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APPENDICES

APPENDIX A DISSERTATION PROPOSAL

Prediction Model of Water Quality in Chaophraya River using Artificial Neural Network

ABSTRACT

Water quality is one of the major concerns of countries around the world. This study aims to predict the water quality parameters in the Chaophraya River. The model is used to analyze historical data generated through monitoring of water quality parameters at 19 water sampling stations on the Chaophraya to predict nine water quality parameters. Water quality parameters are selected for multilayer perceptron (ANN), adaptive neuro-fuzzy inference system (ANFIS) and support vector machine (SVM) modelling.

OBJECTIVES

1. Design and develop the model for predicting water quality in Chaophraya River by using artificial neural network

2. Determine the best set of input parameters for predicting water quality by using artificial neural network

3. Predict water quality in Chaophraya River under different management scenarios by using the proposed model

PROBLEM FORMULATION

Model design for water quality prediction is often difficult due to the complexity of water parameter relations. Several factors are associated with each parameter making difficulty in model prediction and become major problems of water quality modelling.

The best sets of input parameters for predicting water quality are determined.

The model could be used for predicting the water quality of other rivers that are similar to Chaophraya River.

SCOPE OF THE WORKS

In this dissertation, the model is constrained as follows:

- The scope of this dissertation is aimed to design a model from water quality data of Chaophraya River during 2539 – 2556 BE that have been collected by the Pollution Control Department, Ministry of Natural Resources and Environment.

- The model predicts water quality at monitoring stations i+2 by using i and i+1 monitoring station data.

- The historical water quality data of Chaophraya River came from 19 monitoring station along the river that start from Dechatiwong Bridge station to Phra Samut Chedi station

- The model can predict nine water parameters which are pH, dissolved oxygen (DO), total solid (TS), fecal coliforms, nitrate (NO_3^-), phosphate (PO_4^{3-}), turbidity, temperature and biochemical oxygen demand (BOD).

INTRODUCTION

Water is an essential resource needed for all aspects of human health and ecosystems. In addition to drinking water and personal hygiene, water is essential for agricultural production, industrial processes and hydropower generation, waste processing, navigation, recreation, fish and wildlife, and a variety of other purposes. (Biswas, 1981). Water quality is a term used to describe the condition of the water, including chemical, physical and biological characteristics. Water quality is one of the main characteristics of the river affecting the suitability for use (Dogan, et al. 2009).

Water quality modelling is the basis of water pollution control. Models are used to predict trends in water quality based on current water conditions, including pollutant concentrations. Several deterministic and stochastic water quality models have been developed to manage best practices for conserving water quality (Hull et al. 2008; Einax et al. 1999). Most of these models are very complex and require a significant amount of field data to support the analysis. Furthermore, many statistically based water quality models assume the relationship between the response and prediction variables are linear and normally distributed. As water quality can be affected by many factors, traditional data processing methods are no longer sufficient for analysis (Xiang et al. 2006) as many factors exhibit complex nonlinear relationships to water quality predict variables. Therefore, utilizing a statistical approach usually does not provide high precision.

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Recently, neural networks have been applied to computational problems in many branches of science. A number of studies in which neural networks were used to address water resource problems can be considered. Artificial neural networks (ANNs) were first applied by French and Recknagel (1994) to the task of learning to predict algal blooms based on water quality databases. In their application, a feed-forward ANN was trained to make predictions of phytoplankton abundance in the Saidenbach reservoir, Germany. Similarly, Yabunaka et al. (1997) applied ANNs to predict algal blooms by simulating the future growth of five phytoplankton species and chlorophyll-A concentrations in the same lake.

Motivated by success in modelling nonlinear system behavior n a wide range of systems, ANNs have been applied to water quality prediction in complex systems. The literature offers some recent successful ANN applications related to water quality prediction and water resource analysis (Najah et al. 2009; Ahmed et al. 2009; El-Shafie et al. 2008, 2009). The primary goals were to minimize fieldwork ard improve the accuracy of prediction. For instance, Hatzikos et al. (2005) utilized neural networks with active neurons to predict seawater quality indicators such as water temperature, pH, DO, and turbidity. Singh et al. (2009) constructed an ANN model to predict the water quality at Gomti River, India. The coefficients of determination between the measured and model computed values of DO for the training, validation and test sets were 0.70, 0.74, and 0.76, respectively. Kuo et al. (2007) used the back-propagation neural network for predicting the DO in the Te-Chi Reservoir in Taiwan. The correlation coefficients between the predicted values and measured data of DO were above 0.7 for training and testing data sets.

The ANNs models showed reasonable accuracies for average water quality prediction overcoming most of the drawbacks of conventional models. Although ANNs are powerful tools for modelling real-world problems, they also have shortcomings. The ANN model still has a major limitation at extreme events. Therefore, an approach that can provide accurate water quality prediction at average and extreme events is highly necessitated for efficient decision making. Therefore, in these situations, a fuzzy system such as the adaptive neuro-fuzzy inference system (ANFIS) may be a better option. The ANFIS model exhibits significantly higher accuracy and reliability in terms of prediction than ANNs (El-Shafie et al. 2007; Najah et al. 2010). The present study demonstrates the application of ANFIS to predict water quality parameters, with the dynamic processes concealed in the measurement data. The use of the ANFIS model in water quality prediction in the Chaophraya River could be effective in capturing patterns in historical data sets to improve prediction accuracy.

METHODS AND MATERIALS

Study area data analysis

Chaophraya River is the main river of Thailand. Occurred to the combination of four main rivers of the region. Then flow down to the south and prior to the Gulf of Thailand. Chaophraya river basin has an area of 20,125 square kilometers. There are a number of tributaries and canals. The river is used as a transportation industries, and is also a natural drainage as well. By human activities and nature, water quality in the river has changed dramatically over the past several decades.

The water quality of the Chaophraya River is deteriorating because of the increasing levels of several pollutants. It continues to be silted and contaminated by waste given the lack of enforcement by local authorities. These contaminants eventually flow into the estuaries of the Chaophraya River, which are rich habitats that provide spawning and feeding areas for fish and birds.

According to the historical water quality data of Chaophraya River during 2539 – 2556 BE that have been collected by the Pollution Control Department, Ministry of Natural Resources and Environment, we will design and develop a model for predicting the water quality parameters and simulating the river management scenarios.

Selection of appropriate input parameters is a very important aspect in modelling. To use the model structures effectively, the input parameters must be selected with great care. This is strongly dependent on a solid understanding of the problem.

Proposed method

This dissertation is divided into two parts. The first part is the design and development of a model and the second part is the simulation of a few scenarios by using the model. The proposed model consists of three main steps: data imputation, input selection and value prediction. At each step, several techniques are used to compare with each other as shown in figure 1. The inputs of model are the water quality parameters at monitoring stations i and i+1 and output are water quality parameters at monitoring station i+2 at the same monitoring period. There are 18 water quality input parameters (at a single monitoring station and same monitoring period) consisting of monitoring month, monitoring year, pH, electrical conductivity (EC), salinity, dissolved oxygen (DO), suspended solids (SS), total solids [116], total dissolved solids (TDS), total coliforms, fecal coliforms, nitrite (NO2-), nitrate (NO3-), ammonia (NH3), phosphate (PO43-), turbidity, temperature and biochemical oxygen demand (BOD).

The missing values in the original water quality data are imputed by three different techniques (Small value imputation, K-mean imputation anc interpolation). Then the input selection step extracts some important features from imputed data using three techniques. The input selection step starts with feeding all water quality parameters into each of the three techniques. Each of three techniques will generate new features from water quality parameters and then feed these features into each of the three techniques in the Value prediction step in step three. Each technique in step three will predict one output value. After the first iteration, the process in step three is repeated with the same input features excluding the least important feature. Step three is repeated until only one feature is fed into each of the technique in step three. The output parameter from each technique in step three is recorded. Next, step two is repeated. This time one of the parameters is removed, there will be only 17 input parameters that are fed to each technique in step two. Each of the technique will generate new features and feed these new features into the techniques in step three as before. Step two is repeated for the number of selection of n-i parameters from n distinct parameters where i=1,2,...,n-1 and n is the number of all input parameters.

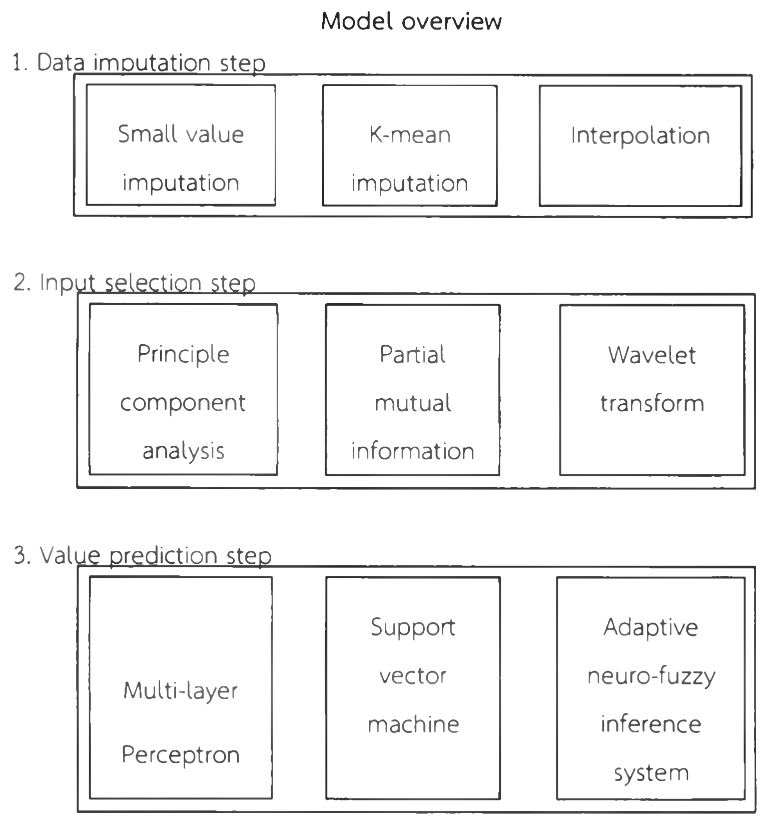

Figure A.0.1 Model overview

The inputs of step three are divided into training set (60%), testing set (20%) and validation set (20%) for all techniques. The training of the model is set the 1000 epochs. After the model was trained, testing set is used for checking the efficiency of the model. In addition, validation set is used to avoid overfitting problem.

The three main steps (consisted of nine mathematical modelling techniques) are fully connected to form 27 combinations of unique models. The output parameter from each unique model is compared with real data to determine prediction efficiency and optimality. The output parameters are pH, dissolved oxygen (DO), total solids [116], fecal coliforms, nitrate (NO3-), phosphate (PO43-), turbidity, temperature and biochemical oxygen demand (BOD). For each output, the model is constructed individually.

The second part of dissertation is the simulation of water quality management scenarios. The model is used to show the water quality when management scenarios are processing. The first scenario is environmental shock avoidance, and the second one is pre-release treatment plant. Environmental shock avoidance (ESA) is pollutant dilution strategy by distributing the major point source pollutant along the bank of the river instead of releasing it at a single point. Pre-release treatment plant (PRTP) is the simple way to treat the water by treating it again before releasing to the river. However, those two strategies are only the pioneer simulation on Chaophraya River.

Performance criteria

The performance of the proposed models will be examined and evaluated using water quality parameter measurements accumulated over a ten-year period. The performance of each module will be evaluated according to two statistical indices. The coefficient of determination (R2) was introduced by Nash and Sutcliffe (1970) and is often used to evaluate model performance. Another metric used for evaluation is the root mean square error (RMSE).

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APPENDIX B COMPLEMENTARY RESULT

B.1 Historical data chart

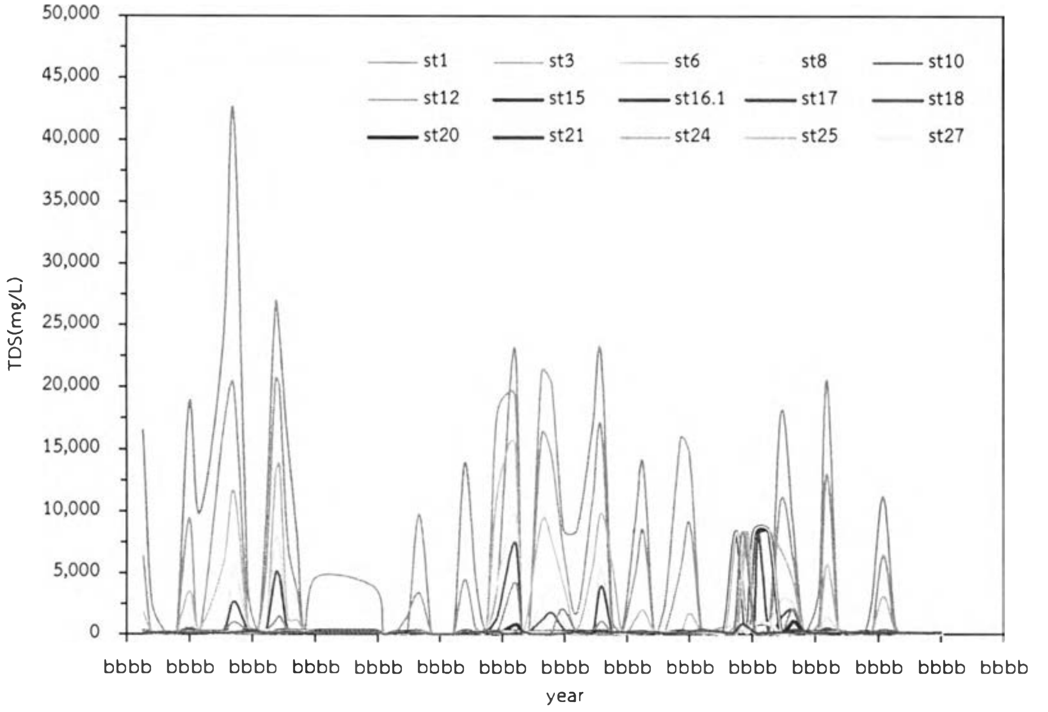

Figure B.0.1 Historical data of total dissolved solid from monitoring stations along Chaophraya River during 2538-2556 B.E.

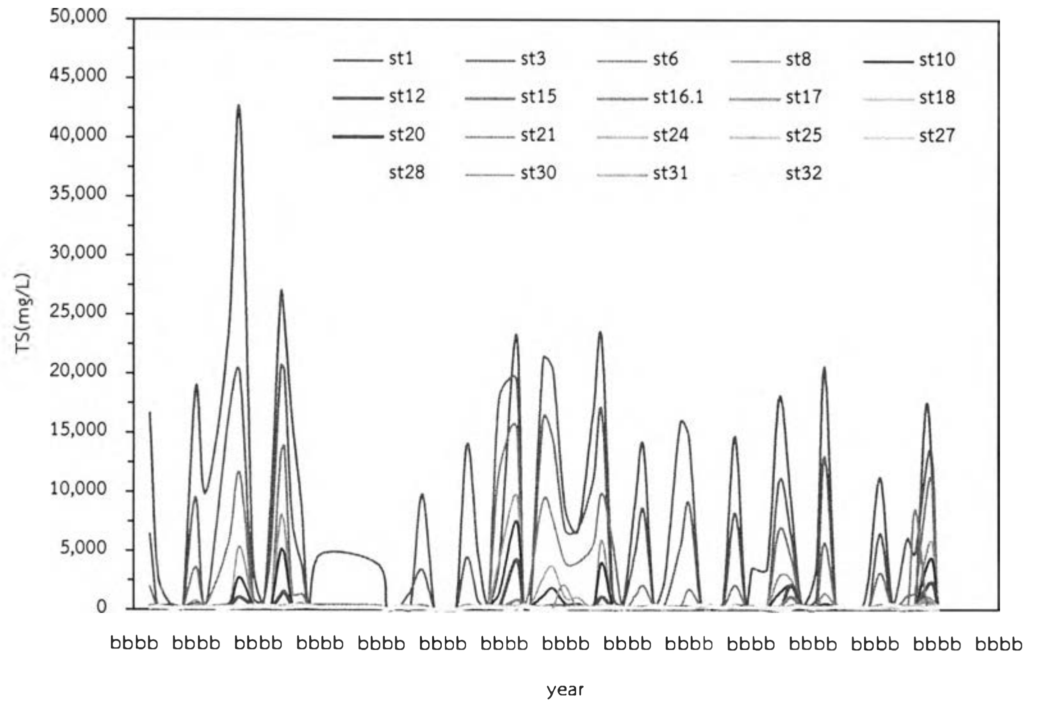

Figure B.0.2 Historical data of total solid from monitoring stations along Chaophraya River during 2538-2556 B.E.

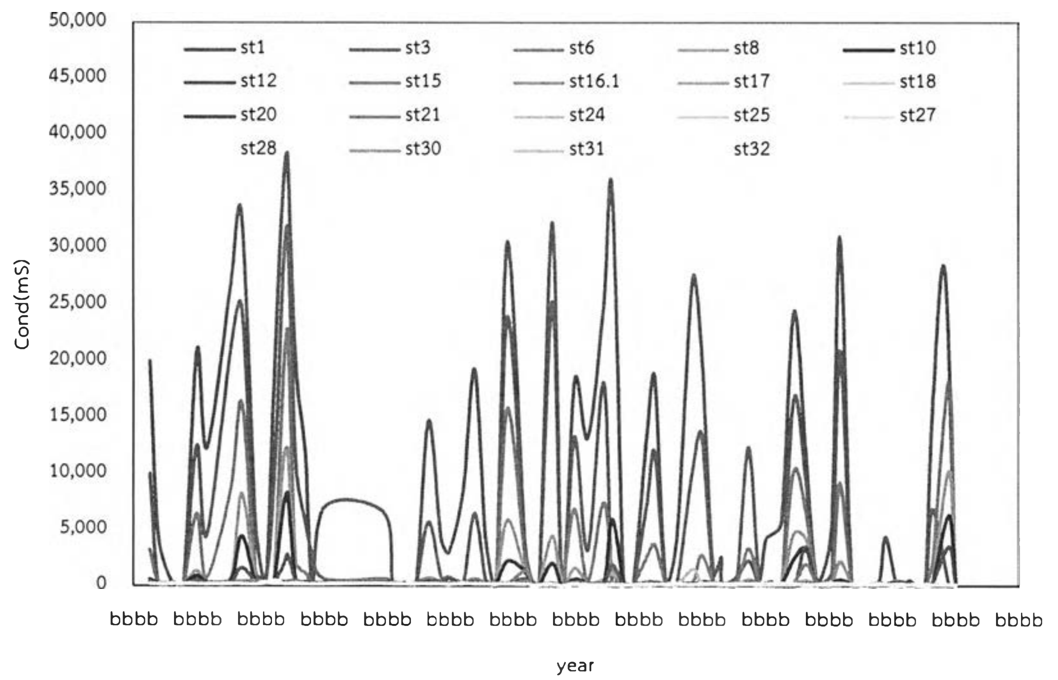

Figure B.0.3 Historical data of EC from monitoring stations along Chaophraya River during 2538-2556 B.E.

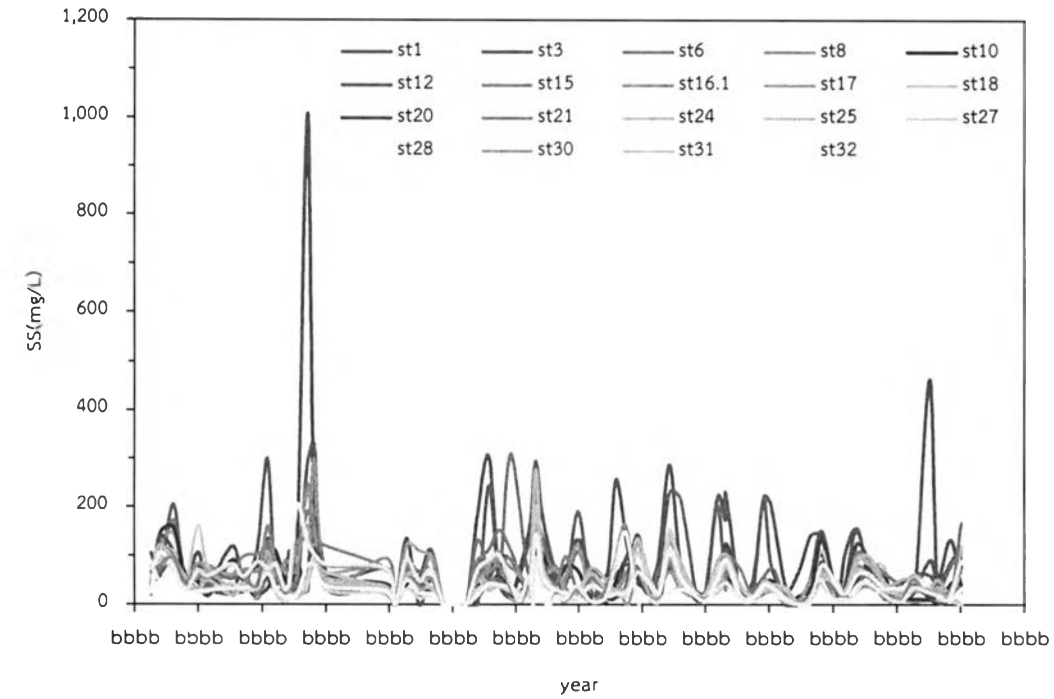

Figure B.0.4 Historical data of suspended solid from monitoring stations along Chaophraya River during 2538-2556 B.E.

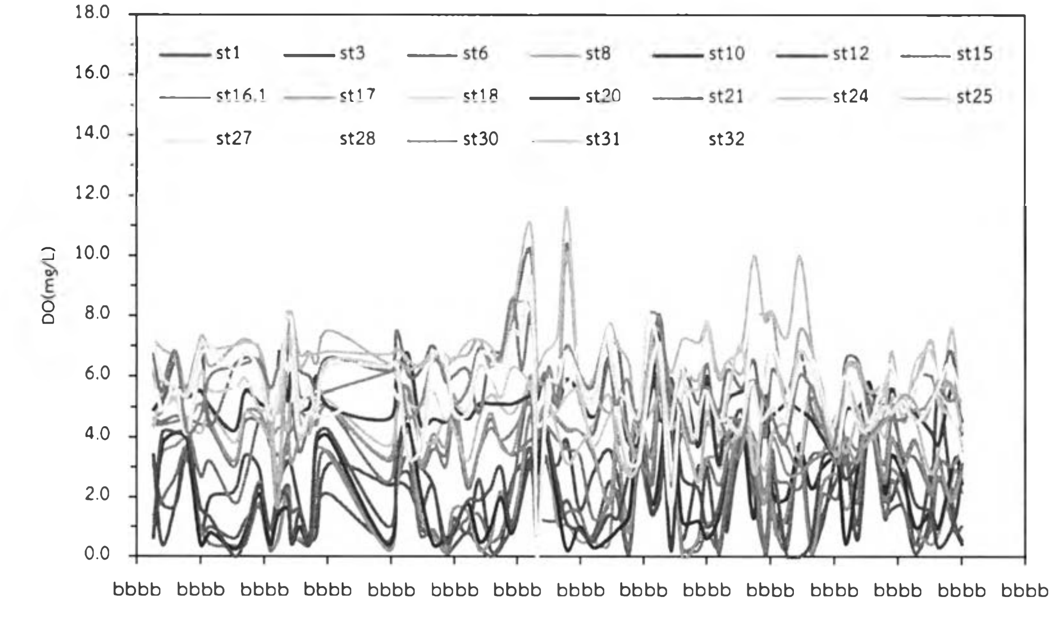

Figure B.0.5 Historical data of dissolved oxygen from monitoring stations along Chaophraya River during 2538-2556 B.E.

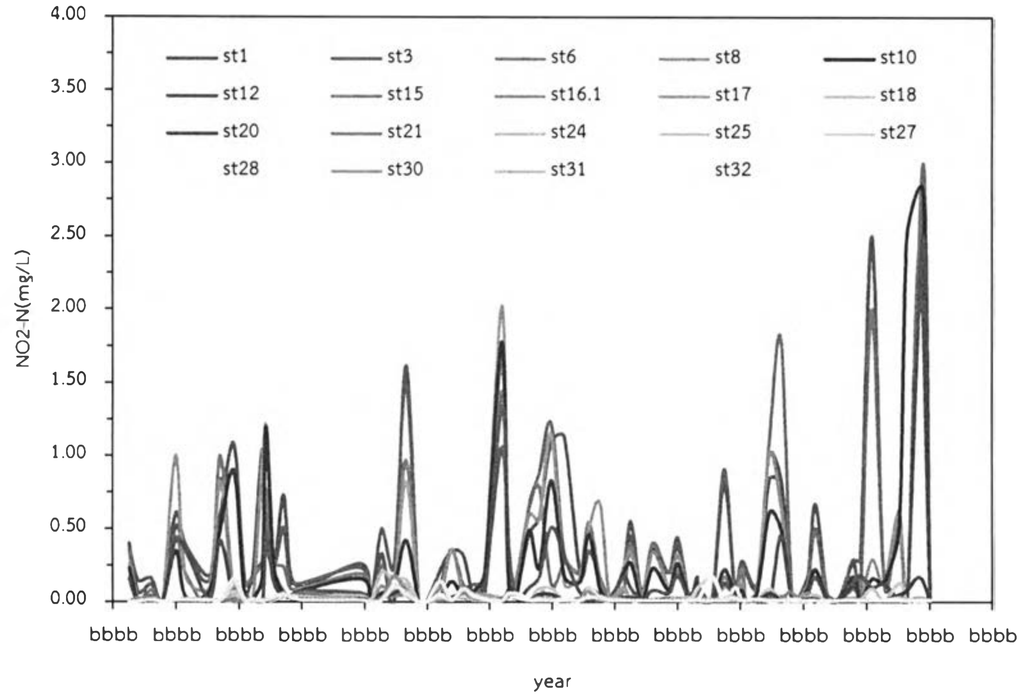

Figure B.0.6 Historical data of NO_2^- from monitoring stations along Chaophraya River during 2538-2556 B.E.

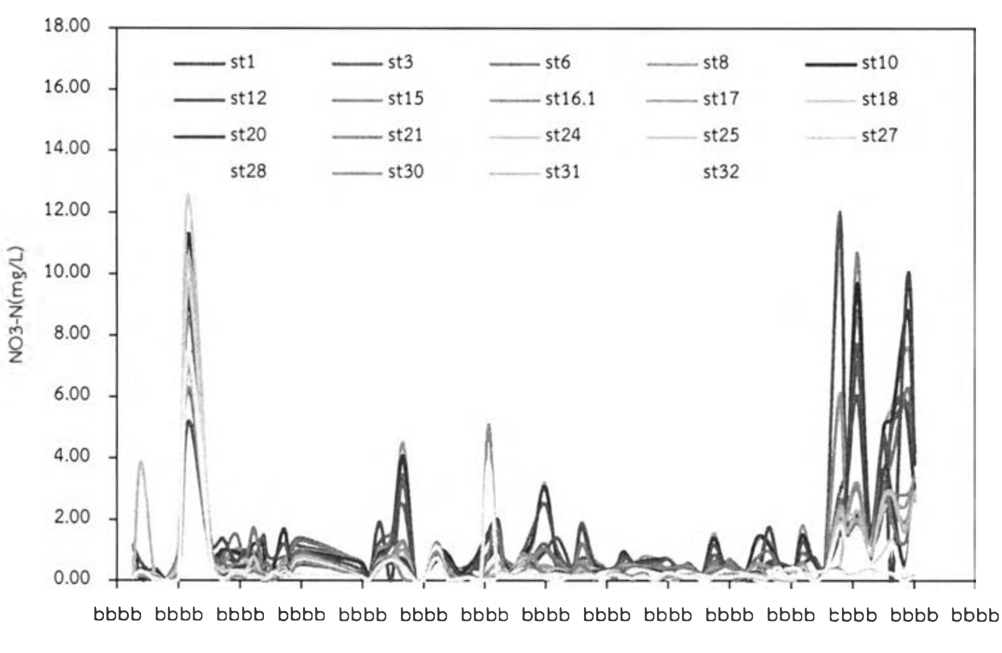

Figure B.0.7 Historical data of NO_3^- from monitoring stations along Chaophraya River during 2538-2556 B.E.

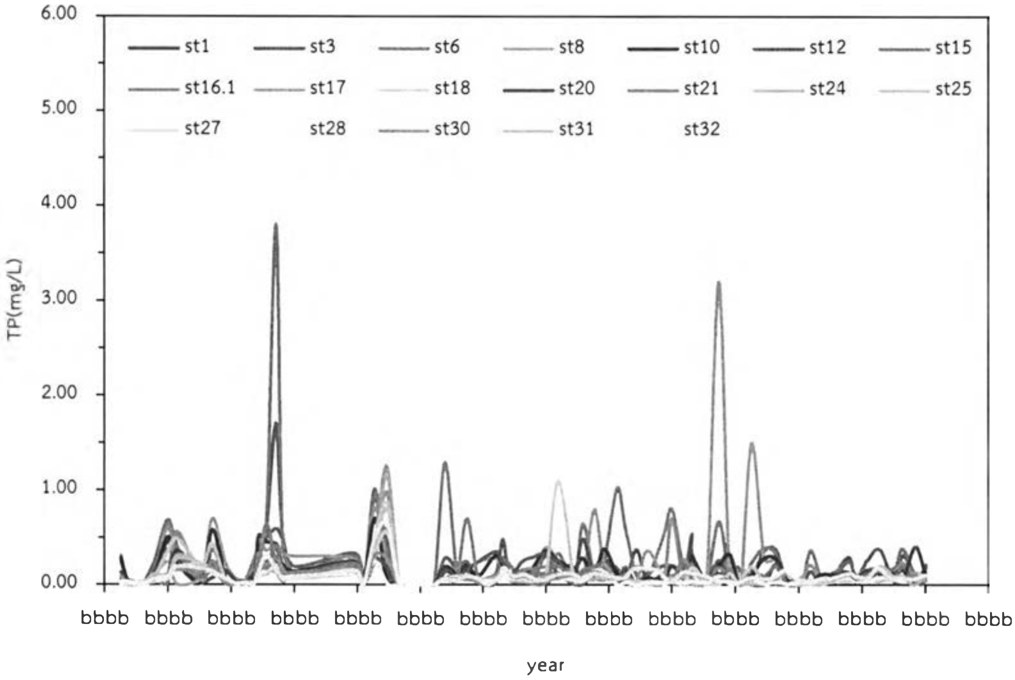

Figure B.0.8 Historical data of PO_4^{3-} from monitoring stations along Chaophraya River during 2538-2556 B.E.

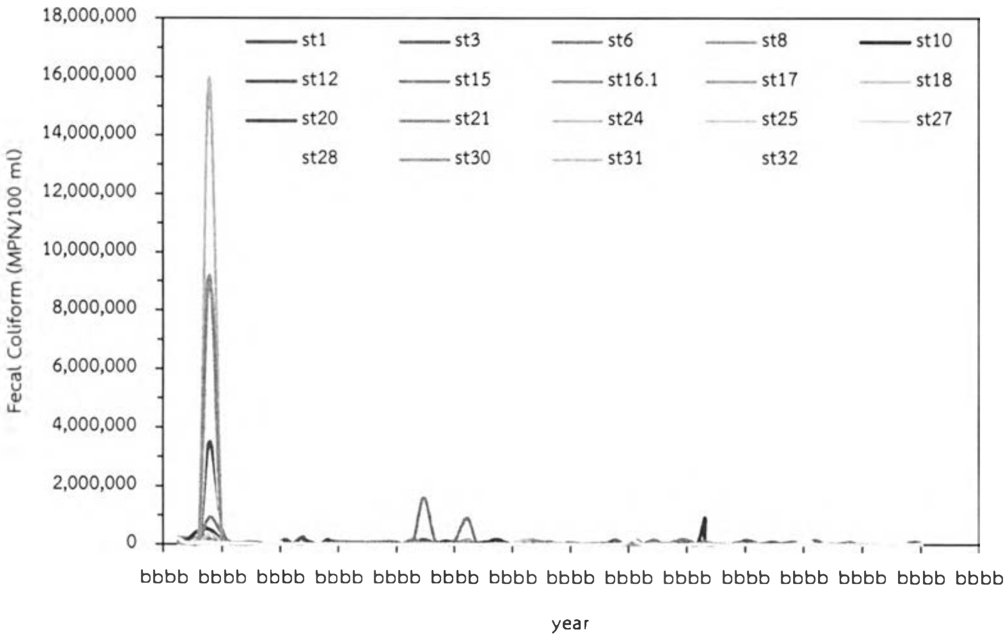

Figure B.0.9 Historical data of fecal coliform from monitoring stations along Chaophraya River during 2538-2556 B.E.

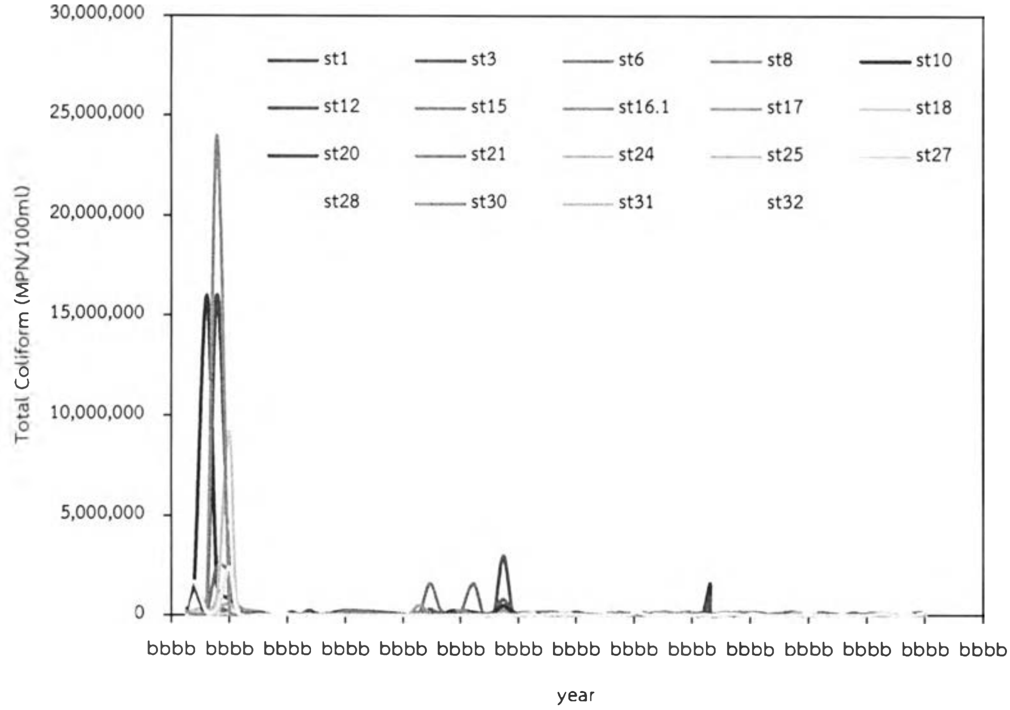

Figure B.0.10 Historical data of total coliform from monitoring stations along Chaophraya River during 2538-2556 B.E.

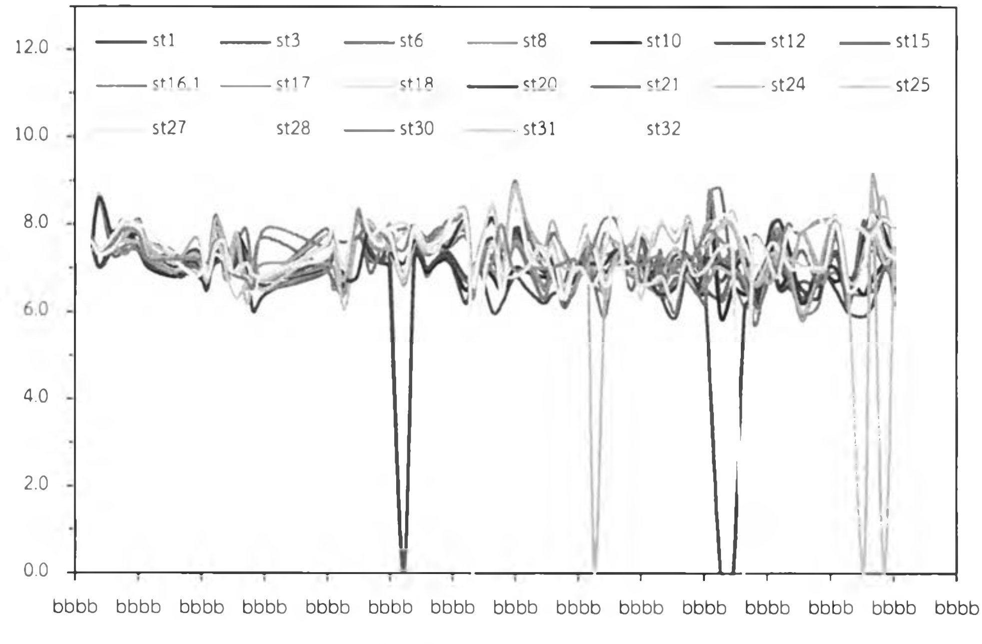

Figure B.0.11 Historical data of pH from monitoring stations along Chaophraya River during 2538-2556 B.E.

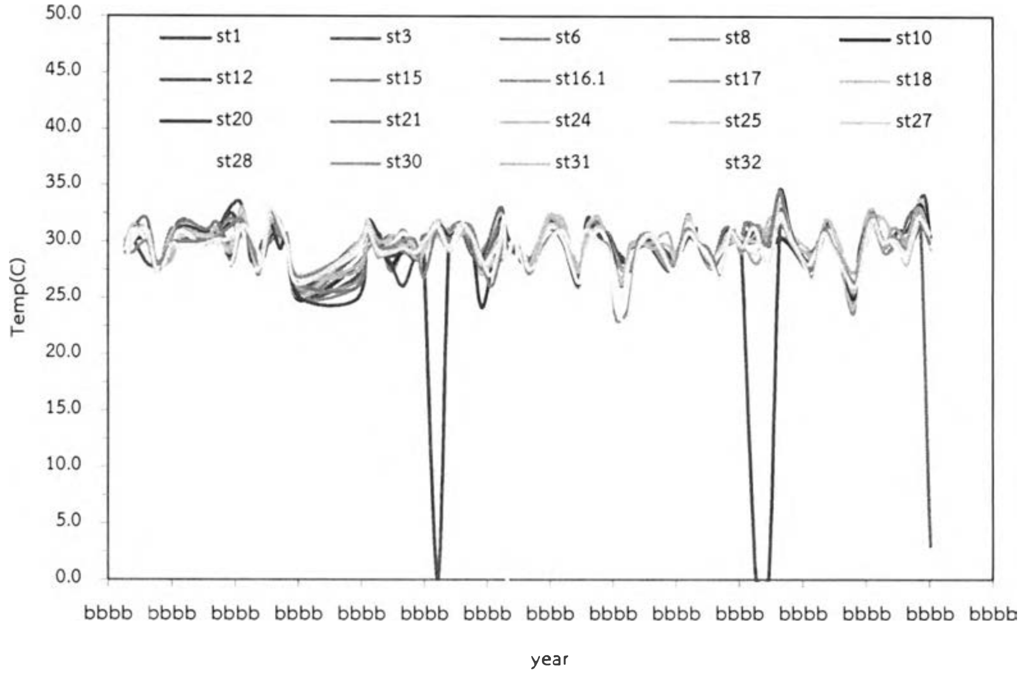

Figure B.0.12 Historical data of water temperature from monitoring stations along Chaophraya River during 2538-2556 B.E.

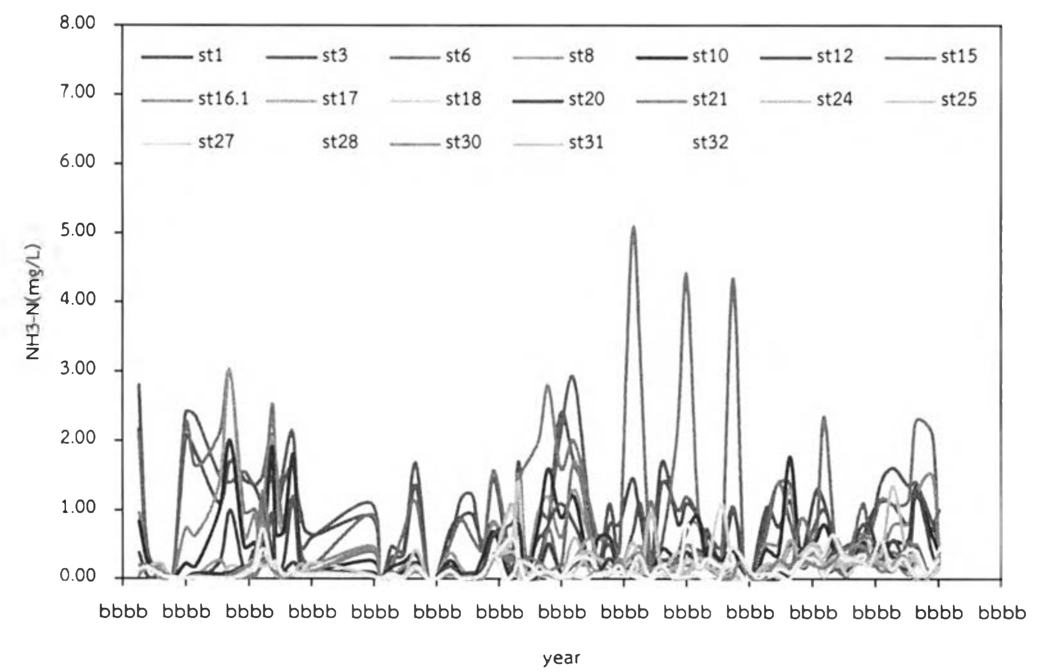

Figure B.0.13 Historical data of NH_3 from monitoring stations along Chaophraya River during 2538-2556 B.E.

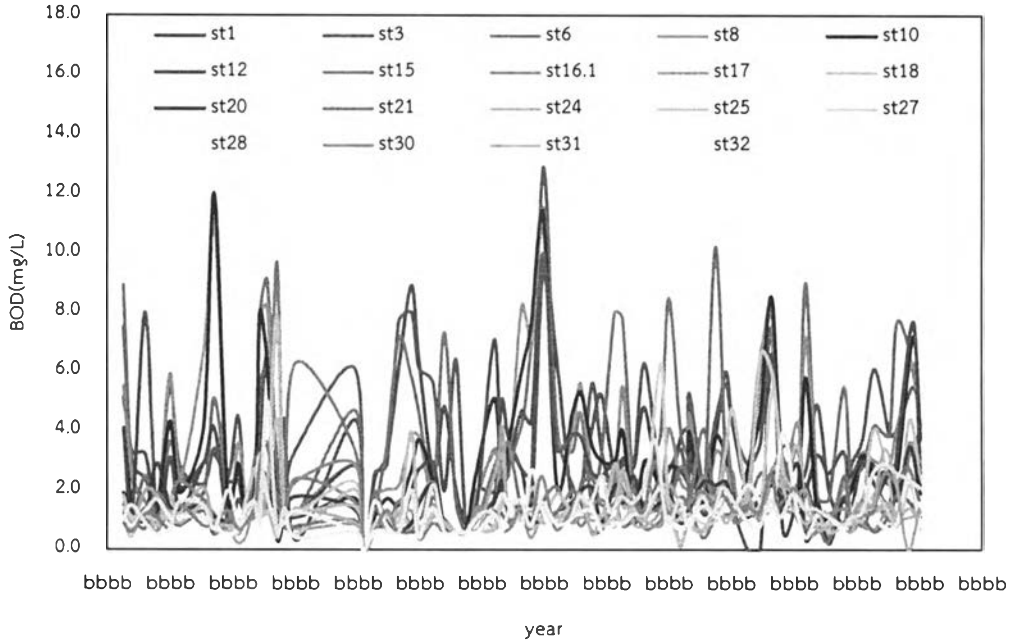

Figure B.0.14 Historical data of biochemical oxygen demand from monitoring stations along Chaophraya River during 2538-2556 B.E.

B.2 Pre-processing result

Table B.0.1 Three imputation methods performance evaluation show by individual model

Model code name	Imputation method	Argument	RMSE	ρ
AveEvoSVM	mean replacement	-	1.419	0.621
AveEvoANN		-	1.417	0.662
Knn2EvoSVM	K-NN	k=2	1.39	0.645
Knn2EvoANN		k=2	1.387	0.675
Knn3EvoSVM		k=3	1.395	0.638
Knn3EvoANN		k=3	1.506	0.696
Knn4EvoSVM		k=4	1.393	0.644
Knn4EvoANN		k=4	1.403	0.687
Knn5EvoSVM		k=5	1.392	0.645
Knn5EvoANN		k=5	1.432	0.687
Knn6EvoSVM		k=6	1.393	0.643
Knn6EvoANN		k=6	1.33	0.693
Knn7EvoSVM		k=7	1.39	0.648
Knn7EvoANN		k=7	1.566	0.689
ANNEvoSVM	ANN		1.54	0.597
ANNEvoANN			1.795	0.626

Table B.0.2 Performance comparison of transformed data and non-transformed data on various models

Model	RMSE	ρ
GA-ANN	0.085	0.671
GA-SVM	0.083	0.665
PCA-ANN	0.096	0.578
PCA-SVM	0.084	0.653
Trans-GA-ANN	0.127	0.663
Trans-GA-SVM	0.124	0.661
Trans-PCA-ANN	0.140	0.631
Trans-PCA-SVM	0.125	0.660

B.3 Parameter selection result

Table B.0.3 Forward selection performance of various BOD model

Model	epoch	RMSE	ρ	#inputs	Selected parameter
	50	1.449	0.640	2	Distance NH
	100	1.483	0.701	4	month DO NO NH_3
	200	1.488	0.700	4	month DO NO NH_3
	300	1.489	0.700	4	month DO NO NH_3
	400	1.493	0.696	4	month DO NO NH_3
ANN	500	1.420	0.685	4	month DO NO NH_3
	600	1.410	0.687	4	month DO NO NH_3
	700	1.430	0.676	4	month DO NO NH_3
	800	1.434	0.674	4	month DO NO NH_3
	900	1.432	0.674	4	month DO NO NH_3
	1000	1.431	0.675	4	month DO NO NH_3
SVM	-	1.318	0.654	3	Distance PO_4^{3-} NH_3

Table B.0.4 Backward elimination performance of various BOD model

Model	epoch	RMSE	ρ	#inputs	Selected parameter
	50	1.464	0.722	7	month WT pH DO PO_4^{3-} NO_3^- NH_3
	100	1.627	0.727	8	month WT pH Con DO PO_4^{3-} NO_3^- NH_3
	200	1.719	0.740	8	month WT pH Con DO PO_4^{3-} NO_3^- NH_3
	300	1.255	0.729	6	month S pH DO NO_3^- NH_3
	400	1.480	0.726	6	month S WT PO_4^{3-} NO_3^- NH_3
ANN	500	1.413	0.730	6	month S WT PO_4^{3-} NO_3^- NH_3
	600	1.380	0.725	6	month S WT PO_4^{3-} NO_3^- NH_3
	700	1.367	0.720	6	month S WT PO_4^{3-} NO_3^- NH_3
	800	1.161	0.720	6	month S WT DO PO_4^{3-} NH_3
	900	1.161	0.725	6	month S WT DO PO_4^{3-} NH_3
	1000	1.175	0.724	6	month S WT DO PO_4^{3-} NH_3
SVM	-	1.516	0.691	5	month WT DO NO_3^- NH_3

Table B.0.5 PCA performance of various BOD model

model	epoch	RMSE	ρ
	100	1.707	0.331
	200	1.632	0.415
	300	1.629	0.422
	400	1.629	0.425
	500	1.612	0.444
ANN	600	1.606	0.449
	700	1.605	0.451
	800	1.604	0.451
	900	1.604	0.452
	1000	1.604	0.453
SVM		1.749	0.292

Table B.0.6 Genetic algorithm performance of various BOD model

Model	epochs	RMSE	ρ	#inputs	Selected parameter
	50	1.250	0.752	7	month pH Con DO PO_4^{3-} NO_3^- NH
	100	1.324	0.736	6	S pH DO PO_4^{3-} NO NH
	200	1.198	0.730	6	S pH DO PO_4^{3-} NO NH
	300	1.315	0.730	5	pH Con DO PO_4^{3-} NH
	400	1.314	0.731	5	pH Con DO PO_4^{3-} NH
ANN	500	1.312	0.733	5	pH Con DO PO_4^{3-} NH
	600	1.310	0.734	5	pH Con DO PO_4^{3-} NH
	700	1.309	0.735	5	pH Con DO PO_4^{3-} NH
	800	1.309	0.736	5	pH Con DO PO_4^{3-} NH
	900	1.657	0.739	7	month S pH Con DO NO_3^- NH
	1000	1.672	0.740	7	month S pH Con DO NO_3^- NH
SVM	-	1.285	0.731	6	month tem pH DO PO_4^{3-} NH

B.4 Selected parameter from proposed model

Parameter name is follow by two number, the first is number of upstream monitoring station and the second is the time delay. Parameter of EC model, TDS model and PO_4^{3-} are shown as follow.

There are 77 parameters selected by genetic algorithm for EC prediction model which are BOD02, BOD11, BOD13, BOD21, BOD22, EC01, EC13, EC21, Distance03, Distance11, Distance13, Distance21, Distance23, DO22, Fecal coliform02, Fecal coliform13, Fecal coliform21, Fecal coliform22, Fecal coliform23, month00, month01, month02, month03, month12, month13, month22, month23, $NH_3$01, $NH_3$02, $NH_3$03, $NH_3$11, NO_2^-01, NO_2^-02, NO_2^-13, NO_2^-23, NO_3^-01, NO_3^-11, NO_3^-12, NO_3^-13, NO_3^-22, pH01, pH02, pH03, pH13, Sal12, Sal13, Sal21, Sal23, SS01, SS11, SS13, SS23, TDS01, TDS02, TDS13, TDS22, TDS23, Temp02, Temp12, Temp22, Total coliform03, Total coliform11, Total coliform13, Total coliform22, Total coliform23, PO_4^-02, PO_4^-03, PO_4^-11, PO_4^-12, TS02, TS03, TS12, TS21, Tur01, Tur11, Tur21, Tur23

There are 52 parameters selected by genetic algorithm for TDS prediction model which are BOD02, BOD11, BOD12, EC01, EC11, EC21, EC22, Distance00, Distance01, Distance02, Distance11, Distance12, DO01, DO22, Fecal coliform01, Fecal coliform02, Fecal coliform12, month00, month11, month21, month22, $NH_3$01, $NH_3$02, $NH_3$12, NO_2^-11, NO_2^-12, NO_2^-21, NO_2^-22, NO_3^-12, pH01, pH12, pH21, Sal21, SS02, SS11, SS22, TDS02, TDS11, TDS21, TDS22, Temp21, Total coliform01, Total coliform02, Total coliform12, PO_4^-12, PO_4^-22, TS01, TS11, TS21, Tur01, Tur02, Tur11

There are 38 parameters selected by genetic algorithm for PO_4^{3-} prediction model which are BOD02, BOD21, BOD22, EC02, EC12, EC22, Distance00, Distance02, Distance11, Distance21, DO11, DO22, Fecal coliform01, Fecal coliform02, month11, $NH_3$01, $NH_3$02, $NH_3$11, $NH_3$12, $NH_3$22, NO_2^-02, NO_2^-11, NO_2^-21, NO_2^-22, NO_3^-02, NO_3^-12, NO_3^-22, pH12, pH22, Sal22, TDS01, Temp22, Total coliform11, Total coliform21, PO_4^-01, PO_4^-02, PO_4^-21 and Tur11.

VITA

Weeris Treeratanajaru was born at Bangkok, Thailand. He received a bachelor degree from Environmental Science Program, Faculty of Science, Chulalongkorn University in 2010. In 2012, He received a master degree from Computer Science and Information Technology Program, Faculty of Science, Chulalongkorn University. Now he is Ph.D. candidate in Computer Science and Information Technology from Chulalongkorn University.

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1. Treeratanajaru, W., Watcharamul, S., and Lipikorn, R. (2016) Comparison of ANN and SVM for Prediction of Biochemical Oxygen Demand in Chaophraya River, in International Technical Conference on Circuits/Systems, Computers and Communications, 2016.

2. Photphanloet, C., Treeratanajaru, W., Cooharojananone, N., and Lipikorn, R. (2016) Biochemical Oxygen Demand Prediction for Chaophraya River Using α-Trimmed ARIMA Model, in The 13th International Joint Conference on Computer Science and Software Engineering, 2016.

3. Treeratanajaru, W., Watcharamul, S., and Lipikorn, R. (2012) Degenerate primer design system for gene biodiversity study using dynamic pattern matching, in Health Informatics and Bioinformatics (HIBIT), 2012 7th International Symposium, pp.102-106.