case 1	Case 4	Case 7
6	Case 2	Case 5	Case 8
12	Case 3	Case 6	Case 9

Taking into account the random Initialization of NN the training process is performed 20 times for each case, the stats of data obtained during this development are in Table 3, where the maximum and minimum value obtained are shown, in addition to the mean and standard deviation (STD). This table shows the best performance value in each case considered, where case 9 is chosen as the best configuration (best minimum value) for the neural network consequently for the system.

Table 3. Stats results for training process.

Results for 2 delays				
Neurons	Max	Min	Mean	STD
3	3.9195e-005	3.7981e-005	3.8728e-005	4.7982e-007
6	3.9105e-005	3.7356e-005	3.8103e-005	4.8738e-007
12	3.7937e-005	3.6304e-005	3.7335e-005	4.0242e-007
Results for 3 delays				
Neurons	Max	Min	Mean	STD
3	3.9207e-005	3.8035e-005	3.8948e-005	3.1945e-007
6	3.8727e-005	3.7254e-005	3.785e-005	4.665e-007
12	3.7662e-005	3.5728e-005	3.6545e-005	4.8448e-007
Results for 5 delays				
Neurons	Max	Min	Mean	STD
3	0.012918	3.7373e-005	0.00068217	0.00288
6	3.8761e-005	3.6844e-005	3.7665e-005	5.1261e-007
12	3.7367e-005	3.5333e-005	3.6654e-005	5.4943e-007

The performance function used is the Mean Square Error (MSE) which is

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(y_r[n]-y_s[n])^2 \quad (1)$$

Where N is the number of total data, y_r real data and y_s simulated data.

The stats results for validation data are shown in table 4.

Table 4. Stats results for validation process.

Results for 2 delays				
Neurons	Max	Min	Mean	STD
3	0.24305	0.0001118	0.012273	0.05432
6	0.00037617	7.5271e-005	0.00013451	5.9443e-005
12	0.013521	8.5654e-005	0.00080155	0.0029943
Results for 3 delays				
Neurons	Max	Min	Mean	STD
3	0.00015013	0.00011894	0.0001283	7.5632e-006
6	0.0016509	0.0001048	0.0002098	0.0003417
12	0.0028866	8.5732e-005	0.00042994	0.00068965
Results for 5 delays				
Neurons	Max	Min	Mean	STD
3	0.014521	0.00010422	0.0011113	0.0033554
6	0.01167	0.00011222	0.00072938	0.0025765
12	0.016045	8.4215e-005	0.0012844	0.003703

The simulation using the best case for Aguadas, Barbosa and Palenquito station is shown in Figures 5, 6 and 7, where is observed a good adjustment of data.

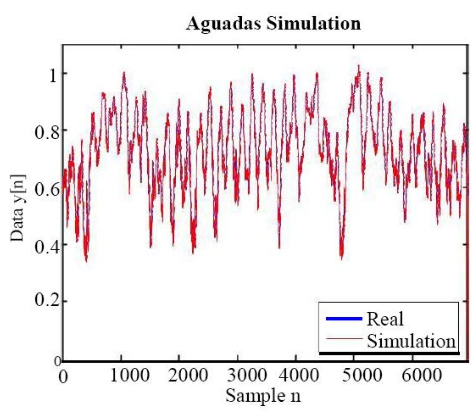

Figure 5. Results of Station 1 simulation.

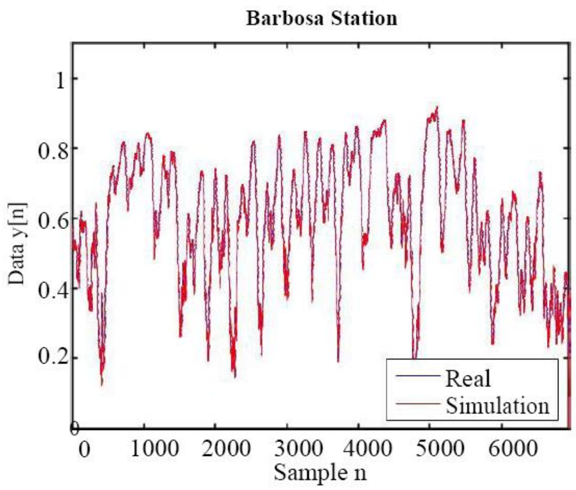

Figure 6. Results of Station 2 simulation.

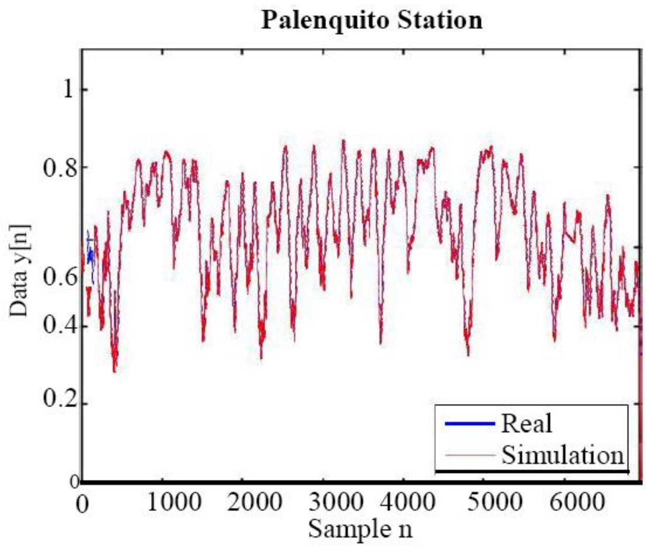

Figure 7. Results of Station 3 simulation.

Cases 1 and 9 show the worst configurations that can be performed for the neural network considering the maximum MSE value. It is also considered that case 4 is a valid option for testing with that configuration because it has a better average value than the other 8 cases.

CONCLUSIONS

From the analysis of information obtained using the data dataset, it is possible to create a predictive system.

The stats of the neural network training enabled to analyze the performance obtained for considered cases, choosing the configuration of case 4, also the case 2 is an option to be considered, and additionally test cases 1 and 9 are not recommended because of their poor performance on tests.

In a future work it is considered to use a neuro-fuzzy system to implement the same model.

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