LAUTECH JOURNAL OF ENGINEERING AND TECHNOLOGY 3(2) 2005: 49 – 52

A NEURO-PREDICTIVE MODEL OF AN INDUSTRIAL WASTEWATER TREATMENT PROCESS USING PRINCIPAL COMPONENTS ANALYSIS

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ABSTRACT

This paper presents a way of predicting the biochemical oxygen demand (BOD) of the output stream of the activated sludge of a food processing industry. A combination of principal components analysis (PCA) and artificial neural networks (ANN) was used to develop the network model structure that contained eight neurons in the hidden layer. PCA was used to preprocess the training data sets comprising of four input variables that have been transformed into four principal components before being fed into a backpropagated neural network. A more satisfactory result was obtained from PCA-ANN model with correlation index 0.998 and performance error (MSE) of 0.007 compared with that of ANN model with correlation index 0.82 and performance error (MSE) of 0.056 for the training process. This result shows that preprocessing data will bring about improvement in prediction.

Keywords: Artificial Neural Networks, Principal Components Analysis, Biochemical Oxygen Demand, Wastewater Treatment and Chemical Oxygen Demand

INTRODUCTION

Campaign for clean and benign environment is now a global issue. Most industrial processes are always characterized with waste generation. Wastewater from industrial processes can become a menace to the environment when not properly treated before discharging effluents into the surrounding. Examples of such industries are food processing industries, breweries e.t.c which are of serious concern. Exiting effluents may contain potentially harmful chemicals, introduced during the brewing operations. Thus, without proper treatment, the wastewater may pollute the environment upon its return to the water source.

In the process industry the use of modern control strategies is required due to increasingly stringent regulation of effluent quality. The modeling traditionally used in bioprocesses is based on balance equations together with rate equations for microbial growth e.t.c, and since microbial reactions coupled with environmental interactions are nonlinear, time-variable and of a complex nature (Lee and Park,1999), traditional deterministic and empirical modeling has shown some limitations (Hamoda et al., 1999).Also, operational control of a biological wastewater treatment plant is often complicated because of variation in raw wastewater compositions, strengths and flow rates owing to the changing and complex nature of the treatment process (Hamoda et al., 1999). Moreover, lack of suitable process variables limits the effective control of effluent quality (Lee and Park, 1999).

Recently, some studies using artificial neural networks (ANNs) in modeling biological wastewater treatment processes have been published, providing an alternative approach (Häck and Kohne, 1996; Gontarski et al., 2000; Hamoda et al.,1999; Lee and Park, 1999, Emuoyibofarhe et al ,2003 and Zhao et al., 1997). Likewise, to enhance ANN performance, principal components analysis (PCA), which is a technique that shows an orthogonal variable transformation, can be used for pruning ANNs and improving nonlinear mapping (Kanjilal, 1995 and Kompany-Zared, 1999). The use of ANNs in combination with PCA has been said to have merits (Cancilla and Fang, 1996; Kompany-Zared et al., 1999 and Oliveira,2002).

The aim of this study is to develop an estimation model that can provide accurate predictions of the biochemical oxygen demands of the output stream of a biological wastewater treatment plant (BOD_{out}).There is a five-day delay in determination of BOD(Hanurd et al., 1985),and when this is added to the hydraulic residence time, it is often too late to make proper adjustments in the wastewater treatment process and hence the need for a faster and accurate means of prediction.

In this work, the predictive models for the estimation of BOD_{out} are calculated from the combination of ANN and Principal Component Analysis (PCA). The data are preprocessed using PCA before they are fed to the neural network for training.

PROCESS DESCRIPTION

This typical wastewater treatment plant is a combination of processes but biological treatment section is of interest since the work is centered on the predictions of biochemical oxygen demand (BOD_{OUT}).The widely used system for biological wastewater treatment is the activated sludge process that consists of aerated tanks and settling tanks. A simplified process flowsheet is as shown on Figure 1.And to construct the model, six variables for the activated sludge and one for the production were chosen that have important effect on the BOD_{OUT} prediction as shown on Table 1.The original data obtained from the plant is about 65 spanning over some range of periods but only 60 data set were used.

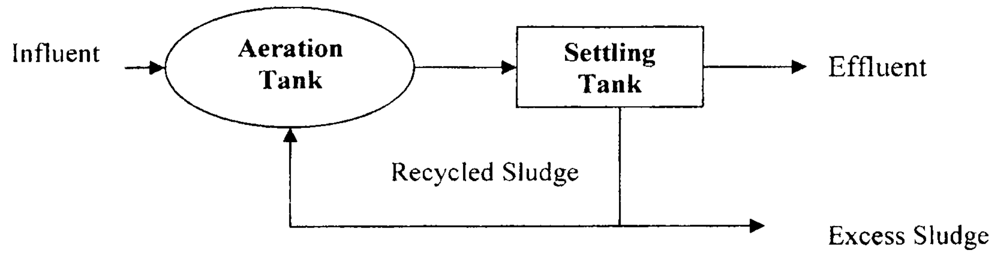

Figure 1: Process flowsheet for wastewater treatment

NEURO-PREDICTVE MODEL OF THE PROCESS

About 60% of all data records were randomly assigned to the training set, while 20% goes to testing and the remaining 20% were relegated to the validation set. The network training was carried out using the standard backpropagation algorithm. The tansigmoidal function was used as the transfer function in the input and purelin transfer function was the output layers due to its suitable application. Also the Levenberg-Marquardt (trainlm) training function was used in each case because of its speed of convergence and accuracy. The stop criteria were based on the Mean Square Error (MSE).

The ANN network composed of eight neurons in the hidden layer; this is because eight neurons happened to be the optimal when ranged from 1 to 10. In order to improve its performance and to prune the ANN structure, input variables were preprocessed, using the PCA technique, before they were fed to the backpropagated ANN. PCA sought relevant directions for the input data that maximize variance. In order to validate the PCA-ANN model obtained, the input/output data of the untrained data were presented to the trained network model to see how well the network model predicts the corresponding output data set. A generalization test with both familiar and unfamiliar data sets was also conducted on the network. The software implementation of this model was carried out on MATLAB 6.5 version while the statistical analysis of the output was done on SPSS computer software.

RESULT AND DISCUSSION

The best result was obtained for the PCA-ANN composed of eight neurons in the hidden layer as earlier mentioned in the modeling section. It has correlation indices of 0.998 for the training set, 0.996 for the validation set and 0.998 for the test data set for the predicted and the observed BOD's. This improvement in the result obtained was as a result of preprocessing of data set with PCA where data that contributed less that 2% of the variance were eliminated to give a better mapping of input/output relation. An initial training of this same set of data was performed using ANN only and the results obtained were inferior to that of PCA-ANN model as shown on Table 2.

As can be seen in Table 2, the best model obtained in term of performance is PCA-ANN with the mean square error (MSE) of 0.0007 for training set, 0.0008 for validation set and 0.0007 for test data set. These consistent performance indices are indications of the stability and competence of the network to predict future unfamiliar data set effectively.

Figure 2 presents a graphical representation of the measured and predicted data of BODout, using the best modeling structure (PCA-ANN), while the network itself is presented in Figure 3. From the results obtained using the correlation indices to do the statistical comparison for the measured and predicted data sets, it is discovered that a combination of principal components analysis and artificial neural networks can form a model that can solve complex nonlinear problems than ordinary ANN by exploiting mapping advantages found in PCA.

Table 1: Simple Statistical Description for Selected Variable

Parameter	Description	Average	Minimum	Maximum	Standard Deviation
BOD_{IN}	Inlet Wastewater BOD(mg/L)	640.4	360.0	867.0	86.4
COD_{IN}	Inlet Wastewater COD(mg/L)	1286.3	960.0	1560.0	117.0
$FLOW_{IN}$	Inlet flow rate(m^3/day)	1860.5	1500.0	2100.0	120.8
BOD_{OUT}	Outlet Wastewater BOD(mg/L)	70.2	40.0	120.0	15.8
COD_{OUT}	Outlet Wastewater COD(mg/L)	384.6	280.0	480.2	46.8
$FLOW_{OUT}$	Outlet flow rate (m3/day)	1420.6	1200.0	1860.0	148.6
Production	Production Output (kg/day)	3786.6	3000.0	4500.0	180.2

Table 2: Results of BOD_{OUT} Prediction by PCA-ANN and ANN Models

Network Model	Training Data Set		Validation Data Set		Test Data Set	
	MSE	Correlation Index	MSE	Correlation Index	MSE	Correlation Index
ANN	0.0056	0.82	0.0053	0.80	0.0058	0.81
PCA-ANN	0.0007	0.998	0.0008	0.996	0.0007	0.998

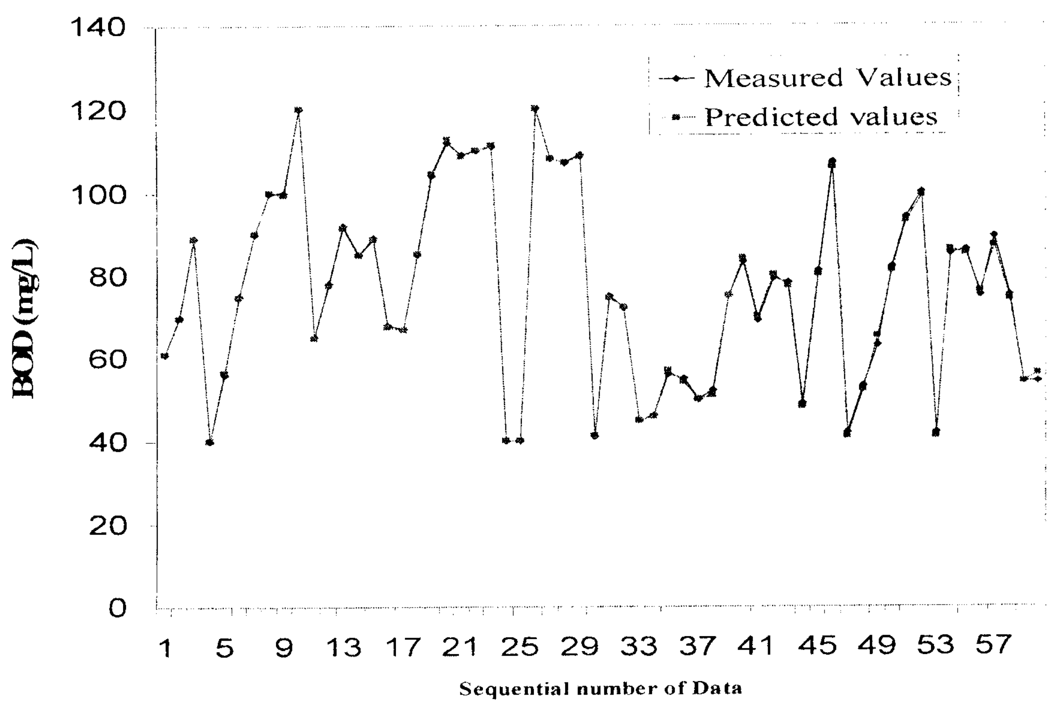

Figure 2:Measured and Predicted BODs using PCA_ANN Structure Model

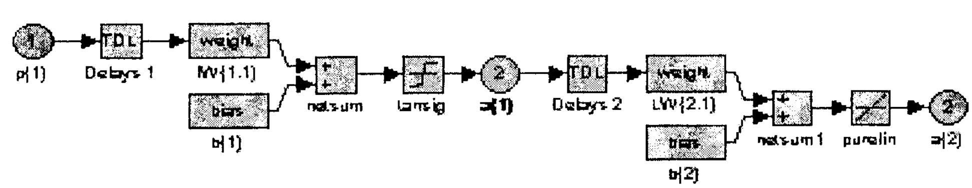

Figure 3: PCA-ANN Network Structure Model

CONCLUSION

It can be concluded from this work that preprocessing data using principal components analysis can improve the performance of an artificial neural network especially in data prediction .The combined use of PCA and ANN provided a predicted result that is statistically superior to those obtained using each technique separately. This can be traced to the mapping ability of the PCA that is brought about by its orthogonal transformation of variables and reduction of system dimensionality. There was very high correlation between the measured and predicted BOD_{OUT} by the PCA-ANN model structure

NOMENCLATURE

Notations	Description
BOD_{IN}	Biochemical Oxygen Demand in the inlet wastewater (mg/L)
COD_{IN}	Chemical Oxygen Demand in the inlet wastewater (mg/L)
$FLOW_{IN}$	Inlet flow rate(m^3/day)
BOD_{OUT}	Biochemical Oxygen Demand in the outlet wastewater (mg/L)
COD_{OUT}	Chemical Oxygen Demand outlet wastewater (mg/L)
$FLOW_{OUT}$	Outlet flow rate (m3/day)
Production	Production Output (kg/day)

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