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Parameter Sensitivity Analysis of Artificial Neural Network for Predicting Water Turbidity

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***Abstract*—**The present study focuses on the discussion over the parameter of Artificial Neural Network (ANN). Sensitivity analysis is applied to assess the effect of the parameters of ANN on the prediction of turbidity of raw water in the water treatment plant. The result shows that transfer function of hidden layer is a critical parameter of ANN. When the transfer function changes, the reliability of prediction of water turbidity is greatly different. Moreover, the estimated water turbidity is less sensitive to training times and learning velocity than the number of neurons in the hidden layer. Therefore, it is important to select an appropriate transfer function and suitable number of neurons in the hidden layer in the process of parameter training and validation.

***Keywords*—**Artificial Neural Network (ANN), sensitivity analysis, turbidity.

I. Introduction

AN Artificial Neural Network (ANN) is a mathematical system having an inter-connected assembly of simple elements, which emulates the ability of biological neural network. ANN technique can represent a complex non-linear relationship between the input and the output of any system. It is a successful tool to be applied to solve various problems [1]-[2]. In our past study, we applied ANN to establish the relationship between upstream rainfall properties and the turbidity of raw water in downstream water treatment plants. The result demonstrates that ANN can well predict the turbidity of raw water in the water treatment plant according to rainfall records, even though rainfall-water turbidity is a non-linear relationship [3]. Most studies demonstrate that ANN has better forecasting ability than conventional models, because it is flexible to represent the relationship between different systems [4].

Although ANN technique has many advantages, model users always spend a lot of time and effort in the process of parameter training and validation. Clear understanding of the parameters of ANN can help us avoid unnecessary waste of time and effort. This study applies sensitivity analysis to assess the effect of parameters in ANN technique on the prediction of turbidity of raw water in the water treatment plant. The objective of this analysis is to enhance the effectiveness in parameter training and validation and to expand the application of ANN.

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II. Methods

A. Site Description

The case area in this study is the Dan-Shui River Basin in Taiwan. There are 5 major rainfall guaging stations in this area. The Ban-Sin water treatment plant is located in the Dan-Shui River Basin. There are 2 water intake points of the Ban-Sin water treatment plant. Fig. 1 displays the locations of rainfall stations, the Ban-Sin water treatment plant and water intake points of the Ban-Sin water treatment plant in the Dan-Shui River Basin. The Ban-Sin water treatment plant, designed to process approximately 0.87 million tons of water per day, plays an important role in public water supply of northern Taiwan. It provides domestic water for about 1.87 million people in Taipei County.

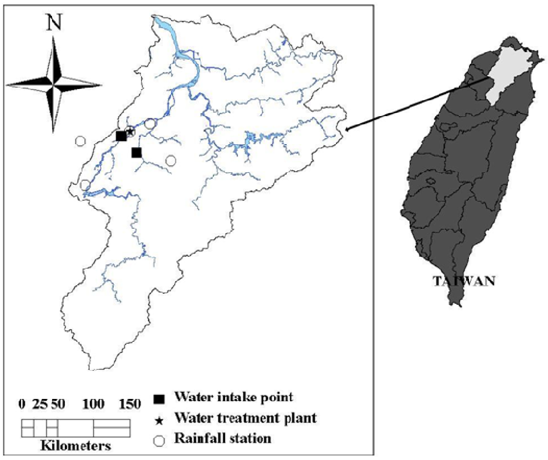


Fig. 1 Case area: the Dan-Shui River Basin

B. Artificial Neural Network (ANN)

The concept of ANN was initially introduced in 1943 [5]. ANN can be regarded as a ‘black box’ model. It imitates the function of neurons in the human brain. Fig. 2 shows a typical multilayer structure of ANN. Because ANN has an ability to learn from examples without the need of explicit physics, it can be applied in different science and management fields. In water environmental science, numerous works applied ANN for modeling the rainfall-runoff process and for predicting environmental responses such as typhoon storm, stream flow, tide, flood and water quality [6]-[13].

Historical data plays an important role in the application of ANN. Many parameters are constantly adjusted (calibrated and trained) in such a way to reach the target that estimated values by ANN technique can be similar to measured values [14]. A base for saving the parameters of ANN, such as training times, learning velocity, number of neuron and type of transfer functions, are determined in a process of parameter training and validation.

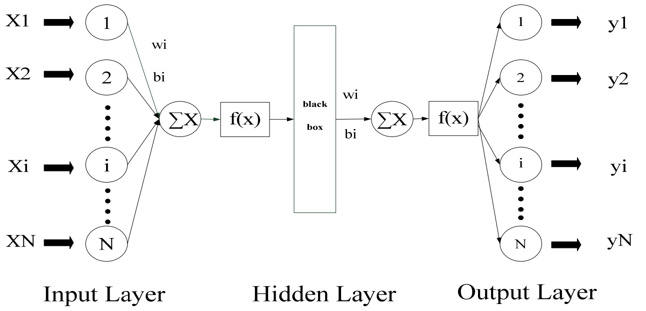


Fig. 2 A typical multilayer structure of ANN

C. Sensitivity Analysis

Sensitivity analysis is an important step before starting a simulation process [15]-[17]. The analysis of model sensitivity can represent the simulation results are more sensitive to some parameters than others [18]. Both the graphical method and the sensitivity-index approach can be used to display the sensitivity of the output parameters over the entire range of the tested input parameters [19]-[20]. When the parameters are relative to one another, sensitivity analysis would be difficult to get definite results. Therefore, it is significant to ensure that each parameter is independent in the process of sensitivity analysis [21].

This study uses a single-value sensitivity index to evaluate the effect degree of parameters of ANN on simulation results. The index is defined as:

$$S = (O_2 - O_1 / I_2 - I_1)(I_{ave} / O_{ave}) \tag{1}$$

where S is the sensitivity index; I_1 and I_2 are the smallest and the largest input values respectively; O_1 and O_2 are the model output values corresponding to I_1 and I_2 respectively; I_{ave} and O_{ave} are respectively the average I_1 and I_2 and the average O_1 and O_2. The greater the absolute value of S, the greater the effect an input parameter has on a particular output (Walker, 1996).

Table I shows the scenarios with different parameters of ANN for sensitivity analysis. 5 training times, 4 learning velocities, 3 numbers of neurons, 3 types of transfer function of hidden layer and 3 types of transfer function of output layer are discussed. The objective is to assess the difference of reliability of simulation results when the parameters of ANN in the original base change.

TABLE I
SCENARIOS FOR SENSITIVITY ANALYSIS

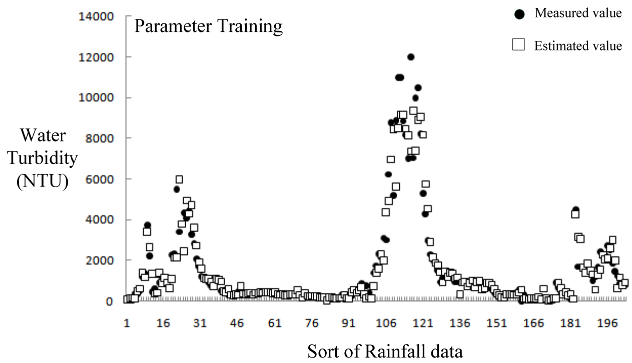
Parameters of ANN	Numbers of scenario	Scenarios
training times	5	100, 200, 300, 400, 500
learning velocity	4	0.1, 0.01, 0.001, 0.0001
number of neurons in hidden layers	3	3, 4, 5
transfer function of output layer	3	L, P, T
transfer function of hidden layer	3	L, P, T

(Note: “L” is Log sigmoid transfer function; “P” is linear function; “T” is hyperbolic tangent sigmoid transfer function.)

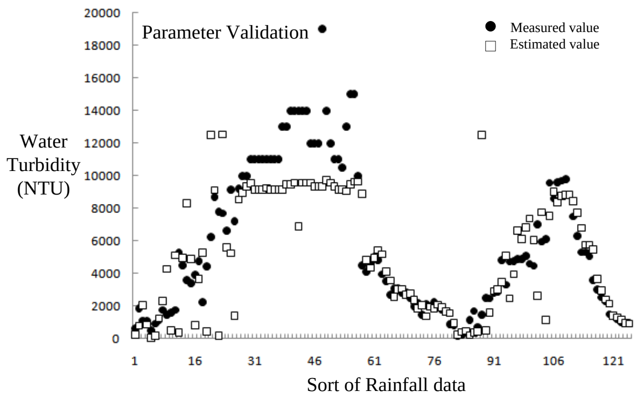
III. RESULTS AND DISCUSSION

A. Rainfall-turbidity Relationship Analysis

After parameter training and validation, a base with a set of parameters for describing the relationship between the rainfall characteristic in the Dan-Shui River Basin and the turbidity of raw water in the Ban-Sin water treatment plant is established. In this base, the training times is 500; the learning velocity is 0.1; the number of neurons in hidden layers is 3; both the transfer function of hidden layer and the transfer function of output layer are “Log sigmoid transfer function”. Fig. 3 shows the measured water turbidity and estimated water turbidity by ANN technique after the process of parameter training and validation. When using the base mentioned above, the R-square (R^2) of measured and estimated water turbidity are 0.88 and 0.64 respectively for parameter training and validation. The result shows that statistical models, such as ANN technique, can be a flexible tool for the prediction of water turbidity.



(a) Parameter training



(b) Parameter validation

Fig. 3 Comparison of measured and estimated water turbidity

B. Sensitivity Analysis of Parameters

Table II shows the difference of simulation results when the parameters of ANN change. The result shows that the R^2 between measured and estimated water turbidity and the absolute value of relative error of water turbidity prediction are various under the scenarios with different parameters. The simulation result of water turbidity prediction is more sensitive to the transfer function of hidden layer and the transfer function of output layer than other parameters. The simulation error highly increases when incorrect transfer functions are selected.

TABLE II
CHANGES OF PREDICTION ACCURACY UNDER DIFFERENT PARAMETERS OF ANN

(a) Scenarios with various training times

Scenario		1-1	1-2	1-3	1-4	base
number of neurons in hidden layers		3	3	3	3	3
transfer function of hidden layer		L	L	L	L	L
transfer function of output layer		L	L	L	L	L
training times		100	200	300	400	500
learning velocity		0.1	0.1	0.1	0.1	0.1
R^2	(Parameter training)	0.88	0.89	0.88	0.89	0.88
R^2	(Parameter validation)	0.55	0.42	0.55	0.56	0.64
absolute value	(Parameter training)	34%	40%	53%	39%	31%
absolute value	(Parameter validation)	36%	42%	43%	39%	33%

(b) Scenarios with various learning velocities

Scenario		2-1	2-2	2-3	base
the number of neurons in hidden layers		3	3	3	3
transfer function of hidden layer		L	L	L	L
transfer function of output layer		L	L	L	L
training times		500	500	500	500
learning velocity		0.0001	0.001	0.01	0.1
R^2	(Parameter training)	0.89	0.89	0.87	0.88
R^2	(Parameter validation)	0.46	0.58	0.5	0.64
absolute value	(Parameter training)	44%	55%	33%	31%
absolute value	(Parameter validation)	39%	44%	33%	33%

(c) Scenarios with different numbers of neurons in hidden layers

Scenario		3-1	3-2	base
number of neurons in hidden layers		5	4	3
transfer function of hidden layer		L	L	L
transfer function of output layer		L	L	L
training times		500	500	500
learning velocity		0.1	0.1	0.1
R^2	(Parameter training)	0.9	0.9	0.88
R^2	(Parameter validation)	0.58	0.54	0.64
absolute value	(Parameter training)	33%	45%	31%
absolute value	(Parameter validation)	41%	34%	33%

(d) Scenarios with different transfer functions of hidden layer

Scenario		4-1	4-2	base
number of neurons in hidden layers		3	3	3
transfer function of hidden layer		T	P	L
transfer function of output layer		L	L	L
training times		500	500	500
learning velocity		0.1	0.1	0.1
R^2	(Parameter training)	0.87	0.74	0.88
R^2	(Parameter validation)	0.58	0.82	0.64
absolute value	(Parameter training)	78%	116%	31%
absolute value	(Parameter validation)	43%	26%	33%

(e) Scenarios with different transfer functions of output layer

Scenario		5-1	5-2	base
number of neurons in hidden layers		3	3	3
transfer function of hidden layer		L	L	L
transfer function of output layer		T	P	L
training times		500	500	500
learning velocity		0.1	0.1	0.1
R^2	(Parameter training)	0.87	0.89	0.88
R^2	(Parameter validation)	0.58	0.67	0.64
absolute value	(Parameter training)	53%	55%	31%
absolute value	(Parameter validation)	44%	41%	33%

(Note: R^2 is the R-square between measured water turbidity and estimated water turbidity)

To identify the sensitivity of parameters, the sensitivity index "S" is useful, although this index cannot be applied for the scenarios with different transfer functions. Table III lists the values of sensitivity index for parameter "training times", "learning velocity" and "number of neurons in hidden layers". The values of parameters are regarded as input values. When the R^2 between measured and estimated water turbidity is regarded as model output value, sensitivity index "S_1" can be calculated by eqn.(1). When the absolute value of relative error of water turbidity prediction is regarded as model output value, sensitivity index "S_2" can be determined by eqn.(1).

The simulation results of water turbidity prediction are more sensitive to parameter "number of neurons in hidden layers" than parameter "training times" and parameter "learning velocity". A negative value for the index indicates that input and output are inversely related. The result shows that the simulation error decreases when the training times or the learning velocity increase. ANN patterns the behavior of human's neuron system. The simulation results would have a little of difference in each calculation process, but the variation is in an accepted range.

TABLE III
SENSITIVITY ANALYSIS BY USING SENSITIVITY INDEX

Parameters	Sensitivity index	
	S_1	S_2
training times	0.0565	-0.07
learning velocity	0.00775	-0.014
number of neurons in hidden layers	-0.0775	0.2775

IV. CONCLUSION

Although ANN is commonly applied for representing a relationship between two systems, few studies discuss the sensitivity degree of parameters of ANN. It is difficult to predict the turbidity of raw water in the water treatment plant by using physical models. Contrarily, statistical models can be useful for predicting water turbidity. ANN can well predict turbidity of raw water in downstream water treatment plant according to upstream rainfall data.

The estimated water turbidity is more sensitive to the transfer function of hidden layer and the transfer function of output layer than other parameters. When the transfer functions are improper, the prediction errors of water turbidity would highly increase. According to the sensitivity index, it is helpful for us to identify the sensitivity of parameters. However, sensitivity index cannot be used in the scenarios with different transfer functions, because transfer functions are not easy to be quantified.

Among the parameter "training times", "learning velocity", and "number of neurons in hidden layers", the estimated water turbidity is more sensitive to parameter "number of neurons in hidden layers"than another two parameters. It is significant to comprehend the parameters of ANN to avert needless waste of time in the process of parameter training and validation. When a proper base for describing rainfall-water turbidity relationship is determined, early warning system can be established for water treatment plant to decrease the risk of water supply due to high-turbidity problems.

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