NEURAL NETWORKS APPROACHES FOR PREDICTING COD CONCENTRATION DURING EFFLUENT TREATMENT PROCESS

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Abstract

Present study reveals that the efficiency of an effluent treatment plant closely relates to the operation of the plant. To forecast and 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. Here, the application of Artificial Neural Network (ANN) techniques is used to predict the Chemical Oxygen Demand for effluent treatment plant. 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 forecasting 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: ANN, Prediction, COD, CETP, Neural Network.

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Introduction

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.(1) 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(2). Common effluent treatment plants are being suggested as a cost-effective option for compliance with the standards for small polluting units in industrial clusters (3).Wastewater coming from different industries has different influent characteristics.

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 (4).

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 (5). 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:

$$I_j = \Sigma W_{ji} X_i + \theta_j \qquad (1)$$

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).

$$Y_j = f(I_j) \qquad (2)$$

The output of a PE can be connected to the input of other PES which process is shown in Figure 2. 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 (6). BPN is a multi-layer, feed forward network consisting of fully connected PES, and is used in this study

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 m^3/day. The designed removal efficiency of COD and BOD was 89% and 95% respectively (7). 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 m^3/day flow was observed as against the designed flow of 900 m^3/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. 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. 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).*

Ann Model Development Process

The procedure used to develop the ANN models is outlined in following (5) Figure1.

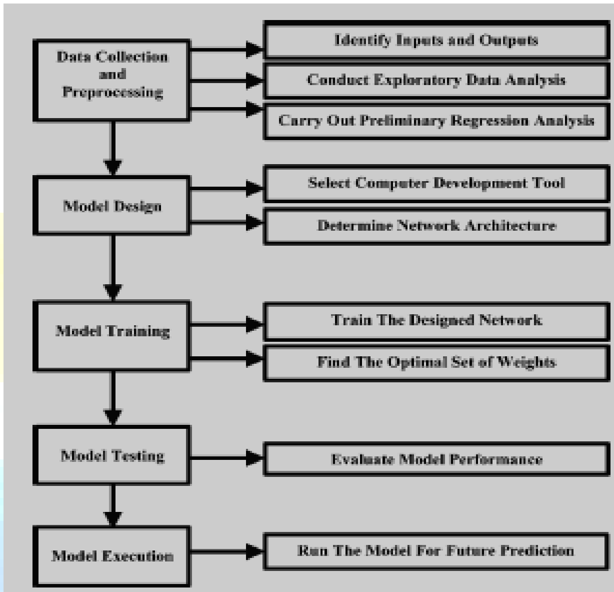

Figure 1 : Procedure used to develop the ANN models

Data Collection and Preprocessing

The raw plant data available for training and testing the ANN has been examined for completeness. The missing values have been estimated by interpolation. Outliers were removed by plotting and examining statistic. The total data set consisted of COD_{Inlet} of six industries, COD_{Outlet} of six industries, COD of equalization tank and outlet COD. The 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. The objective is to achieve the best effluent forecasting with minimum number of inputs. With an increasing number of input variables, the complexity of the model increases and it takes longer to train and estimate effluent, and it may also introduce unwanted noise. Data is collected from common effluent treatment plant Govindpura over a period of 31 months from 1/04/2005- 30/11/2007. The total data set consisted of COD_{Inlet} of seven industries, COD of equalization tank and outlet COD of seven industries.

Model Design

For model development, we used neural ware predict software. In this study, a 3 layer feed forward back propagation. ANN applying normal cumulative delta (NCD) supervised learning rule and hyperbolic tangent (TanH) activation/ transfer function has been used, because of their demonstrated capability in water quality prediction ability.

MODEL Training and Testing

The purpose of the training is to capture the relationship between historical data of model inputs and corresponding outputs. The back propagation is commenced by presenting the training data to the network at the input layer. The input signal flows through the network, producing an output signal, which is a function of the values of the connection weights, the transfer function and the network geometry. The learning process enables the network to find a set of weights that will produce the best possible input/output mapping. The output signal produced is then compared with the desired output signal with the aid of an error (mean squared error) function,

$$E(t) = \frac{1}{2}\sum (d_j(t) - y_j(t))^2$$

where *E(t)* is the global error function at discrete time *t* ; $y_j(t)$ is the predicted network output at discrete time, *t* and $d_j(t)$ is the desired network output at discrete time t. Initially, weights are assigned small, arbitrary values. As learning progresses, the weights are updated or adjusted systematically using 'normal cumulative delta learning rule' in an attempt to reduce the error function. In this study, training has been stopped when there is no further improvement (reduction in root mean square error (RMSE)) in the forecasts obtained using an independent test data set (8).

This value, which is the model predicted value, is compared to the correct value for the given patterns and the connection weights are modified to decrease the sum of squared error according to back propagation learning algorithm The most widely used performance measures for ANN models are root mean square error (RMSE) and average absolute error (AAE) between the actual and predicted values. (8)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(t_i - o_i)^2}{n}}; \qquad AAE = \frac{1}{n}\sum_{i=1}^{n}|t_i - o_i|$$

where $\mathbf{t}_i$ is the target (actual) value; $\mathbf{o}_i$ is the predicted value and n is the number of records.

MODEL EXECUTION

Once the training and testing completed, we can run the model and can obtain the predicted values.

RESULTS AND DISCUSSION

The R (correlation) value, AE (absolute error) and MSE (mean square 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. Results are analyzed by considering following reports in Table 1 and Table 2. Graphical representation for model 1 (Figure 2) and model 2 (Figure 4) also shows a good correlation between actual and predicted values. Also Figure 3 and Figure 5 show the deviation of errors, the errors are within the range that proves that prediction is good.

Table 1 Report of Model - 1

	Training Set	Test Set
No. of rows:	165.00	33.00
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
		R value, Correlation: 0.9078

Table 2 Report of Model - 2

	Training Set	Test Set
No. of rows:	167.00	34.00
Average AE:	9.67	16.22

Average MSE:	197.60	414.38
Tolerance type:	Relative	Relative
Tolerance:	10%	30%
# of Good forecasts:	138 (83%)	31 (91%)
# of Bad forecasts:	29 (17%)	3 (9%)
		R Squared: 0.8131
		Correlation: 0.9078

CONCLUSIONS

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 0.9078 which shows a good correlation between actual COD_{eq} and predicted COD_{eq}..Similarly for Model-2 value of R is 0.9216 shows better results. Accuracy is 90% and 80% for training and testing data set respectively for model1, similarly accuracy is 83% and 91% for training and testing data set for Model-2. 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

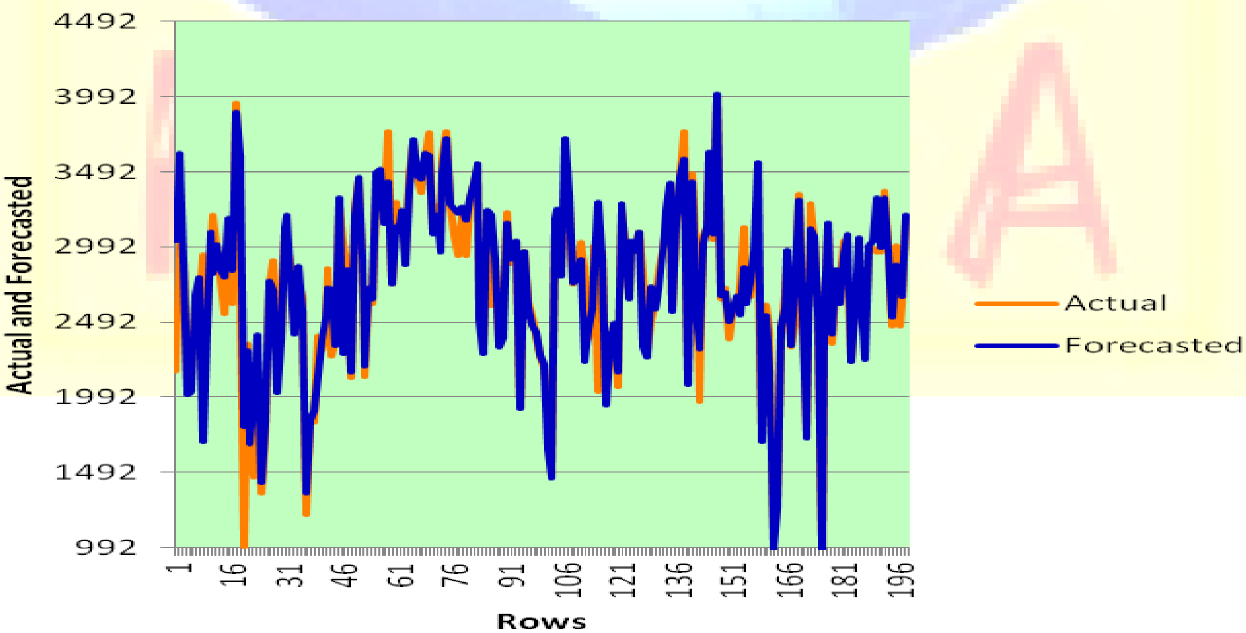

Figure 2: Predicted and actual COD (equalization) of CETP Govindpura,Bhopal vs no of samples (Model1)

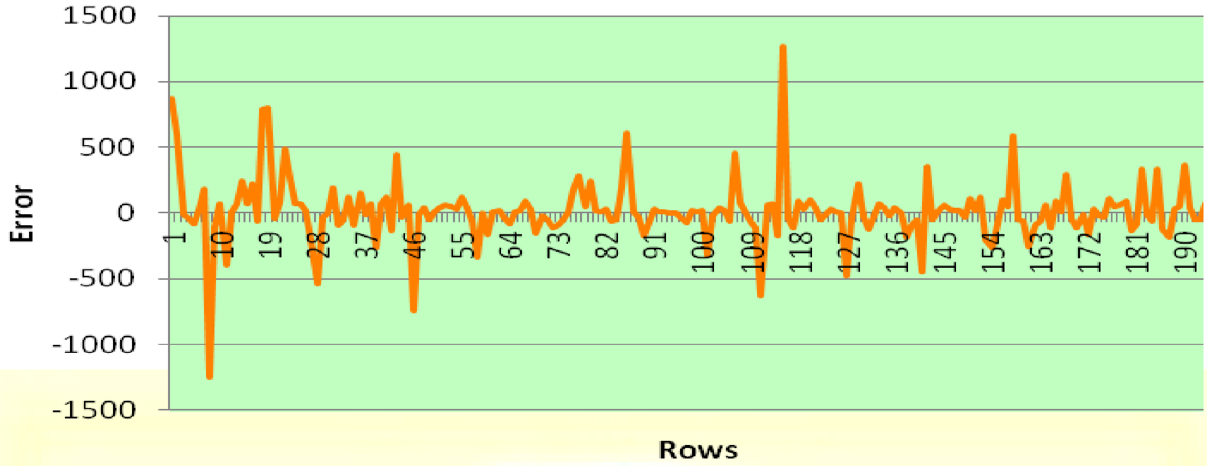

Figure 3 Deviation of error for Model-1

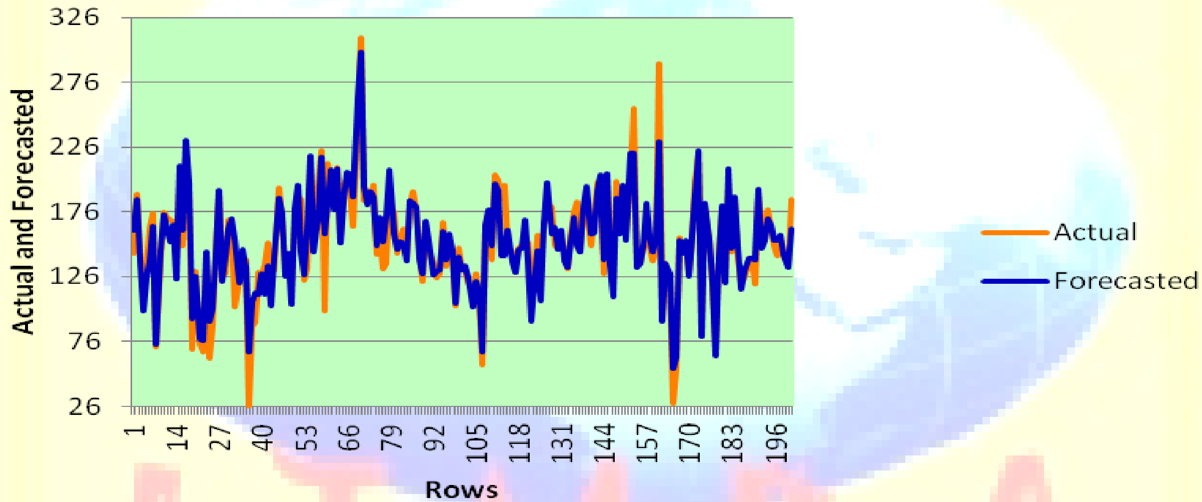

Figure 4 Predicted and actual COD (Outlet) of CETP Govindpura, Bhopal vs no. of samples (Model-2)

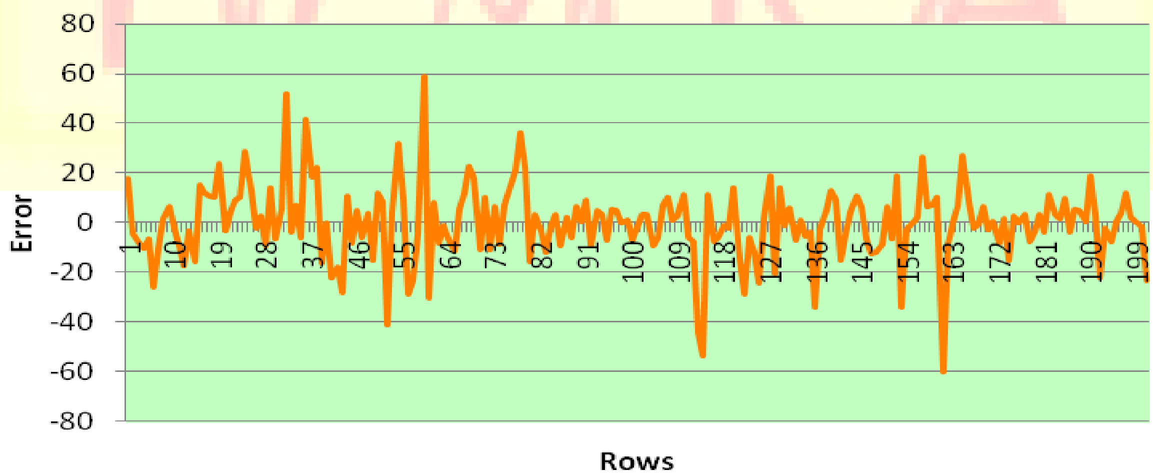

Figure 5 Deviation of error for Model-2

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