UTILIZATION OF ANNS FOR "MODELING THE MODEL" OF UASB

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ABSTRACT

The existence of strong non-linearity effects, time variant parameters and multivariable coupling don't enable the adoption of simple models to predict either the wastewater treatment processes efficiency or its effluent quality. Nowadays, an **A**rtificial **N**eural **N**etwork**s (ANNs)** is recognized as a very promising tool for relating input data to output data. Especially where processes are complex, the applications of ANNs are widespread and vary from process optimization for water and wastewater treatment, scenario evaluation, demand forecasting, on-line steering of wastewater treatment plants and sewage systems, resource optimization and management up to financial modeling.

Besides delineating the approach and methodology for the development of successful ANNs model of Waste Water Treatment **(WWT)** processes, the ability of ANNs to predict the quality (BOD_{out} and COD_{out}) of the raw domestic sewage effluent from **U**pflow **A**naerobic **S**ludge **B**lanket **(UASB)** model was verified in this paper. Using Matlab (version 6.5), various network architectures, differing in the number of hidden layers and nodes were tested in order to find the optimized solution in terms of both precision and learning time. The effectiveness of each ANN configuration was verified by **M**ean **A**bsolute **E**rror **(MAE)** method. Data for calibrating, testing, and verifying the developed ANN of UASB model was obtained from the operation of two identical pilot-scale models simulating UASB reactors that designed, constructed from PVC pipes, 200 mm diameter and 2500 mm height, and built at Kawmeya sewage pumping station, Zagazig, Egypt.

From the present study, it is found that even the simplest ANNs tested were able to correctly describe the BOD_{out} and COD_{out} of UASB. The best ANN architectures were (8-4-1) and (8-6-1) for prediction the effluent BOD and COD concentrations, respectively. By these well-trained ANNs, reasonable predictions of BOD_{out} and COD_{out} were obtained provided the input parameters were appropriately selected.

Keywords: Domestic wastewater, UASB, Artificial Neural Networks, Modeling.

INTRODUCTION

As anaerobic treatment of wastewater can be traced from the beginning of wastewater treatment itself, it is a popular choice for removing organic matter in domestic and industrial wastewater. One of the most popular anaerobic treatment techniques is the Upflow Anaerobic Sludge Blanket (UASB) process. Although the feasibility of the UASB reactor for sewage treatment has been successfully demonstrated in many tropical countries, experience with the application of the UASB in the Middle East countries however is still limited (Zeeman and Lettinga, 1999). Consequently, there is a need to develop methodologies enabling one to determine UASB reactor performance, not only for designing more efficient reactors but also for predicting the performance of existing reactors under various conditions of influent wastewater flows and characteristics.

Based on qualitative understanding of the UASB process gained over the years, several attempts have been made to develop mechanistic models for quantitative description of UASB reactor performance under various operation conditions (Bolle et al., 1986a, Bolle et al., 1986b, Wu and Hikey, 1997). These mechanistic models show some limitations due to their suffering from several shortcomings; namely: (1) the inability of the models to accurately represent the substrate availability to methanogenic microorganisms, (2) excessive simplification of biochemical dynamics in the reactor, and (3) simplistic consideration of the relationship between reactor performance, biomass retention, and specific gas production rates of methanogens and the role of sludge retention mechanisms. Consequently, none of the mechanistic models mentioned above are able to completely explain or predict the performance of UASB treating wastewater from industrial or domestic sources under various input conditions (Sinh et al., 2002).

In recent years, computer-based methods have been applied to many areas of environmental chemistry to overcome the changing and complex nature of the biological wastewater treatment processes due to variation in raw wastewater compositions, strengths and flow rates. Recently, some studies using Artificial Neural Networks (ANNs) in modeling biological wastewater treatment processes have been published, providing an alternative approach (Cote et al., 1995; Häck and Kohne, 1996; Gontarski et al., 2000; Hamoda et al., 1999; Lee and Park, 1999; Pu and Hung, 1995; Wilcox et al., 1995; Zhao et al., 1997). Thibault et al. (1990) described online prediction of the variables associated with the fermentation process using a neural network model. Wilcox et al. (1995) described neural network based bicarbonate monitoring to control anaerobic digestion. However, no publication directly dealing with the simulation of UASB reactor performance using neural network model exists (Sinh et al., 2002).

Given the scenario described above, development of an empirical model, e.g., a neural network model for predicting UASB reactor performance seems to be an attractive proposition. Furthermore, simulation studies using a validated empirical model and subsequent analysis of the simulation results may provide valuable information

regarding behavior of UASB reactor under a variety of conditions. This may result in deeper understanding of the UASB process and thus provide valuable input for "fine-tuning" of mechanistic models for UASB reactors.

Besides delineating the approach and methodology for the development of successful ANNs model of Waste Water Treatment **(WWT)** processes, this paper demonstrates the delineated methodology through the development of the model of BOD and COD removal through UASB. The trained ANN model determines either BOD or COD concentrations effluent from UASB has been targeted as well under certain conditions.

APPROACH OF THE ANNS MODELS OF WWT PROCESSES

Dynamic models of WWT processes can be divided into two main categories: linguistic models and mathematical. Linguistic models, such as expert systems, can relate cause to effect and they do not demand the construction of a mathematical model. Linguistic models are most suitable for describing phenomena in environmental systems that are very hard to represent by a mathematical model. The dynamics of algal populations, the clarification and thickening functions of the secondary clarifier, or the development of a bulking sludge are likely candidates (Beck 1989).

Mathematical models can take many forms. At one extreme, some models are highly mechanistic. These are most useful to the researcher seeking to understand the events occurring in a system. Generally such models are deterministic and incorporate direct links between inputs and outputs through ordinary and partial differential equations that seek to mimic reaction mechanisms. Although a mechanistic model, allows insight into the physical phenomena to be modeled, the many parameters in the model make its calibration a tedious job.

At the other extreme, some models are highly empirical, and they constitute the so-called "black box" class of models. These models can depict relatively complicated systems by identifying the relationships that exist between system inputs and outputs. Black-box models have the predictiveness and adaptiveness capabilities that are needed for a model to be used as part of a real-time control system. They are, however, highly system specific. As a result, they have to be developed specifically for the set of data under study, and hence, they are not easily transportable to new situations. Example of the class of black-box models is Artificial Neural Networks (ANNs).

ANNs go by many names, such as connectionist models and parallel distributed processing models. The ANN modeling approach is an artificial intelligence technique that attempts to simulate some important features of the human nervous system; in other words, the ability to solve problems by applying information gained from past experience to new problems or case scenarios. ANN ideas were developed in the 1950s went into decline in the 1960s, and only in the middle 1980s did their true potential become evident. A book credited with the renewed interest is Rumelhart and

McClelland's *Parallel Distributed Processing* (Rumelhart and McClelland 1986), which was published in 1987 and contains, among other things, the first well-known description of the back-propagation training algorithm.

Analogous to a human brain, an ANN uses many simple computational elements (named artificial neurons) connected by variable weights. Although each neuron, alone, can perform only simple computations, the hierarchical organization of a network of interconnected neurons, or architecture, makes an ANN capable of performing complex tasks such as pattern classification and prediction. Among the many different architectures, the multilayer perceptron architecture is commonly used for prediction, in which neurons are arranged in layers—an input layer, hidden layers, and an output layer. Figure 1 shows a schematic diagram of a multilayer ANN. Input neurons, or nodes, receive values of an instance of the input parameters that are fed to the network after being scaled into a numeric range that is efficient for calculations by the neural model. Outcomes to the output parameters for the instance under consideration are assigned by the output neurons. Hidden neurons connect the input neurons to the output neurons and provide nonlinearity to the network. Each neuron is connected to every neuron in adjacent layers by a connection weight, which determines the strength of the relationship between two connected neurons. The output from a neuron is multiplied by the connection weight before being introduced as input to the neuron in the next layer. Each neuron, except those in the input layer, sums all the inputs that it receives and the sum is converted to an output value according to a predefined activation, or transfer, function.

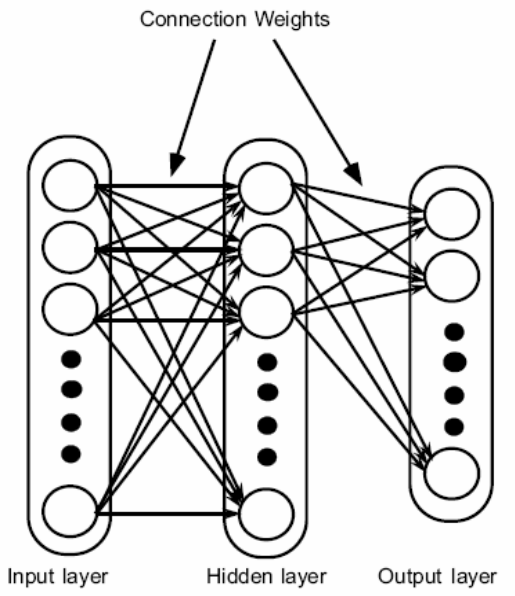

Figure (1): A schematic diagram of a multilayer neural network.

For prediction problems, a supervised learning algorithm is often utilized for teaching the network how to relate input data patterns to output data. The main reason for the popularity of the multilayer perceptron architecture in recent years is the development

of new training algorithms like the back-propagation algorithm. The algorithm requires a continuous differentiable nonlinearity to be used as the transfer function by the neurons. The back-propagation algorithm consists of the following steps: (1) all weights are assigned initial small random values; (2) input data are propagated in a feed-forward manner through the network to produce output data according to the weights and the transfer function; (3) the outputs produced are compared with the target outputs, which are known in advance; (4) the errors generated are then propagated backwards in a certain manner through the network for adjustments of the present weights using two factors, namely, a learning factor and a momentum factor; (5) this procedure is repeated for each training example in the training set; a cycle (an epoch) represents one pass over the whole training set; multiple epochs are required until a satisfactory data mapping is achieved. A mathematical description of the training algorithm is provided elsewhere (Rumelhart and McClelland 1986). The learning factor (ranges from 0 to 1) represents the step size by which the weights are updated and is problem specific. To speed convergence of the back-propagation algorithm a momentum factor (also ranges from 0 to 1) can sometimes be used. The idea is to keep weight changes on a faster and more even path by adding fractions of previous weight changes.

METHODOLOGY OF BUILDING ANNS MODELS OF WWT PROCESSES

To build effective ANN models of wastewater treatment processes, a sequential methodology consisting of four key stages is proposed. The relationship among each of the stages is depicted in Figure (2), while a description of each stage is outlined in the following subsections (Baxter et al., 2002).

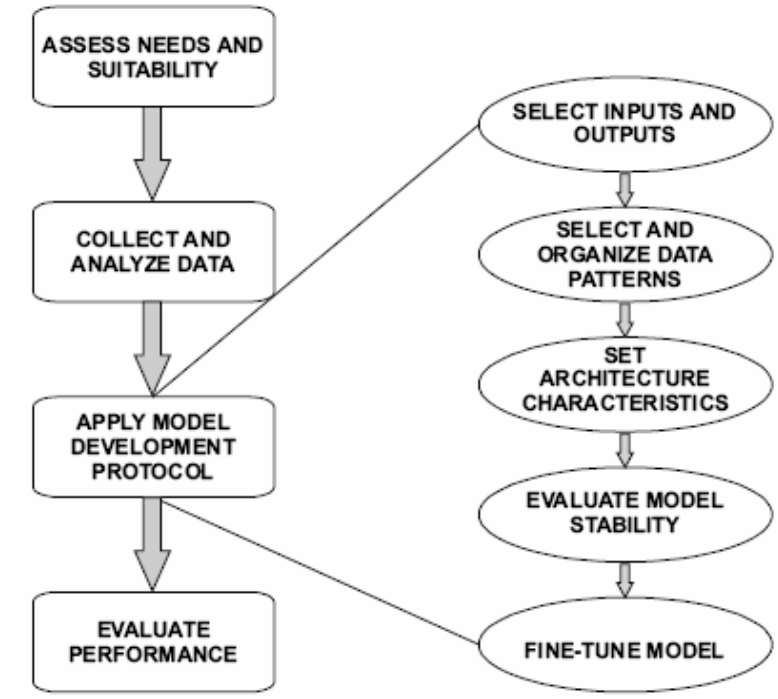

Figure (2): The main stages of developing an ANN process model.

1. Needs and suitability assessment

The first stage of successful ANN model development involves an assessment of the needs of the utility regarding the model and its applications, as well as the suitability of theANN technique for the problem at hand. With regards to the latter, specific data, software, hardware, and personnel requirements must be met to take advantage of the ANN technology. The key requirement of the ANN modeling approach is the availability of relevant data to describe the process being modeled. Data must be available in a useable digital format for each of the process input and output variables. The data used in model development must be representative of facility performance, spanning the range of operating conditions that may be encountered during both routine operations and process upset conditions.

2. Data collection and analysis

To develop successful ANN models, careful attention must be paid to the details of data collection and analysis. In collecting data, several factors need to be considered. First, the availability of the data must be ascertained. For data availability, the variables for which historical data exist, the time frame of historical measurements, and the frequency of data measurement must all be determined. The format and reliability of the data are also key considerations in data collection. Historical data can originate from grab-samples or real-time measurements, and measurements can be discrete or aggregated from a number of samples. The reliability of the available data should be ascertained through an examination of quality assurance and quality control protocols.

Once an appropriate historical data set has been selected, it should be fully characterized and subjected to a comprehensive statistical analysis. Data characterization involves a qualitative assessment of hourly, daily, and seasonal trends of each potential model variable. The statistical analysis involves the determination of measures of central tendency, measures of variation, and a percentile analysis, as well as the identification of outliers, erroneous entries, and non-entries for each data variable. In combination, the data characterization and statistical analysis help to identify the boundaries of the study domain as well as potential deficiencies in the data set.

3. Application of the model building protocol

Unfortunately, there is no widely accepted best method of developing ANN models. When all the possible options in building the ANN model architecture are considered, an almost infinite number of distinct architectures are possible. As such, each model developer may use a different protocol to reduce the number of architectures that are evaluated. What follows is a five-step protocol that found to be useful in developing wastewater treatment ANN process models, represented schematically in Figure (1).

(i) Selection of model inputs and outputs

The first step involved in the selection of model inputs and outputs is the selection of the model output(s). The output(s) are selected on the basis of operational needs, relevant literature, and data availability. Since ANN models train by minimizing the error between the predicted and actual values of model output variables, however, the technique yields better results when a single output is modeled. Where it is desirable to model more than one process output variable, separate models should be developed for each output to reduce overall prediction errors. Once the model output has been selected, model inputs are selected from the available variables. Input selection is based on the existence of a known or suspected relationship with the output variable, relevant literature, and data availability.

(ii) Selection and organization of data patterns

Once the model input and output variables have been identified, the modeling data sets can be constructed. Each data pattern or record should initially be examined for erroneous entries, outliers, and blank entries. Outlier detection involves a high degree of subjectivity. All values that are outside a range of ±2 standard deviations from the mean of a variable may be excluded from the data set, for example. Alternatively, scatter plots of each variable can be used to detect outlier values. Data patterns that contain questionable data should be removed, and a record of removed patterns kept for future reference and analysis.

The remaining data patterns must be divided into three data sets: the training set, the test set, and the production set. The training set is the largest set and is used to train the model. The test set serves as a semi-independent check on the progress of ANN learning. Without the test set, the model would simply memorize the interactions present in each of the training patterns and would not be able to provide accurate predictions on data from outside the training set. Most ANN software packages periodically process the test set through the model during training to ensure that memorization does not occur. The production set is used as an independent validation of the model following training. The trained model is applied to the production set data patterns, to which the model has not been exposed, and an assessment of the accuracy of prediction is made.

(iii) Determination of architecture characteristics

The determination of architecture characteristics is the step where the model architecture is actually built. Among the different architecture factors can be selected and varied are base architecture type, number of hidden layers, number of hidden layer neurons, type of scaling function, type of activation functions, initial range of weights between neurons, and the type of learning rule. The characteristics of each of these factors are discussed in great detail by Baxter (1998). Evaluating the best values for each of the many factors can take a considerable amount of time. On the basis of past modeling experiences, successful process models can be developed using a multilayer perceptron network with a single hidden layer, a linear scaling function in the input

layer, logistic activation functions in the hidden and output layers, random initial weight values, and the back-propagation learning rule (Stanley et al. 2000). This configuration is commonly referred to as a standard three-layer multiplayer perceptron ANN architecture.

(iv) Evaluation of model stability (cross-validation)

To ensure that the prediction performance of the candidate models is independent of the manner in which the data patterns were separated into the three data sets, the patterns in the three sets are redistributed. A simple way to achieve pattern redistribution is to move the first data pattern to the end of the data set after sorting in order of the value of the output variable and prior to assigning the patterns to one of the three modeling data sets. The candidate models are retrained on the new data sets and the results are compared to those of the candidate model. A significant increase in prediction error on the new production set is an indication of model instability. The best candidate models will have similar prediction errors when the data sets are redistributed. If model instability is detected, the data should be re-sorted into the three modeling data sets.

(v) Model fine-tuning

In determining the architecture characteristics, the number of hidden layer neurons is the only major factor that is evaluated. In model fine-tuning, a number of software-specific variables, such as the type of scaling and activation functions and the type of learning rule, can be altered in an attempt to achieve modest decreases in prediction error on the production set. Model fine-tuning is typically user specific and no protocols are known to exist. Some models do not improve during fine-tuning, and the improvement in those that do may not justify the time and effort required for this step. However, where a maximum tolerable prediction error has been mandated for the process being modeled, model fine-tuning can make the difference between acceptable and unacceptable prediction performance.

4. Performance evaluation

The model development protocol delineated above can lead to the development of several candidate models, each offering similar prediction capabilities. The best model is the one that meets the needs defined in the first stage while offering the smallest prediction errors. Prediction errors can be evaluated through a number of statistical and graphical methods. With respect to the former, both absolute and relative measures of error are often reported by the ANN modeling software, as are coefficients of correlation and determination. Graphical analyses of model results provide visual confirmation of model prediction ability. By plotting either the predicted values of the model output variable or the absolute prediction errors, along with the actual historical values, across all data patterns, periods of acceptable and unacceptable model performance can be identified. Such plots are particularly useful for identifying events where the largest prediction errors occurred.

DEVELOPMENT OF ANN MODELS OF UASB

1. UASB Reactor Performance Data

Data for calibrating and testing the developed ANN model of UASB was obtained from the work done by Saad El-Din, (2007) in which two identical pilot-scale models simulating UASB reactors are designed and constructed from PVC pipes, 200 mm diameter and 2500 mm height. The main features of the design and construction of the models are furnishing the model with the appropriate influent, effluent, and gas collection arrangements as well as the compatibility between the raw sewage and the reactor material. Each reactor has an effective volume of 66 L and is furnished with 6 sampling ports equipped with valves and spaced uniformly at 400 mm all-over its effective height.

The pilot-scale models were built at Kawmeya Sewage Pumping Station that receives sewage coming from a combined sewer system collecting the sewage originated from west bank zone of Zagazig city, Egypt. Using a submersible pump, raw sewage was left from the sump of the mentioned pumping station to a constant head holding feeding tank located above the level of the UASB models. The contents of the holding feeding tank were continuously gently mixed to homogenize the UASB models influent. From the bottom of that constant head holding feeding tank, the two UASB models were continuously fed, by gravity, under constant head. On the other hand, the models effluent was drained directly to the sump of the pumping station. Samples of the sewage influent to the model as well as from its effluent and sampling ports were collected and transported to the Environmental Engineering Department Laboratory, Faculty of Engineering, Zagazig University, Egypt to be characterized and/or analyzed according to American Standard Methods for Examination of Water and Wastewater (APHA, 1992).

The extensive experimental program designed and executed by Saad El-Din (2007) consisted of four experimental runs. In the first run, the effect of seeding sludge on the efficiency of UASB was assessed. Applying different hydraulic retention times; namely: 8, 10, 12, 16, and 20 hours in the second set determined the best hydraulic retention time of the raw domestic wastewater in the UASB to be directly treated. The third and fourth runs investigated the enhancement of mixing the seeding sludge with either kaolinite or montmorillonite at different mixing ratios. The utilized mixing ratios (clay to sludge - weight basis) were 0 %, 20%, 40 %, 60% and 80 %. In third and fourth runs, the hydraulic retention time, feeding rate, influent COD concentration, organic loading rate, and up-flow velocity have been kept constant at 12 h, 6.54 l/h, 739 mg COD/l, 1.23 kg COD/m3.d, and 0.175 m/h, respectively.

2. Developed ANN Model of UASB

The ANN model of UASB developed in this study following the building methodology of ANNs models described above shall delineated in this section. This ANN model has been trained such that applying a set of inputs produces the desired set of outputs. The input vector consisted of a set of eight variables including hydraulic retention time, type of clay, clay to sludge - weight basis - mixing ratio, BOD, COD, SS, DS and TS concentrations influent to the model. BOD and COD concentrations effluent from the model in the same sampling day were the specified output.

So, the structure of the trained ANNs in this study was (8-n-1). This structure means that the input variables were eight as mentioned before and the output variable was one (BOD_{out} or COD_{out}). The number of neurons in the hidden layer (n) was varying from 2 to 22 neurons. For each ANN structure, two functions; namely: tansig function and logsig function were used for both BOD_{out} and COD_{out} results as outputs. In this study, the structure of ANN ranged from (8-2-1) to (8-22-1) utilizing different transfer functions as described before. In addition to the structure of the network and the transfer function, the accuracy of learning and the number of learning cycles have been determined for the trained ANN.

2.1 Training of the Developed ANNs Model of UASB

Utilizing Matlab (version 6.5), a computer program has been developed and employed for training the ANN using the data obtained within the experimental program of the work done by Saad El-Din (2007) that included 130 sets of data collected from 130 sampling days and selected for training, validation and testing the proposed ANN. These data sets are the laboratory measurements of the input and output variables and/or parameters, specified above, in the last ten days of each the 13 runs included in the mentioned work. From these data sets and for the training process of the ANN, 109 data sets were used and divided into 80 data sets for training and 29 data sets for validation during the training process. The other 21 data sets were kept aside for network testing or verification.

The program utilized in the present study prepared the data to be suitable as inputs for ANN by scaling the data between 0 and 1. Up to the number of iterations specified to be 30, this program initiates each ANN and repeats it. In the training process, the ANN uses pairs of input and target values to create the weights of the transfer function and then calculates the error and modifies the weights. Using the data sets assigned for training (80 data sets), the ANN predicts the target for one of the validation data sets using the input values of these data sets (29 data sets) and compare it to the measured value. After completing the training and validation processes, the error is calculated and recorded for the first learning cycle. Then, these steps are repeated until the error achieves the determined accuracy or the number of learning cycles reaches the specified number when the learning accuracy can not be achieved. In this study the determined learning accuracy (goal) and number of learning cycles (epochs) were 10^{-2} and 300 respectively.

On the other hand, the program calculates the minimum **M**ean **A**bsolute **E**rror (**MAE**) and determines at which iteration it occurred. The MAE is calculated according to the following equation:

$$\textbf{MAE BOD} = \frac{\sum(\textbf{predicted BOD} - \textbf{measured BOD})}{\textbf{measured BOD}} \quad (1)$$

After that, the program changes the number of neuron in the hidden layer and initiates a new ANN following the same procedure described above until the minimum MAE is reached. Figures (3) and (4) show the yielded measured and predicted BOD_{out} and COD_{out} using UASB and ANN models utilizing all the experimental data sets. It is noticed that the predicted values of BOD_{out} or COD_{out} were closed to the measured values although there is a great variation in the measured values.

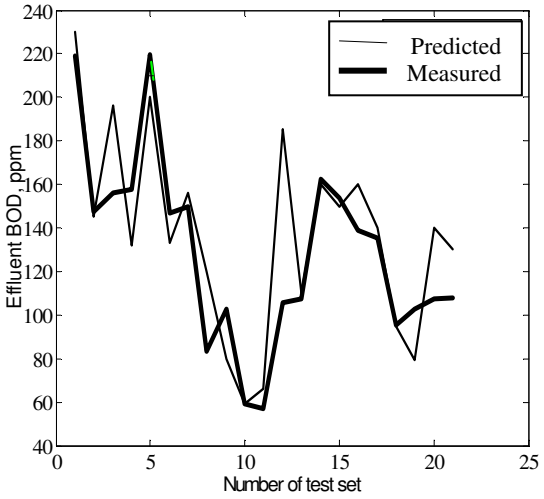

Figure (3): Measured and Predicted BOD_{out} using UASB and developed ANN Models

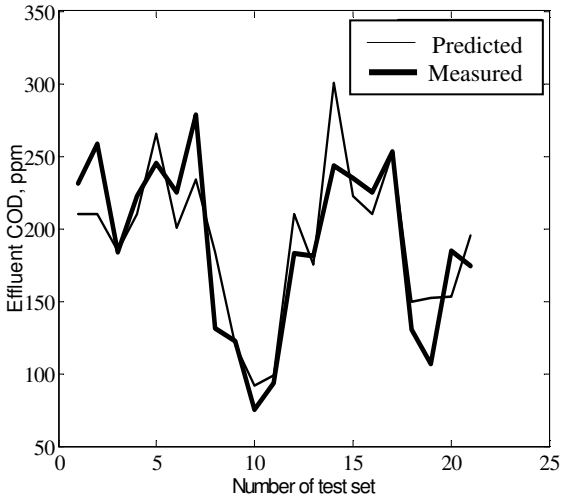

Figure (4): Measured and Predicted COD_{out} using UASB and developed ANN Models

2.2 Evaluation of the Trained ANN Model of UASB

For one of the trained networks, the learning accuracy was achieved at 38 epochs; therefore the training process was stopped. In another network, the minimum learning accuracy (goal) was 0.02625 after completing the determined number of learning cycles (300 epochs). It is found that the structure (8-4-1) has the lowest value (11.2753) of MAE of BOD_{out} at logsig function. On the other hand, the structure (8-6-1) has the lowest value (9.6589) of MAE of COD_{out} at tansig function. Therefore these networks structures (8-4-1) and (8-6-1) shall be utilized to predict the BOD_{out} and COD_{out} of UASB reactor knowing the values of the eight input variables mentioned in section 2.

Figure (5) illustrates the measured BOD_{out} versus the predicted BOD_{out} using the best trained neural network (8-4-1). On the other hand, figure (6) shows the measured COD_{out} versus the COD_{out} predicted using the best trained neural network structure (8-6-1).

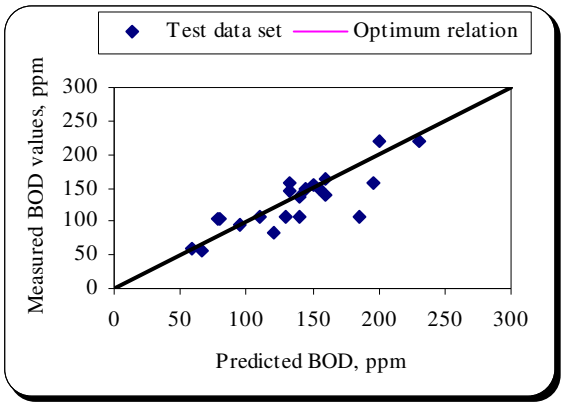

Figure (5): Measured vs. Predicted values of BOD_{out} applying 8-4-1 Structured ANN

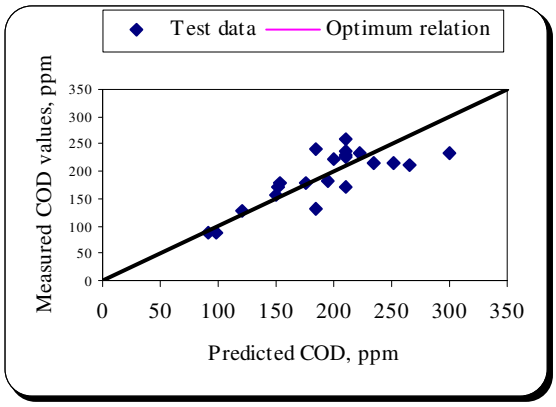

Figure (6): Measured vs. Predicted values of COD_{out} applying 8-6-1 Structured ANN

It is noticed from these figures that the deviation of the predicted BOD_{out} and COD_{out} values using networks structures (8-4-1) and (8-6-1) was relatively low which means that the selected trained network may be used to predict the BOD_{out} and COD_{out} of UASB reactor utilizing different values of the mentioned eight input variables.

3. Verification and Using the Trained ANNs

To verify the best trained network in this study [(8-4-1) for BOD_{out} and (8-6-1) for COD_{out}], 13 data sets were selected from the different experimental runs. These sets represent different operating conditions and influent wastewater characteristics. Also, these sets were not used in training or testing the networks. The values of input variables were feed to the trained networks and they predict the output values (BOD_{out} or COD_{out}) by importing the stored weights of these networks.

Depending on these input values and the stored weights; the best trained network predicted the output value. After that the predicted BOD_{out} or COD_{out} values were compared with the corresponding measured values. This comparison determines the efficiency of this program as illustrated in the print out shown in figures 7 and 8. From these figures, it is obvious that the predicted values of either BOD_{out} or COD_{out} are close to the corresponding measured values.

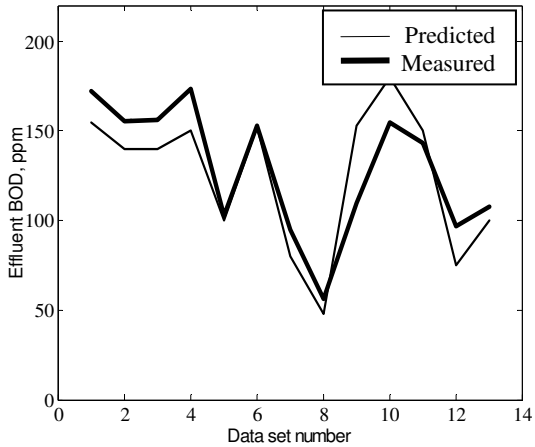

Figure (7): Measured and Predicted BOD_{out} using UASB and ANN Models utilizing the verification data sets

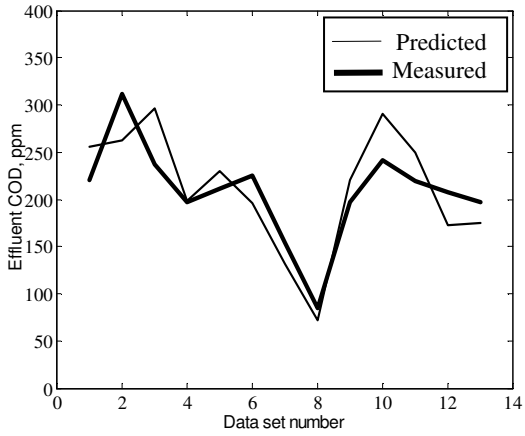

Figure (8): Measured and Predicted COD_{out} using UASB and ANN Models utilizing the verification data sets

CONCLUSIONS AND RECOMMENDATIONS

Based on the results obtained from the ANNs trained within the scope of this paper and limited to the architecture of the ANNs that had been trained, it is found that The ANN-based models provide an efficient and a robust tool in predicting UASB performance. Also, it is found that after training, the ANN-based models were able to generalize very well when tested against an unseen set of data. This confirms that the ANN-based models can be identified without a detailed knowledge of the kinetics of the system to be modeled. In other words, compared to statistical methods, ANNs do provide a more general framework for determining relationships between data and do not require the specification of any functional form.

However, the two specific conclusions regarding the ANN-based modeling the UASB directly treats raw sewage in Egypt; namely: (1) 8-4-1 ANN is the best ANN-based model for predicting the UASB effluent BOD and (2) 8-6-1 ANN is the best ANN-based model for predicting the UASB effluent COD may be drawn.

Although the present work showed the advantage of ANN-based models in their ability to represent highly non linear relationships, even for a system that presents operational data limitations (imprecision associated with measured variables, a limited range of variables, a large number of missing values, etc.), further research is still recommended to assure the predictiveness (i.e., capability of forecasting changes before they occur) and adaptiveness (i.e., capability of adjusting to changes both in the input and in the status of the system itself i.e., variation of the parameters characterizing the processes) of ANN-based models.

REFERENCES

1. Baxter, W., (1998): Full-scale artificial neural network modeling of enhanced coagulation. M. Sc. Thesis, University of Alberta, Edmonton, Alta. 151p.
2. Baxter, W., Stanley, J., Zhang, Q., and Smith, W., (2002): Developing artificial neural network models of water treatment processes: a guide for utilities. J. Environ. Eng. Sci. 1: 201-211.
3. Beck, B., (1989): System identification and control. Dynamic modeling and expert systems in wastewater engineering. Edited by G. Party and D. Chapman. Lewis publishers, Boca Raton, Fla., USA 450p.
4. Bolle WL, van Breugel J, van Eybergen GC, Kossen NWF, Van Gils W. (1986b): An Integral Dynamic Model for the UASB Reactor. Biotechnol Bioeng 27, 1621-1636.
5. Bolle, W.L., van Breugel, J., van Eybergen, G.C., Kossen, N.W.F, Zoetemeyer, R.J. (1986a): Modeling Liquid Flow in Upflow Anaerobic Sludge Blanket Reactors. Biotechnol Bioeng 28, 1615-1620.
6. Cote, M., Grandijean, B. P. A., Lessard, P., Yhibault, J. (1995): Dynamic modeling of the activated sludge process: improving prediction using neural networks. Water Research, 29 (4), 995.
7. Gontarski, C. A., Rodrigues, P. R., Mori, M., Prenem, L. F. (2000): Simulation of an industrial wastewater treatment plant using artificial neural networks. Comput. Chem. Eng., 24, 1719.
8. Häck, M., Köhne, M. (1996). Estimation of wastewater process parameters using neural networks. Water Sci. Technol., 33 (1), 101.
9. Hamoda, M. F., Al-Ghusain, I. A., Hassan, A. H. (1999): Integrated wastewater treatment plant performance evaluation using artificial neural networks. Water Sci. Tech., 40 (7), 55.
10. Lee, D. S., Park, J. M. (1999). Neural network modeling for on-line estimation of nutrient dynamics in a sequentially-operated batch reactor. Journal of Biotechnology, 75, 229.
11. Pu, H., and Hung, Y. (1995): Use of artificial neural networks: Predicting trickling filter performance in a municipal wastewater treatment plant. Envir. Manag. Health, 6 (2), 16.
12. Rumelhart, E., and McClelland, L., (1986): Parallel distributed processing: explorations in the microstructure of cognition. The MIT Press, Cambridge, Mass., USA.
13. Saad El-Din, D., (2007): A study on the treatment of municipal wastewater in small communities using anaerobic process. Dissertation submitted in partial fulfillment for the requirements of Ph. D. in Environmental Engineering, Zagazig University, Egypt.
14. Sinha, S., Bose, P., Jawed, M., and John, S., (2002): Application of Neural Network for Simulation of Upflow Anaerobic Sludge Blanket (UASB) Reactor Performance.
15. Standard Methods for Examination of Water and Wastewater. 18th ed. APHA, AWWA, WEF; 1992.

16. Stanley, J., Baxter, W., Zhang, Q., and Shariff, R., (2000): Process modeling and control of enhanced coagulation. American Water Works Association Research Foundation and American Water Works Association, Enever, Colo. 167p.
17. Thibault J., Breusegem V., Cheruy A., (1990): On-line Prediction of fermentation variable using Neural Networks. Biotechnical Bioeng. 36: 1041-1048.
18. Wilcox, S. J., Hawkes, D. L., Hawkes, F. R., Guwy, A. J. (1995): A neural network, based on bicarbonate monitoring, to control anaerobic digestion. Water Research, 29 (6), 1465.
19. Wu MM, Hickey RF. (1997): Dynamic Model for UASB Reactor including Reactor Hydraulics, Reaction, and Diffusion. Journal Environ. Eng. 123: 244-252.
20. Zeeman G. and Lettinga G. (1999): The Role of Anaerobic Digestion in Closing the Water and Nutrient Cycle at Community Level. Water Sci. Tech. Vol. 39, No. 5, 187-194.
21. Zhao, H., Hao, O. I., Fellow, A. S. C. E., McAvoy, T. J., and Chang, C. H. (1997): Modeling nutrient dynamics in sequencing batch reactor. Journal of Environ. Eng., 123 (4), 863.