Prediction of Sewage Treatment Plant Performance in Lucknow City by Using Artificial Neural Networks

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***Abstract* - To predict the performance of a sewage treatment plant (STP), Artificial neural networks (ANN) models were developed based on past information. The data used in this work were obtained from a Bharwara 345 MLD Gomti nagar sewage Treatment Plant Lucknow, with an average flow rate of 345 million lit/day. Daily records of biochemical oxygen demand (BOD) concentrations through various stages of the treatment process over 4 months were obtained from the plant laboratory. Exploratory data analysis was used to detect relationships in the data and evaluate data dependence. ANN-based models for prediction of BOD concentrations in plant effluent are presented. The appropriate architecture of the neural network models was determined through several steps of training and testing of the models. The ANN-based models were found to provide an efficient and a robust tool in predicting WWTP performance.**

***Index Terms* - Neural networks; Wastewater treatment; Model studies; Prediction; Optimization; Biochemical oxygen demand;**

1.INTRODUCTION

The efficient operation and management of sewage treatment plants (STPs) is receiving increasing attention due to growing concerns about environmental issues. The improper operation of STP can lead to serious environmental and social problems, as its contamination of the host body can cause or spread various diseases to humans. Such stories have been well-read in LUCKNOW, a city that has seen an increase in interest in environmental issues. Better STP control can be achieved by building a robust statistical tool for predicting crop performance based on past observations of certain key parameters. However, modeling STP is a difficult task due to the complexity of treatment procedures. The complex physical, biological, and chemical processes involved in the wastewater treatment process reflect non-linear behavior that is difficult to define by the corresponding mathematical models. This paper presents predictive models based on the concept of artificial neural networks (ANNs) (or simply neural networks), the widely used application of artificial intelligence that has shown promise in a variety of applications in engineering, pattern recognition, and financial market analysis. ANN-based varieties are used at the Barwara 345 MLD Sewage Treatment Plant in Lucknow. Improved models are shown to consistently perform in the face of various accuracy and size of input data. Using these models, plant operators will be able to test the expected liquidity of the plant, given the quality of waste disposal in incinerators.

2.SITE ANALYSIS

The focus of this study is the Bharwara 345 MLD Gomti nagar Wastewater Treatment Plant in Lucknow. The latitude and longitude of the plant extend to 26.85°N and 80.92°E, including the location of the UASB Bharwara Gomti Nagar wastewater treatment plant in Lucknow. The factory receives wastewater from the entire Trans Gomti side, including the Gomti Nagar, Indira Nagar, and Sitapur highway areas that carry wastewater, which are approved for the second phase of the Gomti Action Plan. The plant's capacity is 345 MLD. The total length of the trunk sewer line and the sewer branch is approximately 860 kilometers. The entire sewer pipeline network in Lucknow includes 26 main drainage pipes. Before the appearance of these STPs, these drainpipes were used to discharge raw sewage directly into Gomti. Of these 26 drainage ditches, it has been proposed that 22 lead to Bharwara STP.

3.REVIEW OF LITERATURE

An extensive literature review was carried out by referring standard journals, reference books and conference proceedings. The major work carried out by different researchers can summarized as follows:

Jin wang et al (2020)1 studied the Dynamic modeling of the biomass gasification process in a fixed bed reactor by using artificial neural network (ANN). For dynamic modeling, ANN model was used and the predicted results showed that the decreases in the data recording frequency, increases the prediction error. By expanding the training dataset, reduce discrepancies between predicted and measured results.

Fatih Tufaner et al (2020)2 studied the prediction of biogas production rate from anaerobic hybrid reactor by ANN and nonlinear regressions models. Both model are trained and tested for the future prediction. The results showed that the proposed ANNs and nonlinear regression models performed well in predicting the biogas production rate.

Tanja beltramo et al (2019)3 studied the Prediction of the biogas production using GA and ACO input features selection method for ANN model. The results showed that they identified significant process variables, reduced the model and improved the prediction capacity of ANN models.

Philip Antwi et al (2016)4 studied the estimation of biogas and methane yields in an UASB treating potato starch processing wastewater with backpropagation artificial neural network. in the study for estimate the biogas and methane yield in UASB, three-layer feedforward backpropagation ANN and multipal nonlinear regression MnLR models were developed. Compare with the BP-ANN model and MnLR model demonstrated significant performance, suggesting possible control of the anaerobic digestion process with the BP-ANN model.

Kaan Yetilmezsoy et al (2013)5 studied to development of ANN based model to predict biogas and methane productions in anaerobic treatment of molasses wastewater. In this study two three-layer ANN models were developed and eight process related variables such as operating temperature, OLR, influent and effluent pH, influent and effluent alkalinity, effluent COD and VFA concentrations were selected. The result show that the proposed ANN based model produced smaller deviations and exhibited superior predictive accuracy for the forecasts of biogas and methane production rates.

Ezzat A. Hassanienc et al (2003)6 studied the prediction of wastewater treatment plant performance using artificial neural networks. In this studied ANN model used to predict the performance of WWTP in Greater Cairo district, Egypt based on past information. 10-month daily records of suspended solids (SS) and biochemical oxygen demand (BOD) concentration are obtain from the laboratory of the plant. To evaluate data dependence and detect the data relationships, exploratory data analysis was used. For prediction of SS and BOD concentration in plant effluent, two ANN-based models are used. Through several steps of training and testing of the model, the architecture of the neural network models was determines. The ANN models were found to provide a robust tool for prediction of WWTPs performance.

Moreno-Alfonso et al (2001)7 proposed an intelligent wastewater treatment concept, aided by two sets of neural networks, with the aim of controlling the plant in terms of previously selected parameters. The first neural network is used for regular control of the plant. The other neural network is termed instinctive and is dedicated to the monitoring of the critical parameters. Its output determines whether a drastic decision, like stopping the process, is warranted. They contend that such a two- network system will prove useful in the management of WWTPs

4. BASICS OF ANNS

ANNs are mathematical modeling tools especially useful in the field of forecasting and forecasting in complex situations. Historically, it was intended to mimic, to simplify, the functioning of the human mind. ANN does this by utilizing a large number of highly interconnected objects (neurons), which work together to solve specific problems, such as guessing and recognizing patterns. Each neuron is connected to its neighbors by different chemicals or metals, representing the result of the interaction of different neurons binding to other neurons. There are many types of ANNs. One of the most common types of neural networks is the main feed, where the data is transmitted only when it goes forward. This is the type used in this activity. A basic neuron structure, which has summation type of aggregation and tan sigmoidal activation function, is depicted in Figure 1. Input a1, a2 ...an and a constant input 1 are responsible for the output z. Weights w1, w2 ...wn and bias b that represent the synaptic strengths as in biological neurons are assigned to inputs a1, a2 … an and 1, respectively. Thus, net input z for activation function is evaluated by the equation (1) below:

$$z = b + \sum_{i=1}^{n} w_i a_i \quad (1)$$

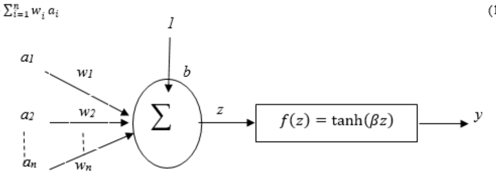

Figure 1: Conventional Model of Neuron with Summation Type of Aggregation

$$z = \mathbf{W}\mathbf{A}^T \quad (2)$$

Where: $\mathbf{W} = [w_0\ w_1\ w_2\ \ldots.w_n]$, $\mathbf{A} = [a_0\ a_1\ a_2\ \ldots\ a_n]$

In this study, the tan-sigmoid activation function, $f_h(x) = 1/(1 + e^{-x})$, is used for the input and hidden layers, and the linear activation function, $f_o(x) = x$, is used as the output activation function.

The activation function is a mathematical "gate" in between the input feeding the current neuron and its output going to the next layer. They basically decide whether the neuron should be activated or not. Neural networks use non linear activation function, which can help the network, learn complex data, compute and learn almost any function representing a question, and provide accurate predictions. Depending on the sum of the inputs to a neuron, an activation function determines magnitude of the neuron output. The most appropriate activation function is, chosen based on the application's requirements. The ability to introduce non-linearity to a neural network is the most important aspect of an activation function. It performs this action by using a log sigmoid or a tan sigmoid function.

Network training is a process by which the connection weights and biases of the ANN are adapted through a continuous process of simulation by the environment in which the network is embedded. The primary goal of training is to minimize an error function by searching for a set of connection strengths and biases that causes the ANN to produce outputs that are equal or close to targets. In other words, training aims at estimating the parameters by minimizing an error function, such as the mean square error (MSE) of the output values expressed as:

$$MSE=\sum_{t=1}^{N}(Yt-Rt)^2/N$$

Where N is the number of data points, Yt is the network predicted value at t^{th} data, Rt is the experimental value at the t^{th} data. The minimization procedure relies on a numerical optimization of a non-linear objective function. A number of optimization routines can be used. In practice, the Levenberg–Marquardt routine often finds better optima for a variety of problems than do the other optimization methods.

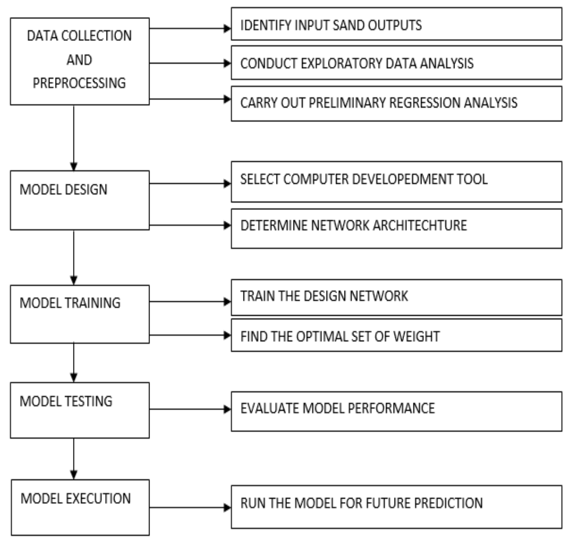

Fig:2 Steps of the model development process.

The structure of a neural network consists of a description of the number of network layers, the number of neurons in each layer, the activation function of each layer, and how the layers interact. The reading rate parameter can also play an important role in network integration, depending on the network setting and structure. The level of learning is used to increase the chances of avoiding the training process in being held in local minority instead of international minimum. Network design and learning level are determined by this task using trial and error method, as described in the following discussion.

Model development- Many steps are performed during the model development process. This is systematically illustrated in figs: 2. The ANN model shares many symbols and steps associated with other non-ANN models.

Data Collection and Preliminary Analysis - The main purpose of data collection is to determine the appropriate locations for the data needed to perform modeling tasks. Although certain parameters may affect plant performance (e.g. pH, temperature, chemical doses), the only data reported by plant suppliers were BOD and SS. Therefore, this function depends only on these two parameters. Apart from minimizing the problem, these two frameworks are considered to be good indicators of plant performance as reported in the literature.

Model construction and network training - The construction model, training method, and training levels are determined using trial and error method. To achieve optimal network performance, multiple tests are performed in each group to reach the appropriate level of learning, the number of hidden layers and the number of neurons in each hidden layer found. Appropriate structures are the ones that produce the least number of errors in both training and testing data. For this task, a supervised training is selected, an algorithm that takes place back-to-back. The back distribution algorithm reduces the MSE between the visual and output predicted in the output layer, by two phases. In the advanced phase, external input signal signals in the input neurons are distributed forward to calculate the output information signal in the outgoing neuron. In the posterior phase, the reinforcement of the connecting threshold is performed on the basis of the variability of the information signals predicted and seen in the outgoing neuron. The performance of each network model was assessed by inserting a square root error (RMSE) and MSE in each test performed in search of the appropriate configuration and in all networks. The structure that led to minor errors is the one selected.

Model test- The actual BOD values in the test data sets are compared with the predicted values for neural network models, to evaluate the performance of the models. Show this BOD output comparison. Visual analysis shows that ANN models have led to positive BOD gains.

Feed forward-back propagation neural networks have been employed for the purpose of determining the effluent BOD of UASB reactor, primarily due to the availability of adequate data relevant to the training. The influent PH, influent temperature, influent BOD and COD, effluent volatile fatty acids, influent alkalinity were given as inputs to the neural network. The output of the neural network is the biochemical oxygen demand (BOD) of UASB reactor effluent. At first, a few neural networks with varying configuration of hidden layers and neurons per hidden layer were considered that performed reasonably well. The best 5 networks of them are listed along with their respective error performances for comparison purpose. The performance of each of the trained networks is assessed based on their regression characteristic and accuracy during the testing process. The performance is presented in tabulation forms for the calculated comparing outputs with target values using the calculation of percentage error.

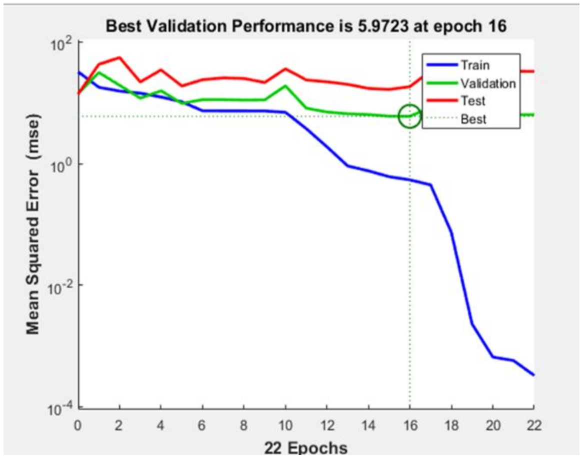

Fig: 3 MSE for network 1 (6-20-10-2-1)

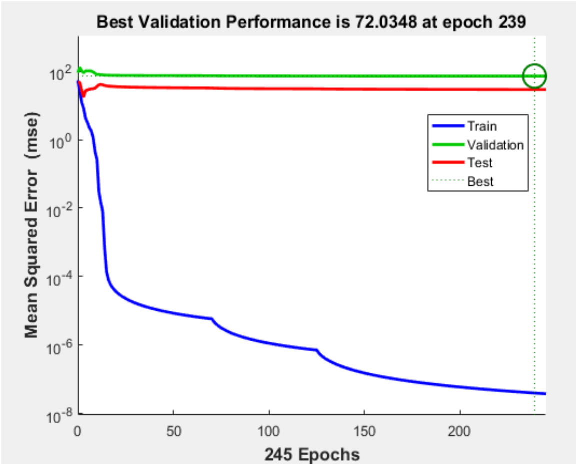

Fig: 4 MSE for network 2 (6-20-11-1)

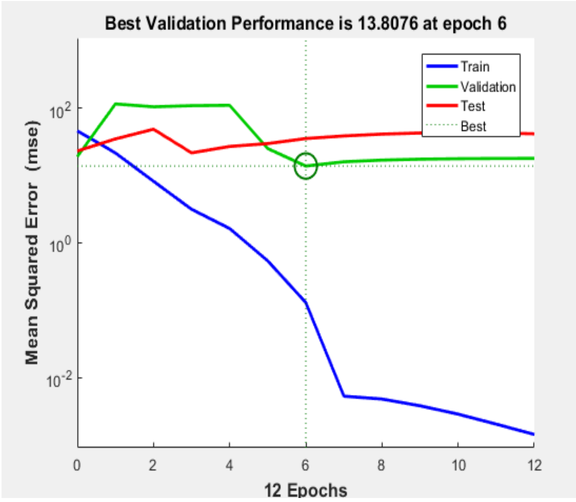

Fig 5 MSE of network 3 (6-20-1)

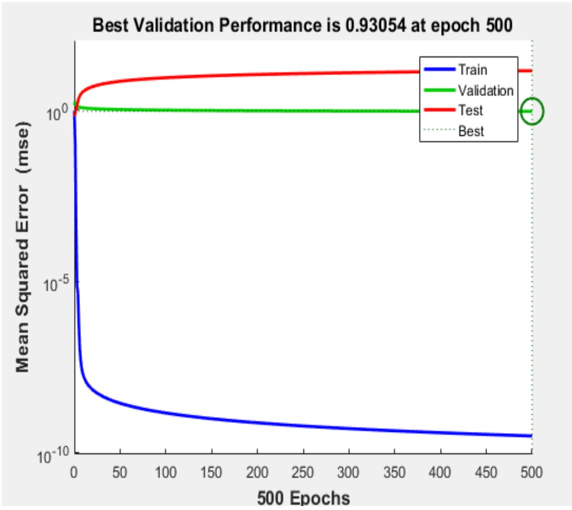

Fig: 6 MSE for network 4(6-21-10-1)

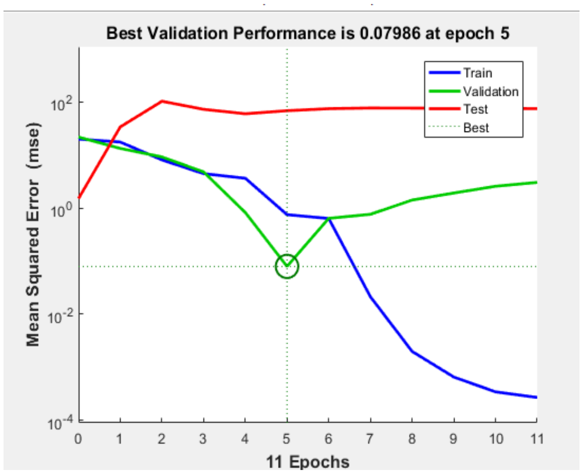

Fig: 7 MSE for network 5 (6-20-7-1)

S.no.	NETWORK	MSE	RMSE
1	Network 1	0.014120	0.11883
2	Network 2	0.004771	0.069075
3	Network 3	0.004714	0.068663
4	Network 4	0.005607	0.074883
5	Network 5	0.006693	0.081812

Table: The value of RMSE, MSE for all networks

The best network configuration for effluent BOD is network 3 (6-20-1), based on RMSE, MSE and accuracy of predicted output.

Summary and conclusions- In this paper, five models based on ANNs were developed to predict the effluent concentrations of BOD for UASB reactor at Bharwara 345 sewage treatment plant. The developed models were trained and tested on weekly sets of BOD measurement over a period of 4 months. The best network configuration for effluent BOD is network 3 (6-20-1), based on RMSE, MSE and accuracy of predicted output. The neural network models provided good estimates for the BOD data sets, which cover a range of data for training and testing purposes. The ANN models provided a robust tool for prediction in that the prediction error varied slightly, and smoothly, over the range of data sizes used in training and testing. The limitation in data, however, should be highlighted. If more data were collected, if the data were less noisy, and if additional parameters were measured (e.g. pH, temperature, etc.), this would have resulted in an improved predictive capability of the network. Nevertheless, the ANN is a tool that is worth consideration in the prediction of WWTPs.

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