Asian Journal of Water, Environment and Pollution, Vol. 12, No. 1 (2015), pp. 81–89.

Short Note

BOD Approximation for Common Effluent Treatment Plant Using ANN

Monika Vyas*, Bharat Modhera[1] and Anil Sharma

Department of Civil Engineering, Maulana Azad National Institute of Technology, Bhopal, India

[1]Department of Chemical Engineering, Maulana Azad National Institute of Technology, Bhopal, India

✉ monikavyas06@gmail.com

Received April 21, 2014; revised and accepted December 11, 2014

Abstract: In developing countries like India, common effluent treatment plants (CETPs) are often suggested as cost-effective options for centralized treatment of effluents emerging from separate waste-streams. The treatment/operation cost of CETPs is met by individual waste generators in proportion to the strength of the waste generated by them. This necessitates the regular determination of parameters such as BOD, which often is cost intensive, requires specialized lab personnel, and is time consuming (3-5 days minimum). Approximation of BOD, therefore, presents a relevant strategy which can save upon cost, effort and time. This paper presents a framework that employs Artificial Neural Network (ANN) technique to approximate influent and effluent BOD for common effluent treatment process. The framework is applied to the case of a CETP at Bhopal city, India. In the present work, a three-layered feed forward ANN that compares two different learning algorithms has been applied, and suitable architecture of the neural network models has been ascertained after several steps of training and testing of the models. The results indicate accuracy above 90%, thereby ANN proves to be a promising tool in the field of modelling.

Key words: BOD, common effluent treatment plants, ANN.

Introduction

Small-scale industries (SSIs) have a very important role in overall industrial development in India and growth of SSI units has been actively promoted by Government of India to induce balanced economic growth and to distribute the benefits of industrial development in an equitable manner. 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 (Common Effluent Treatment Plant: A Solution or a Problem in itself, Toxics Link, November, 2000). However, the quantum of pollutants emitted by SSI clusters may be more than an equivalent large scale industry, since the specific rate of generation of pollutants is generally higher because of the inefficient production technologies adopted by SSIs. Thus concept of CETP was adopted as a way to achieve end-of-pipe treatment of combined wastewater at lower unit cost than could be achieved by individual industries. Wastewater treatment processes, consisting of a sequence of complex physical, chemical and biochemical processes, and their dynamics are non-linear and usually time-varying (Raha, 2007). Thus it is very important to control its dynamic behaviour. With these objectives, there has been a shift of focus from plant design and plant operation to mathematical modelling. Modelling is a valuable tool in both design and operation, and can be used for process optimization and testing of control strategies in order to meet effluent quality requirements at a reasonable cost. In addition, modelling helps researchers to develop a better understanding of the process and provides a significant potential for solving operational problems (Yetilmezsoy, 2007).

*Corresponding Author

Modelling of CETP is important for predicting plant performance and operation. In addition some important process variables cannot be measured on-line, e.g. BOD_5 requires 5-day incubation, and this makes it difficult to find and solve the problematic situation in time (Al-Asheh, 2007). Therefore, modelling of CETP is a difficult task and most of the available models are just approximate ones based on, probably severe, assumptions (Lee, 1999; Hamoda, 1999). 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, 1999). But thanks to the recent developments in automation technology, nowadays instruments, control elements can be used to implement strategies and policies to handle most processes and problems in treatment plants (WWTPs). The intelligent control systems use artificial intelligence (AI) inspired tools to better control complex processes (Luccarini, 2010).

In recent years, artificial neural networks (ANNs) have shown some promise for modelling water treatment processes. The main advantage ANNs have over physically based models is that they are data-driven and underlying relationships using examples of the desired input-output mapping (Maier, 2001).

In present work, ANN models were developed for the approximation of BOD at the inlet and at outlet. The models were applied to the influent and final effluent streams of CETP at Govindpura industrial area in the Bhopal (M.P.), India. The objective of present work is to achieve the best effluent forecasting with minimum number of inputs.

Methodology

Artificial Neural Network (ANN)

ANN consists of an information-processing paradigm and a pattern recognition tool inspired by how the biological nervous systems process information. The artificial model of the brain is known as Artificial Neural Network (ANN) or simply Neural Networks (NN). ANN uses input-output response patterns to map a function approximation to the underlying governing rules of the output responses corresponding to specific inputs in a convoluted physical space. Neurons usually operate in parallel and are configured in regular architectures. They are often organized in layers. The first is the input layer that receives the input and processes it to the hidden layer. The nodes of the hidden layer enhance the ability of ANN to model complex relationships. The number of hidden nodes depends on the number of training patterns, the amount of data noise, and the complexity of the function that ANN is approximating. The output layer presents ANN predicted output.

The artificial model of neuron consists of three elements: (1) A set of synapses or connection links, each of which is characterized by a weight or strength of its own. Specially, a signal x_j at the input of synapse j connected to neuron k is multiplied by the synaptic weight w_{kj}. Unlike a synapse in the brain, the synaptic weight of an artificial neuron may lie in a range that includes negative as well as positive values. (2) An adder for summing the input signals, weighted by the respective synapses of the neuron. (3) An activation function or transfer functions for limiting the amplitude of the output of a neuron (Ulku, 2005).

The neuron model can also include an externally applied bias, denoted by b_k. The bias b_k has the effect of increasing or lowering the net input of the activation function depending on whether it is positive or negative, respectively (Ulku, 2005) as per Figure 1.

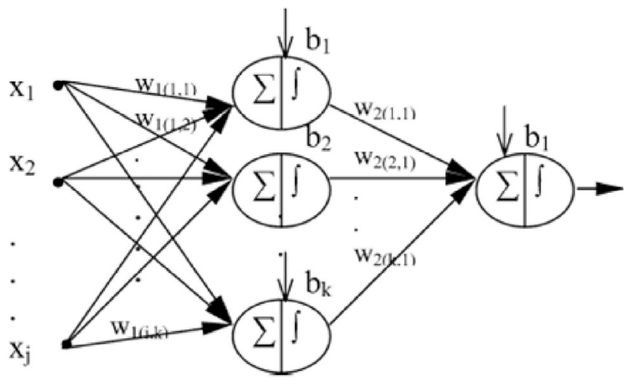

Figure 1: Structure of three-layer ANN.

Mathematically, the neuron k will be described by the following equation:

$$u_k = \sum_{j}^{m} w_{kj} x_j \tag{1}$$

where $\{x_1,\ldots, x_m\}$ are the input signals and $\{w_{k,1},\ldots, w_{k',m}\}$ are the synaptic weights of neuron k. The activation function, denoted by *f(net),* defines the output of a neuron which considerably influences the behaviour of the network,

$$\text{net} = u_k + b_k \tag{2}$$

$$y_k = f\,(\text{net}), \tag{3}$$

where b_k is threshold value and f is activation function in ANN.

Work Area Details

General Description of Plant, CETP Govindpura (Bhopal)

For treatment of combined industrial wastewater from Govindpura Industrial Area, an agency known as Govindpura Audhyogik Kshetra Pradushan Nivaran Pvt. Ltd. (GAKPNPL) had installed a Common Effluent Treatment Plant (CETP). Designed capacity of CETP is 900 m^3/day. The designed removal efficiency of COD and BOD is 89% and 95% respectively. The treatment system consists of equalization tank, holding tanks, buffer tank, anaerobic treatment unit (Upflow Anaerobic Sludge Blanket, 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.

At present, six industries are participating in the Govindpura treatment plant for the wastewater treatment. Lilasons Breweries and Ramani Ice-cream industries are major contributors whereas the other industries which include EEI capsules, Rajsons dairy, Bhopal incinerators and Specialty organics are the minor ones (Table 1). After entering the treatment plant, wastewater is allowed to homogenize in equalization tank. This sets up the standard for treating the waste from variety of industries simultaneously. Waste from the equalization tank moves to the holding tank where it is held for about one hour. This facilitates settling and separation of heavy particles in the wastewater. Thereafter waste water is transferred to the neutralization tank where the pH of the wastewater is maintained by suitable alkali and acid dosing whichever is required. The effluent from the equalization tank is transferred to buffer tank where it is retained for a small period of one hour. The buffer tank accepts re-circulation flow from the UASB reactor along with raw wastewater. The buffer tank is provided to trigger the acitogenesis phase in the anaerobic treatment and pre-conditioning of the effluent before entering into the UASB (Figure 2). The effluent from buffer tank is then pumped to UASB reactor through a series of distribution pipes. This ensures a uniform flow of liquid throughout the sludge blanket making maximum use of available high bacterial population. The liquid rises to the top of UASB reactor along with biogas generated and also some sludge particles. The BOD of treated effluent is reduced by about 80%. The effluent from UASB reactor is subjected to flash aeration to increase the DO level in the effluent before discharge (Cicon Environment Technologies Ltd., Operation and Maintenance Manual, 2009).

Table 1: BOD contribution from various industries

Industries	*BOD (mg/l)*	*Remarks*
Lilasons breweries	1400-1950	Regular
Ramani ice-cream	1700-2000	Regular
EEI capsules	1800-2200	Regular
Rajsons dairy	1700-2000	Regular
Bhopal incinerators	500-750	Regular
Speciality organics	6000-9000	Regular

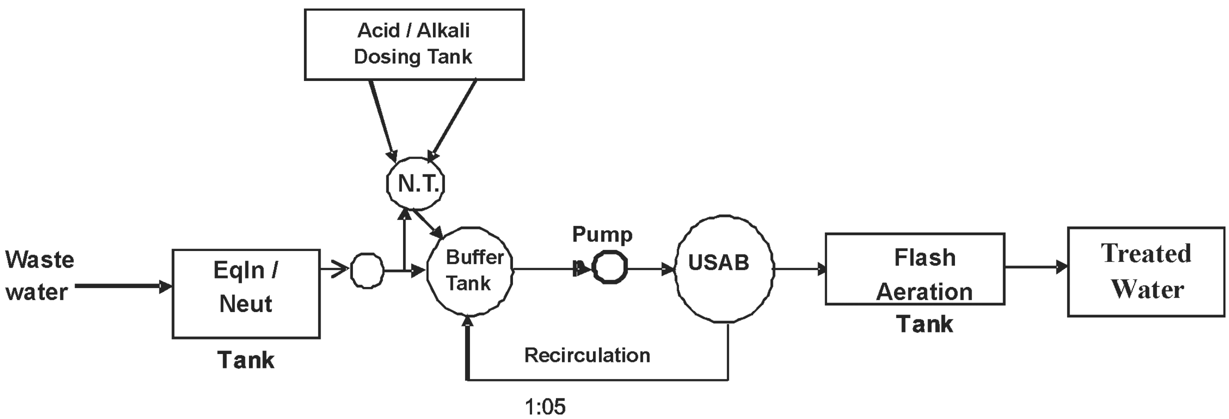

Figure 2: Flow diagram of Common Effluent Treatment Plant, Industrial Area, Govindpura, Bhopal, MP, India.

ANN Based BOD Models

Biological Oxygen Demand (BOD) Models

In an industry, the BOD test is used to measure waste loads to treatment plants, determine plant efficiency (in terms of BOD removal), and control plant processes. It is also used to determine the effects of discharges on receiving waters. But the analysis of BOD is time consuming. It requires 5-day incubation, and this makes it difficult to find and solve the problematic situation in time (Hamoda, 1999). In this study two artificial neural-networks (ANN) models were developed for the prediction of BOD, i.e. BOD at equalization and BOD at outlet, as shown in Figure 3. Model 1 predicts the BOD at equalization tank and model 2 predicts the BOD at the outlet of the plant. Data is collected from CETP, Govindpura over a period of five years from 01/04/2005 to 30/08/2010. In ANN modelling, it is important to determine the dominant model inputs, as this reduces the size of the network, avoid unwanted noise, makes rule extraction easier, reduces training time and increases processing speed and the generalization ability of the network for a given data set (Lawrence, 1996; Castellano, 1997). This also reduces the requirement for quantity of training records to efficiently estimate the model parameters e.g. the connection weights (Cheng, 1994; Lachtermacher, 1994).

For larger networks, computational costs are high and might overfit the training data with too many nodes, and they generally require a large number of training samples to achieve good generalization ability (Bebis, 1994). For ANN-based modelling, single output is preferred, as they are generally more accurate than multiple-output models (Baxter, 1999). Inputs that are linearly correlated are avoided (Boger, 1997). The ANN input and output variables for present case study has been chosen based on engineering judgment on which input and may have a significant effect in predicting effluent BOD (see Table 2). The performance of one-hidden layer ANN is found to be better than two hidden layers ANN (Hamoda, 1999; Maier, 1998). Nodes in the hidden layers, although are very important for feature extraction from the patterns of input time series (Lee,

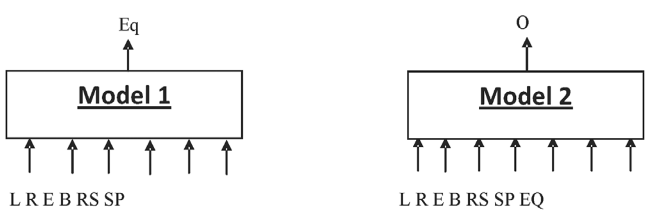

Figure 3: Model 1 and Model 2.

Table 2: Input/output parameters for BOD Model

Variable	*Input (I) or Output (O)*	*Symbol*
BOD of Lilason breweries industry	I	L
BOD of Ramani ice cream	I	R
BOD of E.E.I. capsules	I	E
BOD of Bhopal incinerators	I	B
BOD of Rajsons dairy	I	Rs
BOD of SP organics	I	SP
BOD of equalization tank	I/O	Eq
BOD of outlet point	O	O

1991; Maier, 1995), they normally have a very small weight changes and learn very slowly (Gallant, 1993); too many of them results in learning the noise present in the training database (El-Din, 2002). Here single hidden layer is used to create feed-forward fully-connected neural network (multi-layer perceptron). For both hidden and output layers hyperbolic tangent activation function is employed.

Results and Discussion

It is very important to clearly define the criteria by which the performance of model will be judged. In present application, performance criteria include network architecture in terms of node optimization in the hidden layer; also each network model is evaluated in terms of mean absolute error, training speed and correlation coefficient (R). Also performances of these models are compared on the basis of learning algorithm,

For Model 1, the architecture having six nodes in hidden layer proves to be the best network from the list of various networks (see Table 3). Similarly for Model 2, best architecture is [7-8-1], as chosen on the basis of fitness criteria (see Table 4). The fitness is calculated as inversed mean absolute network error on the test set. It is evident that increasing the number of nodes does not increase the performance. To search the best architecture is purely trial and error process.

Total data set is divided into training set (68%), validation set (16%), and test set (16%). Minimization of the error function is the main objective of neural network training as shown in Tables 5 and 6. The simplest and the most commonly used condition is to stop training to fix the maximum number of iterations (500) so that network should not over-train (i.e. to memorize data instead of generalizing and encoding

Table 3: Verified architecture for Model 1

[6-1-1] fitness: 0.010948
[6-15-1] fitness: 0.011149
[6-9-1] fitness: 0.010977
[6-5-1] fitness: 0.011208
[6-7-1] fitness: 0.010875
[6-3-1] fitness: 0.010433
[6-6-1] fitness: 0.011725
[6-6-1] architecture had the best fitness

Table 4: Verified architecture for Model 2

[7-1-1] fitness: 1.046393
[7-18-1] fitness: 1.105153
[7-11-1] fitness: 0.963219
[7-7-1] fitness: 0.999775
[7-4-1] fitness: 0.960999
[7-9-1] fitness: 0.973048
[7-5-1] fitness: 0.981003
[7-8-1] fitness: 1.118431
[7-8-1] architecture had the best fitness

Table 5: Summary of training for Model 1

Parameters	*Training*	*Validation*
Absolute error	102.97	104.21
Network error	0.02	0
Iteration	501	501
Training speed (iter/sec)	357.85	388
Architecture	(6-6-1)	
Training algorithm	Back propagation	
Training stop reason	All iteration done	

Table 6: Summary of training for Model 2

Parameters	*Training*	*Validation*
Absolute error	1.178	1.532
Network error	0.003	0
Iteration	501	501
Training speed (iter/sec)	227.72	297.56
Architecture	(7-3-1)	
Training algorithm	Back propagation	
Training stop reason	All iteration done	

Table 7: Testing results for Model 1

	Target	*Output*	*AE*	*ARE*
Mean	1855.09	1831.50	101.98	0.053
Std. deviation	271.36	241.49	59.98	0.031
Min	1148.00	1341.73	1.636	0.0001
Max	2666.00	2444.29	398.92	0.202
Correlation	R 0.912			
R-Squared	0.84			

Table 8: Testing results for Model 2

	Target	*Output*	*AE*	*ARE*
Mean	84.653	84.096	1.216	0.014
Std. deviation	14.39	13.88	1.964	0.028
Min	38	46.26	0.0003	0.000
Max	129	120.78	19.41	0.376
Correlation	R 0.988			
R-Squared	0.972			

data relationships). After the completion of training test, testing operation starts and testing results are shown as Tables 7 and 8.

Performance is measured in terms of average absolute error and correlation between actual and predicted BOD "R". For model 1, R is 0.912 and for model 2 value of R is 0.988. Model 2 shows quite good results.

ANN BOD Model 2 which predicts results at the outlet indicates a standard value of 100 mg/l of BOD for the CETP. But the effluent 15 times (Fig. 5) exceeds the standard value, stretched over a period of five years. For such periods wherein excessive BOD effluent is likely to be discharged, the operator needs to keep vigil, and precautionary measures should be taken. The evolved models were then used to prepare input importance tables, to delineate the contribution of load of individual industries into the CETP for possibly evolving a sustainable financial mechanism for charging individual industries as per their respective loads. From input importance tables (Figures 6 and 7), it is clear that Lilason brewery, Rajsons dairy and Bhopal incinerators are the prime contributors of BOD to the CETP.

Performance is also compared on the basis of two neural network (NN) algorithms, online back-propagation and Levenberg-Marquardt algorithm, using mean absolute error and correlation factor as

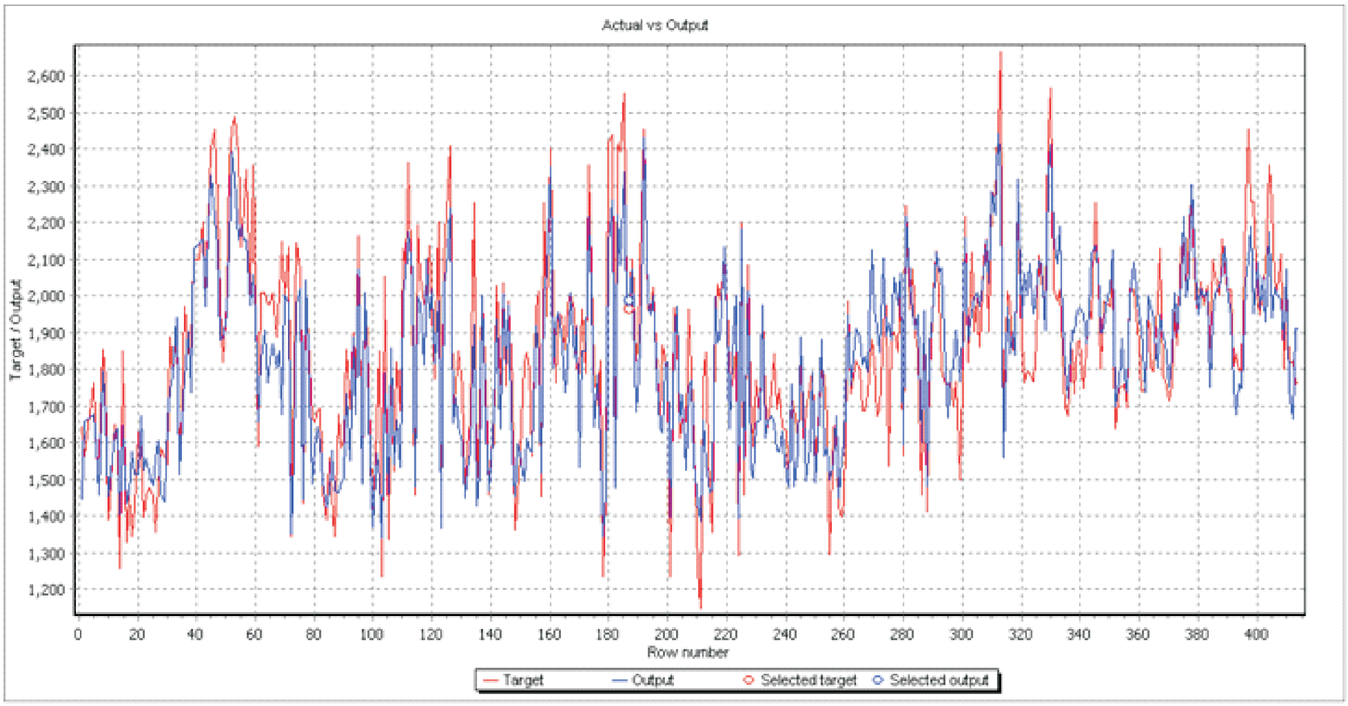

Figure 4: Graph between Actual versus Predicted BOD for Model 1.

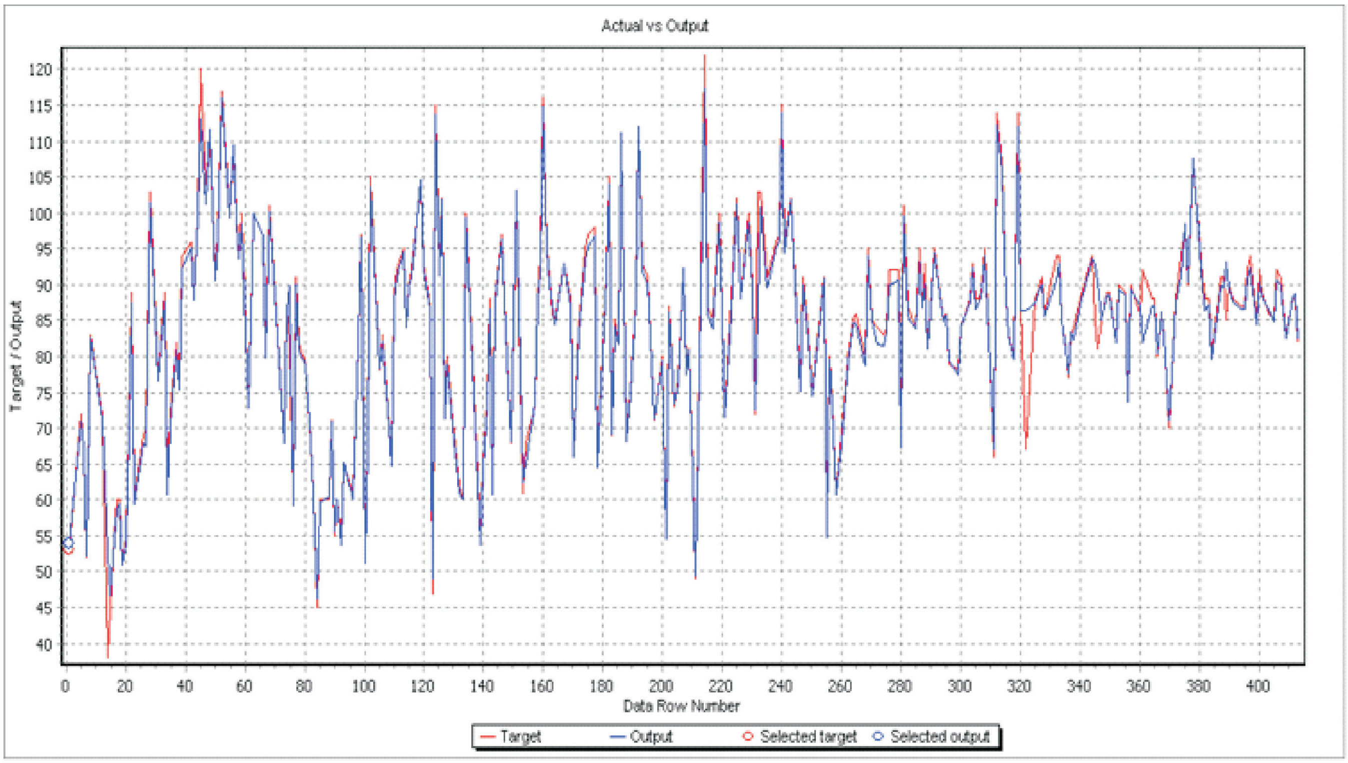

Figure 5: Graph between Actual versus Predicted BOD for Model 2.

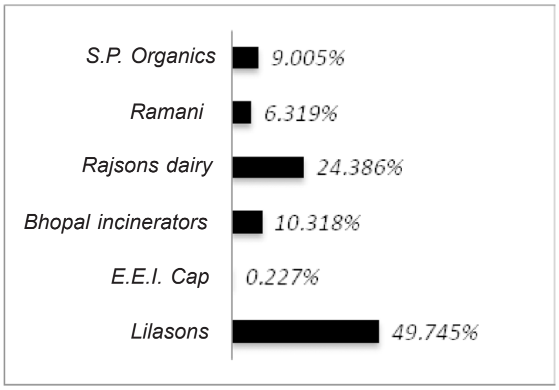

Figure 6: Input importance table for Model 1.

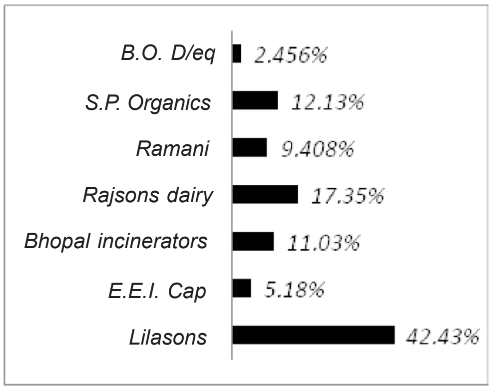

Figure 7: Input importance table for Model 2.

Table 9: Comparison of performance of Model 1 by Levenberg-Marquardt and back propagation algorithms

Architecture	*Training algorithm*	*Avg. test error*	*Correlation*	*R-squared*
(6-6-1)	Online-back propagation	97.58	0.912	0.84
(6-6-1)	Levenberg-Marquardt	98.54	0.903	0.82

Table 10: Comparison of performance of Model 2 by Levenberg-Marquardt and back propagation algorithms

Architecture	*Training algorithm*	*Avg. test error*	*Correlation*	*R-squared*
(7-3-1)	Online-back propagation	1.681	0.988	0.972
(7-3-1)	Levenberg-Marquardt	2.695	0.974	0.945

performance indicators as shown in Tables 9 and 10. The correlation coefficient for model 1 using online back propagation is 0.912 and by using LM is 0.903 and for model 2 it is 0.988 using online back propagation and 0.974 for LM. Also the mean absolute error (Test Set) is slightly more in case of LM than BPN. Thus, for this study results obtained by online back propagation are better than LM.

Conclusions

This paper approximates the BOD removal efficiency of a CETP using ANN by applying two different models. The developed BOD models predict the BOD at equalization tank and at outlet of the CETP. Following are the conclusions of the analysis:

1. Both ANN models have learnt very quickly and the training speed is quite high (> 200), which implies that the models are able to learn and map the relationships between inputs and output (effluent BOD) efficiently.
2. The major contributors in predicting BOD at equalization and at outlet have been identified using a sensitivity analysis or input importance table. This implies that the industry which has the largest contribution (Lilason Brewery) needs to be regulated to a greater extent by the authorities such as the Pollution Control Board, India which facilitate in implementing the "polluter pays principle (PPP)" through load-based licensing (LBL) to protect, maintain and improve the quality of water environment.
3. Here single hidden layer is fixed and then the number of nodes in each of these layers has been chosen according to fitness criteria, to create parsimonious ANN structure. It is evident that increasing the number of nodes does not increase the performance. Moreover smaller networks usually have better generalization ability, have higher processing speed, and can be implemented on hardware more easily. On the other hand, larger network over fits the training data with too many nodes.
4. In recent years, there has been a major focus in ANN research on the development of more efficient training algorithms. In the present study, two neural network (NN) algorithms—online back-propagation and Levenberg-Marquardt algorithm—

are compared according to their mean absolute error and correlation factor. LM have the ability to escape local minima in the error surface and thus produce optimal or near-optimal solutions but with a slow convergence rate. The training speed for model 1 using BPN is 357.85 itr/sec and by using LM, it is 52.5 itr/sec. Similarly for model 2 using BPN, training speed is 227.72 itr/sec and by using LM, it is 48.6 itr/sec. Thus if training speed is a major concern, there is no reason why the back propagation algorithm cannot be used successfully. It is also worth noting that feed forward networks trained with the back-propagation algorithm have already been used satisfactorily in many applications in water and waste water modelling.

Both models approximate BOD proficiently ($R > 0.9$) at equalization tank and at outlet of the CETP. Although at certain points effluent BOD exceeds the standard limit (Fig. 5), the incidents are predicted by the graph and timing of their occurrence can also be easily identified. For such periods wherein excessive BOD (above standard limit) is likely to be discharged, operator may take following precautionary measures:

1. Buffering in the equalization tank.
2. Asking the most polluting industry to discharge its effluent after a delay, if possible, and intermittently.
3. Making appropriate dilutions by mixing temporarily with water available in the plant.

The operation acting on any of these is likely to control the CETP performance to the desired levels needed as per the requisite standards. Thus neural network do not perform miracles. But if used sensibly they produce some amazing results which can be effectively used by policy makers, planners and plant operators.

References

Al-Asheh, S., Mjalliy, F.S. and H.E. Alfadalaz (2007). Forecasting influent-effluent treatment plant using time series analysis and artificial neural network wastewater techniques. *Chemical Product and Process Modeling*, **2(3):** 1-22.

Baxter, C.W., Stanley, S.J. and Q. Zhang (1999). Development of full scale artificial neural network model for the removal of natural organic matter by enhanced coagulation. *IWSA Journal of Water SRT-Aqua*, **48(4):** 129-136.

Bebis, G. and M. Georgiopoulos (1994). Feed-forward neural networks: Why network size is so important. *IEEE*, 27-31.

Boger, Z. and G. Hugo (1997). Knowledge extraction from ANN models. *IEEE*, 3030-3035.

Castellano, G., Fanelli, A.M. and M. Pelillo (1997). An iterative pruning algorithm for feedforward neural networks. *IEEE Transactions on Neural Networks*, **8(3):** 519-531.

Cheng, B. and D.M. Titterington (1994). Neural networks: A review from statistical perspectives. *Statistical Science*, **9(1):** 2-54.

Cicon Environment Technologies Ltd. (2009). Operation and Maintenance Manual for Common Effluent Treatment Plant at Govindpura Audhyogik Kshetra Pradushan Nivarana Ltd. Bhopal, India.

Common Effluent Treatment Plant: A Solution or a Problem in itself. *Toxics Link*, (November 2000). URL: http://www.toxicslink.org/docs/06038_CETP_Report.pdf (Retrieved on 6th October, 2009).

El-Din, A.G. and D.W. Smith (2002). A neural network model to predict the wastewater in flow incorporating rainfall events. *Water Research*, **36:** 1115-1126.

Gallant, S.I. (1993). Neural network learning and expert systems. MIT Press, Cambridge.

Hamoda, M. F., Al-Ghusain, I.A. and I. Hassan (1999). Integrated wastewater treatment plant performance evaluation using artificial neural networks. *Water Sci. Tech.*, **40(7):** 55-65.

Lachtermacher, G. and J.D. Fuller (1994). Back-propagation in hydrological time series forecasting. *Stochastic and Statistical Methods in Hydrology and Environ. Eng.*, **3:** 229-242.

Lawrence, S., Giles, C.L. and A.C. Tsoi (1996). What size neural network gives optimal generalization? Convergence properties of back-propagation. Technical Report UMIACS-TR-96 22 and CS-TR-3617. Institute for Advanced Computer Studies, University of Maryland, College Park, MD 20742.

Lee, B.W. and B.J. Shen (1991). Hardware annealing in electronic neural networks. *IEEE Transactions on Circuits and Systems*, **38:** 134-137.

Lee, D.S. and J.M. Park (1999). Neural network modeling for on-line estimation of nutrient dynamics in a sequentially operated batch reactor. *J. Biotechnol.*, **75:** 229-239.

Luccarini, L., Bragadin, G.L., Colombini, G., Mancini, M., Mello, P., Montali, M. and D. Sottara (2010). Formal verification of wastewater treatment processes using events detected from continuous signals by means of artificial neural networks. Case study: SBR plant. *Environ. Model. Soft.*, **25:** 648-660.

Maier, H.R. and G.C. Dandy (2001). Neural network based modelling of environmental variables: A systematic approach. *Mathematical and Computer Modelling*, **33:** 669-682.

Maier, H.R. and G.C. Dandy (1995). Comparison of the Box-jenkins procedure with ANN methods of univariate time series modeling. Res. Rep. R127, Dept. of Civil and Env. Eng., Univ. of Adelaide, Adelaide, Australia.

Maier, H.R. and G.C. Dandy (1998). The effect of internal parameters and geometry on the performance of back-propagation neural networks: An empirical study. *Environ. Model. Software*, **13:** 193-209.

Raha, D. (2007). Exploring artificial neural networks (ANN) modeling for a biological nutrient removal (BNR) sewage treatment plant (STP) to forecast effluent suspended solids. *Indian Institute of Chemical Engineers*, **49(3):** 205-220.

Ulku, S., Osman, N.U., Cuma, B. and O. Namık (2005). Modeling of SO_2 distribution in Istanbul using artificial neural networks. *Environmental Modeling and Assessment*, **10:** 135-142.

Yetilmezsoy, K. and Z. Sapci-Zengin (2007). Stochastic modeling applications for the prediction of COD removal efficiency of UASB reactors treating diluted real cotton textile wastewater. *Stochastic Environmental Research and Risk Assessment*, **23(1):** 13-26.

Calendar of Events

International Conference on Science and Environment (ICSE) Bangkok, Thailand
4th to 5th January 2015
Bangkok, Thailand
Website: http://icsethailand.blogspot.com/
Contact person: Dr. Lazarus
Organized by: ICSE Secretariat

2015 International Conference on Substantial Environmental Engineering and Renewable Energy (SEERE-15)
13th to 14th January 2015
Abu Dhabi, United Arab Emirates
Website: http://seere.org/
Contact person: Co-ordinator, SEERE-15

2015 International Conference on Environment and Renewable Energy (ICERE 2015)
8th to 9th February 2015
Rangoon, Myanmar
Website: http://www.icere.org/
Contact person: Mickie Gong
Organized by: CBEES

6th International Conference on Environmental Science and Development - ICESD 2015
14th to 15th February 2015
Amsterdam, Netherlands
Website: http://www.icesd.org/
Contact person: Issac Lee
Organized by: CBEES

48th International Conference on Stormwater and Urban Water Systems Modeling
25th to 26th February 2015
Toronto, Ontario, Canada
Website: http://www.chiwater.com/Training/Conferences/conferencetoronto.asp
Contact person: Mark Randall
Organized by: Computational Hydraulics International

Wastewater Innovation 2015
5th March 2015
London, United Kingdom
Website: http://marketforce.eu.com/events/water/wastewater-innovation-2015
Contact person: Haroon Ahzaz Ahmed

International Conference on Sustainable Energy and Built Environment
12th to 13th March 2015
Vellore, Tamilnadu, India
Website: http://www.asceis-ices.com/conference.php
Contact person: Dr. Ravibabu Mandla, Program Chair, Civil Engineering Dept., VIT University, ravi.mandla@vit.ac.in
Organized by: ASCEIS

18th International Water Technology Conference
12th to 14th March 2015
Sharm el Sheikh, Egypt
Website: http://iwtc.info
Contact person: Dr. Magdy Abou-Rayan