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THE PREDICTION OF CHEMICAL OXYGEN DEMAND (COD) OR SUSPENDED SOLID (SS) REMOVAL USING STATISTICAL METHODS AND THE ARTIFICAL NEURAL NETWORK IN THE SUGAR INDUSTRIAL WASTEWATERS

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ABSTRACT

A static model and Artificial neural network for the prediction of COD or Suspended solid (SS) removal by chemical coagulation have been examined in a sugar industrial wastewaters and the performance of ANN model has been compared with the statistical model based on central composite experimental design. Three independent variables which effecting amount of COD or SS removal were selected. Namely are; quantities of the chemicals, pH and mixing rates. Amount of COD or SS removal were chosen as the dependent variable (target data). A second order statistical model has been considered to show the dependence of the amount of COD and SS removal on the operating parameters. A back-propagation ANN has been used to develop a model relating to amount of COD removal. It is observed that a neural network architecture having one input layer with three neurons, one hidden layer with three neurons, one output layer with one neuron and an epoch size of 48 gives better prediction. The predictions are more accurate than those obtained from regression models.

Keywords: chemical oxygen demand, model studies, neural networks, optimization, prediction, suspended solids, waste water treatment.

INTRODUCTION

Sugar factories, which are one of the main components of the industrial processes, have undertaken many indispensable functions like agricultural development and income sharing, responding of basic feeding necessities of the society. With these qualities, they have also quite fundamental tradition in the development strategy of countries all over the world. With this respect, the planning and practices directed towards to this industry must be a product of contemporary scientific realism and careful and detailed studies (Aliplik, 2010).

Chemical wastewater treatment methods deserve more interest recently according to the specific features like simple operating, quick start-up and relatively high yields (Özkan *et al*., 2003; Kastl *et al*., 2004; Arya *et al*., 2011; Al-Mutairi *et al*., 2004).

Neural network has the ability to learn from the pattern acquainted before. The network has been trained which has sufficient number of sample date sets, it can make predictions, on the half of its previous learning, about related to new input data set of the similar pattern. Hence, ANN is being successfully used in many industrial areas as well as in research area for the prediction of various complex parameters from simple input parameters (Mete *et al*., 2012).

In order to determine the operating conditions in sugar industrial wastewaters, we have used a statistical model and artificial neural network. Standard statistical methods generally place constraints such as continuous differentiable otherwise well behaved etc. However, Artificial Neural Networks (ANN) has an ability to learn and generalize any complex system without making any model assumption. Hamed *et al*. investigate artificial neural networks (ANN) models to predict the performance of a wastewater treatment plant (WWTP) based on past information. The ANN-based models were found to provide an efficient and a robust tool in predicting WWTP performance (Hamed *et al*., 2004). The use of on-line process analyzers for continuous measurement of wastewater components is often accompanied by unpredictable breakdown or necessary maintenance work at the analyzers, leading to fault time in the measurements. Hack *et al*. presented, allowing the approximate calculation or estimation of those process parameters which are temporarily not available. The correlations between these auxiliary parameters and the process parameters actually of interest (COD, NH_4, etc.) are detected and used for the estimation of the process parameters in case of a breakdown. Information processing is executed by a neural network, enabling the detection of non-linear static or dynamic correlations, based only on information given by the measured values. The network is trained by data recorded before the breakdown of an on-line analyzer. By this, an optimal adaptation to the current wastewater composition is possible. This method was tested on a municipal wastewater treatment plant near Siegen (Germany) (Hack *et al*., 1996)

The experimental data used in the preparation of this statistical model were obtained according to by the use of experimental design (Two level factorial or central composite etc.). That has been used over a wide range of industrial process (Montgomery, 1991). In the statistical model, two level factorial experimental designs, active experimentation, has been used in mathematical modeling of the industrial process and optimization. This

experimental modeling technique allows the determination of the regression equation in a very short time. The parameter (factor) such as quantities of the chemicals, pH and mixing rates are changed according to predetermines levels. Response surface methodology using experimental design was used to determine the response of three input variables (Özkan *et al*., 2010).

In this study, the effect of quantities of the chemicals used, pH and system mixing rates on the Chemical Oxygen Demand (COD) and suspended solid (SS) removal are investigated in the sugar industrial wastewaters by chemical coagulation method. Using MATLAB package program, optimization process is applied for each chemical, according to this, optimization parameters special to system and unit costs are evaluated and the best results are taken for $FeCl_3.6H_2O$. For this chemical, at the mixing rate of 100 rpm and considering the economical criteria, evaluated optimum pH 7.28 and chemical quantity is 2.29 g/l and in reply to this, the removal of COD is 48.95 % and SS is 55.7%. On the other hand statistical methods and artificial neural network are used to prediction on the percentage of COD or Suspended solid (SS) removal. Leaving apart some stray cases, the artificial neural network is able to predict the amount of COD or SS removal with reasonably low prediction error. For the set of data used for constructing the network, the mean square errors are comparatively lower in the neural network model than the regression model.

MATERIAL AND METHOD

Chemicals

Tests can be divided into three groups depending on the coagulant used. These chemicals were Alum, $Al_2(SO_4)_3$. 18 H_20 (Merck), $FeSO_4.7H_2O$ (Merck), and $FeCl_3.6H_2O$ (Merck).

Jar-tests

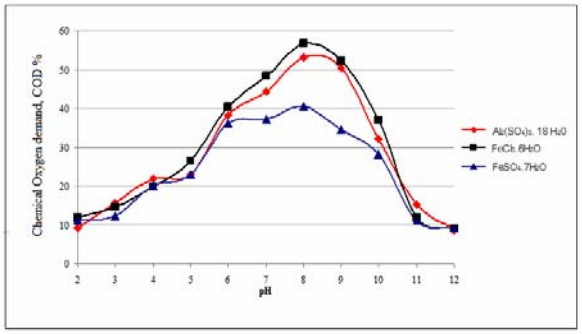
Figure-1. Scheme of experimental setup.

Jar-test is a well-known tool for chemicals selection for physical-chemical wastewater treatment (Figure-1). Jar-test results show the treatment efficiency in terms of suspended matter and organic matter removal. The experiments were performed in a jar test apparatus, which consists of six identical beakers, each equipped with a stirrer. The procedure consisted in introducing 500 mL of the sample in the jars, then the coagulant was added, pH value was settled and rapidly mixed (150 rpm) during 5 min. After that, the paddles velocity was decreased down to 50 rpm during 15 min. At last, the paddles were withdrawn so that the particles could settle during 60 min. In all tests chemical oxygen demand (COD), pH and suspended solid (SS) were measured using APHA (2005) 5220 C procedure, pH meter, APHA (2005) 2540 D method and Millipore mark with AP40 (0, 45 µm) filter, respectively.

Jar-tests results

Effect of pH

The efficiency of coagulation is highly dependent on a number of operational parameters that govern the removal of colloidal pollutants in wastewater. pH value may be of foremost importance since it greatly contributes to the colloid removal efficiency when using constant coagulant dosage. Jar tests were conducted for the determination of the optimal pH value at dosage 2, 5 g/L, and the results is shown in Figure-2.



a)

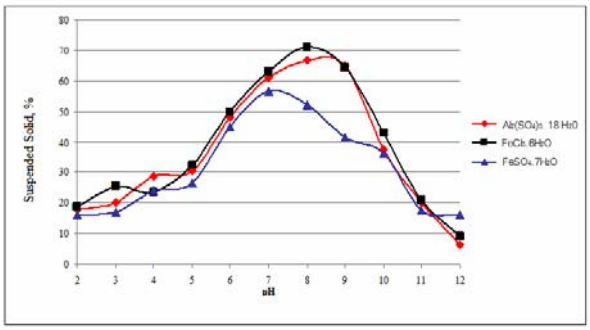


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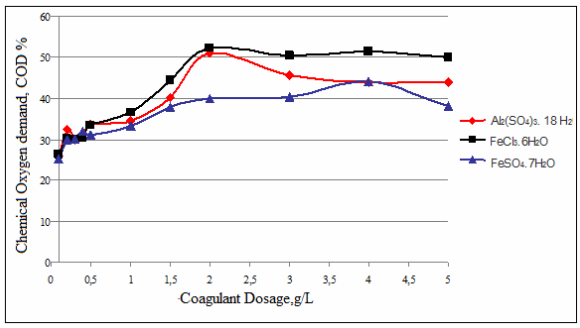
Figure-2. Jar-tests results (effect of pH) a) chemical oxygen demand b) Suspended solid.

It can be seen that both COD and SS showed dramatic changes with pH. The best values are 8. Previous jar-tests showed that wastewater pH was in the appropriate range at 8 for the coagulants addition. In Figure-3, COD and SS values after the tests with the three coagulants and pH=8 can be observed. The variation of the COD and SS

values with the coagulants concentration can also be observed. It must be commented that the coagulants concentration range of the Figures were the effective range for COD reduction.



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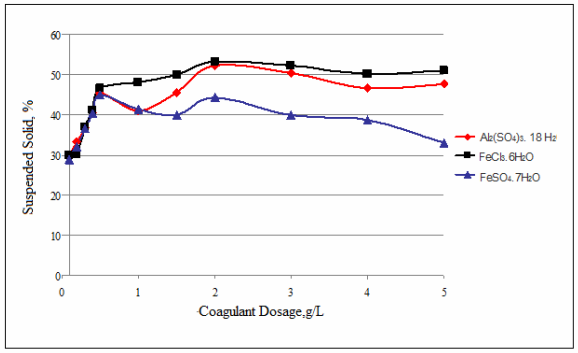

b)

Figure-3. Jar-tests results (effect of Coagulant Dosage) a) Chemical oxygen demand b) Suspended solid.

The best results in terms of COD of the clarified wastewater were $FeCl_3.6H_2O$. Besides, at the highest concentrations, the pH values of the clarified water are more appropriate for an additional biological treatment due to the acidic character of the coagulant.

STATISTICAL TECHNIQUE RESULTS

In order to obtain amount of COD and SS removed were evaluated by utilizing the response surface methodology. A suitable function of relationship between the dependent and independent variables can be obtained by using statistical models. In this work quadratic model is studied.

In the experimental design there are n variables (factors). These factors are controlled at different levels. In these types of designs one works in dimensionless coordinate system using following definitions.

The levels of these parameters are given in Table-1. For this reasons 18 experiments were done to identify the regression model.

The design matrix included coded values of the independent and un coded dependent variables. Table-2 shows the interrelation between the coded independent variables. The column (Table-2) under X_0 contains the dummy variable, which is equal to 1 in order for the model to include an intercept. All the weights will be unity. The relationship between coded and real values is shown below:

$$X_i = \frac{U_i - U_{iav}}{\Delta U_i} \quad , i = 1,2,\ldots\ldots\ldots,n \qquad (1)$$

$$U_{iav} = \frac{U_i^{max.} + U_i^{min.}}{2} \quad , i = 1,2,\ldots\ldots\ldots,n \qquad (2)$$

$$\Delta U_i = \frac{U_i^{max.} - U_i^{min.}}{2} \quad , i = 1,2,\ldots\ldots\ldots,n \qquad (3)$$

The model coefficients, by using experimental data were calculated by using Matlab software and shown below.

Final equation in terms of un coded factors

$$COD=-80.91701+29.53734*U_1+12.54894*U_2-0.037291*U_3+0.17474*U_1*U_2-.83750E-03*U_1*U_3-0.016398*U_2*U_3-1.97886*U_1^2-1.27704*U_2^2+6.49818E-004*U_3^2 \qquad (4)$$

$$SS=-37.09824+23.72277*U_1+15.04723*U_2-0.27897*U_3+0.15612*U_1*U_2-.75000E-04*U_1*U_3-0.018673*U_2*U_3-1.68773*U_1^2-1.62531*U_2^2+1.38964E-003*U_3^2 \qquad (5)$$

Quadratic model fitted well with the experimental data. The model F value of 5.173 implies that the model was significant. Values of "Prob>F" is less than 0.05 indicate significant model terms. Thus U_1 and U_2 were significant model terms.

After the identification of the statistical model for the process, the 3D contour plot of the effect of two significant variables on the amount of COD was shown in Figure-4. Figure-4 showed that optimum pH 7.28 and chemical quantity is 2.29 g/l and in reply to this, the removal of COD is 48.95% and SS is 55.7% (For $FeCl_3.6H_2O$).

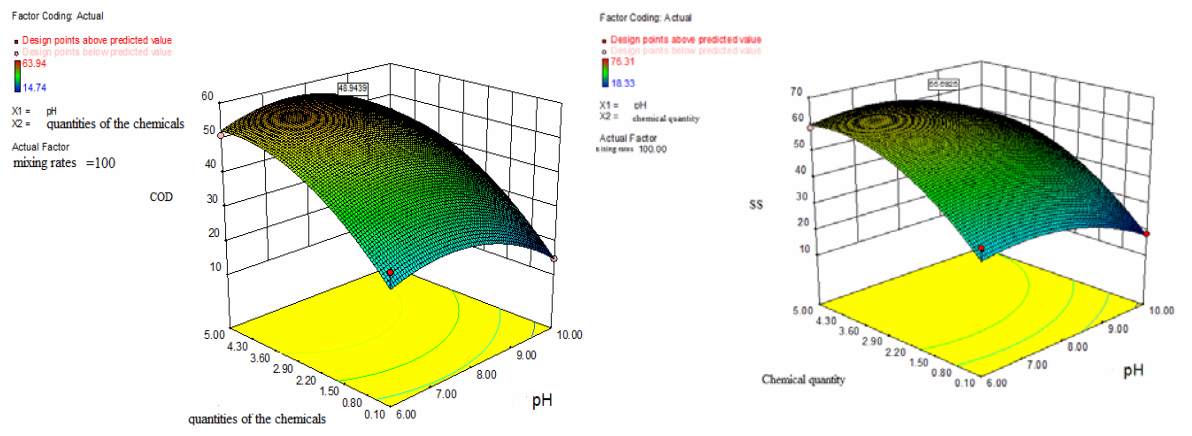

Figure-4. 3D diagram showing the contour plot for grades quantities of the chemicals and pH rate on the amount of COD and SS removal.

ARTIFICIAL NEURAL NETWORK TECHNIQUE RESULTS

Application of ANN is as follows (Fausett., 1996; Özkan *et al*., 2010):

a) Data collection and preparation including statistical experimental design or experiments.
b) Neural network training includes selection of ANN structure, training function and algorithm.
c) Neural network evaluation, simulation, prediction and validation.

In this study, we selected the feed forward BPANN. The transfer function in the hidden layers was differentiable tan-sigmoid function (tansig). The transfer function in the output layer was linear function (purelin). The BPANN was categorized as 3+3+1, which means one input layer with three neurons, one hidden layer with three neurons and one output layer with one neuron. The values from three independent factors quantities of the chemicals, pH and mixing rates; the prediction of COD or SS removal by chemical is the target value of the neuron in the output layer. Data obtained from experimental design was used for training of the ANN and the data of other experimental was used for testing the trained network. The training data set was given to the network and a feed forward algorithm automatically adjusted the weights so that the output response to input values was as close as possible to the desired response. Prediction was made and results were compared with the desired value. Then the prediction error was distributed across the network in a manner which allowed the interconnection weights to be modified according to the scheme specified by the learning rule. This process was repeated while the prediction error decreased. Levenberg Marquardt (trainlm) was used to train the BPANN. This algorithm works by iteratively adjusting the weights and biases of the network to minimize the performance function than gradient descent (traingd). The performance function is the mean squared errors (MSE) between the output and the target values. Figure-5 show the training curves of this algorithm. The training epochs (iterations) for trainlm were 42.

ANN and statistical model prediction

After construction and training, the output of the ANN was compared with the experimental data for the trained and test data sets in Figure-6 and Figure-7, respectively. Also the output of the ANN was compared with the statistical model data for the trained and test data sets in Figure-6 and Figure-7, respectively. Experimental data are distributed along the ANN predicted line which indicates the ANN prediction is bather than statistical model data.

CONCLUSIONS

Artificial neural networks (ANN) model and the statistical regression model were developed to predict the performance of a wastewater treatment plant based on experimental design. The performance of ANN model has been compared with the statistical model. The artificial neural network is able to predict the properties with reasonably low prediction error. The mean square errors of statistical regression model for training and test data are 228.6589 and 133.3352. They are 0.2810 and 15.8235 for ANN model. The mean square errors are comparatively lower in the neural network model than the statistical regression model.

Table-1. The levels of independent variables.

	pH $X_{1(Coded)}$, $U_{1(Uncoded)}$	**Quantities of the chemicals,** $X_{2(Coded)}$, $U_{2(Uncoded)}$	**Mixing rates** $X_{3(Coded)}$, $U_{3(Uncoded)}$
Minimum (-1)	10	5	200
Maximum (+1)	6	0.1	100

Table-2. Optimal design matrix.

X_0	X_1	X_2	X_3	COD
1	1	1	1	41.4
1	1	-1	1	24.93
1	0	0	1	63.94
1	0	0	0	54.09
1	0	0	-1	46.66
1	0	0	0	48.19
1	0	0	0	44.16
1	0	0	0	44.81
1	-1	-1	1	36.49
1	1	1	-1	45.02
1	0	-1	0	28.14
1	1	0	-0	43.61
1	0	1	0	63.88
1	-1	-1	-1	30
1	-1	+1	-	50.82
1	-1	0	0	47.91
1	-1	1	1	55.31
1	1	-1	-1	14.74

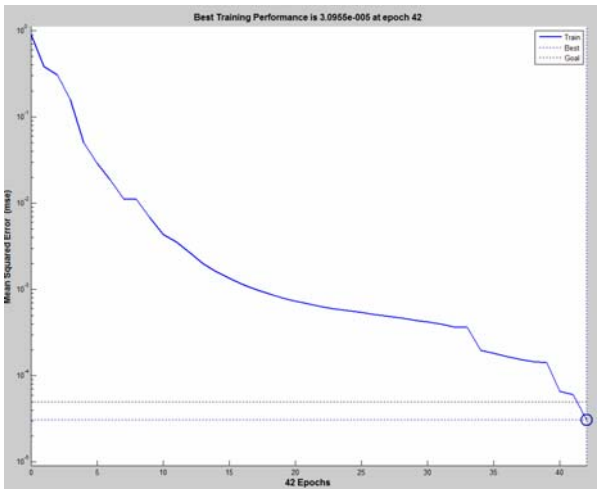

Figure-5. Training curve of levenberg marquardt algorithm.

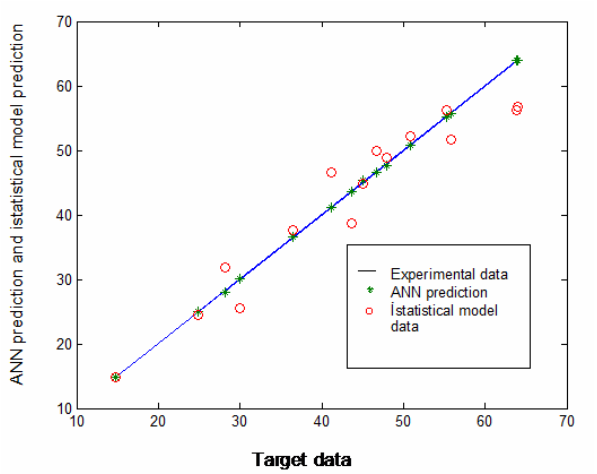

Figure-6. Performance of ANN model has been compared with the statistical model data and target data (training data set).

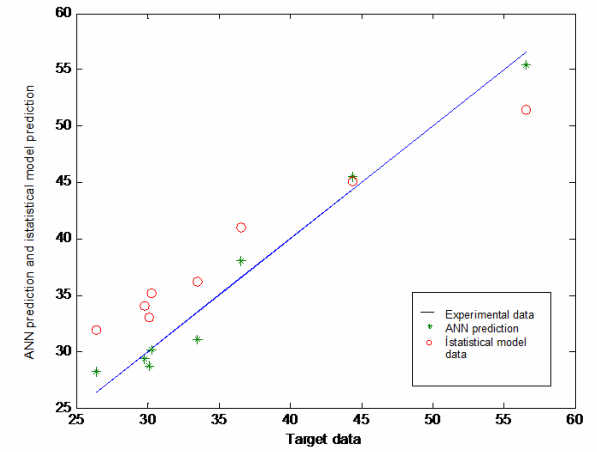

Figure-7. Performance of ANN model has been compared with the statistical model data and target data (test data set).

Nomenclature

U_i Real value of the parameters
U_{iav} Average values of the parameters
U_i^* Average value of the independent variables at centre points
ΔU_i Incremental value of the parameters,
X_1 Coded value of the pH
X_2 Coded value of the quantities of the chemicals
X_3 Coded value of the mixing rates

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