The Using Artificial Neural Network to Estimate of Chemical Oxygen Demand

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***Abstract*—**Nowadays, the increase of human population every year results in increasing of water usage and demand. Saen Saep canal is important canal in Bangkok. The main objective of this study is using Artificial Neural Network (ANN) model to estimate the Chemical Oxygen Demand (COD) on data from 11 sampling sites. The data is obtained from the Department of Drainage and Sewerage, Bangkok Metropolitan Administration, during 2007-2011. The twelve parameters of water quality are used as the input of the models. These water quality indices affect the COD. The experimental results indicate that the ANN model provides a high correlation coefficient (R=0.89).

***Keywords*—**Artificial neural network, chemical oxygen demand, estimate, surface water.

I. Introduction

CHEMICAL Oxygen Demand (COD) is the amount of oxygen used to oxidize chemical substances through chemical processes [1] and concerned water quality index in surface water [2]. Water with high COD is shown that compose with high organics substance and this high COD value is infer to unclean water. The analysis of the COD value that takes a short time in average 3 hours and suitable for used in waste water treatments because can be used this value to analyze and solve problem in time. COD) is will greater than Biochemical Oxygen Demand (BOD) value always in the same water source.

Modeling of water resource variables is a very active field of study and there have been still a lot of researches to be done in this area. In the initial stages, modeling of water resource variables was done using the traditional statistical models. In recent years, modern techniques have been proposed as efficient modeling tools. Artificial Neural Networks (ANNs) are a branch of Artificial Intelligence (AI), in which 'connectionist' paradigms are used to extract and store implicit knowledge embedded in the data [3]. The idea of developing ANNs was inspired from biological nervous system in human brain, with the ability to organize its neurons and learn through 'experience' [1]. In recent years, Artificial Neural Network (ANN) methods have become increasingly popular for prediction and forecasting in a number of disciplines, including water resources and environmental science. ANNs are developed through the use of computer software to recognize the patterns of the data by [1] a set of known processes or simple mathematical formula through supervised learning [4]. Many modeling studies have been carried out to compute [5] COD concentration in river, and canals. ANNs have been vastly used for the past few years in many area of research, including bioinformatics, image analysis, speech recognition and financial forecasting. The structures of ANNs are composed of nodes interconnected with each other which represent relationship between each node. The number of nodes is determined and variables can be adjusted chosen to build neural model. The outcomes of the model are based on the nodes, hidden layer and variables chosen for the model [1]. The main purpose of this study is to analyze the performances of neural network (NN) models in estimating of COD of Saen Saep canals in Bangkok.

This paper is organized as follows: Section II describes the data and area used in the experiments. Section III contains the methodology in the experiments. The experiment and results are shown in Section IV. Finally, Section V concludes the paper.

II. Data and Site Description

Saen Saep canal consists of 11 sampling sites. This network of canal is important for the daily life of the people in Bangkok. This canal is used for consumption, transportation and recreation. Therefore, the rapid growths of industry, condominiums, high-rise and low-rise buildings, and other infrastructures, have had a significant effect on the canal water quality [10]. COD is an important parameter for the condition of surface waters. The estimation COD results can be utilized in water management and treatment systems.

In this study, water quality data are provided by the Department of Drainage and Sewerage, Bangkok Metropolitan Administration, during 2007-2011. There are 523 records of data. Each record consists of 13 parameters, namely: temperature, pH value (pH), Hydrogen Sulfide (H2S), Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Suspended Solids (SS), Total Kjeldahl Nitrogen (TKN), Ammonia Nitrogen (NH3N), Nitrite Nitrogen (NO2N), Nitrate Nitrogen (NO3N), total Phosphorous (T-P), total coliform and Chemical Oxygen Demand (COD). Table I shows unit of surface water quality parameters [12]. Reviewing 43 research papers in which neural networks were utilized for prediction and forecasting of water resources variables. They observed that network models always work well. Their usages in the study of water are growing due to their ability to handle large amounts of non-linear, non-parametric data.

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TABLE I
LIST OF SURFACE WATER QUALITY PARAMETERS

Name of Parameters	Unit of measurement
Temperature	Celsius
pH value	Standard Units
Hydrogen Sulfide	Milligrams per liter
Dissolved Oxygen	Milligrams per liter
Biochemical Oxygen Demand	Milligrams per liter
Chemical Oxygen Demand	Milligrams per liter
Substance Solid	Milligrams per liter
Total Kjeldahl Nitrogen	Milligrams per liter
Ammonia Nitrogen	Milligrams per liter
Nitrite Nitrogen	Milligrams per liter
Nitrate Nitrogen	Milligrams per liter
Total Phosphorous	Milligrams per liter
Total Coliform	Most Probable Number per 100 Milliliter

III. METHODOLOGY

Artificial neural network and measure of performance are described in this section.

A. Artificial Neural Network

ANNs are sensitive to the composition of the training data set and to the initial network parameters [3], it comprised of three independent layers, the input layers, where the data introduce to the ANN, the hidden layers, where data are processed that can be either multiple layers or a single layer, and output layers, where the result of ANN are produced [6]. Each layer consists of several processing neurons. Each neuron in a layer operates in logical similarity. Information is transmitted from one layer to others in serial operations. The most widely used training algorithm for neural networks is the back propagation algorithm [7].

Fig. 1 shows the architecture of a multilayer perceptron network. Fig. 1 shows the architecture of a multilayer perceptron network. The multilayer perceptron (MLP) is an example of an artificial neural network that is used extensively to solve a number of different problems, including pattern recognition and interpolation [8], [9] that feed the input data to the neural layer to produce desire output [1]. Each layer is composed of neurons. In each neuron, a specific mathematical function called the activation function accepts input from previous layers and generates output for the next layer. Each layer is interconnected with each other by weights. In the experiment, the activation function used is the hyperbolic tangent sigmoid transfer function [11] which is defined as in (1):

$$f(s) = \frac{1-e^{-2s}}{1+e^{-2s}} \tag{1}$$

where $s = \sum_{i=0}^{n} w_i x_i + b$, in which w_i are weights, x_i are inputs of neuron, b is bias and n is the number of variables.

The MLP is trained using the Levenberg–Marquardt technique as this technique is more powerful than the conventional gradient descent techniques [8].

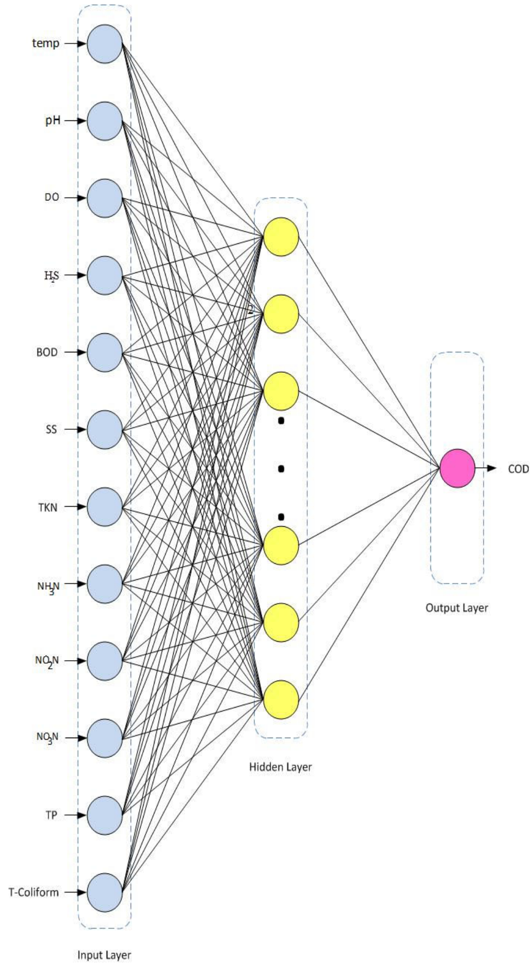

Fig. 1 The architecture of a multilayer perceptron

B. Measurement of Performance

The performance of model was evaluated by calculating the following statistical parameters: correlation coefficient (R) and root mean square error (RMSE) defined by (2) and (3), respectively.

$$R = \frac{\sum (Q_o - M_o)(Q_p - M_p)}{\sqrt{\sum (Q_o - M_o)^2 \sum (Q_p - M_p)^2}} \tag{2}$$

$$RMSE = \sqrt{\frac{1}{n} \sum (Q_o - Q_p)^2} \tag{3}$$

where Q_o and Q_p are the observed and estimated concentrations at the time step, M_o and M_p are the mean of the observed and estimated concentrations respectively, and N is the total number of observations of the data set.

IV. EXPERIMENT AND RESULTS

This section discusses data preprocessing, experimental data and neural network model.

A. Data Preprocessing

At the initial stage of the experiment, data were scaled or normalized to within the range 0.1-0.9 using following (4):

$$x_{new} = 0.8\frac{x - x_{\min}}{x_{\max} - x_{\min}} + 0.1 \qquad (4)$$

where x_{new} is the normalized value of a original parameter, x is the original data point, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the data set, respectively. This normalized form [6] is chosen because it tends to provide a better outcome on the water quality application obtained from available data series includes all of the extreme events. The test set should consist of a representative data set. The test set should be approximately 10-40% of the size of the training set of data.

B. Neural Network Model

The ratio of training to test data records employed in the experiment is 70:30. This means that with 523 data records, there are 367 records for the training set and 156 records for the test set. The Levenberg-Marquardt algorithm uses input vectors and corresponding target vectors to train the neural networks. The number of hidden units directly affects the performance of the network. Therefore, many experimental investigations are conducted. The number of hidden nodes determined to provide the optimal result is 10.

Finally, the architecture of the network is 12-10-1. The number of input nodes is 12, representing the parameters of water quality that affect COD. The number of the hidden nodes is set to 10. The number of output nodes is 1, representing COD.

The stopping criteria for the training are: MSE below 0.01 or a number of epochs greater than 10000. Fig. 2 shows the plot comparing the observed (actual) values of COD with the estimated COD from the network. The correlation coefficient, which measures the strength and direction of the linear relation between two variables (actual and predicted values) is R=0.89. The root mean square error (RMSE) of the model is equal to 15.16.

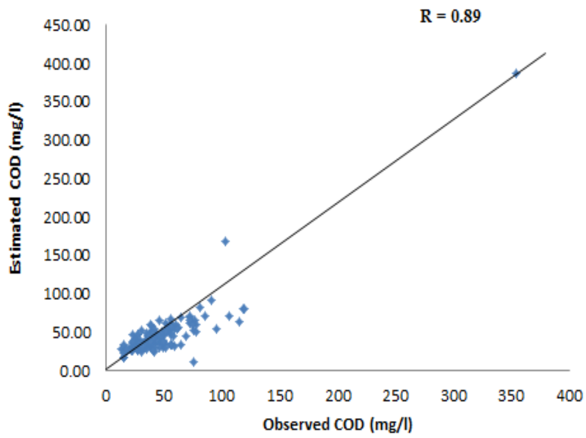

Fig. 2 Scatter plot between observed and estimated COD values using the ANN model

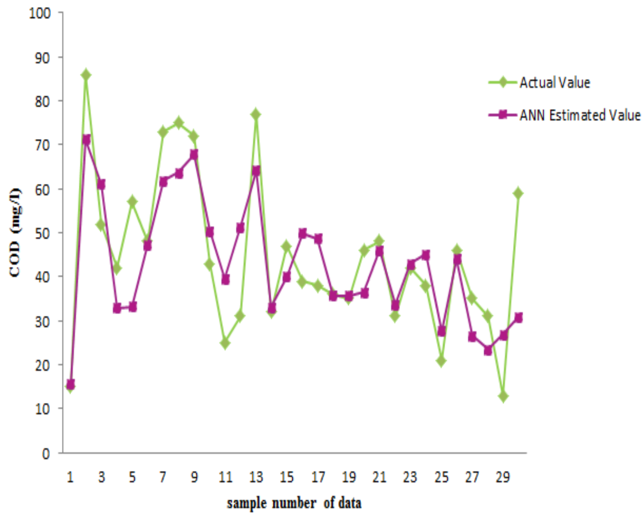

Fig. 3 Comparison of actual COD value and estimated COD value from the network on select sample points

Fig. 3 demonstrates the sample points of actual COD values compared with the estimated value from the neural network. The graph illustrates that estimated values from the artificial neural network is close to the COD actual value.

V. Conclusion

In this paper, we used artificial neural network model for the estimation of COD in Saen Saep canals, Bangkok. The results showed that the neural network model provided high correlation coefficients (R=0.89) and root mean square error (RMSE= 15.16). COD is mostly concerned water quality index in wastewater treatment plants, which is the sum of carbonaceous components, and it is also a key factor in environmental protection. Since COD is an important index for super-nutrition canals, it is one of the remarkable indexes for the water quality of canals. These results indicated that the ANN predicted COD values were closer to observed COD which reduce expense and time to analyst COD for water quality management.

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