International Journal of Earth, Energy and Environmental Sciences
ISSN: 2517-942X
Vol:6, No:9, 2012

Application of Artificial Neural Network to Classification Surface Water Quality

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***Abstract*—**Water quality is a subject of ongoing concern. Deterioration of water quality has initiated serious management efforts in many countries. This study endeavors to automatically classify water quality. The water quality classes are evaluated using 6 factor indices. These factors are pH value (pH), Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD), Nitrate Nitrogen (NO_3N), Ammonia Nitrogen (NH_3N) and Total Coliform (T-Coliform). The methodology involves applying data mining techniques using multilayer perceptron (MLP) neural network models. The data consisted of 11 sites of canals in Dusit district in Bangkok, Thailand. The data is obtained from the Department of Drainage and Sewerage Bangkok Metropolitan Administration during 2007-2011. The results of multilayer perceptron neural network exhibit a high accuracy multilayer perception rate at 96.52% in classifying the water quality of Dusit district canal in Bangkok Subsequently, this encouraging result could be applied with plan and management source of water quality.

***Keywords*—**artificial neural network, classification, surface water quality

I. Introduction

SURFACE water contamination from agricultural and urban runoff and wastewater discharges from industrial and municipal activities is of major concern to people worldwide. Classical models can be insufficient to visualize the result because the water quality variables used to describe dynamic pollution sources are complex, multivariable, and nonlinearly related. Artificial intelligence techniques with the ability to analyses multivariate water quality data by means of a sophisticated visualization capacity can offer an alternative to current models [1].

The aim of this investigation is to find an automated methodology that can quickly and efficiently classify the water quality of canals in Dusit district, Bangkok. Recently, several machine learning algorithms have been used to find patterns to classify water quality such as decision tree and artificial neural networks (ANNs). Classification and regression tree (CART) is a type of decision tree methodology. Classification and regression tree have the advantage of expressing regularities explicitly and thus being convenience to inspect for water quality validity [2].

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Artificial Neural Networks have become the central focus of many scientific disciplines, such as ecology [3], analytical chemistry [4], and water quality. Literature on modeling water quality using ANNs includes [5], [6], [7], [8]. In this study, using multilayer perceptron neural network to find efficiently model classify water quality of canals in Bangkok.

This paper is organized as follows: Section II describes the related work concerned this research. Section 3 describes the materials used in the experiments. Section 4 demonstrated the methodologies used in the experiments. The experiments and results are shown in Section 5. Finally, Section 6 concludes the paper.

II. Related Work

A relatively new concept in river water flow and quality modeling, the use of these ANNs allow non-linear relationships between variables to be ‘learnt’ through repeated presentation of input-output data sets. The ANN technique is well suited to model complex problems where the relationship between the model variables (input-output) is unknown [26], [27]. Applications of ANNs to various aspects of environmental modeling are widely reported in the literature. However, although ANNs have already been shown to produce models that perform well with respect to conventional models [28], [29], [30], [31], [32], [33], [34] their application is still restricted to the research in environment.

In recent years, modern techniques have been proposed as efficient modeling tools. Hence, there is always an attempt to investigate the most efficient technique for a particular application. Gamal El-Din [23] applied Artificial Neural Networks (ANNs) to model wastewater treatment processes. This was a comparative study between conventional deterministic models and ANNs. They observed, in addition to the information contained in the conventional models, that neural networks contained a great deal of extra information with regard to the system being modeled. S.Areerachakul et al. [12] analyzed and compared the performances of neural network (NN) with Classification and regression trees (CART) models in classify water quality of canals in Bangkok. Jain [24] employed neural networks to model the short-term water demand at the Indian Institute of Technology (IIT), Kanpur, India. Six network models, five regression models and two time series models were developed and compared. All of the network models, generally, displayed better performance when measured against other models. Maier [25] conducted a study 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.

III. Materials

Data and surface water quality standard are described in this section.

A. Data and Site description

Dusit district is one district of Bangkok which comprised of 11 sites of canals. This network of canals is important for the daily life of the people in Bangkok. Bangkok is the capital city, as well as, the economic center of Thailand. Its activities, which include commercial, industrial and service have caused the expansion of the city and its population to accumulate environmental pollution to the point that nature cannot cope with the pollution loading; especially for water quality [9]. The understanding of different levels of water quality can be utilized in water management and treatment systems.

In this study, water quality data are provided by Department of Drainage and Sewerage Bangkok Metropolitan Administration during 2007-2011. There are 385 records of data. Each record consists of 6 parameters namely; pH value (pH), Dissolved Oxygen (DO), Biochemical Oxygen Demand(BOD),Nitrate Nitrogen (NO_3N), Ammonia Nitrogen (NH_3N) and Total Coliform (T-Coliform). The classifications of canal water quality are based on surface water standards [10].The lower the number of class, the better the quality of water quality.

B. Suface Water Quality Standards

Many parameters can influence the surface water quality. Six parameters are selected for the investigations.

In Thailand, the surface water quality can be classified as in Table 1 [11]. Generally, surface water quality can be divided into five classes; class I , extra clean fresh surface water resources use for conservation that are not necessary to pass through water treatment processes and require only ordinary processes for pathogenic destruction and ecosystem conservation where basic organisms can breed naturally; class II, very clean fresh surface water resources use for consumption that require ordinary water treatment processes before use by aquatic organisms in conservation, fisheries and recreation; class III, medium clean fresh surface water resources use for consumption, but are passed through an ordinary treatment process before use; class IV, fairly clean fresh surface water resources use for consumption, but requires special water treatment processes before use; and class V, the sources which are not within class I to class IV and are used for navigation[12].

TABLE I
SURFACE WATER QUALITY STANDARDS

Pollutants Index	Class				
	I	II	III	IV	V
pH (mg/l)	<5	5-9	5-9	5-9	>9
DO (mg/l)	>6	6	4	2	<2
BOD (mg/l)	<1.5	1.5	2	4	>4
NO_3N (mg/l)	<5	5	5	5	>5
NH_3N (mg/l)	<0.5	0.5	0.5	0.5	>0.5
T-Coliform (MPN)	<50	50	200	>200	>200

IV. Methodology

In this section, we demonstrated Multilayer perceptron neural network

A. Multilayer perceptron Network

The artificial neural network (ANN) or neural network in short, is inspired by simulating the function of a human brain. A neural network can be used to represent a nonlinear mapping between input and output vectors. Neural networks are among the popular signal-processing technologies. In 0engineering, neural networks serve two important functions: as pattern classifiers and as nonlinear adaptive filters [13], [14]. A general network consists of a layered architecture, an input layer, one or more hidden layers and an output layer [15].Fig.1 shows a typical 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 [16], [17]. Each layer is composed of neurons, which are interconnected with each other by weights. In each neuron, a specific mathematical function called the activation function accepts input from previous layers and generates output for the next layer. In the experiment, the activation function used is the hyperbolic tangent sigmoid transfer function [18] which is defined as in equation (1):

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

where $s_i = \sum_{i=1}^{n} w_i x_i$, in which w_i are weights and x_i are input values.

The MLP is trained using the Levenberg–Marquardt technique as this technique is more powerful than the conventional gradient descent techniques [16].

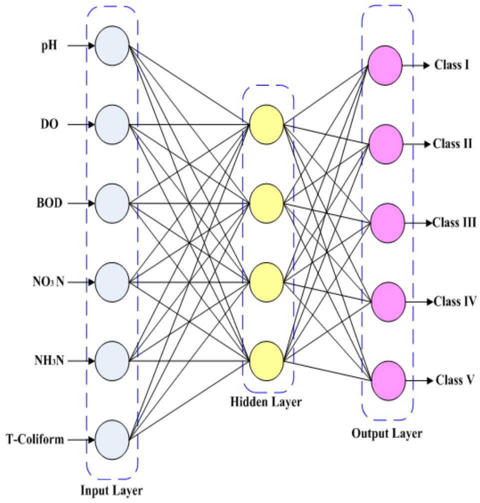

Fig. 1 A typical Multilayer Perceptron ANN Architecture

The Levenberg-Marquardt (LM) algorithm [19] is the most widely used optimization algorithm. It outperforms simple gradient descent and other conjugate gradient methods in a wide variety of problems. If a function $V(x)$ is to be minimized with respect to the parameter vector $\underline{x}$, then Newton's method would be:

$$\Delta\underline{x} = -[\nabla^2 v(\underline{x})]^{-1}\nabla v(\underline{x}) \tag{2}$$

where $\nabla^2 v(\underline{x})$ is the Hessian matrix and $\nabla v(\underline{x})$ is the gradient. If $v(\underline{x})$ reads:

$$v(\underline{x}) = \sum_{i=1}^{N} e_i^2(x) \tag{3}$$

then it can be shown that:

$$\nabla v(\underline{x}) = J^T(\underline{x})\underline{e}(\underline{x}) \tag{4}$$

$$\nabla^2 v(\underline{x}) = J^T(\underline{x})J(\underline{x}) + S(\underline{x}) \tag{5}$$

where $J(x)$ is the Jacobian matrix

$$J(x) = \begin{bmatrix} \frac{\partial_{e1}(\underline{x})}{\partial x_1} & \frac{\partial_{e1}(\underline{x})}{\partial x_2} & \cdots & \frac{\partial_{e1}(\underline{x})}{\partial x_N} \\ \frac{\partial_{e2}(\underline{x})}{\partial x_1} & \frac{\partial_{e2}(\underline{x})}{\partial x_2} & \cdots & \frac{\partial_{e2}(\underline{x})}{\partial x_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial_{eN}(\underline{x})}{\partial x_1} & \frac{\partial_{eN}(\underline{x})}{\partial x_2} & \cdots & \frac{\partial_{eN}(\underline{x})}{\partial x_N} \end{bmatrix} \tag{6}$$

and

$$s(\underline{x}) = \sum_{i=1}^{N} e_i \nabla^2 e_i(\underline{x}) \tag{7}$$

For the Gauss-Newton method it is assumed that $s(\underline{x}) \approx 0$, and equation (2) becomes:

$$\Delta\underline{x} = \left[J^T(\underline{x})J(\underline{x})\right]^{-1} J^T(\underline{x})\underline{e}(\underline{x}) \tag{8}$$

The Lavenberg-Marquardt modification to the Gauss-Newton method is:

$$\Delta\underline{x} = \left[J^T(\underline{x})J(\underline{x}) + \mu I\right]^{-1} J^T(\underline{x})\underline{e}(\underline{x}) \tag{9}$$

The parameter μ is multiplied by some factor (β) whenever a step would result in an increased $V(\underline{x})$.

When a step reduces $V(\underline{x})$, μ is divided by β. When the scalar μ is very large the Levenberg-Marquardt algorithm approximates the steepest descent method. However, when μ is small, it is the same as the Gauss-Newton method. Since the Gauss-Newton method converges faster and more accurately towards an error minimum, the goal is to shift towards the Gauss-Newton method as quickly as possible. The value of μ is decreased after each step unless the change in error is positive; i.e. the error increases. For the neural network-mapping problem, the terms in the Jacobian matrix can be computed by a simple modification to the back-propagation algorithm [20].

V. Expreiment and Results

A. Preprocessing Data

At the initial stage of experiment, data was scaled or normalized using equation (10)

$$x_{new} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{10}$$

where x is the original data point, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values in the data set, respectively. This is done in order to ensure that the minimum value in the data set is scaled to zero, and that the maximum value is scaled to one [21].

B. Experimental Data

In this study, we use the water quality data of canal in Bangkok, over a period of five years from 2007 to 2011. The main water quality indices include pH value (pH), Dissolved Oxygen (DO), Biochemical Oxygen Demand (BOD),Nitrate Nitrogen (NO_3N), Ammonia Nitrogen (NH_3N) and Total Coliform (T-Coliform). According to the above indices, the water quality can be classified into 5 categories based on surface water quality standards in Thailand. 385 samples are available for the analysis in water quality classification.

Here, data are categorized into two sets: train or learning set, and test set. The train set is used to determine the adjusted weights and biases of a network. The test set is used for calibration, which prevents overtraining of the networks [22]. In addition, the test set can be used to measure the performance the network. Generally, a good training set 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 [5].

C. Neural Network Model

Here, the ratio of the train and test set employed in the experiment is 70:30. This means that with 385 data record, there are 270 records for the train set and 115 records for the test set.

The Levenberg-Marquardt algorithm uses input vectors and corresponding target vectors to train neural networks. All the training records were fed into the network to make it learn the potential relationships between water quality indices and their corresponding categories. Accordingly, the 6 input layer nodes represent 6 water quality indices, while the 5 output layer nodes represent the 5 different class categories. The trained neural networks can provide an output representing the specific class for each of water quality indices. The testing samples are used to verify its classification ability.

Many experimental investigations are conducted. The number of hidden nodes that provided the optimal result is 4 hidden nodes. Therefore, the architecture of the network is 6-4-5. The target mean square error (MSE) is 0.001 after 1000 iterations. Equation (11) shows the mean square error.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} e_i^2 \qquad (11)$$

D. Results

Fig. 2 illustrates the confusion matrix for the experiment results. The confusion matrix demonstrates information about the target (actual class of surface water standard) and the output (predicted class by the network). In the matrix, each column of the matrix represents a target (actual) class, whereas, each row represents an output (predicted) class.

Performance of the neural network approach can be evaluated using data in the matrix. The examples of interpretations include:

Vertically reading from Target Class III, there are 2 records classified correctly. The accuracy percentage is 0.00%.

Vertically reading from Target Class IV, there are 17 records classified correctly. The accuracy percentage is 88.23%.

Vertically reading from Target Class V, there are 96 records classified correctly. The accuracy percentage is 100.00%.

It is important to note that, according to the collected data during 2007-2011, there are no records match for the water quality standard in class I and II.

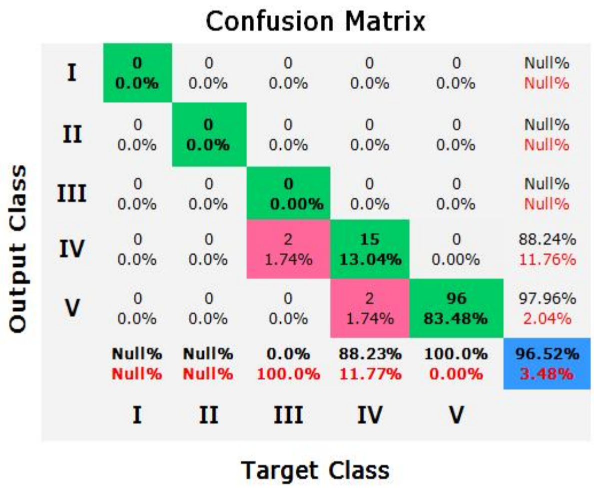

Fig. 2 Confusion Matrix for Classification

Table II demonstrates the percentage accuracy of canal water quality classification. It can be seen that the network correctly classified 111 records from a total of 115 records. The accuracy percentage is 96.52 %

TABLE II
RESULT OF PERCENTAGE ACCURACY IN THE TEST SET

Number of Records	Number of Correctly Classified Records	Accuracy Percentage (%)
115	111	96.52

VI. CONCLUSION

In this paper, a MLP neural network using the Levenberg-Marquardt algorithm is applied to classify the water quality of Dusit district canals of Bangkok, Thailand. The results indicate that the neural network perform with a high accuracy classification percentage of 96.52%. This encouraging result may be applied to automate water quality classifications in this area. As a result, the cost and time of water resource management could be minimized.

ACKNOWLEDGMENT

The authors would like to thank Suan Sunandha Rajabhat University for scholarship support. Thanks to the Department of Drainage and Sewerage, Bangkok Metropolitan Administration, for the provided data.

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