



Research Article

**ARTIFICIAL NEURAL NETWORK BASED MODEL IN
EFFLUENT TREATMENT PROCESS**Monika Vyas^{*a}, Bharat Modhera^b, Dr. A. K. Sharma^a**Address for Correspondence**^a Department of Civil Engineering, Maulana Azad National Institute of Technology, Bhopal (INDIA).^b Department of Chemical Engineering, Maulana Azad National Institute of Technology, Bhopal (INDIA).

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ABSTRACT

During the past 30 years the industrial sector in India has quadrupled in size, thus it increases the pressure on wastewater treatment industries to produce higher quality treated water at a lower cost. The efficiency of a treatment process closely relates to the operation of the plant. To improve the operating performance, an Artificial Neural Network (ANN) paradigm has been applied to an effluent treatment plant. An ANN which is able to learn the non-linear performance relationships of historical data of a plant has been proved to be capable of providing operational guidance for plant operators. In this investigation the application of Artificial Neural Network (ANN) techniques are used to predict the Chemical Oxygen Demand for effluent treatment process. Sets of historical plant data of COD were collected from common effluent treatment plant at Govindpura, Bhopal (India). Data were collected over a period of 3 years from the influent and effluent streams of the station. Two ANN-based models for prediction of COD concentrations at influent and effluent points were formed using a three-layered feed forward ANN, which uses a back propagation learning algorithm. Using Forecaster xl software the correlation factor(R) for model 1 is found to be 0.9078 and for model 2 is 0.9216. Thus ANN proved as a good tool for prediction and forecasting the effluent treatment plant parameters.

KEYWORDS Artificial Neural Network (ANN), Effluent Treatment Process, Chemical Oxygen Demand (COD), Back Propagation.

INTRODUCTION

Common Effluent Treatment Plant is the concept of treating effluents by means of a collective effort mainly for a cluster of small scale industrial units. This concept is similar to the concept of Municipal Corporation treating sewage of all the individual houses. The main objective of CETP is to reduce the treatment cost for individual units while protecting the environment and to achieve economical waste treatment, thereby reducing the cost of pollution abatement for individual factory (9). The Ministry of India has undertaken a Centrally Sponsored Scheme for enabling the Small Scale Industries (SSI) to set-up Common Effluent Treatment Plants in the country for installation of pollution control equipment for treatment of effluents. The industrial pollution control regime in India is based on the standards and regulation approach. Source specific concentration based standard have been laid down for polluting units and penalties for non compliance, disconnection of electricity/water supply and closure of the units. The standards are same for large and medium units as well as for small units. While most of the large and medium polluting units have been able to erect and operate effluent treatment plants, this option does not appear to be viable for many small units because of their small size, and technical, financial and managerial constraints (1). Common effluent

treatment plants are being suggested as a cost-effective option for compliance with the standards for small polluting units in industrial clusters (2). Wastewater coming from different industries has different influent characteristics. Some industries effluent has high BOD value while some has lower BOD. Similarly, some effluents have high pH value with basic nature while some have lower and are acidic. One needs to know the characteristics of the incoming wastewater to the CETP for its homogenization and effective treatment. Thus Chemical oxygen demand (COD) is the good indicator of characteristics of waste water as it measures non-biodegradable as well as biodegradable waste.

This paper presents predictive COD models based on the concept of artificial neural networks (ANNs) (or simply neural networks), a widely used application of artificial intelligence that has shown quite a promise in a variety of applications in engineering, pattern recognition, and financial market analysis.

Artificial Neural Network Technology

The ANNs are mathematical modeling tools that are especially useful in the field of prediction and forecasting in complex settings. Artificial neural networks can be used for two broad categories of problems: data classification and variable prediction. For data classification problems, the ANN uses a specified algorithm to analyze data

cases or patterns for similarities and then separates them into a pre-defined number of classes. For variable prediction problems, the ANN learns to accurately predict the value of an output variable given sufficient input variable information. The main applications of the ANN technique in the water treatment industry are in the development of water quality and process models and model-based process-control and automation tools. These applications can be categorized as variable prediction problems (3). Historically, there were meant to operate through simulating, at a simplified level, the activity of the human brain. The ANN accomplishes this through a large number of highly interconnected processing elements (neurons), working in unison to solve specific problems, such as forecasting and pattern recognition. Each neuron is connected to certain of its neighbors with varying coefficients or weights that represent the relative influence of the different neuron inputs to other neurons (4).

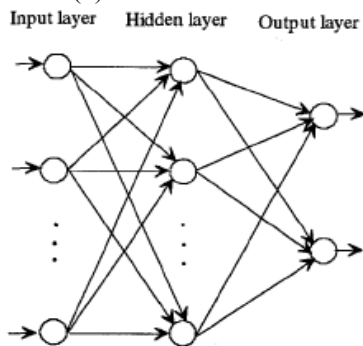


Figure 1. Layers of ANN

These weights are adjusted, depending on the task, to improve performance, that is, the accuracy of prediction made by the ANN. The first layer, called the input layer, consists of PES which simply takes on the input values of a pattern. The last layer is termed the output layer and produces the pattern outputs. The layer, or layers, in between is called hidden layers. The hidden layers also consist of PES and carry out several calculations (Figure 1). Firstly, they multiply all inputs by a weight, add a constant value and then sum the result.

That is:

$$I_j = \sum W_{ji} X_i + \theta_j \tag{1}$$

where, W_{ji} are the connection weights between PES and X_i are the inputs. In the second calculation phase carried out by the PE, the output Y_j is calculated using a non-linear transfer function (e.g., sigmoid or hyperbolic tangent).

$$Y_j = f(I_j) \tag{2}$$

The output of a PE can be connected to the input of other PES which process is shown in Figure 2.

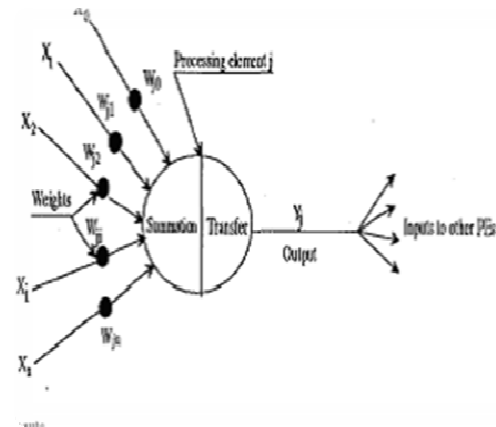


Figure 2. PE to PES inputs

The most common type of ANN is the Back-Propagation Network (BPN). The BPN is able to model the nonlinear relationship between parameters by relating the desired output parameter values to the known input parameter values (7). BPN is a multi-layer, feed forward network consisting of fully connected PES, and is used in this study

Methodology of Building ANNs Models of WWT Proacesses

To build effective ANN models of wastewater treatment processes, a sequential methodology consisting of four key stages is proposed. The relationship among each of the stages is depicted in Figure (3).

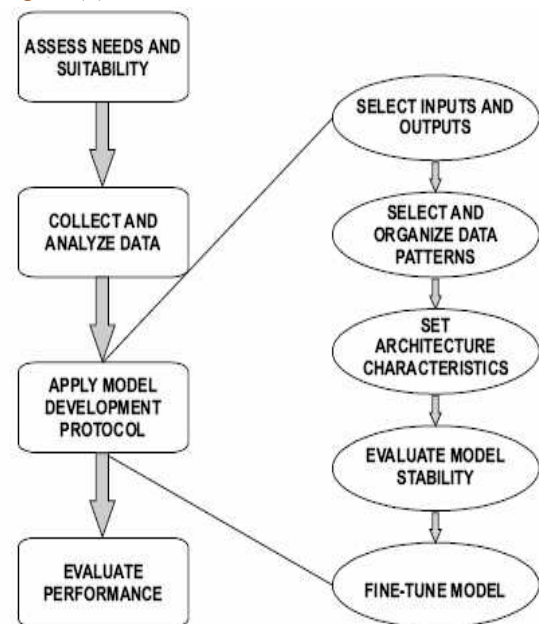


Figure 3. The main stages of developing an ANN process model

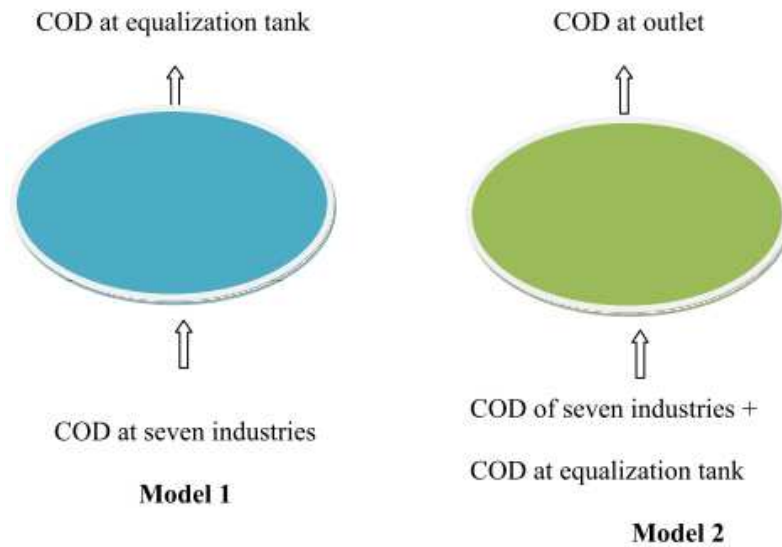


Figure 4. Schematic ANN models for CETP Bhopal

General Description of Treatment Plant

CETP Govindpura (BHOPAL): For treatment of combined industrial wastewater from Govindpura Industrial Area an agency known as Govindpura Audhyogik Kshetra Pradushan Nivaran Pvt. Ltd. (GAKPNPL), had installed a Common Effluent Treatment Plant (CETP). Designed capacity of CETP was 900 m³/day. The designed removal efficiency of COD and BOD was 89% and 95% respectively. The treatment system consists of equalization tank, holding tanks, buffer tank, anaerobic treatment unit (Upflow Anaerobic Sludge Blanket, UASB) and flash aeration tank. For evaluating the performance of CETP Composite sampling was done for 24 hours. Grab samples were also collected. V-notch was provided for measuring the flow. During monitoring, 492 m³/day flow was observed as against the designed flow of 900 m³/day (6).

At present, eight industries are participating in the Govindpura treatment plant for the wastewater treatment. Lilasons Breweries and Ramani Ice-cream industries are major contributors whereas the other industries which include EEI capsules, Rajsons dairy, Bhopal incinerators, Saviour caps, Specialty organics and Anik organic are the minor ones. After entering the treatment plant, wastewater is allowed to homogenize in equalization tank. This sets up the standard for treating the waste from variety of industries simultaneously. Waste from the equalization tank moves to the holding tank

where it is held for about 1 hour. This facilitates settling and separation of heavy particles in the wastewater.

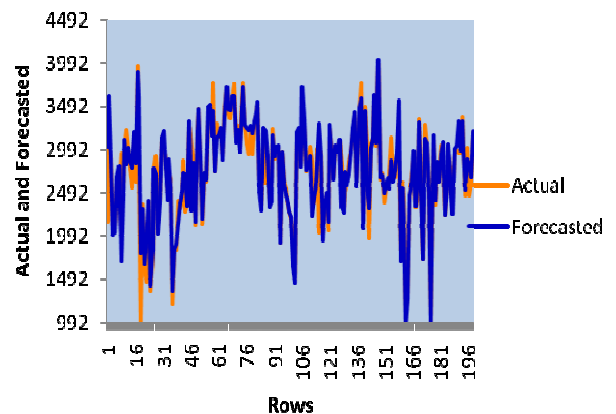


Figure 5. Predicted and actual COD (equalization) of CETP Govindpura, Bhopal vs no of samples (Model-1)

Thereafter waste water is transferred to the neutralization tank where the pH of the wastewater is maintained by suitable alkali and acid dosing whichever is required. The effluent from the equalization tank is transferred to buffer tank where it is retained for a small period of one hour. The buffer tank accepts re-circulation flow from the UASB reactor along with raw wastewater. The buffer tank is provided to trigger the acitogenesis phase in the anaerobic treatment & pre-conditioning of the effluent before entering into the UASB.

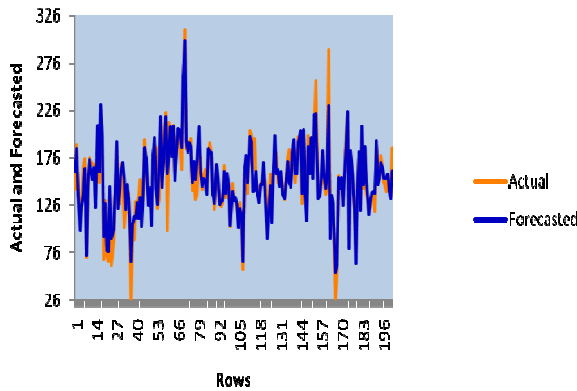


Figure 6. Predicted and actual COD(Outlet) of CETP Govindpura, Bhopal vs no. of samples (Model - 2)

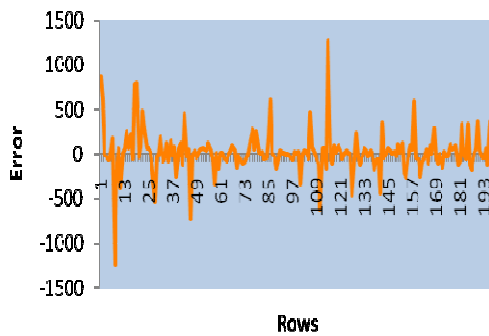


Figure 7. Deviation of error for Model-1

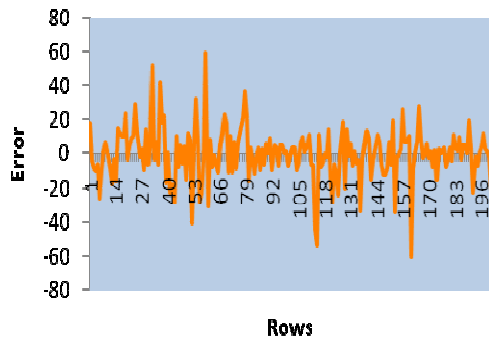


Figure 8. Deviation of error for Model - 2

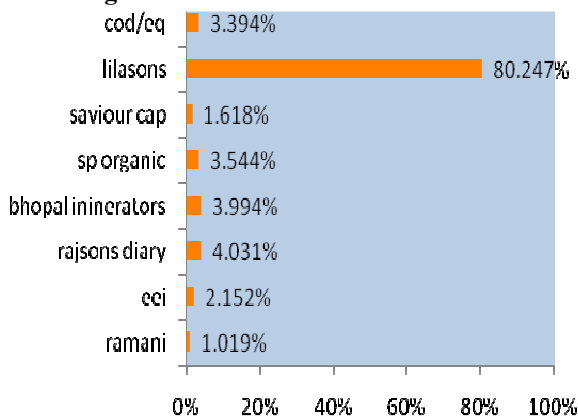


Figure 9. Input Importance for Model - 1

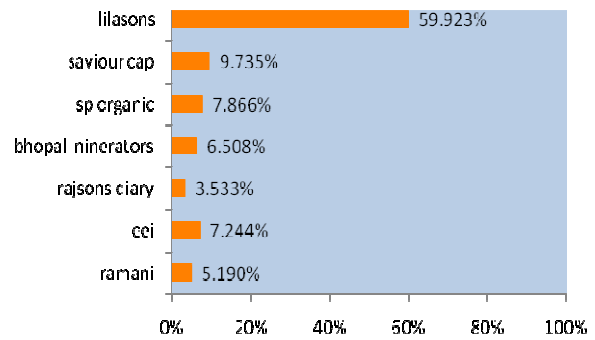


Figure 10. Input Importance for Model - 2

The effluent from buffer tank is then pumped to UASB reactor through a series of distribution pipes. This ensures a uniform flow of liquid throughout the sludge blanket making maximum use of available high bacterial population. The liquid rises to the top of UASB reactor along with biogas generated and also some sludge particles. The BOD of treated effluent is reduced by about 80%. The effluent from UASB reactor is subjected to flash aeration to increase the DO level in the effluent before discharge. (Source: data was provided by the CETP, Govindpura)

Table 1 : Reports of Model 1

	Training Set	Test set
No.of rows:	165	33
Average AE:	101.49	295.19
Average MSE:	27970.18	200268.46
Tolerance type:	Relative	Relative
Tolerance:	10%	30%
# of Good forecasts:	149 (90%)	29 (88%)
# of Bad forecasts:	16 (10%)	4 (12%)
	R Squared: 0.8131	
	Correlation: 0.9078	

Table 2 : Reports of Model 2

	Training set	Test set
No. of rows:	167	34
Average AE:	9.6730299	1
Average MSE:	197.60591	49
Tolerance type:	Relative	Relative
Tolerance:	10%	30%
# of Good forecasts:	138 (83%)	31 (91%)
# of Bad forecasts:	29 (17%)	3 (9%)
	R Squared: 0.8492	
	Correlation: 0.9216	

Data Collection and Processing

Data is collected from common effluent treatment plant Govindpura over a period of thirty-one months from 01/04/2005 - 30/11/2007. ANN input and output parameters were chosen based on the engineering judgment. The total data set consisted of COD_{Inlet} of seven industries, COD of equalization tank and outlet COD. ANN input and output variables of CETP has to be chosen based on engineering judgment on which input and output may have a significant effect in predicting effluent COD. Using Forecaster xl software proper training and testing is done and proprietary constructive algorithm is applied to the network. Two models are prepared one predicting COD at equalization tank and second one predicting COD at final outlet point (Figure 4).

RESULTS AND DISCUSSION

Results are analyzed by considering following parameters

Absolute Error

An error value indicates the "quality" of neural network training, which was calculated by subtracting the current output values with the target output values of the neural network. The smaller the network error is, the better the network had been trained.

Mean Squared Error (MSE)

This is an absolute error measure that squares the difference between values from your target column and network output to keep the positive and negative deviations from canceling each other out. To calculate the MSE the errors for each record are squared, added together and divided by the number of records. MSE gives a single number that summarizes the overall network error

R VALUE

The **R** value and **RMS** error indicate how "close" one data series is to another – in our case, the data series are the *Target* (actual) output values and the corresponding *predicted* output values generated by the model. **R** values range from -1.0 to +1.0. A larger (absolute value) **R** value indicates a higher correlation. The R values for the model on the training and test sets are close to each other, which mean the model generalizes well and is likely to make accurate predictions (8).

CONCLUSION

Present study reveals that prediction of COD using ANN proves to be better technique than

conventional mathematical modeling. Treatment of waste water by CETP consists of a sequence of complex physical, chemical and biochemical processes, and their dynamics are non-linear. Still ANN gives very satisfactory results for both the model. For Model 1, value of R is 0.90 which shows a good correlation between actual and predicted COD. Similarly for Model 2, value of R is 0.9216 shows better results. ANN learns from plant historical data so as the time passes on ANN will give more accurate results. Artificial Neural Network is the promising tool in the prediction and forecasting of water variables.

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