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Application of Artificial Neural Networks to the Prediction of Total Suspended Solids (TSS) and Chemical Oxygen Demand (COD) at an Urban Wastewater Pumping Station in the Abidjan District (Côte d'Ivoire)

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Abstract

Conventional wastewater characterization relies on time-consuming and costly physicochemical analyses that are poorly suited to real-time monitoring. In this context, turbidity is an easily measurable optical indicator with potential for the indirect estimation of global pollution parameters. This study aimed to develop artificial neural network (ANN) models to predict total suspended solids (TSS) and chemical oxygen demand (COD) concentrations using turbidity as the sole input variable. Two hundred (200) wastewater samples were collected at the Blockauss pumping station in Abidjan during different seasons. Turbidity, TSS, and COD were determined according to NF EN ISO 7027, NF T 90-105, and CEAEQ methods. The normalized dataset was divided into training (50%), validation (25%), and testing (25%) subsets. Multilayer perceptrons with 1 to 15 hidden neurons were optimized and evaluated using R, R^2, RMSE, and MRD. The selected 1-1-1 architecture for TSS showed good performance ($R^2 = 0.80$; RMSE = 0.127; MRD = 7.46%). For COD, the 1-2-1 architecture yielded more moderate performance ($R^2 = 0.66$; RMSE = 0.246; MRD = 12.83%), indicating that turbidity explained a smaller proportion of COD variability, owing to the complex composition of wastewater and the influence of environmental and climatic factors on COD concentrations. Further improvement of COD prediction requires the integration of additional variables, such as pH, temperature, conductivity, and dissolved oxygen. Model validation and recalibration are also recommended before extrapolation to other wastewater treatment stations.

Keywords

Wastewater, Turbidity, Total Suspended Solids (TSS), Chemical Oxygen Demand (COD), Artificial Neural Network (ANN), Modeling, Wastewater

1. Introduction

The characterization of wastewater has traditionally been carried out on the basis of *in situ* sampling and laboratory measurements [1] [2]. This conventional characterization is subject to several constraints, namely: the transport of the effluent to the laboratory, its preservation, delayed-time analysis in the laboratory, the prohibitive cost of reagents and analyses, and the time required to obtain results. These constraints represent a difficulty for the proper characterization of the environment. Consequently, various continuous *in situ* measurement techniques are now available for use. Among these, turbidity measurement makes it possible to estimate the loads of total suspended solids (TSS) and chemical oxygen demand (COD) circulating in urban sanitation networks. Indeed, TSS and COD constitute overall pollution indicators. The most appropriate strategy is therefore to predict these loads from turbidity. The present study aims to predict, using an artificial neural network, the concentrations of the overall pollution parameters COD and TSS from turbidity measurements. In other words, this study proposes models for predicting COD and TSS concentrations from turbidity.

2. Materials and Methods

2.1. Study Area

The Blockauss pumping station, located in Cocody near Saint Peter's Catholic Church, provides the pumping of wastewater originating primarily from Félix Houphouët-Boigny University, the Cocody University Hospital (CHU), and the Cocody Ambassade district, before conveying it to the Treichville Market trunk sewer through a sub-lagoon crossing (**Figure 1**).

2.2. Sampling

Wastewater samples were collected at the Blockauss pumping station, located in the municipality of Cocody within the Abidjan District, using an automatic sampler equipped with an adiabatic enclosure (**Figure 2**). Sampling was carried out at the Blockauss station and at the Digue pre-treatment station using the automatic sampler. The sampler was programmed to operate on 24-h sampling cycles. Accordingly, six (06) 24-h sampling campaigns were conducted at each site from February 2024 to December 2024, covering both dry and rainy seasons, with one campaign conducted every two months. The automatic sampler was programmed to collect 1-h integrated samples by collecting 200 mL of wastewater every 12 min. Five sampling series were performed over 1 h to constitute a 1-L sample. Samples were collected at the raw wastewater inlet of the respective stations. Thus, twenty-four (24) daily samples were obtained per site and transported to the laboratory for analysis.

Figure 1. Blockauss pumping station.

Figure 2. Hourly wastewater sampling at the Blokauss station.

2.3. Sample Analysis

In the laboratory, all wastewater samples were analyzed for physical parameters (turbidity and TSS) and a chemical parameter (COD) in accordance with the French standard [3] and the methods developed by the Centre of Expertise in Environmental Analysis of Québec (CEAEQ) [4]. All methods are summarized in **Table 1**.

Table 1. Analytical methods for the physical and chemical parameters.

Measured parameter	Analytical method
Turbidity	Nephelometric method with formazine (NF EN ISO 7027)
TSS	Glass-fiber filtration method (NF T 90-105)
Chemical oxygen demand (COD)	Closed-reflux method followed by colorimetric determination with potassium dichromate

2.4. Modeling of TSS and COD from Turbidity Using an Artificial Neural Network

Modeling of total suspended solids (TSS) and chemical oxygen demand (COD) from turbidity was performed using an artificial neural network (ANN) implemented in Matlab R2014 (MathWorks Inc., USA). The backpropagation algorithm used made it possible to establish an empirical model of the general form:

$$Y = \sum \lambda_i \cdot y_i + b \quad (1)$$

where:

Y is the TSS or COD concentration value, *i.e.*, the network output (response);

λ_i is the weighting coefficient assigned to the hidden-layer neurons;

y_i is the summation of the values resulting from the different activation functions; and b is the bias, *i.e.*, the error made by the network.

2.5. Database Construction and Preparation

The experimental data (200 observations) were normalized to the interval [−1; +1] according to Equation (2):

$$y_i^{\circ} = \frac{2\left(y_i - y_{\min}\right)}{\left(y_{\max} - y_{\min}\right)} - 1 \quad (2)$$

where:

y_i° = is the normalized experimental value;

y_i = is the experimental value;

$y_{\min}$ = is the minimum experimental value;

$y_{\max}$ = is the maximum experimental value.

The data were then randomly divided into three sets: training (50%), validation (25%), and testing (25%).

2.6. Design of the Artificial Neural Network Structure

The architecture selected was a multilayer perceptron comprising an input layer (turbidity), an output layer (TSS or COD), and a hidden layer whose number of neurons (k = 1 to 15) was optimized. A hyperbolic tangent sigmoid transfer function was adopted as the activation function, expressed as follows:

$$y_i = \tanh\left(\sum x_i \cdot p_i + b\right) \quad (3)$$

where:

tanh is the hyperbolic tangent function, used as the activation (transfer) function;

Y : is the value resulting from the activation function;

λ_i : is the new (normalized) transformed value;

y_i : is the weight of the element (observation) in the network, which determines the network's output response; and

b : is the bias, *i.e.*, the error made by each neuron.

2.7. Validation of the Neural Model

Validation of the optimized neural model was carried out using the correlation coefficient (R) and the mean square error (MSE). In accordance with Yeh [5] and Hsu [6], a model is considered acceptable when $R^2 \geq 0.5$, *i.e.*, $R \geq 0.71$. The mean square error (MSE) is expressed as follows (4),

$$R = \frac{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)\left(y_c - \overline{y_c}\right)}{\sqrt{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)^2}\sqrt{\sum_{i=1}^{N}\left(y_c - \overline{y_c}\right)^2}} \tag{4}$$

where y_e and y_c represent, respectively, the experimental values and the values calculated by the network for $i = 1,\cdots,N$; $\overline{y_e}$ and $\overline{y_c}$ are the respective means of the experimental values and the values calculated by the network.

N represents the number of observations.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(y_e - y_c\right)^2 \tag{5}$$

$$\chi^2 = \frac{\sum_{i=1}^{N}\left(y_e^\circ - y_c^\circ\right)^2}{N - z} \tag{6}$$

$$\text{SSE} = \frac{100}{N}\sum_{i=1}^{N}\left(y_e^\circ - y_c^\circ\right)^2 \tag{7}$$

where:

y_c and y_e are, respectively, the values calculated by the network and the experimental values for $i = 1,\cdots,N$, with

N: the number of input variables.

2.8. Performance Testing of the Neural Model

This stage evaluates the relevance of the connection weights and their ability to explain the phenomenon under study, using the 25% of samples reserved for testing. Model performance is assessed through the coefficient of determination (R^2) and the mean relative deviation (MRD). A model is considered satisfactory when R^2 tends toward 1, reflecting a good fit, and when the MRD remains below 10%. The MRD is calculated as follows:

$$R^2 = \frac{\sum_{i=1}^{N}\left(y_{pred} - \overline{y_e}\right)^2}{\sum_{i=1}^{N}\left(y_e - \overline{y_e}\right)^2} \tag{8}$$

where:

y_e and y_{pred} represent, respectively, the experimental and calculated values for $i = 1, \cdots, N$, and corresponds to the mean value of the measured or experimental data.

$$\mathrm{MRD} = \frac{100}{N} \sum_{i=1}^{N} \left| \frac{y_e^\circ - y_c^\circ}{y_e^\circ} \right| \tag{9}$$

$$\mathrm{RMSE} = \left[\frac{\sum_{i=1}^{N} \left(y_e^\circ - y_c^\circ \right)^2}{N} \right]^{1/2} \tag{10}$$

where:

y_e = is the normalized experimental value for $i = 1, \cdots, N$;

y_c = is the normalized value calculated by the network for $i = 1, \cdots, N$; and N is the number of observations.

3. Results and Discussion

3.1. Modeling of TSS Concentrations

3.1.1. Artificial Neural Network Architecture

Table 2 presents the correlation coefficients (R) obtained during the respective training and validation phases for TSS concentrations. This coefficient ranges from 0.870 to 0.923 during the training phase and from −0.185 to 0.928 during the validation phase. A hidden-layer neuron count of 1 gives the highest correlation simultaneously in both the training phase (R training = 0.923) and the validation phase (R validation = 0.928). Accordingly, the selected neural architecture is 1-1-1. This neural topology comprises 1 neuron in the input layer (turbidity), 1 neuron in the hidden layer, and 1 neuron in the output layer (TSS).

Table 2. Correlation coefficients of the training and validation sets of the ANN (TSS).

Number of hidden-layer neurons	R training	R validation
1	**0.923**	**0.928**
2	0.876	0.914
3	0.877	0.912
4	0.882	0.907
5	0.884	0.913
6	0.885	0.903
7	0.895	0.895
8	0.917	−0.185
9	0.905	0.578
10	0.907	0.281

Continued

11	0.905	0.490
12	0.912	0.113
13	0.920	0.191
14	0.870	0.426
15	0.914	0.246

3.1.2. Determination of the Linear Model of the Optimized Neural Architecture

The linear model for the 1-1-1 (**Figure 3**) neural architecture was constructed first from the weights and bias associated with the input variable, and then from the linear weights connecting the hidden layer to the output layer. The resulting model is:

$$\text{TSS} = -3.243387331\, y1 + 0.786129812 \tag{11}$$

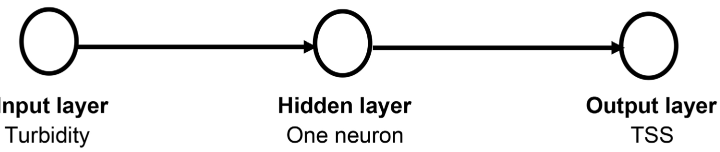

Figure 3. Schematic representation of the optimized neural network architecture (1-1-1).

3.1.3. Neural Model Validation

The neural model is validated since the correlation coefficient in the validation phase (R validation = 0.928 ≈ 0.93) is very high and close to 1 ($R \geq 0.93$). According to Yeh [5] and Hsu [6], the minimum acceptable threshold is $R^2 = 0.5$, whose square root is $R \approx 0.71$. Furthermore, the mean-squared errors generated by these neural models are low and tend virtually toward zero (**Figure 4**).

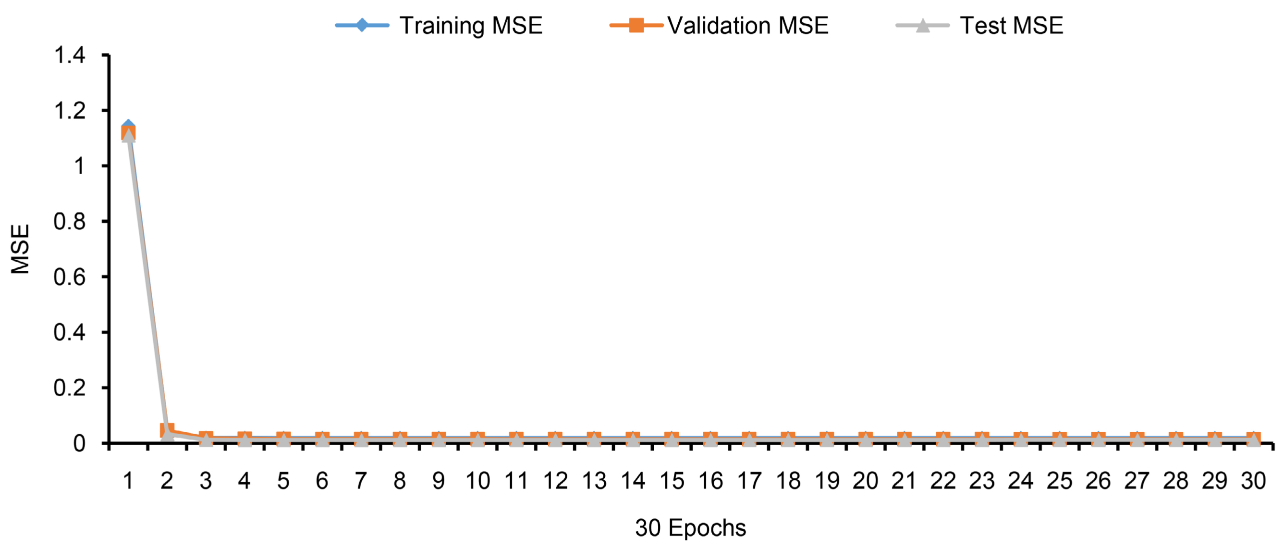

Figure 4. Evolution of the mean squared errors of TSS concentrations generated by the ANN.

3.1.4. Prediction Model Performance

The suspended solids (TSS) prediction model demonstrated good performance, with a coefficient of determination (R^2) of 0.80, an RMSE of 0.127, and a mean relative deviation (MRD) of 7.46% (**Table 3**). These results indicate good agreement between the experimental concentrations and those estimated by the artificial neural network (ANN). The R^2 value indicates that turbidity accounts for approximately 80% of the variability in TSS concentrations, while the MRD below 10% reflects an overall low relative prediction error.

Table 3. TSS prediction performance criteria.

Performance criterion	Value
R^2	0.80
RMSE	0.127
MRD	7.46%
R	0.88

The testing phase further confirmed these performances, with a correlation coefficient of $R = 0.88$ between the experimental and predicted values (**Table 3**). The good agreement between the trends observed (**Figure 5**) in confirms the model's ability to reproduce overall variations in TSS concentrations. These results are consistent with the findings of Zare Abyaneh [7], who demonstrated the usefulness of artificial neural networks for predicting wastewater quality parameters, particularly TSS and COD. In that study, conducted at the Ekbatan wastewater treatment plant in Tehran, ANN model performance was assessed using, among other criteria, the correlation coefficient and RMSE.

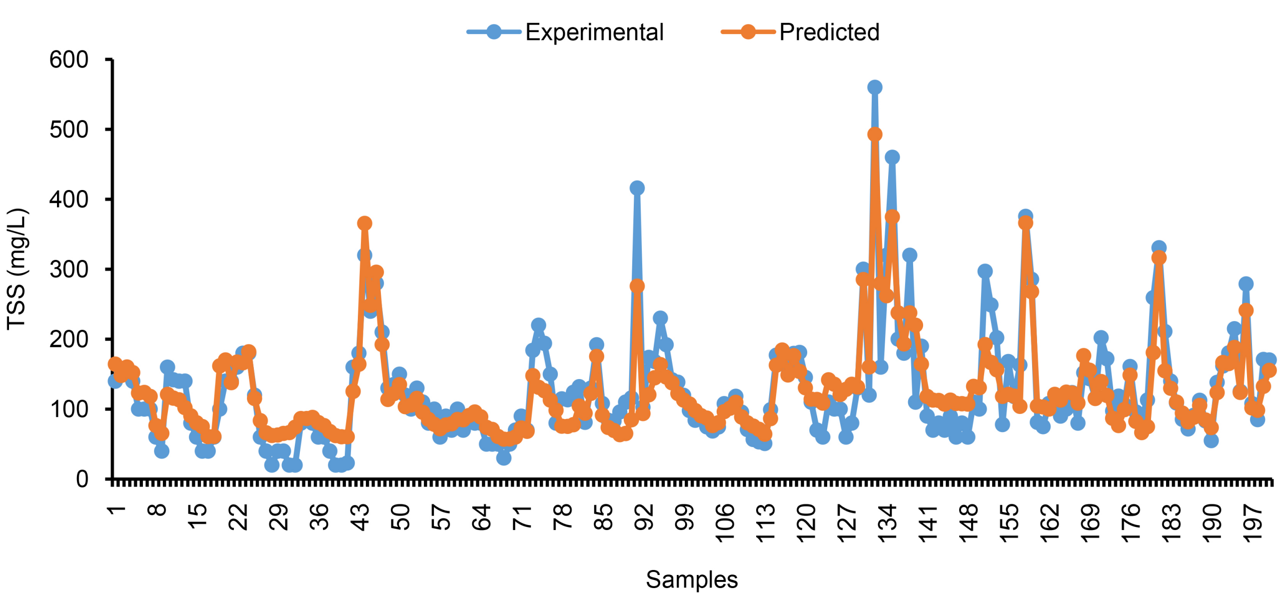

Figure 5. Comparison of the trends in experimental TSS concentrations and those predicted by the artificial neural network.

The good performance obtained in the present study can be primarily explained by the close relationship between turbidity and TSS [8], particularly when measurements are performed at 860 nm in the infrared range. Turbidity is an optical indicator directly influenced by the presence of suspended particles and can therefore be used as an indirect variable to estimate TSS concentrations in sewer systems. Bertrand-Krajewski [9] demonstrated that a site-specific empirical relationship could be established between continuously measured turbidity and TSS concentrations determined from samples, thereby allowing TSS concentrations to be estimated from turbidity measurements. This relationship was also investigated by Bertrand-Krajewski *et al.* [10], who showed that turbidity could be used to continuously estimate TSS concentrations and, under certain conditions, COD concentrations in sewer systems. However, the authors emphasized that the quality of the turbidity-TSS relationship depends on wastewater characteristics, flow conditions, and sensor calibration.

The differences observed between the experimental and ANN-predicted concentrations (**Figure 5**) may therefore be attributed to variations in the physical characteristics of suspended particles. The relationship between turbidity and TSS is not universal, since the optical response depends, in particular, on the size, shape, nature, concentration, and optical properties of the particles. Experimental studies have shown that different sensors may produce different turbidity readings for the same suspended solids concentration, although site-specific turbidity TSS relationships may nevertheless exhibit high coefficients of determination.

Thus, the differences observed in the present study do not undermine the usefulness of the model but rather reflect the inherent limitations associated with the use of an indirect optical measurement to estimate TSS. Nevertheless, the developed model demonstrated satisfactory performance ($R^2 = 0.80$; $R = 0.88$; RMSE = 0.127; MRD = 7.46%) and may therefore constitute a complementary tool for the rapid estimation of TSS concentrations in wastewater from the Blokauss treatment plant. However, in accordance with the recommendations of Bertrand-Krajewski *et al.* [10], its application to other wastewater treatment plants would require site-specific validation and calibration, given the variability in particle and wastewater characteristics.

3.2. Modeling of COD Concentrations

3.2.1. Artificial Neural Network Architecture

According to **Table 4**, the correlation coefficients obtained range from 0.794 to 0.861 during the training phase and from 0.006 to 0.844 during the validation phase. The best correlation during training is achieved with 14 neurons, whereas during validation, it is achieved with 2 neurons. Several architectures (1-1-1, 1-2-1, 1-3-1, 1-4-1, 1-5-1, 1-7-1) appear to offer good compromises.

The best neural model was determined by comparing the error indicators and correlation coefficients between the experimental and predicted COD concentrations. The final analysis thus identifies the 1-2-1 architecture as the most efficient, with 1 input neuron (turbidity), 2 hidden neurons, and 1 output neuron (COD) (**Table 5**).

Table 4. Correlation coefficients of the training and validation sets of the ANN (COD).

Number of hidden-layer neurons	*R* training	*R* validation
1	0.794	0.792
2	0.812	**0.844**
3	0.815	0.826
4	0.816	0.835
5	0.829	0.833
6	0.846	0.581
7	0.836	0.836
8	0.848	0.521
9	0.847	0.688
10	0.837	0.765
11	0.855	−0.006
12	0.858	0.052
13	0.857	0.278
14	**0.861**	0.266
15	0.860	0.158

Table 5. Error indicators and correlation coefficients of the tested architectures (COD).

Model	RMSE	SSE	χ^2	*R*
1-1-1	0.256	6.55	0.06590	0.8
1-2-1	**0.246**	**6.05**	**0.06083**	**0.84**
1-3-1	0.248	6.17	0.06199	0.79
1-4-1	0.342	11.71	0.12	0.77
1-5-1	0.350	12.29	0.12354	0.8
1-7-1	0.271	7.35	0.07391	0.75

3.2.2. Determination of the Linear Model of the Neural Architecture

The linear model of the 1-2-1 (**Figure 6**) neural architecture was established in two steps: first from the weights and bias associated with the input variable, and then from the weights connecting the hidden layer to the output and the associated bias. The resulting model is:

$$\text{COD} = -1.206349065 y_1 - 0.65620481 y_2 + 0.670702445 \quad (12)$$

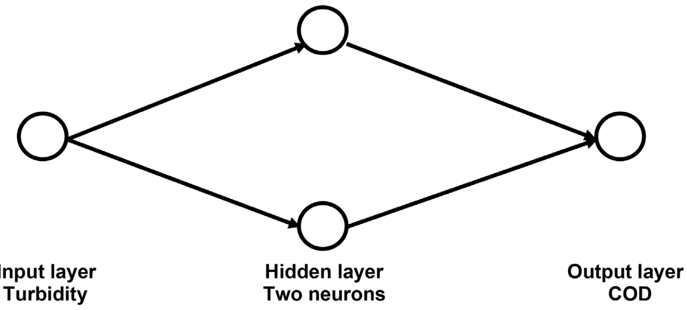

Figure 6. Schematic representation of the optimized neural network architecture (1-2-1).

3.2.3. Neural Model Validation

The 1-2-1 neural model is validated, with a correlation coefficient in the validation phase of Rvalidation = 0.84, close to 1. The mean-squared-error curves for the training, validation, and test phases are decreasing, and tend toward zero (**Figure 7**). This result is confirmed by the studies of Yeh [5] and Hsu [6].

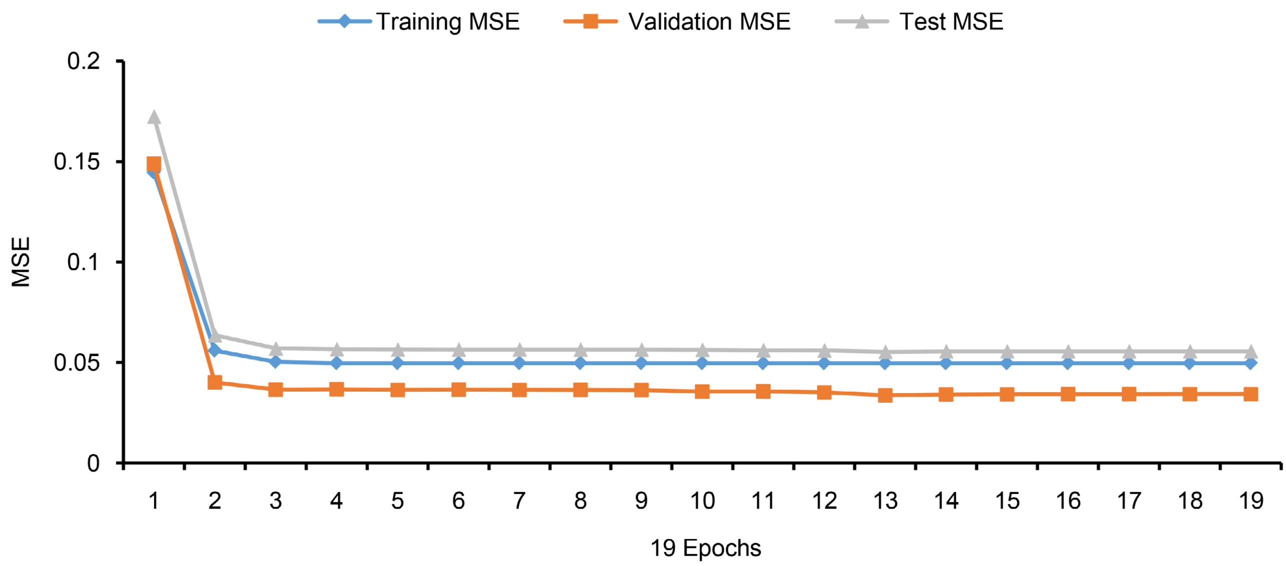

Figure 7. Evolution of the mean squared errors of COD concentrations generated by the ANN.

3.2.4. Prediction Model Performance

The COD prediction model developed using turbidity as the sole input variable yielded a coefficient of determination (R^2) of 0.66, an RMSE of 0.246, and a mean relative deviation (MRD) of 12.83% (**Table 6**). Thus, turbidity accounted for approximately 66% of the variability in the total COD measured experimentally in the wastewater from the Blockauss treatment plant. These results indicate moderate predictive performance but demonstrate that turbidity can provide useful indirect information for estimating COD concentrations. This relationship has also been reported in previous studies, which highlighted associations between turbidity, total suspended solids (TSS), and COD [11] [12].

The testing phase yielded a correlation coefficient of approximately 0.80 between the experimental and predicted concentrations (**Table 6**), with an overall agreement in the observed trends (**Figure 8**). Bersinger *et al.* [12] reported a positive relationship between turbidity and COD in a sewer system, confirming the potential of turbidity as an indirect indicator of organic load. However, the strength of this relationship depends on wastewater characteristics as well as hydrodynamic and seasonal conditions.

Table 6. COD prediction performance criteria.

Performance criterion	Value
R^2	0.66
RMSE	0.246
MRD	12.83%
R	0.80

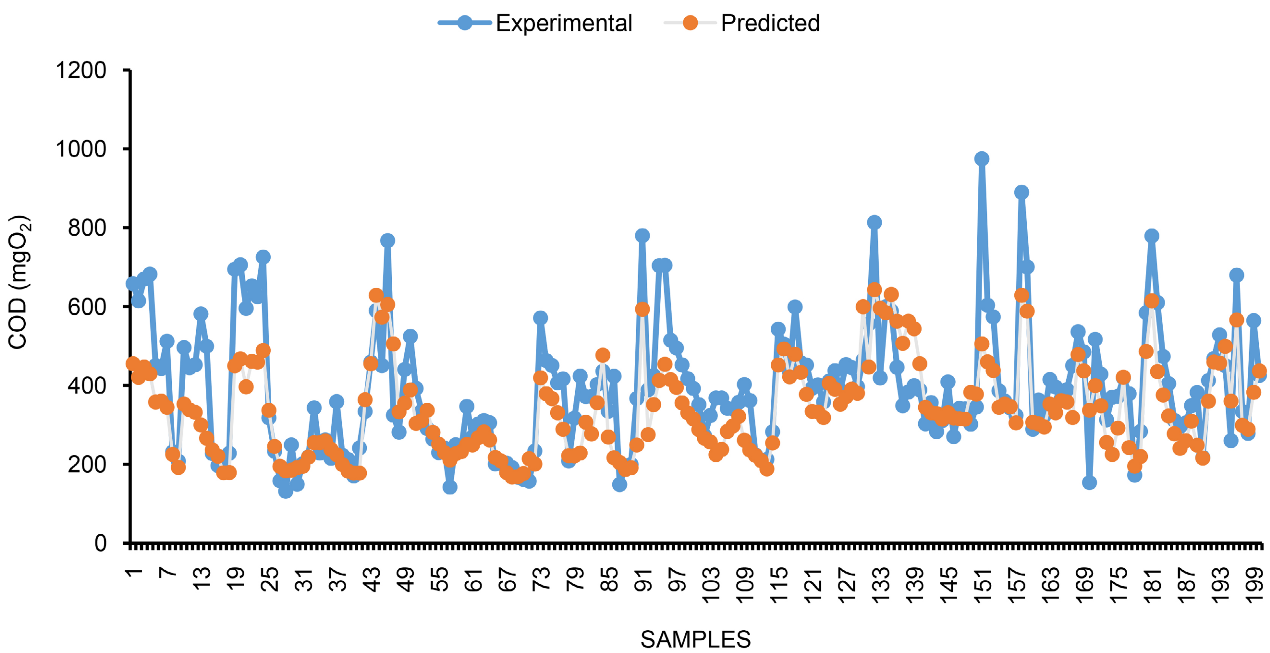

Figure 8. Comparison of the trends in experimental COD concentrations and those predicted by the artificial neural network.

The performance obtained is consistent with previous studies on COD modelling using artificial neural networks (ANNs). Matheri *et al.* [13] demonstrated that ANNs can effectively predict COD concentrations in wastewater, while emphasizing the importance of input variables in determining model performance. Similarly, Abba and Elkiran [14] achieved improved predictive performance by using several physicochemical parameters as explanatory variables. Aghdam *et al.* [15] also demonstrated that COD prediction could be improved by incorporating multiple wastewater quality parameters, particularly TSS.

The relatively lower performance of the COD model compared with that developed for TSS may therefore be attributed, at least in part, to the use of turbidity as the sole explanatory variable and to the intrinsic complexity of COD. Incorporating additional parameters, such as pH, temperature, electrical conductivity, TSS, and dissolved oxygen, could improve predictive performance. However, such an approach would require additional data and independent validation to minimize the risk of overfitting and assess the model's generalization capability. Finally, given the specificity of the model to wastewater from the Blockauss treatment plant, its application to other treatment plants should be preceded by validation and, where necessary, recalibration using site-specific data.

4. Conclusions

At the end of this modelling study, two optimized neural network models were selected: the 1-1-1 architecture for TSS and the 1-2-1 architecture for COD. The results showed a strong correlation between the measured and turbidity-based predicted concentrations, with correlation coefficients equal to or greater than 0.80. However, the TSS model performed better than the COD model, with $R^2 \geq 0.80$ and prediction errors below 10%. In contrast, the COD model exhibited a lower R^2 of 0.66 and larger discrepancies, which may be related to the complex composition of COD and the influence of environmental and climatic factors on COD concentrations.

The present artificial neural network model was calibrated based on the specific characteristics of wastewater from the Blockauss treatment plant. Its application to other wastewater treatment plants should therefore be preceded by independent validation and, where necessary, recalibration using site-specific data. This precaution is particularly important given the variability in wastewater composition and the relationships between water quality parameters.

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Author Contributions

GAEJEY, KMOS, and ADGM participated in the design of the project. Sampling and laboratory analyses were performed by GAEJEY. The manuscript was written in French by GAEJEY, ADGM, and KMGR, and translated by BTGN and KMGR under the supervision of YOB. All authors read and verified the final version of the manuscript.

Declaration on the Use of Artificial Intelligence

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during writing or editing of this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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