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Predictive modeling of the primary settling tanks based on artificial neural networks for estimating TSS and COD as typical effluent parameters

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ABSTRACT

A predictive model based on artificial neural networks (ANNs) for modeling primary settling tanks' (PSTs) behavior in wastewater treatment plants was developed in this study. Two separate ANNs were built using input data, raw wastewater characteristics, and operating conditions. The output data from the ANNs consisted of the total suspended solids (TSS) concentration and chemical oxygen demand (COD) as predictions of PSTs' typical effluent parameters. Data from a large-scale wastewater treatment plant was used to illustrate the applicability of the predictive model proposal. The ANNs model showed a high prediction accuracy during the training phase. Comparisons with available empirical and statistical models suggested that the ANNs model provides accurate estimations. Also, the ANNs were tested using new experimental data to verify their reproducibility under actual operating conditions. The predicted values were calculated with satisfactory results, having an average absolute deviation of <20%. The model could be adapted to any large-scale wastewater plant to monitor and control the operation of primary settling tanks, taking advantage of the ANNs' learning capacity.

Key words: artificial neural networks, chemical oxygen demand, primary settling tanks, process modeling, total suspended solids, wastewater treatment plants

HIGHLIGHTS

- A predictive model of the PSTs behavior using ANNs was developed.
- The proposed model accurately predicts the TSS concentration and COD in the effluent.
- The wastewater treatment plant (WWTP) in Ibarra, Ecuador, was considered a case study to show the applicability and reproducibility of the model.
- A reliable predictive model would improve the monitoring of WWTPs.

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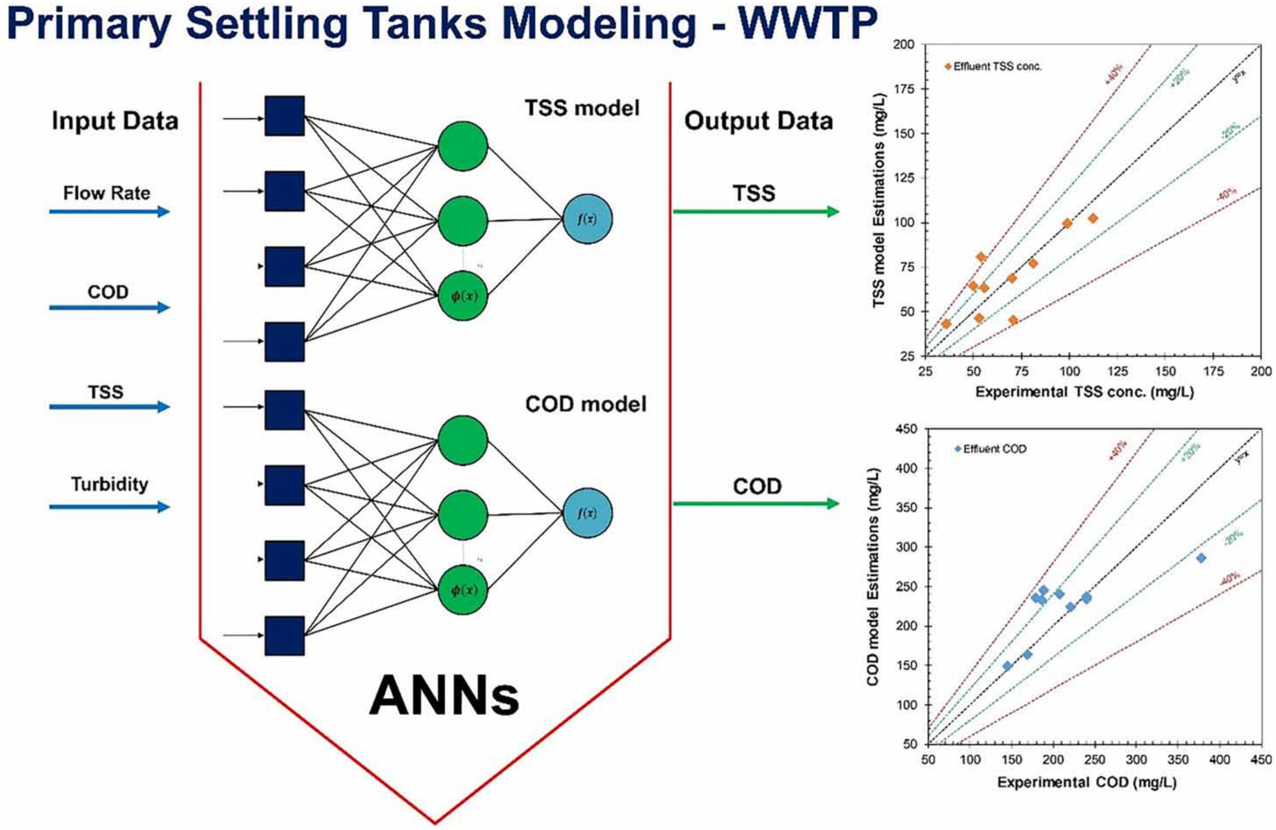
GRAPHICAL ABSTRACT



NOMENCLATURE

AAD	average absolute deviation (%)
ANNs	artificial neural networks
BOD	biochemical oxygen demand (mg/L)
COD	chemical oxygen demand (mg/L)
COD-09	COD model architecture using nine hidden nodes
COD-10	COD model architecture using 10 hidden nodes
$f(x)$	activation function in the output layer
MLP	multilayer perceptron
MSE	mean square error
PSTs	primary settling tanks
purelin	linear function
R^2	coefficient of determination
tansig	hyperbolic tangent function
TSS	total suspended solids (mg/L)
TSS-07	TSS model architecture using seven hidden nodes
x	original value(s)
x_{max}	maximum value(s)
x_{min}	minimum value(s)
x_{norm}	normalized value(s)
WWTP	wastewater treatment plant

Greek letters

$\phi(x)$ activation function in the hidden layer

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1. INTRODUCTION

Primary settling tanks (PSTs) are one of the principal controlling equipment in the performance and removal efficiency of wastewater treatment processes (Baki & Aras 2018). Therefore, modeling the performance of PSTs is essential for improving the whole process control at a wastewater treatment plant (WWTP). However, modeling the PSTs is difficult because of the intricacy of the treatment processes (Hamed *et al.* 2004; Bozkurt *et al.* 2016; Behera *et al.* 2020). They involve several complex and non-linear mechanisms, which are difficult to predict or explain by linear statistical or empirical mathematical models (Abba & Elkiran 2017). This complexity is further enhanced by the chemical, physical, and biological processes occurring during the raw sewage collection, transport, and treatment, making WWTP operations and control a complicated task (Raha 2007; Nasr *et al.* 2012). Hydraulic efficiency models utilizing tracer studies and deterministic models based on mathematical formulation have been applied to describe the dynamic behavior of full-scale settling tanks with limited success (Martínez-González *et al.* 2009; Zamanikherad *et al.* 2022). In practice, modeling the performance of full-scale primary settling tanks has been frequently done using regression-based models. These are empirical relationships derived strictly from daily average influent and effluent data, which better work under steady-state conditions (Jover-Smet *et al.* 2017; Al Bazedi & Abdel-Fatah 2020).

Many attempts to model the PSTs' performance have been developed using computational tools that describe their behavior in recent years. Models based on artificial intelligence – especially artificial neural networks (ANNs) – have been increasingly applied for modeling effluent quality in wastewater treatment processes (Raha 2007; Bagheri *et al.* 2015; Guo *et al.* 2015). Few studies on developing models based on ANNs applied to modeling primary settling tanks are reported (Zeng *et al.* 2003; Shahrokhi *et al.* 2011; Gamal & Smith 2002a).

This study aimed to develop a predictive model based on ANNs to describe the behavior of full-scale primary settling tanks to simplify and optimize the wastewater treatment and monitoring process. The proposed ANNs model consisted of two independent neural networks, using influent data of raw sewage and WWTP operating conditions to predict the characteristics of the clarified effluent. The first network determined the total suspended solids (TSS) concentration, and the second estimated the effluent's chemical oxygen demand (COD). The Ibarra wastewater treatment plant in Ecuador was considered a case study to illustrate the applicability of the proposed model.

2. IBARRA WASTEWATER TREATMENT PLANT

Ibarra is a city located in the north of Ecuador, and it is the capital of the Imbabura province. The Ibarra WWTP has been operating since September 2018, and it processes an average sewage flow of 43,200 m^3 per day from municipal effluents. The process consists of four steps: (1) pretreatment, (2) primary treatment by settling, (3) secondary treatment using biological means, and (4) sludge treatment based on anaerobic digestion. The treated effluent is finally discharged into the Tahuando river, where the natural purification process continues to reduce the levels of pollutant concentration. Two circular settling tanks operate in the plant, and they function as primary or secondary settling tanks. Both tanks have a diameter of 34 m and an effective volume capacity of 2,902.32 m^3. The settling tanks operate with a hydraulic retention time of 2.3 hours. A surface skimmer system is fitted in each settling tank to remove the floating material. Chemical flocculants are not used during the settling process. More technical details about the Ibarra WWTP can be found in González *et al.* (2017).

3. METHODS

The methodology (Figure 1) developed in this study consists of three main sections: (1) process analysis, (2) ANNs configuration, and (3) performance analysis.

3.1. Process analysis

3.1.1. Selection of input and output parameters

Daily records of chemical, biological, and physical parameters related to the wastewater at the inlet and outlet of the primary settling tanks were carried out for one month (August 2019). The analyses were accomplished in the laboratory located in the installations of the Ibarra WWTP. The timing difference between the upstream and downstream measurements was approximately two hours. It was established based on the hydraulic retention time of the primary settling tanks at design operating conditions.

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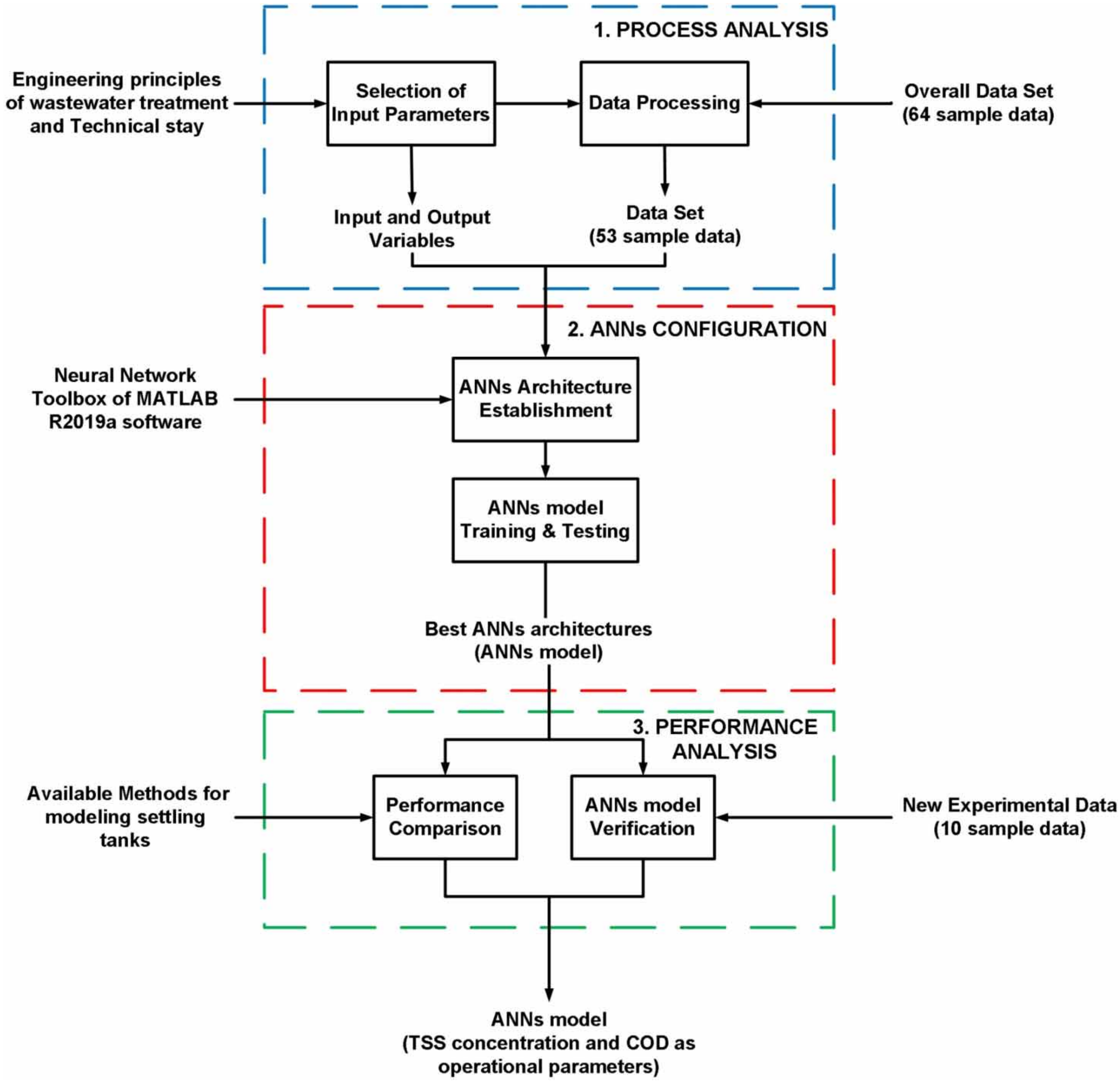

Figure 1 | Methodology proposal: outline.

The operational variables and wastewater characteristics measured were classified to obtain the most representative information about the performance of the primary settling unit. The objective was to acquire more accurate predictions of the clarified effluent characteristics from the PSTs using a simplified ANNs model with fewer input parameters. Many input parameters would complicate the ANNs learning process, and unnecessary input parameters could reduce the prediction ability of ANNs models (Raha 2007; Snieder *et al.* 2020).

A four-week technical stay was carried out in the Ibarra WWTP to analyze and identify the critical variables related to the settling unit processes. The operational experience of the technical department staff was used to determine the selection of the critical variables, appealing to expert opinions (Ayyildiz *et al.* 2021). The input parameters selected for the proposed ANNs model were (1) inlet flow rate, (2) influent COD, (3) influent TSS concentration, and (4) influent turbidity. The output parameters were effluent COD and effluent TSS concentration. These output parameters were essential for monitoring the removal efficiency of the PSTs and controlling the operating conditions of subsequent process units (Bozkurt *et al.* 2016;

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Behera *et al.* 2020). Furthermore, parameters such as TSS, COD, and turbidity are significant factors in determining water quality (Kiron *et al.* 2021; Carreres-Prieto *et al.* 2022).

3.1.2. Data processing

Figure 2 shows the value range for the above input and output variables (see Table A.1). The proposed model is intended to be applicable under a typical range of wastewater characteristics and operating conditions in the treatment process.

The overall data set was used to establish a suitable data set for the ANNs training phase. Before being introduced to the networks, the data set was scaled linearly (normalized) into the range [−1,1] using Equation (1):

$$x_{norm} = 2 \cdot \frac{x - x_{min}}{x_{max} - x_{min}} - 1 \tag{1}$$

where x_{norm} is the normalized value, x is the original value, x_{max} and x_{min} are the maximum and minimum values of the concerned variable, respectively. Normalization performs data smoothing and data normalization preparatory to modeling, and it is helpful for training algorithms used in ANNs (Guo *et al.* 2015; Asami *et al.* 2021).

3.2. ANNs configuration

The proposed ANNs model consisted of two separate ANNs. The first network was trained to predict effluent TSS concentration (labeled the TSS model), and the second one estimates effluent COD (labeled the COD model). The configuration was designed for each network to predict only one effluent parameter. This facilitated the training phase because each network would adjust the internal network parameters to only one output. A multi-layer perceptron (MLP) feedforward network was used in both cases. Figure 3 shows the multilayer-neural network architecture proposed for the TSS model and COD model. The input data for both networks consisted of the selected influent parameters, i.e., inlet flow rate, COD, TSS, and turbidity. In both cases, one hidden layer and one output node were used in the MLP neural network architecture. The hyperbolic tangent function ($\phi(x) = tansig$) and a linear function ($f(x) = purelin$) were used as activation functions in the hidden and the output layer, respectively. The number of hidden nodes ranged from 5 to 10 to determine the optimum number of neurons in the ANNs architecture. Finally, the output node provided the estimated value, which must be returned to the initial range to obtain the actual value. Similar configurations of layers and activation functions have been used with successful results (Nasr *et al.* 2012; Ruben *et al.* 2018; Gamal & Smith 2002a). A detailed mathematical description of internal network functions can be found elsewhere (Hamed *et al.* 2004; Sakiewicz *et al.* 2020). The Neural Network Toolbox of MATLAB R2019a software was employed to design the architecture and the ANNs model's training phase.

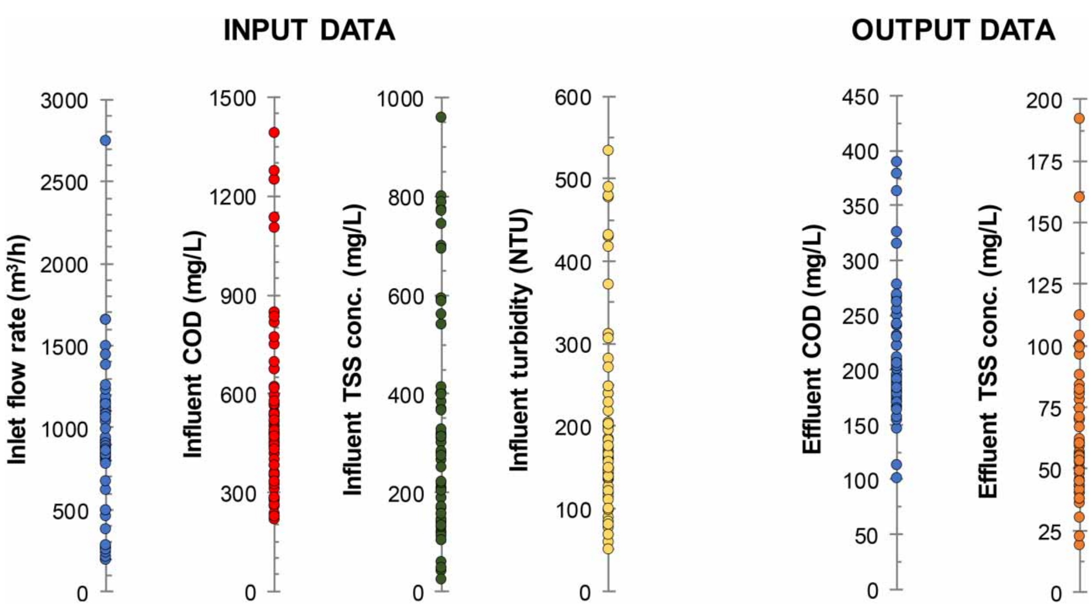

Figure 2 | Overall data set distribution: input and output data range.

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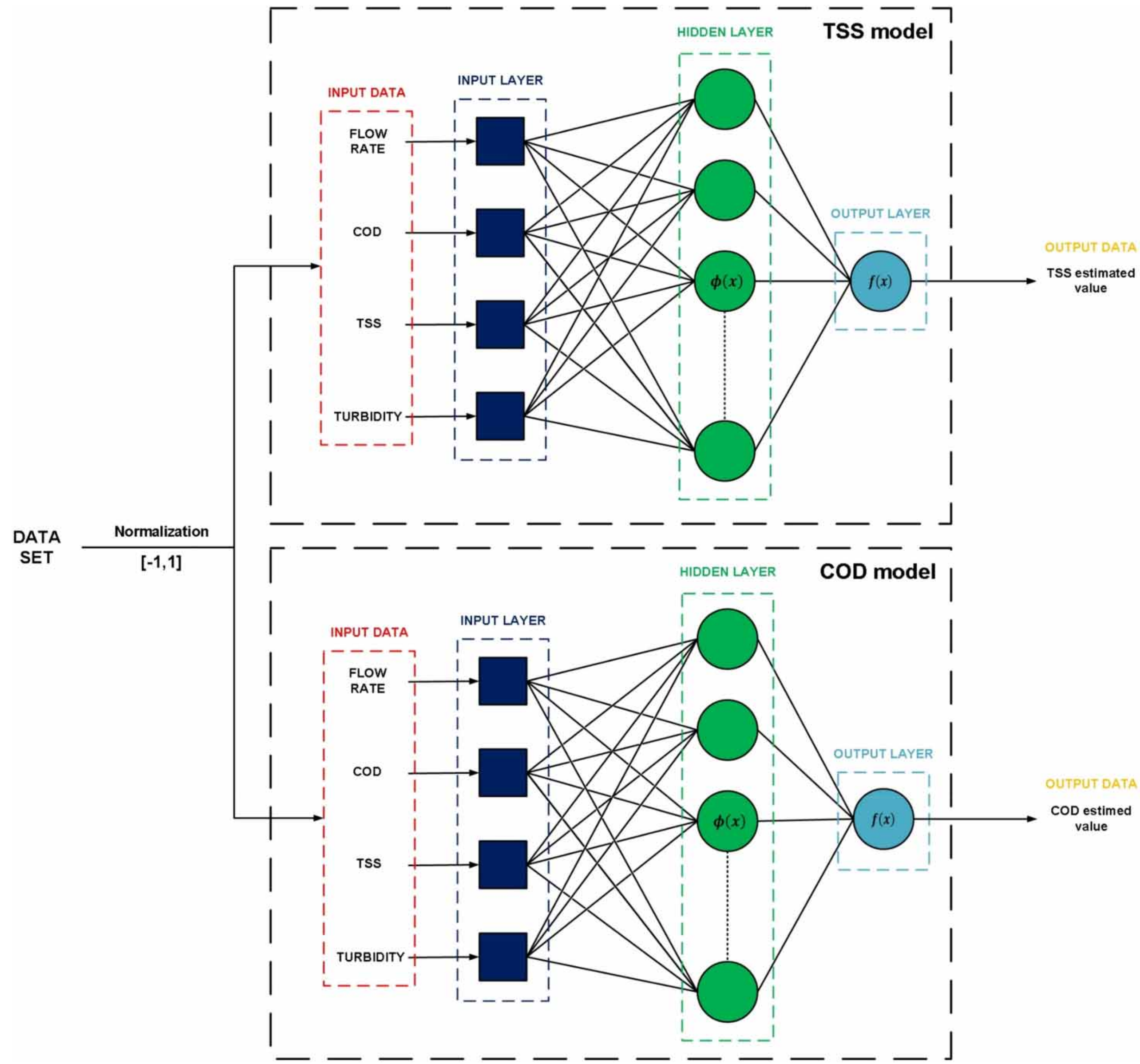

Figure 3 | ANNs model proposal: MLP feedforward network architecture.

A supervised learning algorithm was used for the training phase of both artificial neural networks to teach them how to relate input data patterns with output data, given by the treatment process, obtained downstream of the PSTs (Gamal & Smith 2002a). This training minimized the error between the MLP network output and the target output on the training data set. It was carried out using the Levenberg-Marquardt algorithm, a more powerful technique than the conventional gradient descent methods. This algorithm is more accurate (Kim 2017). The mean square error (MSE) was selected as the cost function for the training algorithm because of its simplicity and easy implementation. Initial random values were assigned to all internal ANNs parameters (commonly labeled weights). Batch mode processing for adjusting weights (updates were done after each epoch and not after each training pattern) was used during the training phase to minimize the mean square error function. In addition, a value of 1,000 was established as the maximum number of epochs (Aggarwal 2018).

The data set used in the learning process was randomly distributed in 70, 15, and 15% into training, validation, and testing steps. The data set distribution was required for implementing the algorithm employed in the training phase. de Menezes *et al.* (2018) successfully used this distribution in the water treatment process from Camaçari WWTP (Brazil). The prediction

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capability of the ANNs model was evaluated by considering the following statistical criteria: coefficient of determination (R^2), MSE, and average absolute deviation (AAD).

3.3. Performance analysis

3.3.1. Comparison with available methods

Once the best ANN structure was obtained for each case, the proposed model was compared with methods for modeling the PSTs reported in the literature. For the comparison, the following methods were used: (i) an empirical relationship reported by Jover-Smet *et al.* (2017) to determine TSS removal efficiency, and (ii) a dynamic model proposed by Gamal & Smith (2002b) based on a combination of stochastic and transfer-function components. Since the model proposed by Jover-Smet *et al.* (2017) is applicable only for TSS removal estimations, an additional correlation reported by Christoulas *et al.* (1998) was considered to approximate the COD removal efficiency from the TSS removal estimations. These methods were evaluated with the same data set used for the ANNs model training stage. The performance analysis was based on the AAD.

3.3.2. ANNs model verification

To evaluate the applicability and reproducibility of the proposed model under actual operating conditions, the ANNs model was tested using new experimental data collected from the Ibarra WWTP two months (October 2019) after the training phase. This new data set corresponded to a continuous sampling program of two weeks. It was used to assess the prediction capability of the ANNs model under the actual operating conditions of the Ibarra WWTP. The verification process is essential to analyze the future incorporation of the proposed model in the monitoring system and process control of primary settling tanks in WWTPs. The difference between ANNs model estimations and experimental measurements was evaluated using AAD criteria. Average absolute deviations of ± 20 and $\pm 40\%$ were considered to analyze the model's accuracy (Korkerd *et al.* 2021).

4. RESULTS AND DISCUSSION

4.1. ANNs architecture establishment

Figure 4 presents the R^2, MSE, and AAD values obtained during the training phase for different numbers of hidden nodes in MLP networks for both the TSS model and COD model. Figure 4(a) shows the variation of the coefficient of determination with the number of hidden nodes for the ANNs model. The R^2 value ranges from 0 to 1 (from no correlation to a perfect fit), indicating how the variance of the measured data could be explained by the model (Guo *et al.* 2015). Typically, values of R_2 greater than 0.5 are considered acceptable (Kim 2017; Aggarwal 2018). Thereby, the possible structures of the ANNs model that did not obtain an $R^2 \geq 0.5$ were discarded. R^2 values ranged from 0.44 to 0.60 for the TSS model and 0.47 to 0.60 for the COD model. The best performance for the TSS model was achieved using seven hidden nodes (TSS-07), which corresponded to the maximum R^2 value. The best performance was obtained using 10 nodes in the hidden layer (COD-10) in the COD model. The relatively low R^2 values obtained were probably the result of data noise in both cases (Hamed *et al.* 2004). Guo *et al.* (2015) and Gamal & Smith (2002a) got similar results of R^2 values for modeling effluent pollution concentration in WWTPs and primary settling tanks using machine learning models, respectively. Figure 4(b) shows the variation of MSE as a function of the number of hidden nodes for both the TSS model and COD model. The lower MSE values represented better network performance (zero value means no error). Therefore, the TSS model reached the best performance using seven hidden nodes, and this configuration obtained the minimum MSE value. In the case of the COD model, the minimum MSE value was achieved using 10 nodes in the hidden layer.

Figure 4(c) illustrates the variation of the AAD value as a function of the number of hidden nodes in the ANNs model. For the TSS model, the values of AAD varied in the range from 22.87 to 28.97%. The minimum AAD value was achieved using the TSS-07 architecture. After this point, the AAD increased as the number of hidden nodes incremented. This suggests that the difference between the estimated value and experimental measurement will increase if more than seven nodes in the hidden layer are used. Therefore, employing more than seven hidden nodes for the TSS model would decrease the accuracy of model predictions. On the other hand, similar values of AAD were obtained using different numbers of nodes for the COD model. The AAD values range from 11.12 to 13.74%. The minimum AAD value was reached using nine nodes in the hidden layer (COD-09). The best performance in terms of AAD was obtained using the COD-09 network for the COD model. There was no clear tendency between the number of hidden nodes and the AAD value for the COD model. However, the value of AAD remained constant through all the ranges in general terms.

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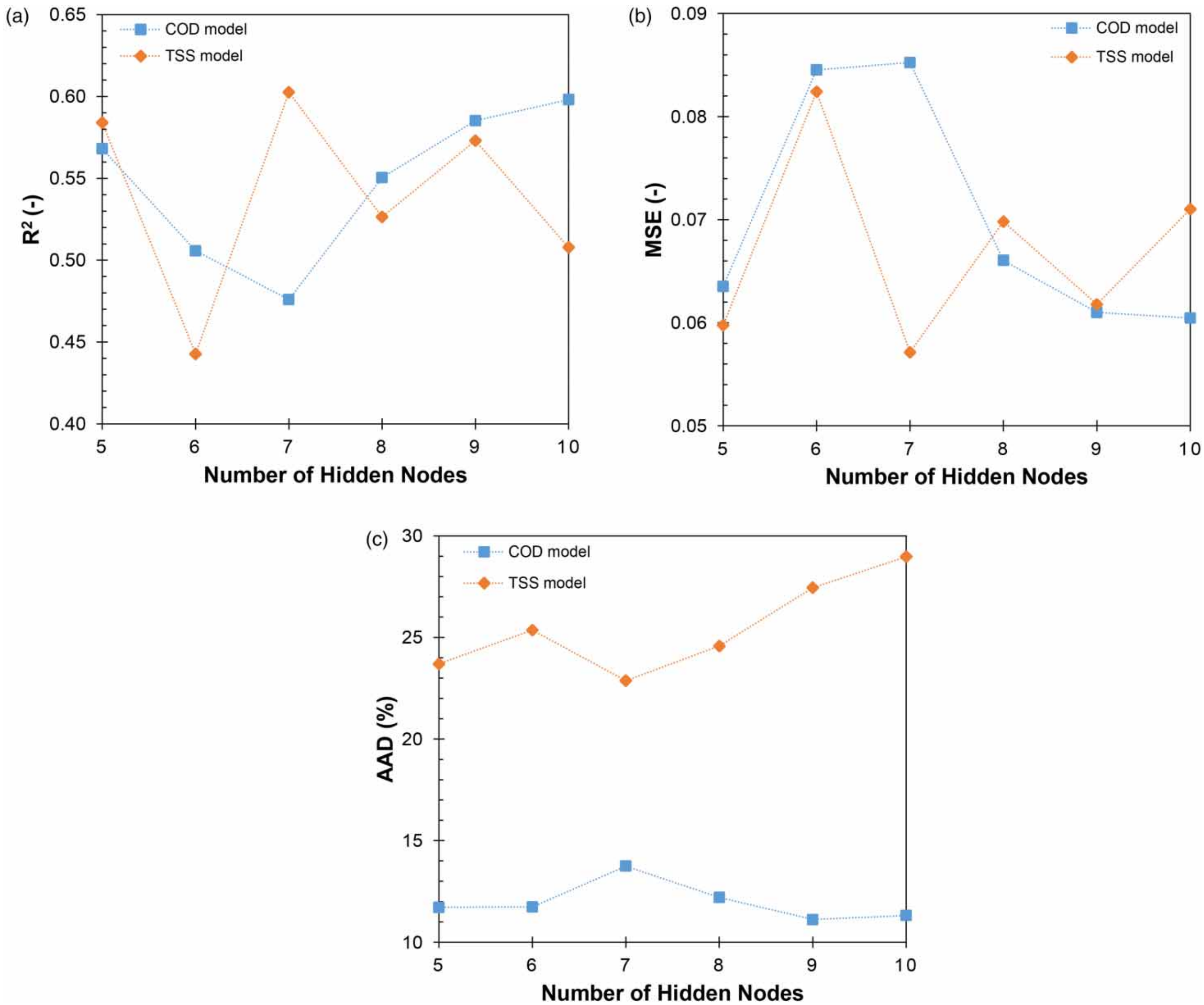

Figure 4 | ANNs architecture establishment – main performance parameters: (a) R^2; (b) MSE; (c) AAD.

Shahin (2013) and Rezazadeh *et al.* (2019) established that the best measure for the performance of neural network models should be based on the highest values of R^2 and the lowest MSE values. The TSS-07 and COD-10 architecture achieved the best performance according to these criteria. Nevertheless, simplicity is an essential factor that should be considered in the model selection. It is crucial to preserve the parsimony principle to improve the generalization capacity of ANNs models; it states that using simpler models is usually preferable to more complicated ones (Kim 2017; Aggarwal 2018). For the TSS model, the network architecture of seven hidden nodes showed a significant difference from the other options.

The TSS-07 structure represented the optimum structure for the TSS model based on performance and simplicity. Also, it preserved the simplicity principle according to the Kolmogorov theory (Thomas *et al.* 2015), which establishes that the optimum number of hidden nodes must be less than two times that of node numbers used for the input layer. Using more nodes in the hidden layer leads to overfitting problems and weak performance of network estimations (Bashipour & Hojjati 2019). Then, the TSS-07 architecture was selected as the best option to predict the effluent TSS concentration.

The simplicity factor was also considered in selecting the optimum structure for the COD model. Both the COD-09 and COD-10 networks obtained similar results in terms of R^2, MSE, and AAD parameters. The COD-10 architecture showed a slight improvement in comparison to the COD-09 architecture. However, the COD-09 network obtained similar results with fewer nodes, which indicates that the model would achieve optimum performance with simpler network architecture. Kolay *et al.* (2008) highlighted that using more than 10 nodes in the hidden layer will cause saturation of the neural network,

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which results in lesser-quality simulated results because of undesirable feedback to the network. The COD-09 architecture was selected as the best option to predict the effluent COD to avoid saturation problems and preserve the principle of simplicity.

4.2. Performance analysis

4.2.1. Comparison of models (ANNs model vs. available models)

The prediction ability of the ANNs model developed in this work was compared with both the empirical model reported by Jover-Smet *et al.* (2017) and the dynamic model proposed by Gamal & Smith (2002b). The comparison of estimated values obtained by the ANNs model and the other models is shown in Figure 5.

If there is a perfect agreement between the model estimations and experimental measurements, all the points will lie along the 45° line (y=x). It can be seen that the values simulated by models spread around the 45° line, which implies neither overestimation nor underestimation (Naderpour *et al.* 2010). The difference between the estimated value and experimental measurement was considered in terms of AAD because this better illustrates the error of the models' estimations. Hence, an estimation error range of $\pm$20 and $\pm$40% was established to analyze the models' accuracy. In Figure 5(a), it is observed that the TSS model estimations were mainly concentrated within the $\pm$20% error range. However, few estimated values were within the error range from 20 to 40%, which was related to the ANNs model's variability and precision of estimations. In contrast, the other models provided less accurate predictions than the TSS model. A significant amount of the estimated values generated by the Jover-Smet *et al.* (2017) and Gamal & Smith (2002b) models were outside the established $\pm$40% error range.

The comparison between the ANNs model and other models based on COD measurements is shown in Figure 5(b). It suggests that the COD model reached a better performance in predicting experimental values than the previously reported models. The COD model predictions were mainly concentrated in the $\pm$20% error range. There were no values outside the $\pm$40% error range. On the other hand, many of the predicted values generated by the other models were outside the $\pm$20 and $\pm$40% error range. Furthermore, in both cases, the available models in the literature reached lower R^2 values ($R^2<0.1$) than the proposed model ($R^2>0.5$).

There were few estimations of the ANNs model outside the $\pm$40% error range, but these were unusual cases related to random fluctuations of wastewater parameters. These cases did not align with the proposed model during the ANNs training phase. A sudden change in the wastewater characteristics will produce incorrect predictions. In the case of temporary shock loads and dilutions in the influent, it is inevitable to experience fluctuations through the overall process units (Yel & Yalpir 2011). In particular, effluent discharged to the PSTs is often variable because of stormwater and intermittent discharges from an industrial process (Flynn 2018). Consequently, these extreme cases will be associated with a higher concentration of

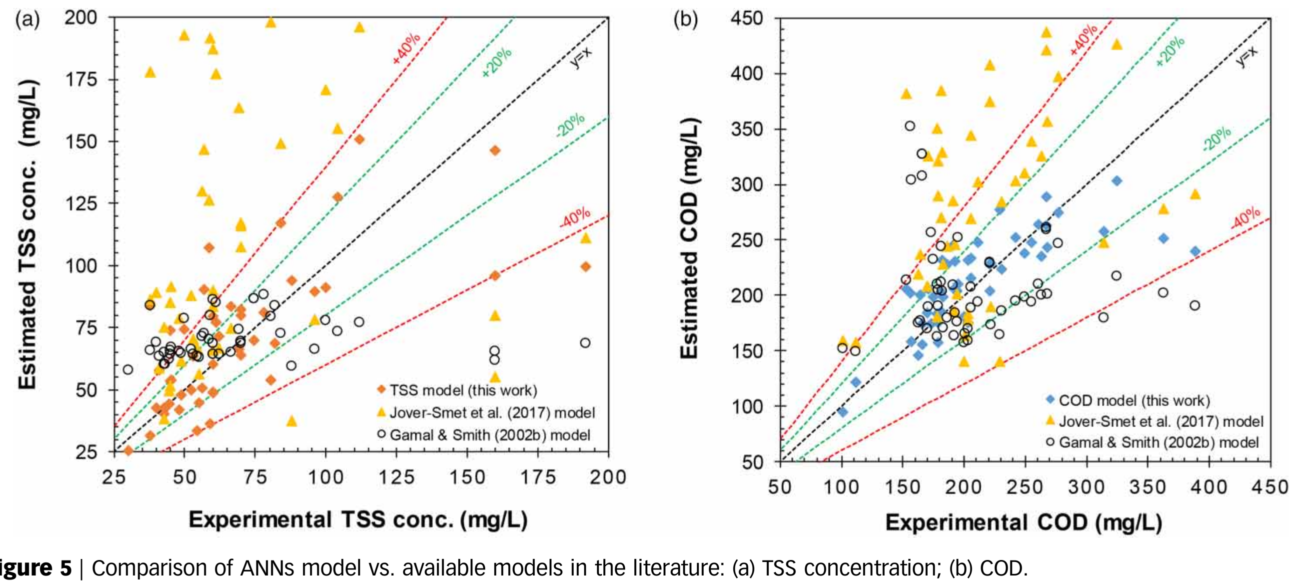

Figure 5 | Comparison of ANNs model vs. available models in the literature: (a) TSS concentration; (b) COD.

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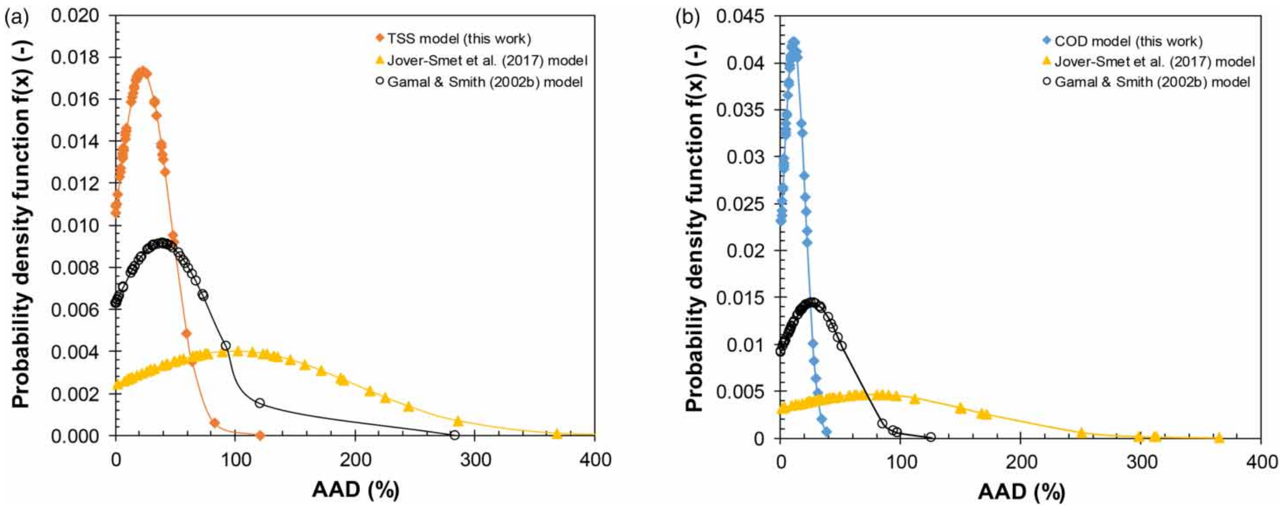

Figure 6 | Normal distribution errors: (a) TSS concentration; (b) COD.

pollutants in stormwater and industrial discharges, affecting raw wastewater's COD and TSS concentration. However, the ANNs model obtained more accurate estimations than the literature reports in these particular cases.

Testing residuals also analyzed the difference between experimental values and estimated values provided by each model in terms of AAD criteria. Normal distribution was employed to analyze and compare the estimation error associated with each model. Figure 6 shows the distribution of estimation errors associated with each model. The statistical parameters related to each model's error distribution are detailed in Table 1.

Figure 6(a) illustrates the distribution of estimation errors related to the TSS concentration measurements. It is observed that the distribution associated with the estimations of the TSS model obtained the lowest mean AAD value. A significant reduction of mean error was obtained using the TSS model (22.87%) in comparison to the other models. Moreover, the distribution described by the TSS model estimations presented the lowest standard deviation value (22.98%), which indicated that the TSS model provides estimates with less error variability. Despite the TSS model showing a relatively high value of standard deviation, it was considerably lower than the values obtained with the Jover-Smet *et al.* (2017) and Gamal & Smith (2002b) models (99.57 and 43.64%, respectively). Therefore, the dispersion of errors associated with the TSS model estimations mainly concentrated on the mean value within a smaller variation range than the other models. These results indicated that the TSS model provided more accurate estimates with less variability than the Jover-Smet *et al.* (2017) and Gamal & Smith (2002b) models.

Figure 6(b) shows the distribution of estimation errors associated with the COD measurements. The distribution of the errors related to the COD model obtained the lowest mean AAD% value (11.12%) in comparison to the Jover-Smet *et al.* (2017) and Gamal & Smith (2002b) models (75.84 and 26.58%, respectively). A significant reduction in mean estimation error was observed using the COD model, and in addition, the dispersion and variability of error estimation were also reduced through the COD model. The distribution of errors associated with the COD model estimations had the lowest standard deviation value (9.43%) compared to the other models considered in the analysis. In particular, the proposed model generated assessments with an error variability of less than 10%. The proposed ANNs model obtained a better performance estimating

Table 1 | Comparison of distribution errors: statistical parameters

		Mean error (%)		Standard deviation (%)	
Model	**Description**	**TSS**	**COD**	**TSS**	**COD**
ANNs model (this work)	ANNs	22.87	11.12	22.98	9.43
Gamal & Smith (2002b)	Stochastic model	38.49	26.58	43.64	27.65
Jover-Smet *et al.* (2017)	Empirical correlation	100.15	75.84	99.57	86.17

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TSS concentration and COD measurements than the models reported by Jover-Smet *et al.* (2017) and Gamal & Smith (2002b). The narrow range of error measures obtained using the ANNs model indicated the model's robustness (Hamed *et al.* 2004). Therefore, the robustness of the proposed ANNs model was also shown to be superior to the statistical model and the empirical model considered in this study.

4.2.2. ANNs model verification

A new experimental data set (10 sample data, see Table A.2) was used to verify the reproducibility and practical application of the ANNs model under the actual operating conditions of the Ibarra WWTP. Figure 7 corresponds to the relationship between the estimated values by the ANNs model and the experimental measurements of the new data set. Based on the error range observed in the training stage, average absolute deviations of ± 20 and $\pm 40\%$ were considered as the error ranges to analyze the performance of the ANNs model.

The relationship between TSS model estimations and TSS experimental measurements is exposed in Figure 7(a). Few sample patterns lay along the 45° line, implying a perfect agreement between the TSS model predictions and experimental data. Some points were within the $\pm 20\%$ error range, indicating reasonable estimations with a slight deviation of the measured value. Few estimated values were outside the $\pm 20\%$ error range, but they were inside the $\pm 40\%$ error range. Only one point had an estimation error higher than $\pm 40\%$, which would be related to several factors' variability and fluctuations of the sewage. Therefore, the TSS model had satisfactory results in predicting the TSS concentration of the clarified effluent in general terms.

Figure 7(b) corresponds to the relationship between estimated values by the COD model and COD experimental data. Some points lay along the 45° line; the COD model provided high accurate estimations for these cases. Some of the estimated values were outside the $\pm 20\%$ error range. However, the error associated with these estimations outside the expected error range was slightly higher than $\pm 20\%$. In these cases, the COD model at least supplied a good approximation of the COD of the clarified effluent. The COD model was suitable for estimating COD measurements under actual operation conditions after the training phase.

In general, the proposed ANNs model achieved satisfactory performance in both the TSS concentration and COD estimations. It should be mentioned that the ANNs model has been trained on a minimal data set; however, it still was able to provide reasonable estimates. The calculated errors fell within the acceptable limits as the analytical error intervals were much higher in the measurements of these parameters (usually around $\pm 20\%$ error range) (Yel & Yalpir 2011). Furthermore, predictive models based on ANNs are flexible. Adaptive models that can be continuously adjusted to new scenarios. This flexibility is essential because ANNs models can be retrained and adapted to variations in wastewater characteristics or operating conditions using actual data. The development of predictive models is not only relevant for improving the process

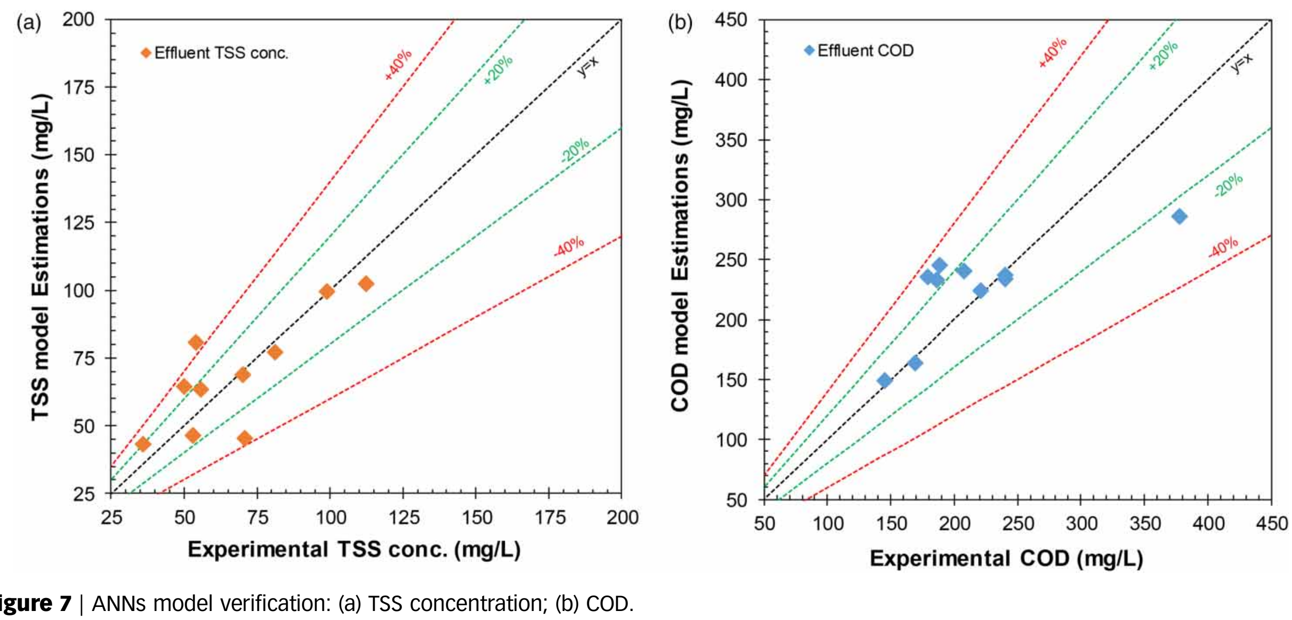

Figure 7 | ANNs model verification: (a) TSS concentration; (b) COD.

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control system and operation of the treatment process. It also reduces economic costs and time associated with the regular laboratory analysis of wastewater to monitor effluent quality.

5. SUMMARY AND CONCLUSIONS

The ANN model developed to predict the TSS concentration and COD of the clarified effluent from a primary settling tank obtained satisfactory and accurate results during the training phase. Moreover, it showed a better performance and more accurate estimation than the available models reported in the literature. Something novel about this study was the verification process, which was carried out as a second test two months after the modeling phase to evaluate the proposed model's applicability and reproducibility over time. It turned out that the ANNs model achieved a satisfactory performance during the verification process, estimating the TSS concentration and COD of the effluent wastewater under actual operating conditions. It provided estimated values with high accuracy ($\pm$20% error range), which could be valuable information for operating the wastewater treatment process. Therefore, these results would represent a significant advantage to the applicability of this type of model in developing process control systems in the future. However, future studies are necessary for improving the modeling approach to the dynamic response of settling tanks.

The proposed ANNs model could be used for two main potential applications. First, ANNs can be used to simulate the response of PSTs. This could be a suitable strategy for operating the primary treatment unit. Then, this information about PSTs' responses can then be used as input data to develop control systems or operational plans for the downstream biological process. Moreover, settling tanks can also be improved using information obtained from simulations. In addition, this type of model could be adapted to the online monitoring and control system of PSTs. It would be a useful operational tool for monitoring the PSTs operation in real-time.

Predictive models based on artificial neural networks can be used to determine other analytical parameters in the treated effluent, such as biochemical oxygen demand (BOD), nitrates, phosphates, and ammoniacal nitrogen. Some studies could be planned to expand the ANNs model developed in this study, according to the operational needs or technical requests of WWTPs.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST STATEMENT

The authors declare there is no conflict.

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