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Optimization of Anaerobic Treatment of Petroleum Refinery Wastewater Using Artificial Neural Networks

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Abstract: Treatment of petroleum refinery wastewater using anaerobic treatment has many advantages over other biological method particularly when used to treat complex wastewater. In this study, accumulated data of Up-flow Anaerobic Sludge Blanket (UASB) reactor treating petroleum refinery wastewater under six different volumetric organic loads (0.58, 1.21, 0.89, 2.34, 1.47 and 4.14 kg COD/m^3·d, respectively) were used for developing mathematical model that could simulate the process pattern. The data consist of 160 entries and were gathered over approximately 180 days from two UASB reactors that were continuously operating in parallel. Artificial neural network software was used to model the reactor behavior during different loads applied. Two transfer functions were compared and different number of neurons was tested to find the optimum model that predicts the reactor pattern. The tangent sigmoid transfer function (tansig) at hidden layer and a linear transfer function (purelin) at output layer with 12 neurons were selected as the optimum best model.

Keywords: Anaerobic digestion, artificial neural networks, chemical oxygen demand, petroleum refinery wastewater, UASB

INTRODUCTION

Petroleum refinery wastewater is hazardous to the environment as there are several organic and inorganic pollutants found in petroleum refinery wastewater of environmental concern including ammonia, oil, phenol, sulphur based contaminants and heavy metals (Vohra *et al*., 2006). One of the most important monitoring parameters for wastewater treatment plant is Chemical Oxygen Demand (COD) as it required relatively shorter time (Khan *et al*., 2006).

Anaerobic treatment of high-strength petroleum refinery wastewaters (generally>1000 mg COD/L) (Behling *et al*., 1997) has been shown to provide a very cost-effective alternative to aerobic processes with savings in energy, nutrient addition and reactor volume. Petroleum refinery wastewater is degraded under anaerobic conditions and many toxic and recalcitrant organic compounds that found in petroleum wastewater are serving as a growth substrate (Metcalf and Eddy, 2003). The Up flow Anaerobic Sludge Blanket (UASB) reactor is one of the most notable developments in anaerobic treatment process technology that commonly used for treating a wide range of industrial wastewater. UASB is a high rate system that can retain biomass with high treatment capacity and low site area requirement in addition to other advantages (Zinatizadeh *et al*., 2007).

The use of software to simulate existing historical experimental data and predict unknown data based on a model representing the process, help to minimize efforts and creates more data which doesn't exist. The modeling and simulation of processes have been developed using ever more complex deterministic models, due to the recent evolution of personal computer (Gontarski *et al*., 2000).

Neural Networks (NN) or widely known as Artificial Neural Networks (ANN) is a mathematical modeling tool used to simulate complex relationships following a simplified level of the activity of the human brain through a large number of highly interconnected processing elements (neurons); and have been used in application of artificial intelligence that has shown quite a promise in engineering, pattern recognition and analysis (Hamed *et al*., 2004). Anaerobic digestion is a non-linear process which requires a non-linear control strategy; whereby artificial neural networks is the choice when a large amount of anaerobic digestion data are available but no reliable model and little knowledge of how the process works (Ward *et al*., 2008).

ANN has being used to model existing data and simulate for predicted behavior in many wastewater treatment processes to ease the operation activities. Artificial neural networks are claimed to have a distinctive advantage over some other nonlinear estimation methods used for bio-processes as they do

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not require any prior knowledge about the structure of the relationships that exist between important controlling variables (Holubar *et al*., 2002).

ANN has being used to simulate full working wastewater treatment plant using a model that was developed using laboratory data for ten months. Modeling of this wastewater treatment process used a configuration with tan sigmoid activation function for the input and hidden layers, while the linear activation function was used as the output activation function, resulted in R^2 values ranged from 0.63 to 0.81 for Biochemical Oxygen Demand (BOD) and from 0.45 to 0.65 for Suspended Solids (SS) (Hamed *et al*., 2004). Using the same mentioned configuration, Chemical Oxygen Demand (COD) removal was modeled using ANN in a wastewater treatment process for the prediction and simulation of degradation. The configuration of the back propagation neural network with 14 neurons and Levenberg-Marquardt back propagation training algorithm (TRAINLM) predicted the actual experimental results with correlation coefficient (R^2) of 0.997 and MSE of 0.000376 (Elmolla *et al*., 2010).

Anaerobic biological treatment of wastewater was modeled based on integrated fuzzy systems and neural networks for the simulation and control of complex anaerobic treatment systems (anaerobic fluidized bed reactor and up-flow anaerobic sludge blanket) (Tay and Zhang, 1998).

Several Feed-Forward Back Propagation neural networks (FFBP) were trained in order to model and subsequently control, methane production in four anaerobic continuous stirred tank reactors. The model was able to predict gas production and avoid shock loadings (Holubar *et al*., 2002).

Utilizing a neural network simulation, anaerobic wastewater treatment process has been modeled to define the potentially damaging events that occur during disturbances to an anaerobic digestion. The neural network was capable of rapid recognition of disturbances that in the form of an increase in influent COD concentration and by utilizing data from an on-line bicarbonate alkalinity sensor (Wilcox *et al*., 1995).

A high strength wastewater (7300 mg COD/L) batch from a local petroleum refinery was treated in UASB as part of a train of biological reactor; the COD removal was found to be 80% (Gasim *et al*., 2012a). Two parallel UASB reactors were used to evaluate the treatment efficiency of petroleum refinery wastewater under six organic volumetric loading rates (0.58, 0.89, 1.21, 1.47, 2.34 and 4.14 kg COD/m^3·d, respectively); the COD removals efficiencies were 78, 82, 83, 80, 81 and 75%, respectively as the load increased (Gasim *et al*., 2012b, c).

The present study follows from the previous investigation by modeling the anaerobic treatment of petroleum refinery wastewater considering the influent and effluent COD concentration under different loads; the developed model was then used to simulate the reactor performance.

MATERIALS AND METHODS

Experimental data: The original raw data were adapted from previous work in which the data were representing two laboratory-scale Up-flow Anaerobic Sludge Blanket (UASB) reactors that were operated in parallel (A and B) at room temperature to treat petroleum refinery wastewater. The raw petroleum refinery wastewater was collected from a local petroleum refinery and fed to the two reactors in different concentration ranging on average from 982 to 6972 mg COD/L over approximately 180 days. Chemical Oxygen Demand (COD) was tested for influent and effluent samples following colorimetric method using a HACH DR 2000 spectrophotometer, other parameters were measured according to Standard Methods (APHA, 1980). The data that were gathered from this experiment were 160 entries for influent and effluent.

ANN procedure: The COD monitoring results during different loading were used for modeling. Artificial neural network was used as mathematical tool to simulate and predict the pattern of the reactor. Optimal generalization was targeted from this tool, therefore, the Levenberg-Marquardt algorithms was used as training function and batch gradient descent with momentum back propagation algorithms (TRAINGDM) as adaption learning function, Feed-Forward Back propagation network type was selected. The number of neurons has to be determined as it is related to the converging performance of the output error function during the training process. Increasing the number of neurons usually results in a better learning performance, as too few number of neurons limit the ability of the neural network to model the process, but too many number of neurons may results in losing the generalization and learning the noise present in the database used in training (Holubar *et al*., 2002).

Normalization of input data was performed by dividing all the input data with the maximum input; this resulted in the data to be in the range of 0 to 1. Output data were normalized by dividing all the output data with the maximum output; this resulted in the date to be in the range between 0 and 1.

Neurons were tested and varied the number of neurons in the range from 5 up to 35. For better initialization of the model, the model was run 100 times at every neuron tested. Optimum number of neuron was selected in this study based on:

- Minimum Root Mean Square Error (RMSE)
- Maximum Variance Accounted For (VAF)
- Maximum correlation coefficient (R^2)

- Minimum Mean Absolute Percentage Error (MAPE)

Neural Network in MATLAB (R2009a) software was used with back propagation neural network three layers in two configurations. First, with Log Sigmoid transfer function (LOGSIG) at hidden layer and a linear transfer function (PURELIN) at output layer. Second, with Tangent Sigmoid transfer function (TANSIG) at hidden layer and a linear transfer function (PURELIN) at output layer. The linear activation function (PURELIN) was used for both configurations for the output neuron since it is appropriate for continuous valued targets (Hamed *et al*., 2004).

RESULTS AND DISCUSSION

Modeling results: The raw data from anaerobic reactor was modeled using artificial neural networks software. Logsig-Purelin transfer function was compared to Tansig-Purelin transfer function to define the optimum model. The selected model was then used to predict the reactor performance. The simulation data were then used to find the optimum performance.

During testing and validation of data, number of neurons was tested ranging from 5 to 35. Table 1 shows the number of neurons tested and the score registered for RMSE, VAF, R^2 and MAPE during evaluation of Logsig-Purelin and Tansig-Purelin transfer functions.

Although the number of neurons are in the range of 5-35, but from Fig. 1 it is noted that after neuron 15 and from plotted line representing the R^2 from the training set is losing similarity with R^2 from validation set, indicating over fitting and the model will not be able to generalize the pattern of the data that used as training set during validation (Jeon, 2007).

Thus, the number of neurons was limited to the range between 5-15 neurons and the optimum neuron was selected as shown in Table 1 based on minimum RMSE, maximum VAF, maximum R^2 and minimum MAPE.

Logsig-Purelin transfer function indicated 15 neurons is the optimum, while Tansig-Purelin suggested 12 neurons. It is usually preferable to use of simpler models, with fewer number of parameters than more complicated ones with more parameters, whenever feasible (Hamed *et al*., 2004; Holubar *et al*., 2002). Thus, tangent sigmoid transfer function (tansig) at hidden layer and a linear transfer function (purelin) at output layer with 12 neurons is the optimum transfer function.

Figure 2 showed the measured experimental data and the predicted using ANN for eighty entries of data that were used for training. Figure 3 showed the measured experimental data and the predicted using

Table 1: Number of neurons tested and the score for evaluation parameters

	Logsig-purelin				Tansig-purelin			
Neurons	RMSE	VAF	R^2	MAPE	RMSE	VAF	R^2	MAPE
5	0.076	85.952	0.859	16.878	0.076	86.027	0.860	17.035
6	0.076	86.134	0.860	17.340	0.076	86.104	0.860	16.552
7	0.075	86.249	0.862	17.255	0.075	86.229	0.862	17.279
8	0.076	85.956	0.859	16.884	0.075	86.147	0.861	16.622
9	0.075	86.250	0.862	16.694	0.075	86.170	0.861	15.971
10	0.075	86.500	0.864	16.810	0.075	86.154	0.861	16.576
11	0.075	86.516	0.864	16.977	0.075	86.388	0.864	16.750
12	0.074	86.741	0.867	17.585	0.074	86.638	0.866	16.827
13	0.074	86.608	0.866	16.426	0.075	86.424	0.864	16.023
14	0.075	86.133	0.861	16.204	0.076	86.111	0.860	16.907
15	0.074	86.724	0.867	16.205	0.075	86.412	0.864	16.427
16	0.074	86.796	0.867	16.516	0.075	86.136	0.861	16.832
17	0.074	86.589	0.865	16.585	0.074	86.756	0.868	17.353
18	0.073	87.119	0.871	15.706	0.074	86.778	0.868	15.532
19	0.074	86.716	0.867	17.047	0.073	86.949	0.869	17.307
20	0.074	86.492	0.865	16.317	0.073	86.949	0.869	16.809
21	0.076	85.834	0.858	17.072	0.073	86.981	0.870	16.355
22	0.074	86.680	0.867	16.713	0.074	86.478	0.865	16.020
23	0.075	86.480	0.864	15.911	0.075	86.242	0.862	16.362
24	0.073	86.999	0.870	16.576	0.073	86.993	0.869	16.514
25	0.073	87.008	0.870	15.617	0.073	87.067	0.871	17.009
26	0.071	87.577	0.876	16.561	0.073	87.119	0.871	17.088
27	0.073	86.956	0.869	15.467	0.074	86.674	0.865	16.072
28	0.073	86.983	0.870	16.659	0.074	86.711	0.867	16.339
29	0.071	87.825	0.878	15.832	0.074	86.468	0.865	16.621
30	0.074	86.751	0.867	16.916	0.075	86.330	0.863	16.449
31	0.068	88.734	0.887	16.171	0.072	87.368	0.873	15.808
32	0.071	87.777	0.876	16.889	0.076	85.953	0.859	15.702
33	0.071	87.756	0.877	15.273	0.073	87.088	0.869	15.789
34	0.064	89.933	0.899	15.950	0.068	89.544	0.889	13.591
35	0.062	90.687	0.907	14.955	0.075	86.372	0.863	15.382

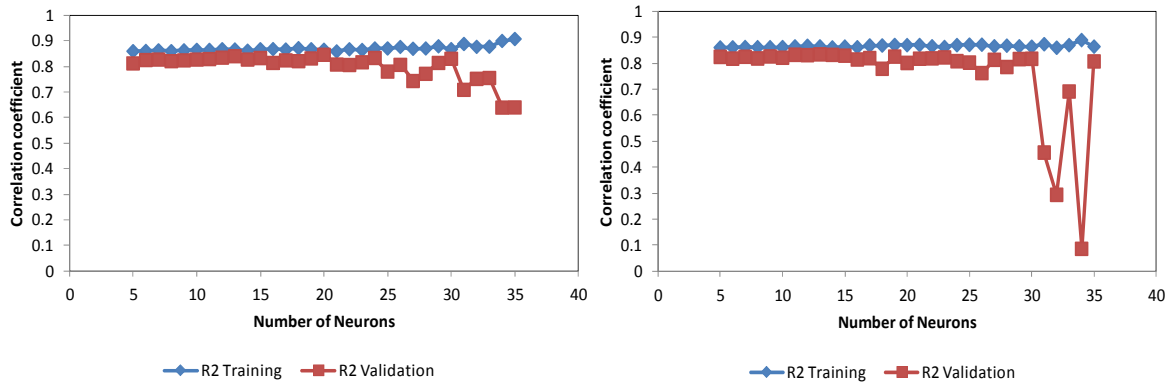

Fig. 1: R^2 scores versus number of neurons tested for logsig-purelin (left) and tansig-purelin (right) transfer functions

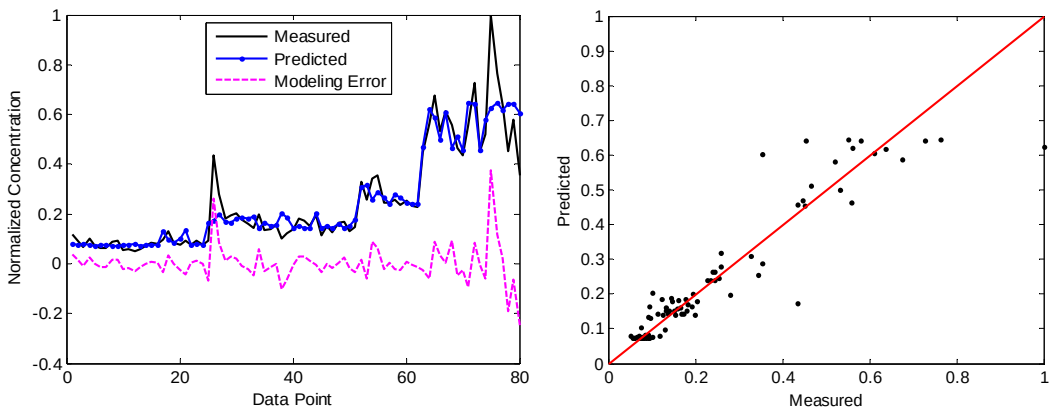

Fig. 2: Measured and predicted normalized data for training set

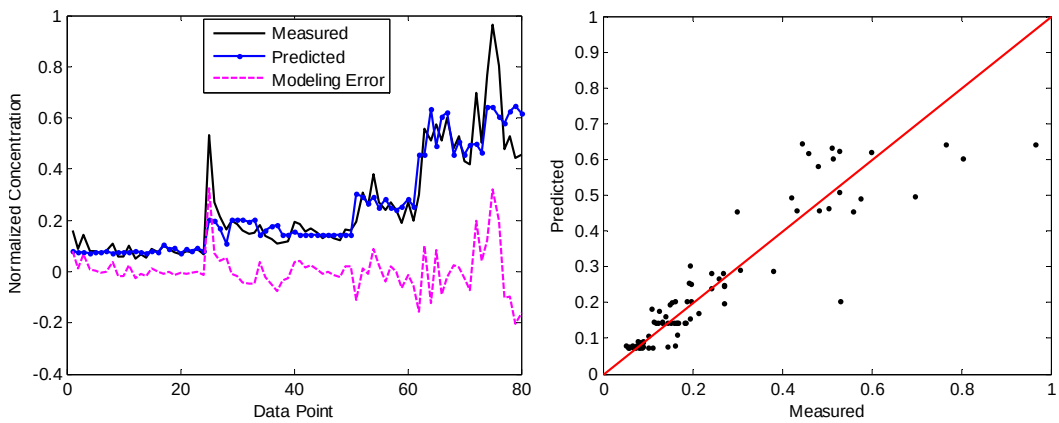

Fig. 3: Measured and predicted normalized data for validation set

ANN for eighty entries of data that were used for validation. The best selected model shows significant prediction of actual experiment; hence, it was then used for simulation.

Simulation results: The best model with Tansig-Purelin transfer function and 12 neurons was used to simulate random data to find out the optimum efficiency. Figure 4 shows all the hundred and sixty data set that was used for both the training and validation, used here for simulation.

Random data entries ranged from 500 to 10000 was used to simulate the reactor performance. Figure 5 shows the simulated influent and effluent

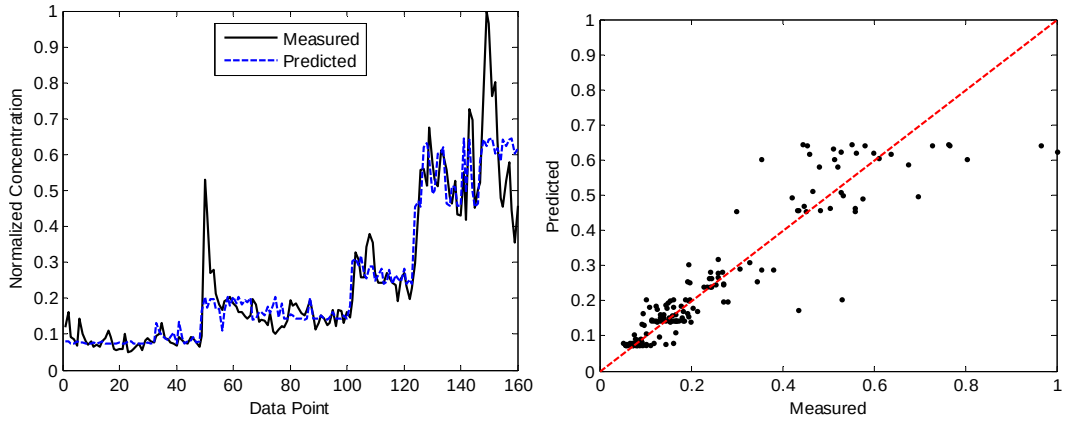

Fig. 4: Measured and predicted normalized data for actual data simulation

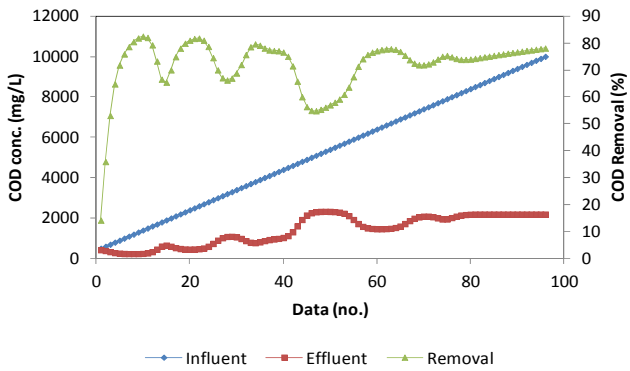

Fig. 5: Influent, effluent and removal efficiency versus data entries using best selected model for tansig-purelin transfer function

concentrations in addition to removal efficiency. Highest removal efficiency observed was 82% at influent 1400 mg COD/L and effluent 245 mg COD/L.

CONCLUSION

Raw data from petroleum refinery wastewater treatment with different loads using two UASB reactors were successfully used for modeling. Modeling resulted in a model that used tangent sigmoid transfer function (tansig) at hidden layer and a linear transfer function (purelin) at output layer with 12 neurons as the optimum transfer function. Simulation using the optimum model with random data entries ranged between 500 to 9000 resulted in a pattern that simulates the reactor performance for data that were never really experimentally tested in the lab. Lab experiment was showing highest removal of 82% which confirmed by using the best selected model that developed using mathematical model.

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