Elaboration of an artificial neural model for the estimation of turbidity and dosages proposal for wastewater treatment in the poultry industry

Elaboración de un modelo neuronal artificial para la estimación de turbiedad y proposición de dosificaciones en el tratamiento de aguas residuales de la industria avícola

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Resumen

El crecimiento de la industria avícola en Colombia y el cambio en la normatividad ambiental vigente, conlleva a un mejoramiento en el sistema de tratamiento de las aguas residuales, mediante técnicas alternas entre coagulantes y floculantes. Los costos de estas técnicas requieren dosificar de manera óptima los principales productos allí involucrados. En este trabajo se usó un modelo neuronal artificial basado en redes neuronales multicapa feedfoward-backpropagation, para la estimación del valor de la turbidez de salida en el tratamiento de las aguas residuales. Posteriormente, se usaron las redes neuronales entrenadas para proponer dosificaciones óptimas de los productos y mejorar las condiciones de operación, lo que permitió obtener aguas residuales clarificadas, para lo cual se elaboraron cartas de optimización. Respecto a la evaluación del desempeño del modelo neuronal, se usó como indicador de desempeño el factor de correlación lineal R. Los resultados de correlación entre los valores estimados y reales de la turbidez de salida muestran la confiabilidad en la aplicación como herramienta de predicción.

Palabras clave: aguas residuales; turbidez; prueba de jarras; industria avícola; inteligencia artificial; redes neuronales artificiales.

Abstract

The growth of the poultry industry in Colombia, and the change in current environmental regulations, lead to an improvement in the wastewater treatment system, through alternate techniques between coagulants and flocculants. The cost of these techniques requires the optimal dosing of the main products involve. In this work, we used an artificial neural model based on feedforward-backpropagation multilayer neural networks, to estimate the value of output turbidity in the treatment of wastewater. The trained neural networks subsequently used to propose optimal dosages of the products and improve the operating conditions that allow obtaining clarified wastewater, so we develop optimization charts. We used the R linear correlation factor as a performance indicator, for the evaluation of the performance of the neural model. The correlation results between the estimated and the real values of the output turbidity show its reliability in the application as a prediction tool.

Keywords: residual waters; turbidity; jar testing; poultry industry; artificial intelligence; artificial neural networks.

1. Introduction

In the last 50 years, Colombia has had high growth in poultry production, reporting an annual growth of 7.1 %, going from contributing 7.0 % of the total national meat production to a value of 50.4 % (Aguilera-Díaz, 2014), an activity that during its production process generates contamination with wastewater that contains both organic and inorganic substances (Gómez-Daza, 2012). The organic component refers to generally biodegradable materials conducive to the appearance and growth of microorganisms with pathogenic potential (Ocampo-Vélez; Rodríguez-Montes, 2011). For its part, the inorganic component refers mainly to the use of chemicals used for cleaning and disinfecting poultry houses, as well as industrial equipment and machinery, which deteriorate the physical and chemical quality of the water (Padilla-Gasca; López-López; Gallardo-Valdez, 2011).

As treatment alternatives, there are the primary ones (physical-chemical) that condition the residual water, before entering the secondary (biological) treatment. Particularly, in Colombia, this type of industry uses primary treatments due to the availability of spaces and their costs. Furthermore, they discharge their wastewater directly to sewage systems or natural receiving water sources, thus requiring better treatment of them (Toc-Aguilar, 2012).

In Colombia, environmental legislation in this area is increasingly stringent to reduce pollution and organic burden on natural water sources (Aguilera-Díaz, 2014). One of the purposes is to transform wastewater into clarified water. Organic biological catalysts have been shown to help fat breakdown, allowing better treatment by the physical-chemical procedure (Rubio-Clemente; Chica; Peñuela, 2014; Chalén-Medina; Peñafiel-Pazmiño; Saltos-Sánchez, 2017). However, its application costs require tools that allow obtaining economic dosages from optimization processes.

The literature reports various works of modeling in wastewater processes from different techniques or tools, such as multivariate regression mathematical models, response surface methodology, use of software, and artificial neural networks. In some cases, the modeling has been oriented towards understanding the treatment process, in others the effect of the variables involved in mentioned processes on the quality of the treatment and in others the effect of the dosages of coagulant and flocculant on the value of turbidity (MartínezNavarro, 2007; Acuña-Zambrano, 2008; Salgado-Reyna, 2013; Salgado *et al*., 2013; Vásquez-Almazán; Martínez-Morales, 2014; González-Martínez, 2017).

For its part, artificial intelligence, a term coined in 1960 by Minsky (1961a, 1961b), in its broadest sense indicates the ability of an artifact to perform the same types of functions that characterize human thought and in these terms, its methods are a response to the desire to bring human behavior and thought closer to different systems for the solution of certain problems (Haugeland, 1996, 1997; Andler, 2006). One of these methods is artificial neural networks, a functional abstraction of the biological neuronal structure of the central nervous system (see Figure 1), which recreates from a biological perspective the structure of a human brain (Bishop, 2006).

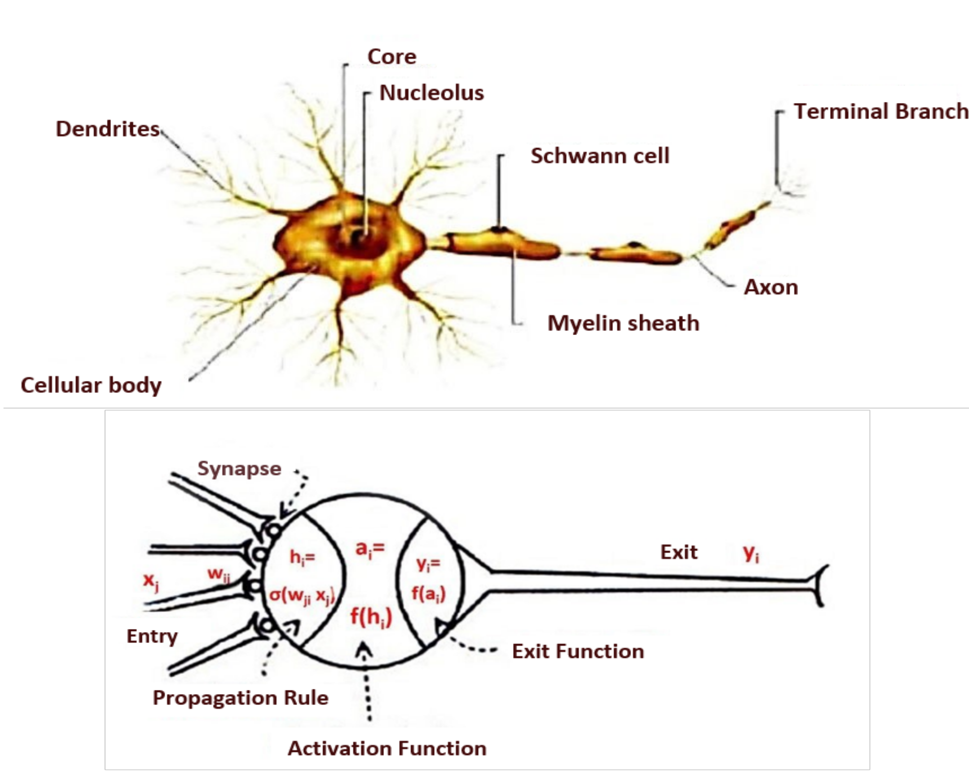


Figure 1. a) Biological neuron b) Computational neuron
(Adapted from Serrano, Soria, Martín, 2010).

Artificial neural networks today are considered as powerful pattern recognizers and classifiers (Bishop, 2006), used in the solution (prediction) of engineering problems as an alternative in complex systems characterized by interaction factors, in systems of statistical approximations nonlinear, or computational solution systems based on complex and extensive algorithms (Haykin, 2005). In turn, they involve quantitative and qualitative variables and that relating them in mathematical models become difficult.

In their historical context (Widrow; Lehr, 1990), artificial neural networks began as a single-layer network called the Simple Perceptron that could only perform solutions of some logical functions such as OR, AND, and NOT, without numerical estimates; later, its development allowed numerical estimates, being known as the ADALINE network. Today, many engineering problems are addressed from networks with three or more layers such as the Multilayer Perceptron network, with a supervised learning procedure, since networks are trained from the error of approximation against the true results (Bishop, 2006).

On the other hand, in industrial activity and in particular, in the food agribusiness (Arias-Hoyos; HernándezMedina; Castro-Valencia; Sánchez-Peña, 2017), different materials are used to decrease the turbidity of wastewater such as coagulants, flocculants and biological catalysts, whose quantities will depend on environmental situations such as temperature, pH, quantity and type of turbidity to be treated, among others. The quantity of the mentioned products is generally determined by the performance of an experiment known as the Jar Test (Fúquene; Yate, 2018). However, this experimental test consumes time and quantities of the products for the treatment and its procedure also contains errors (Ovalle-Celis; Moreno-Ripe, 2014). This leads to carrying out several experimental runs of the test until turbidity is found in the wastewater or an acceptable condition of clarified water to be reused is obtained (Fúquene; Yate, 2018) from a dosage of treatment products that are not optimum, since the costs of the process are increased, so it is of interest to optimize it.

Even so, for Fúquene and Yate (2018) the jar test is one of the most important experiments in the control of the chemical water coagulation process, in which variations in the coagulant-flocculant doses are used that determine the reduction of colloids in suspension and organic matter through the flocculation process, simulating the unit processes of coagulation, flocculation, and sedimentation, until reaching the values in which flocculation achieves its best results.

On the other hand, Haghiri; Moharramzadeh; Nahvi; Daghighi (2014) mention that the determination of the optimal dose in terms of coagulants is of particular significance, in which complex relationships between the factors that influence the efficiency of the coagulant and the results of the test lead to the problem of optimization to the field of artificial neural networks.

In this regard, the literature shows a good number of works that address the problem of optimizing the water treatment process using artificial neural networks (Fernández; Galvis, 2003; Acuña, 2008; Olanrewaju; Muyibi; Salawudeen; Aibinu, 2012; Salgado *et al.*, 2013; Villarreal-Campos; Caicedo-Bravo, 2013; Haghiri *et al*., 2014; PeñaRojas; Flóres del Pino, 2014; Prasannasangeentha, 2015; Bui; Giang-Duong; Nguyen, 2016; Barajas-Garzón; León -Luque, 2016; Peña-Rojas, 2016; Rodrigues-dos Santos; Henriques-Librantz; Days; Gozzo-Rodrigues, 2017; De Menezes; Fontes; Oliveira-Esquerre; Kalid, 2018, Haghiri; Daghighi; Moharramzadeh, 2018; Messaoud; Hellal; Imed; 2018), is limited in the treatment of wastewater from agro-industrial processes and specifically in the poultry industry.

Thus, in the present study, an artificial neural model based on artificial neural networks with multilayer architecture, forward information feeding, and backward propagation and error adjustment methodology/learning, called feedforward multilayer perceptron, is used. to propose joint dosages of a biological organic catalyst and coagulants-flocculants, commercially available elements in the treatment of wastewater from the poultry industry. Artificial neural networks were trained to predict the turbidity leaving the wastewater from the Pitcher Test. Neural network performance based on the linear correlation coefficient (R> 0.98) shows a reliable tool to be used in the simulation of the output turbidity determination for different treatment dosages. The result of the simulations graphed in the output turbidity result charts for different conditions of entry of the residual water, allows to define which are the most optimal dosages to obtain clarified water with the quality required for compliance with environmental regulations.

2. Methodological procedure

2.1. Project location

The study was carried out in a commercial chicken processing plant located in the municipality of Guacarí, Valle del Cauca, Colombia, which processes 11,000 chickens/day with a bodyweight of 1,800 - 2,200 g / chicken (García-Núñez, 2017).

2.2. Experimental fieldwork and construction of the training set

Starting from experimental fieldwork where a wastewater sampling was made called jar test and its corresponding characterization of pH, input, and output turbidity, a database was created to train the artificial neural model (ICONTEC, 2010). To evaluate the contribution of the biological catalyst, the samples were divided into two groups: the first group, with dosages of coagulant and flocculant (48 records), and the second group, in addition to the two mentioned products, with the addition of biological catalyst (48 records). A mixture of aluminum polychloride was used as a coagulant, a flocculation aid polymer as a flocculant, and a highly concentrated bio-organic catalyst as a biological catalyst, commercially available elements (GarcíaNuñez, 2017). A portable turbidimeter was used to estimate both input and output turbidity (Hach Company, 2004).

For both groups, the variables considered were: input pH [PH], input turbidity (raw water) [TE], coagulant dose [COA], flocculant dose [FLO] and output turbidity [TS]. For the second group, the dose of the biological catalyst [CAT] was added as a variable. Regarding the database, the information was stored in a matrix arrangement to have in both groups the output variable at the output turbidity (clarified water) as shown in Table 1.

Table 1.

Input and output variables considered in the configuration of artificial neural networks for the estimation of output turbidity in clarified wastewater

Exploration	Input variables, the unit of measurement, [representation]	Output variable, the unit of measurement, [representation]
1	pH, without unit, [PH] Raw water turbidity, NTU, [TE] Coagulating dose, ppm, [COA] Flocculant dose, ppm, [FLO]	Clarified water turbidity, NTU, [TS]
2	pH, without unit, [PH] Raw water turbidity, NTU, [TE] Coagulating dose, ppm, [COA] Flocculant dose, ppm, [FLO] Biological catalyst dose, ppm, [CAT]	Clarified water turbidity, NTU, [TS]

Source: self-made.

2.3. Elaboration and training of the artificial neural model for the estimation of turbidity (exit turbidity) in clarified waters

With the aforementioned training sets that relate the input variables to the output variable, a proposal of a neural model was developed for each one and a multilayer artificial neural architecture fed forward and with the backward training, the methodology was proposed (see Figure 2), called Feedforward - backpropagation Multilayer Perceptron and whose characteristics are defined by Rumelhart, Hinton, and Williams (1986) and Hinton (1987, 1988).

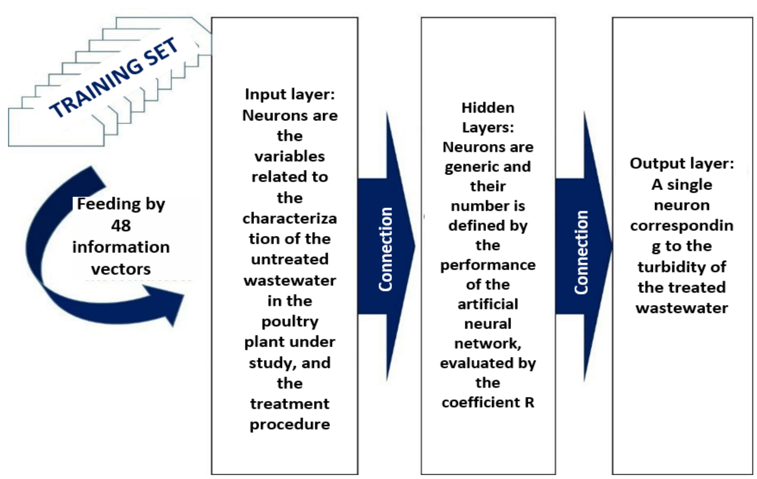


Figure 2. Neural model proposal for the estimation of turbidity in treated wastewater, in a poultry plant
Source: own elaboration.

The connections between neurons in the layers are represented by activation functions. Thus, the connection between the neurons of the input layer to each hidden layer is made employing the sigmoid function described by Hinton (1987, 1988). The connection between the last hidden layer and the neuron to be estimated, located in the output layer, is made using the linear function, to allow the comparison of the estimate and the true result, as described in supervised training (Rumelhart *et al*., 1986; Hinton, 1987, 1988). The training procedure for each set was carried out, according to what was described by García-Nuñez (2017), with 156 confirmations of artificial neural network topologies, obtained from the product between 12 backpropagation training methods and 13 neuron layer architectures hidden. These conformations were evaluated using the linear correlation factor R (Equation 1) (Vásquez ...), a statistic used to assess the quality of the supervised artificial neural models (Steel; Torrie, 1960; Ibáñez-Quispe, 2009; Barría-Sandoval, 2009 cited by Machaca-Apaza, 2016). For the computational functioning of the training procedure, an algorithm was coded using the M programming language, typical of the MATLAB ® software tool for the Windows ® platform (The Math…). The code uses the library contained in the Neural Networks Toolbox of the same software (Beale ...), which allows implementing the models of the type of network that has been described.

$$R = \sqrt{1 - \left(\frac{\sum_{i=1}^{n} \left(TS_{real,i} - TS_{estimated,i} \right)^2}{\sum_{i=1}^{n} \left(TS_{real,i} \right)^2} \right)} \quad (1)$$

Where, TSreal, i is the output turbidity obtained using the Jar Test, the output turbidity estimated by the artificial neural network corresponds to the position of the correlated data pair and corresponds to the total data in each subset. The 48 information vectors of each training set were categorized into three subsets that made up the same number of phases in the training of a neural network: 1) learning, where the synaptic weights in the connections between neurons were configured; 2) test, with which the moment in which to stop training and optimize the structure of the neural network and the specifications of the internal model were determined, following the learning method used by the backpropagation algorithm; and 3) validation, where the ability to generalize the model for the range of information that was used for the calibration was tested. From the performance indicator, the estimates of the neural networks and the actual outputs of the databases were evaluated, in the subsets of each training phase (Learning, Testing, Validation and an additional Simulation with the total data, for which 60, 20, 20 and 100% of the data were considered, respectively, and grouped by a random division of the data).

The results of this process showed that for both case studies (without catalyst and with catalyst), the architecture with two hidden layers and with the Levenberg-Marquardt learning method obtained better, adequate and reliable performances (R> 0.99), than the other training methods used (Bayesian Regularization, QuasiNewton of BFGS Algorithm (Broyden-Fletcher-Goldfarb-Shanno), Resilient Back Propagation, Conjugate Gradient Stepped, Powell / Beale Reset Conjugate Gradient, Fletcher-Powell Conjugate Gradient, Pollak-Ribiere Conjugate Gradient, One Step Dryer, Descending Gradient with Variable Learning Rate, Descending Gradient with Moment and Descending Gradient).

In this way, the best neural network architecture was then configured for the first case study (without biological catalyst) with an input layer with four input variables: a first hidden layer with 10 neurons, a second hidden layer with 30 neurons, an output layer with a response variable, and a Levenberg-Marquardt backpropagation learning algorithm. On the other hand, in the second case study (with a biological catalyst), the architecture of the best network was configured with an input layer with five input variables: a first hidden layer with 10 neurons, a second hidden layer with 20 neurons, an output layer with a response variable and a Levenberg-Marquardt backpropagation learning algorithm.

2.4. Optimization simulation

After the elaboration and training of the artificial neural model for the estimation of turbidity, the best neural networks were selected for each study case, with which a computational simulation process of the Jar Test was carried out, for which, through a computational code in M language, each neural network assigned to each group of information was used and the input and output information of the Jar Test was simulated with the following characteristics: 1) the conditions of input turbidity and pH; 2) a variation of the coagulant doses was made for fixed doses of flocculant and catalyst (in the case of the second group), and 3) an output turbidity result estimated by the trained neural network was obtained for each study case. This simulation allowed recreating various optimization charts of the added products (a variation of characteristic 2, would correspond to varying the flocculant dose for fixed doses of coagulant and catalyst) in the treatment of wastewater from this poultry farm.

3. Results and Discussion

3.1. Wastewater treatment and characterization in this poultry farm

From the environmental and sanitary point of view for all the tests carried out, it was observed that the use of the biological catalyst allowed a better treatment based on the decrease of the turbidity values of the outlet (clarified water), which is inferred to the improvement in the degradation of organic matter. This is mentioned by Ekama and Wentzel (2017), who explains that in the removal of organic matter, the biological process by which said organic matter present in this type of wastewater is transformed into a mass of volatile suspended solids as ordinary heterotrophic organisms (anabolism) with an associated transfer of oxygen electrons and a loss of energy in the form of heat (catabolism), generating in the complete process of degradation via catabolism, a better performance.

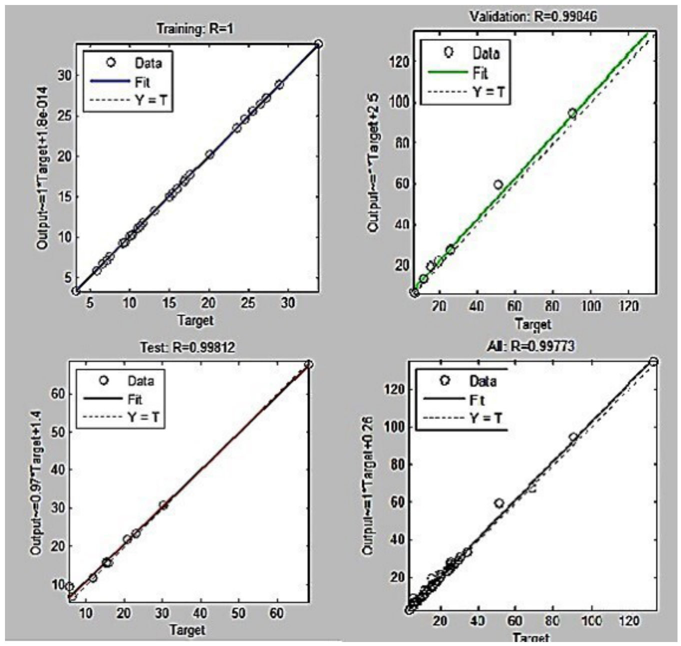
As reported by Conde-García (2012), the decrease in turbidity is mainly because in addition to the aforementioned degradation, the fat is solubilized, and the coagulant and flocculant can act on the solids as inferred in the case of treatment of residual waters from the slaughter of cattle. This suggests using low catalyst dosages (for cost) and then optimizing the coagulant and flocculant dosages, the simulated process in optimization using the proposed artificial neural model.

3.2. Artificial Neural Model Training

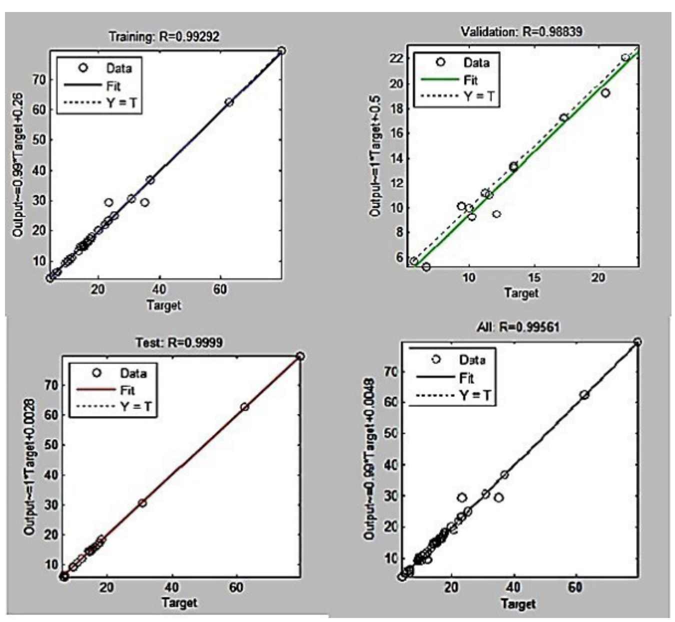
From the elaboration of an artificial neural model based on neural networks, corresponding to a supervised artificial neural network of the Multilayer Perceptron type, with forwarding feeding and training/learning for the propagation of the error backward, the turbidity estimation was made outlet (clarified waters) in wastewater from the poultry farm, in a process of treating mentioned wastewater for two cases: with the use of coagulant and flocculant, and with the use of three components by adding biological catalyst.

For the first group (without biological catalyst), the neural model consisted of an artificial neural network of an input layer with four input variables: a first hidden layer with 10 neurons, a second hidden layer with 30 neurons, a layer of output with a response variable corresponding to the estimation of turbidity in clarified waters and the Levenberg-Marquardt learning algorithm. For the second group (with a biological catalyst), the model consisted of an artificial neural network consisting of an input layer with five input variables: a first hidden layer with 10 neurons, a second hidden layer with 20 neurons, an output layer with a response variable corresponding to the estimation of turbidity in clarified waters and the LevenbergMarquardt learning algorithm.

Figure 3 shows the performance results of the selected neural networks in both study cases and for each of the training stages of the same (training, testing, computational validation, and simulation with the entire training set). For the stages where the selected networks estimate the output turbidity, a comparison is made between the result obtained by the artificial neural network (output) and the value obtained using the experimental protocol of the Jar Test (target), for which associates with this comparison the linear correlation factor R.



a.



b.

Figure 3. Performance results for the artificial neural network trained to estimate the turbidity of the clarified water: a) without biological catalyst and b) with biological catalyst. For both cases, the correlation coefficient R between the turbidity is shown output obtained with the Pitcher Test and estimated by the neural model, for each phase of learning (training, testing, validation and simulation with all data)
Source: self-made.

This performance based on the linear correlation factor R (R> 0.99), according to Anscombe (1973) and Achen (1982), showed for both cases a strong positive linear relationship between the output turbidity value obtained at from the experimental protocol of the Pitcher Test normalized in NTC 3903 (ICONTEC, 2010), and that obtained by predicting the selected artificial neural networks, which allows us to infer that the computational tool is adequate and reliable to make such estimates. According to Martínez-Rodríguez (2005), the values of the linear correlation coefficient R in both cases show that there is an approximation of the result obtained by prediction, which verifies the goodness of fit of said prediction, allowing us to infer that the model computational based on artificial neural networks can be used as a complementary methodology for the Jar Test in the estimation of the turbidity of the residual water both in treatments with coagulant-flocculant and with a flocculant-coagulant-biological catalyst (p.322).

The literature reports various works on modeling in wastewater treatment through the development of mathematical models, the use of process modeling software, the response surface methodology, and artificial neural networks. In these reports, in some cases, it is sought to understand the treatment process, while in others it is sought to relate the effects of the flocculant and coagulant type compounds for their optimization.

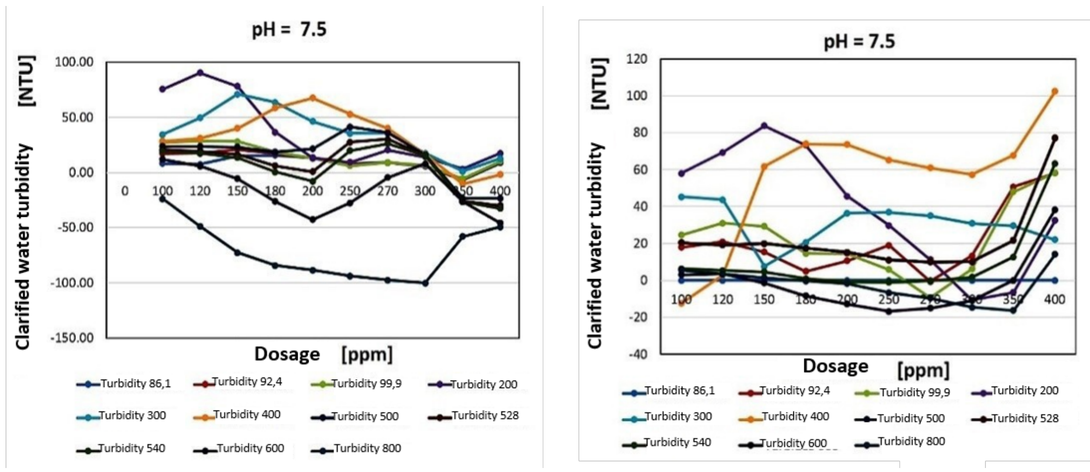
Regarding the use of artificial neural networks, Salgado-Reyna (2013) and Salgado *et al*., (2013) elaborated and developed multilayer backpropagation neural networks to estimate the reverse osmosis unit data in the treatment of wastewater from a plant producer of containers, in a process of optimization of the flocculant and the coagulant, obtaining in the correlation a determination coefficient R = 0.99. Acuña-Zambrano (2008) reports the use of multilayer backpropagation neural networks for the correlation of pH, turbidity, color, and alkalinity, to optimize the dose of coagulant in a drinking water treatment plant in an urban population, obtaining a correlation in the specific case of the estimation of the turbidity and the dose of the coagulant of R = 0.88. Vásquez-Almazán and Martínez-Morales (2014) report the development of artificial neural networks, of the multilayer backpropagation type and radial base functions, for the estimation of the turbidity of the effluent in a dam, obtaining correlation coefficients R = 0.9927 and R = 0.986, respectively.

In recent years, studies on the use of artificial neural networks and coagulant optimization in water treatment are reported in the literature to reduce, but not replace, the number of trials in the Jar Test for measurement. output turbidity. In this regard, Rodrigues-dos Santos *et al*., (2017) (R = 0.989), Haghiri *et al*., (2018) (R = 0.949) and De Menezes *et al*., (2018) (R = 0.900) conclude, in general, that the use of artificial neural networks is an adequate tool to determine the best control conditions for the water treatment process, mainly to estimate the optimal dose of the coagulant, allowing a reduction in the raw material of the treatment and the possibility of conducting additional research to improve results on cost reduction and raw material consumption.

For the artificial neural networks elaborated in the present study and trained to estimate the outlet turbidity in two cases of wastewater treatment (without catalyst and with catalyst), their performance results evaluated from the linear correlation coefficient R, show that These estimates are concordant with the previously mentioned and developed works, with which it is inferred that the use of artificial neural networks can be used reliably as prediction tools to complement the experimental results involved in wastewater treatment and, in particular, in the Jar Test to estimate the output turbidity. However, the literature does not report the use of artificial neural models in the estimation of turbidity in the case of wastewater from livestock farming, nor in the use of three products (coagulant, flocculant and biological catalyst) for mentioned treatment, which provides a future agenda in this field, focused on optimizing the dosages of the proposed treatment products.

3.3. Simulation of an optimization process using artificial neural networks

The selected artificial neural networks were used to simulate a Pitcher Test process for various input conditions. A simulation was performed for both case studies. As an example, the case in which there are a pH = 7.5, different inlet turbidity values, and different coagulant doses is shown, and in the second case study in addition to a constant value of the biological catalyst. This simulation process allows in each case to build an optimization chart as shown in Figure 4. The graphic results allow by drawing a horizontal line that represents the normative value of turbidity accepted in the clarified water, to define in each case the dosage of the coagulant to use. The results confirm that the use of the biological catalyst (Figure 4-b), in all cases in a constant dose, leads to using a lesser amount of the coagulant.



a. **b.**

Figure 4. Example of using the artificial neural model to create optimization charts of the coagulant for a pH = 7.5: a) without biological catalyst; and b) with a biological catalyst. The lines show for stable pH value, the different conditions of the residual water to be treated (turbidity of the raw water) and through the use of the neural network the exit turbidity is estimated (vertical axis), according to a coagulant dose (horizontal axis)
Source: self-made.

In the same way, Figure 4 shows how a total treatment of the residual water is achieved in the process (in the case of the negative values estimated by the model, and which in reality would correspond to "zero" turbidity), and how in In many cases, the use of additional values of the coagulant and/or the catalyst leads to "soiling" the clarified water again, which again leads to a positive turbidity value (in this case the contaminant corresponds to the same treatment product). Some reports mention the adverse effects in the treatment due to the excess mainly of coagulants (Andía-Cárdenas, 2000; Castrillón-Bedoya; Giraldo, 2012; Díaz-Claros, 2014).

4. Conclusions and recommendations

The work shows the training of an artificial neural model, based on *feedforward-backpropagation* multilayer neural networks, to be used in wastewater treatment, in this case for the estimation of the clarity of water turbidity (turbidity obtained after treatment of the residual water). The use of these neural networks allows in this application the reduction of the number of trials of the Jar Test, which leads to a saving of resources (time, flocculant and coagulant), focusing the experimental part on a reduced number of the trial around the optimal estimate of coagulant and/or flocculant. It can be concluded that, according to the performance indicator and the graphic behavior between the relationship of the estimated and actual values, the trained artificial neural model and based on this type of neural network, are suitable for carrying out the proposed estimate.

The reliability of the artificial neural networks trained in each case, in the treatments without catalyst and with catalyst, respectively, allows them to be used for other computational exploration processes, as in this study, in an optimization tool, which recreates the Test. Pitchers and optimization cards are made. In the same way, it allows confirming the effectiveness of the actual operating results with the incorporation of new products (biological catalyst) in the treatment of wastewater.

The applicability of the artificial neural model in the theme of the work presented, allows us to explore its use in wastewater treatment processes for various livestock productions, that is, to be used in other areas, such as, for example, the raising of pigs or cattle. Likewise, the exploration of its use is suggested incorporating other variables of physical-chemical or biological characterization, as in the case of the biological and chemical demands of oxygen, color, and odor of raw and treated water (these last two are appropriate qualitative variables to be included in artificial intelligence models), to adapt the treatment to more rigorous processes from the environmental and health point of view.

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