A BEHAVIOR AND PREDICTION OF TURBIDITY IN THE FRO RIVER (CUNDINAMARCA, COLOMBIA) THROUGH ARTIFICIAL NEURONAL NETWORK (NAR ALGORITHM)

JULIAN CAMILO PERDOMO¹, OCTAVIO JOSÉ SALCEDO PARRA² & MIGUEL J. ESPITIA R.³

¹Faculty of Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

²Faculty of Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

³ Faculty of Engineering, Universidad Distrital Francisco José de Caldas, Bogotá, Colombia

ABSTRACT

The present paper considers the behavior and prediction of turbidity in the Frio River, through the application of an Artificial Neural Network (ANN) through the Non-Linear Autoregressive method with the purpose of knowing the characterization of this parameter of raw water quality that has an impact on the purification of water.

KEYWORD: Turbidity, Raw Water, Artificial Neuron Network & Prediction

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INTRODUCTION

The turbidity in raw water is a physical characteristic due to the presence of particles such as clays, silt, plankton and others, which establishes a limiting condition (pre sedimentation with turbidities greater than 1000 NTU and maximum 3000 NTU for purification) in the sources of supply and, therefore, in the processes and operations of purification of water [1, 2, 3], however the optimum is to have a turbidity below 100 UNT for an adequate operation of purification [4, 5, 6].

It is significant to know the behavior of turbidity in a body of surface water, therefore the technique used was Artificial Neural Network (ANN) and this has different algorithms of training as Back propagation, Newton, Leven berg Marquardt (LM) among others; in the case of the present investigation with which the best results were obtained, it was the Non-Linear Autoregressive (NAR) method. The NAR artificial neural network is a feed-forward neural network. This network is composed of individual processing elements called neurons that resemble to the brain neurons [7]. The model of each neuron can be represented as $A = F(WP + b)$ where $W = [w_{1,1}, w_{1,2}, \dots, w_{1,R}]$ and $P = [p_1, p_2, \dots, p_R]$, the vector P are the inputs, W is the vector of the weights of each input, the parameters w_1 , R and b are adaptive [8]. Each neuron adds the weighted inputs and then applies a linear or non-linear function to the resulting sum to determine the outputs. Between the most commonly used functions are the step function, sigmoid and ramp [9]. Neurons are arranged in layers and combine through excessive connectivity. This allows the specification of multiple entry criteria and the generation of multiple exit recommendations [7]. The NAR algorithm is a non-linear optimization algorithm based on the use of second order derivatives [9]. The NAR algorithm finds the minimum of the function $F(x)$ which is a sum of squares of non-linear functions.

$$F(\mathbf{x}) = \frac{1}{2} \sum_{i=1}^m [f_i(\mathbf{x})]^2 \quad (1)$$

Take the Jacobean from $f_i(\mathbf{x})$ which is referred to as $J_i(\mathbf{x})$, then the Levenberg-Marquardt method looks for the solution of P given by the equation.

$$(J_k^T J_k + \lambda_k I) P_k = -J_k f_k \quad (2)$$

Where λ_k are not negative scalars and I is the identity matrix [10, 11, and 12].

Artificial Neural Networks (ANN) as artificial intelligence technique, have been conducted studies by Lin (2008), Dogan (2009) and Singh (2009) using neural networks for prediction of river water quality in watersheds. However, it has also been found in studies by Beck (2005) an effect of accumulated error in period of several years, which even generates considerable approximation in the cumulative predictions in multiple time periods, which is highly significant and influential in the water quality in the river basin [13]. Other results of studies by Hamada (1999) and Grieu (2005), have established that the performance of the WWTP can be predicted through a neural network and also other studies such as Hamed (2004) and Mjalli (2007), Tomenko (2007), have shown, that neural networks has outperformed the regression models used in wastewater treatment plants [13]. In addition, it has been worked in topics of centralized cooling of ice water, prediction of water consumption and river flows, in the assessment of the quality of drinking water, in the control of water treatment processes, management of wastewater treatment plants, purification of groundwater and identification of sources of water pollution, in terms of dioxins and sediments in rivers [14]. Linear statistical and neural network models for the application of water management in watersheds have been applied, taking into account the effluents of wastewater treatment plants and non-point sources (rainfall run-off). For this reason, in this work the behavior and prediction of the turbidity in the Frio River will be valued as an input for the decision making in the purification of water.

MATERIALS AND METHOD

The method used is a combination of real, exact observation and knowledge of an empirical, complex situation and inductive reasoning, which would consist of deriving a new knowledge from particular phenomena and knowledge already obtained, and establishing propositions analyzed from their causes and real effects, that is, from the particular to the general [8, 9]. It is worth mentioning that, according to the analysis and scope of the results, the type of research is analytical- quasi - experimental, since analyzes an event and understands in terms of its obvious aspects, and also discover elements that make up the totality and connections that explain their integration, i.e., it promotes the study and deeper understanding of the event under study [10, 11, 12].

The water quality information provided by the Autonomous Regional Corporation of Cundinamarca in the period from 2012 to 2016.

RESULTS

Frio River Basin

The Frio River located in the province of the central savannah in the Cundinamarca Department, is born in the Guerrero paramour in the northeast of the Zipaquira Municipality, at a height of 3700 meters above sea level and this river is a tributary of the Bogotá River, which delivers its waters near the Municipality of Chia at an altitude of 2500 meters above sea level. This river is a structuring axis for the development and agricultural growth of the basin that constitutes it

(administratively the municipalities of Cajicá, Chia, Cogua , Cota, Tabio , Tenjo , Pacho, Subachoque and Zipaquirá), benefiting the network of fences (small channels with constant water flow), irrigation districts and water supply for the adjacent community; presents vegetal coverage of high Andean primary forest and secondary forest; the climatic condition of the river is humid, with moderately fine texture, soils with saturated horizons and with high susceptibility to water erosion; the flows(supply) of the river in dry season of 1.47 m³/s and rainy season of 2.82 m³/s ,the demand is 9.2 m³/s (domestic, agricultural, industrial, ecological) and the shortage index is high (dry season) and medium high (rainy season); the area of the basin is 202 km² and the urban population density is 272 Hab/ Km² and rural 66 Hab/Km . Some inconveniences found in the basin, is the increase of the torrential regime due to the decrease of the infiltration, erosion (by high slopes, hydric and by mining) in the basin, overflow of the river, organic contamination of the surface water body. [15, 16, 17].

Method Non-Linear Autoregressive (NAR)

The implementation of the artificial neural network through the NAR algorithm was obtained across the import of the data over time and then the turbidity in the raw water was estimated according to the historical input data, for this the following design.

Figure 1: Proposed Feed forward Neural Network Model.
Source: Authors

In figure 1 a block of entries was observed in the first layer, with acceptable results of four layers that can be used in the second stage of network design, which corresponds to a standard design of the artificial neural network known as Feed forward, which usually has one or more hidden layers with the respective training method, followed by a linear output layer. In terms of the training layer (hidden) it is characterized by having a training or activation criterion, which can be explicitly used the SCG algorithm, which has a function expressed as follows: $F(x) = \frac{1}{2} \sum_{i=1}^m [f_i(x)]^2$, be the Jacobian $f_i(x)$ defined as $J_i(x)$, in such a way that the algorithm searches iteratively, in the given direction, for the solutions to the required equations: $(J_k^T J_k + \lambda_k I) p_k = -J_k^T f_k$, where λ_k are the non-negative scalars and I corresponds to the identity matrix. Based on the above, the neuronal network is formed in MATLAB and 50 neurons were defined, the decision of the number can become subjective, given the fact that, depending on the application, the decisive factor lies in the result obtained. By using the SCG Neural Network, you get the following.

Figure 2: Turbidity Data in Raw Water. Source: Authors

In Figure 2, the analyzed data traffic generates a high variability and heterogeneity in the reported values of turbidity in the surface water body, values lower than 100 NTU, indicates that the raw water has a low presence of silt and clays in the water, due to the condition of climatic variability that is found in the year, essentially due to the medium water erosion presented in the river, which generates less retention in the soil and therefore present in the raw water. Maximum turbidity values are observed above 200 NTU, due to the transport of classic sediment (silt and clay) in the rainy season in the body of water, that is when the adjacent soils are saturated, which presents a high-risk condition for the treatability in the purification of water, according to the cloud of data analyzed in the analysis period 2012 - 2016.

Figure 3: Prediction of Turbidity in Raw Water. Source: Authors

Figure 3 shows how the line entities are the indicator of turbidity in raw water, there is a volatile fluctuation with a high recurrent frequency in the period analyzed (2012 - 2016), with a high dispersion of the turbidity results for the surface water body; it is observed a highly variable prediction in the next period of 2016, indicating transport of silt and clay in the raw water due to the presence of water erosion and inputs mining in the basin, well saturation soils close to the river bank cause turbidity of less than 200 NTU and this means that the operability of water purification is medium risk in terms of adequate water treatment.

Figure 4: Performance of Tests. Source: Authors

In Figure 4, the performance of the tests, training, validation and total result in the development of the NAR method is observed, which establishes that significant adjustments must be made to obtain better performances in the prediction of the turbidity of the raw water, even greater historical information of the basin.

CONCLUSIONS

When using artificial neural network with the Non Linear Autoregressive (NAR) algorithm to estimate turbidity in the body of surface water in the case of Frio River, it is observed that when using as layers compiled neurons and a layer of training, the result is very favorable in predicting the same as the results of performance, which serves to make environmental decisions in any space of time, inclusive in inter annual periods analysis that serves to predict the behavior of the parameter (turbidity in raw water) in later periods and establish according to the use of water for the treatment of water for human consumption and consider actions to improve or maintain the quality of raw water in the river basin.

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