VOL. 6, NO. 1, JANUARY 2011 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

PERFORMANCE FORECASTING OF COMMON EFFLUENT TREATMENT PLANT PARAMETERS BY ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Use of Artificial Neural Network (ANN) models is progressively increasingly to predict waste water treatment plant variables. This forecasting helps the operators to take corrective action and manage the process accordingly as per the norms. It is a proved useful device to surmount a few of the limitations of usual mathematical models for wastewater treatment plants for the reason that of their complex mechanisms, changing aspects-dynamics and inconsistency. This analysis considers the relevance of ANN techniques to predict influent and effluent biochemical oxygen demand (BOD) for effluent treatment process. Here, a three-layered feed forward ANN, using a back propagation learning algorithm, has been applied for predicting effluent BOD. After collecting historical plant data of BOD from common effluent treatment plant at Govindpura, Bhopal, India. Efficiency of plant for removal of BOD is found to be around 80% (3 years data was collected from the influent and effluent streams of the station). Two ANN-based models for prediction of BOD concentrations at influent and effluent points were formed. The suitable architecture of the neural network models was ascertained after several steps of training and testing of the models. The ANN based models were established to offer an efficient and a robust tool in prediction and modeling.

Keywords: model, effluent treatment plant, performance, artificial neural network, biochemical oxygen demand (BOD) forecasting.

INTRODUCTION

Water is the basic need of all life, human, well-being and also for economic development. Because of increasing industrialization, urbanization and other anthropogenic activities, and the water quality is getting degraded day by day. This hazardous wastewater can't be discharged directly on the ground or in the water bodies. It requires necessary treatment before discharging. It is difficult for each industrial unit to provide and operate individual wastewater treatment plant because of the scale of operations or lack of space or technical manpower. However, the quantum of pollutants emitted by small scale industries may be more than an equivalent large-scale industry. 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. 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 [1]. Wastewater treatment processes, consisting of a sequence of complex physical, chemical and biochemical processes, and their dynamics are non- linear and usually time –varying [2]. Effective control of dynamic behavior of unit process depends on three factors [2].

a) Ability to relate causes (input and controls) to effects (output response).
b) The capacity to act by manipulating the control inputs to correct undesirable effects or to bring more desirable effects.
c) The ability to observe the state of process and its response to various perturbations [2].

With these objectives there has been a shift of focus from plant design and plant operation to mathematical models. Modeling of common effluent treatment plant (CETP) is important for predicting plant performance and operation. In addition some important process variables cannot be measured on-line, e.g. BOD5 requires 5-days incubation, and this makes it difficult to find and solve the problematic situation in time. Therefore, modeling a CETP is a difficult task and most of the available models are just approximate ones based on, probably severe, assumptions. These features make it difficult to achieve optimum performance of the CETP using conventional modeling techniques. Thus, in turns, necessitates development of more advanced modeling techniques to predict the behavior of CETP [3].

Thus neural networks have been found promising technique in forecasting historical data. ANN model can predict concentration of effluent parameter. It inspired by the structure and operation of the brain and central nervous system.

The goal of ANN is to map a set of input patterns onto a corresponding set of output patterns by first learning from a series of past examples defining sets of input and output for the given system. The network then applies what it has learned, to a new input pattern to predict the appropriate output. They require minimal specific knowledge of the intrinsic processes of the system under study [2].

The ANN modeling approach does not require a description of how the processes occur in either the micro or macro environments and requires only the knowledge of important factors that govern the process. They can handle incomplete data, generalize and provide a certain

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degree of fault tolerance. Specifically, ANN can solve problems involving complex non-linear mapping or relationships, which do not lend themselves to conventional algorithmic solution [4].

In this work, two artificial neural-networks (ANN) models were developing for the prediction of BOD, i.e., BOD at inlet and BOD at outlet. The models were applied to the influent and final effluent streams of common effluent treatment plant in the Bhopal (M.P.) India at Govindpura industrial area. Using the results of this modeling process, the plant operator will be able to have an assessment of the expected characteristics of plant influent and effluent streams, and thus proper action can be taken.

MATERIALS AND METHODS

CETP Govindpura (Bhopal)

The industries in Govindpura, Bhopal established an agency known as Govindpura Audhyogik Kshetra Pradushan Nivaran Pvt. Ltd. (GAKPNPL), which has installed a Common Effluent Treatment Plant (CETP) for treating combined industrial wastewater from Govindpura Industrial Area. Only seven units were contributing the effluent to CETP. Designed capacity of CETP was 900 m^3/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 (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. M/s. Lila Sons Breweries contributed 99% of effluent and only small quantity was contributed by M/s. EEI Capsules and M/s. Bhopal Incinerator Ltd.

It was observed that the COD and BOD removal efficiency of UASB was 85.8% and 92.5%, which was later nullified by the ill-maintained aeration tank with no post settling arrangement. The pH values varied from 6.94 to 7.82 [5].

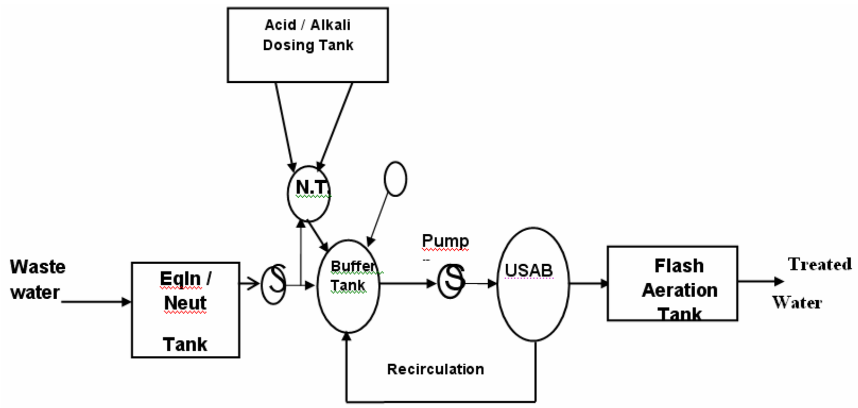

Figure - 1. Flow diagram of common Effluent Treatment Plant, industrial area, Govindpura, Bhopal, MP

ANN model development

The procedure used to develop the ANN models is outlined in Figure-2 [6].

Data collection and pre-processing

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 BOD_{Inlet} of six industries, BOD of equalization tank and outlet BOD 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 BOD. 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.

Model design

For model development we use neural ware predict software. In this case study, 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 [4].

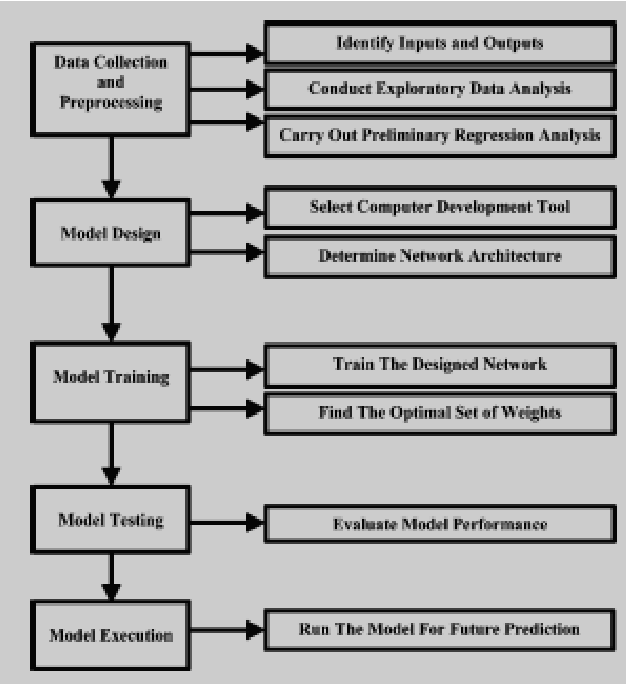

Figure-2. Steps of the model development process.

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

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. The amount by which each connection weight is adjusted depends on the learning rate, the momentum value, the epoch size, the derivative of the transfer function and the node output. In this study, training has been stopped when there is no further improvement (reduction in RMSE) in the forecasts obtained using an independent test data set [4].

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 [4].

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

Where t_i is the target (actual) value; 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.

Data collection

Data is collected from common effluent treatment plant Govindpura over a period of 31 months from 1/04/2005 to 30/11/2007. Total 224 data is selected and from this 156 are used for training and 68 for testing. ANN input and output parameters (Table-1) were chosen based on the engineering judgment.

Table-1.

Variable	Input (I) or output (0)	Symbol
BOD of Leelason braveries industry	I	L
BOD of Ramani ice	I	R
BOD of E.E.I cap	I	E
BOD of Bhopal incinerators	I	B
BOD of Raj sons dairy	I	Rs
BOD of SP organics	I	SP
BOD of equalization tank	O	Eq
BOD of outlet point	O	O

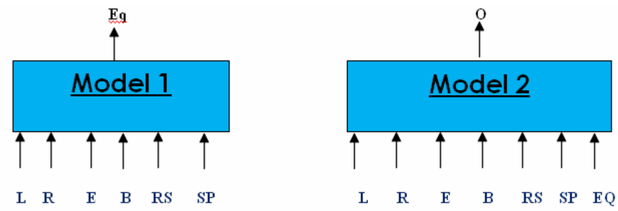

Figure-3. Schematic ANN models for CETP Bhopal.

RESULTS AND DISCUSSIONS

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 means the model generalizes well and is likely to make accurate predictions [7].

ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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Accuracy (%) - The percentage of predicted outputs falls within the user-specified tolerance band of the corresponding target values.

Confidence Interval (%) - Establishes with a specified degree of confidence the range (Target Value ± confidence interval) in which the corresponding predicted output occurs [7].

Model analysis

156 data are used for training and 68 for testing out of total data 224. Results obtained from Neural Ware predict software is as under:

Model-1

B.O.D/eq	R	RMS	Accuracy (20%)	Conf. interval (95%)	Records
All	0.906378	139.2867	0.902143	272.5291	224
Train	0.924761	126.457	0.900769	248.1364	156
Test	0.870159	164.9921	0.905294	327.7384	68

Model-2

B.O.D/outlet	R	RMS	Accuracy (20%)	Conf. interval (95%)	Records
All	0.732543	7.310813	0.883929	14.30438	224
Train	0.781309	6.839836	0.910256	13.42126	156
Test	0.645239	8.290804	0.823529	16.46875	68

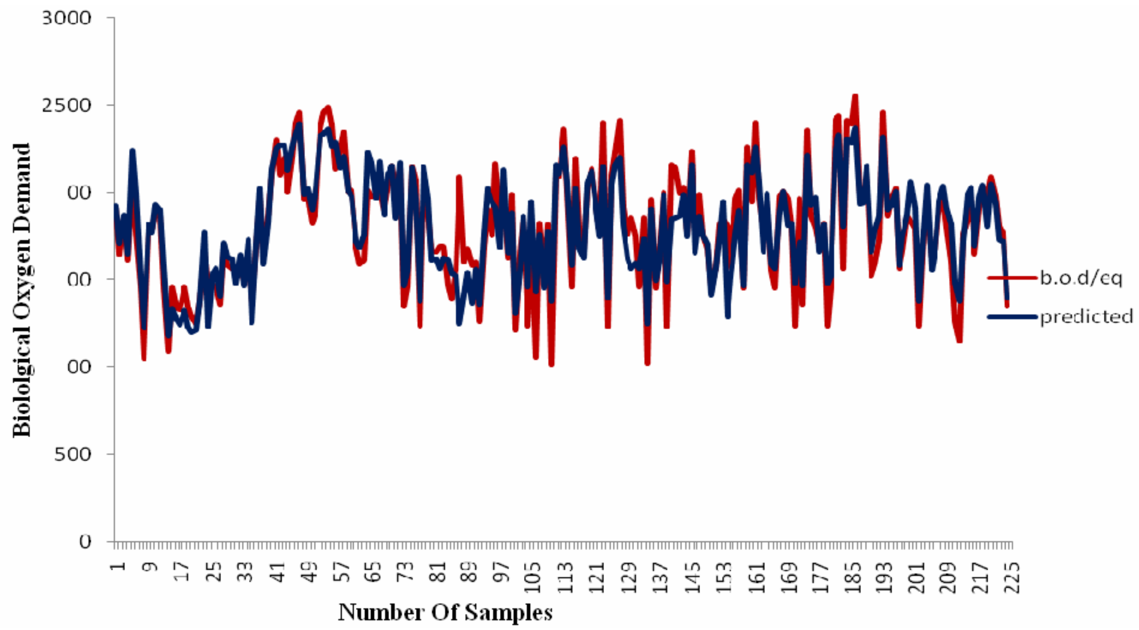

Figure-4. Predicted and actual BOD (equalisation) of CETP Govind pura, Bhopal vs No. of samples.

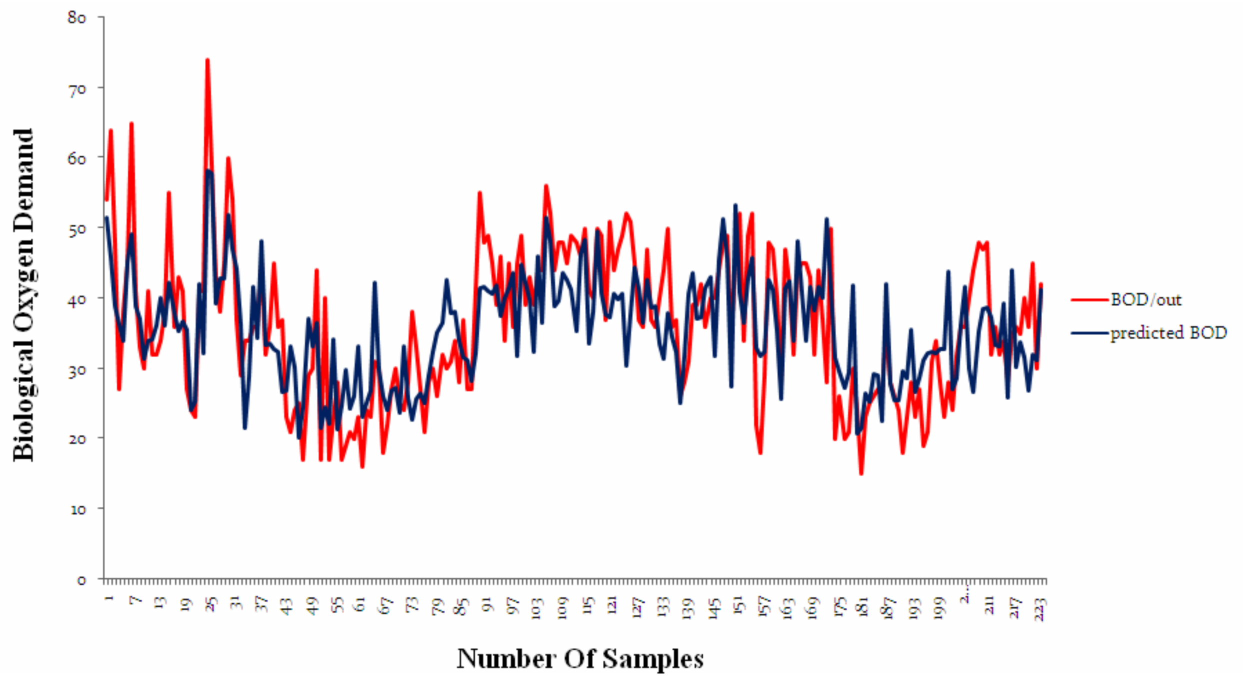

Figure-5. Predicted and actual BOD (outlet point) of CETP Govindpura, Bhopal vs No. of samples.

CONCLUSIONS

Artificial Neural Network is the promising tool in the prediction and forecasting of water variables. Present study reveals that prediction of BOD 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 BOD_{eq} and predicted $BOD_{eq.}$ Similarly for model-2 value of R is 0.73 and RMS is 7.31 shows better results. Accuracy is 90% for model1 and 88% for model-2. ANN learns from plant historical data so as the time passes on ANN will give more accurate results.

ACKNOWLEDGEMENTS

The authors gratefully appreciate the assistance of all technologists in the Civil Engineering Department, Environmental Lab., MANIT, Bhopal and Govindpura Audhyogik Kshetra Pradushan Nivarana Ltd., Bhopal, India.

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