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APPLICATION OF ARTIFICIAL NEURAL NETWORK FOR WATER QUALITY MANAGEMENT

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ABSTRACT: A new artificial neural network based on decision-making approach for water quality management to control environmental pollution is presented. Previous research on water quality management problems has shown that traditional optimization techniques and an expert-system approach do not provide an educated solution comparing with decision making approach, which is related to the interpretation of data based on certain set of rules. Under such conditions, the Artificial Neural Network (ANN) learns the rule governing the decision-making through a series of experiments. In the present study, ANN was used to evaluate the relative effects of various pollution sources on the quality of river water. Using a back-propagation algorithm of a feed forward neural network, the relative effects of pollution sources were evaluated for strategic planning of water quality management. The case study for the Hanjiang River of China was selected to demonstrate the procedure and performance of a neural network-based approach for analysis and discussion.

Key words: Back propagation, neural network, pollution sources, water quality management

INTRODUCTION

Artificial Neural Networks are computational systems whose architecture and operation are inspired from our knowledge about biological neural cells (neurons) in the brain. A real neural network is a collection of neurons, the tiny cells that our brains are composed of. A network can consist of a few to a few billion neurons connected in an array of different methods. ANNs attempt to model these biological structures in terms of both their architecture and operation. Their function can be described either as mathematical computational models for non-linear function approximation, data classification, and clustering / non-parametric regression, or as a simulations of the behavior of a collection of model biological neurons in the human. Neural networks have provided a system that can reliably perform the decision-making in placing of the human brain and that can act as an alternative to expert systems for the few decades. In such a system, the rules governing the decision-making process related to data interpretation are learned either experimentally or by simulation using a complicated non-linear dynamic. The applications for neural networks have increased rapidly in the field of water quality management (Wen and Lee 1998), economic analysis, water resources planning and hydrologic time series, as described in Chakraborty et al. (1992), Windsor and Harker (1990), Lachtermacher and Fuller (1994) and Schizas et al. (1994). A typical feed forward neural network is shown in Fig. 1. In recent years, ANNs have been successfully used in the field of water quality management and planning for water pollution control of river systems, wetlands and low land areas. The neural network approach to multi-objective optimization for water quality management has provided an educated solution to aid in the decision-making process for river systems (Ching and Chih 1998). In other studies, it has provided a viable means of forecasting of water quality parameters (Holger and Graeme 1996). Similarly, Sovan et al. (1999) have described the development and validation of an artificial neutral network for the purpose of estimating and predicting the inorganic total nitrogen (TN) concentration from various nonpoint sources of watershed features for example agriculture and domestic land uses. In the present study, we took a new approach based on the methodology adopted by Karayiannis and Venetasanopoulos et al.

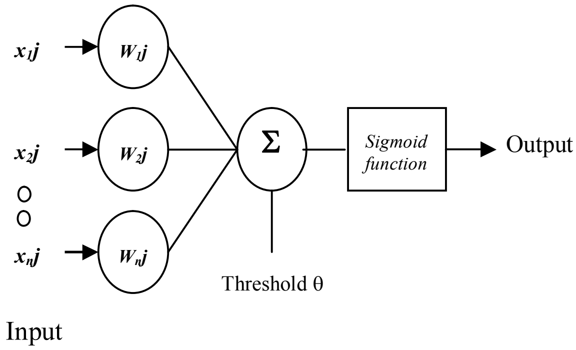

Fig. 1 Typical feed forward neural network with synapses oriented from left to right

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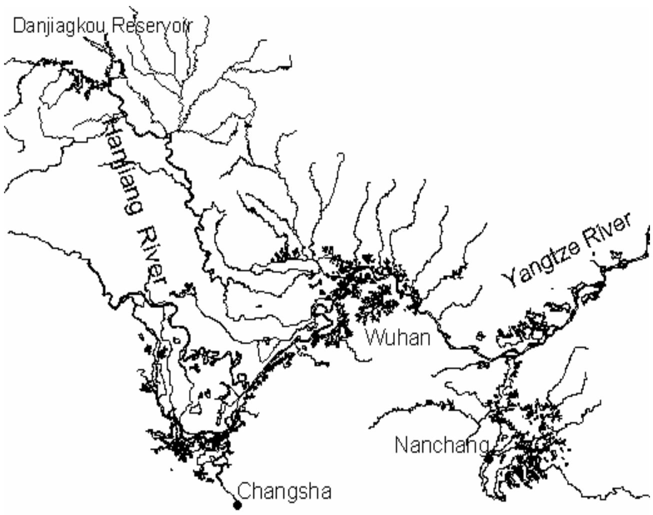

Fig. 2 Schematic map of the Hanjiang River

(1990a) to control water environmental pollution. A neural network was used to solve the problems involving decision-making to evaluate the relative effects of various pollution sources on water quality in addition of predicting water quality parameters and carrying out multi-objective optimization of water quality management.

TRADITIONAL APPROACHES VERSUS ARTIFICIAL NEURAL NETWORK

Regarding traditional approaches to water quality management and water pollution control of river systems, methods like simulated, deterministic, and statistical methods have all been used for the last two decades. The majority of existing water quality models are the mechanistic and are based on differential equation derived by applying mass balance (O'Connor et al. 1973) for the water quality parameters of interest such as chemical oxygen demand (COD), bio-chemical oxygen demand (BOD), sediment oxygen demand (SOD), ammonia (NH_3), suspended solids (SS) and dissolved oxygen (DO). These equations have analytical solutions only for specific boundary conditions as in the case of the deterministic model of Miller and Jenning (1979) and the stochastic models of Thayer and Krustschkoff (1967). In most of the practical cases, however an analytical solution does not exist and therefore it is necessary to solve the differential equation numerically using finite difference schemes (James 1984). Moreover, in all the above procedures, little research has been carried out regarding the relative effects of various pollution sources in river systems. Because many rivers are polluted in different ratios of waste materials, including domestic, agricultural and industrial wastes, regulatory agencies need to determine the relative effects of all pollution sources before implementing a waste allocation program for waste-load reduction and river pollution control. Karayiannis and Venetasanopoulos (1991) have utilized a learning algorithm to evaluate the performance of various neural network architects. In the present study, a neural network system was developed to provide information making it possible to transform a real-world problem into a potential neural network application.

MATERIAL AND METHODOLOGY

The basic idea behind our approach was to evaluate the relative effects of the waste load from various kinds of domestic and industrial sources in the water environment. Training of the neural network was achieved by using the presences of certain chemical pollutants exceeding the permissible limit of class II according to Chinese national water quality standards (GB 3838-88). The standards values are based on the classification of water in accordance with its particular uses. The main pollution sources for the Hanjiang River (Fig. 2) are organic material discharged from the domestic sources (DS) and industrial sources such as pulp and paper (PP), fertilizers (FL), dyes and chemicals (DC) and metals (MET). The daily levels of ten pollutants, including BOD_5, COD_{mn}, NH_3-N, suspended solids (SS), total phosphorous (TP), chlorides (Cl^{-1}), fluorides (F^{-1}), cyanide (CN^{-1}) and sulphide (S^{-2}) were determined for a period of 10 days after the discharge of effluents from each pollution sources every day using a one-dimensional water quality model (Zaheer and Cui 2002). The key issue in this study was the formation of an input and output set of data for the training and evaluation of the relative effects of each pollutants source. The available information makes it an excellent data set for use with artificial neural networks.

EXISTING WATER QUALITY OF THE HANJIANG RIVER

The Hanjiang River is one of the main water resources in the Hanjiang River basin fed by the Danjiangkou Reservoir in the north of China. It flows from northwest to southeast and supplies ample amounts of water for domestic, industrial, and agricultural activities in the basin. The transfer of water from the Danjiangkou Reservoir to the north may cause water-quality problems in the downstream area, particularly during the middle flows. Moreover, the economic development activities in the area may pose pollution problems downstream from the main stream. Presently, the water quality falls in the class II category according to the Chinese National Standard, and the quality is expected to worsen due to the discharge of

Table 1 Appearance of chemical pollutants during the period of ten days after the discharge of pollutants in the river simulated through 1D-water quality model

Number of days	Chemical Pollutants (CP)									
	BOD_5	COD_{mn}	NH_3-N	NO_3-N	SS	TP	Cl	F	CN	S_2
	1	2	3	4	5	6	7	8	9	10
1	1	0	1	1	1	0	0	1	1	1
2	0	0	1	1	0	1	0	1	1	1
3	1	1	1	1	0	1	1	1	1	0
4	1	1	1	0	0	1	1	1	1	0
5	1	1	1	0	1	1	1	1	0	1
6	1	0	1	1	1	1	0	1	0	0
7	1	1	0	0	0	1	1	1	1	1
8	0	0	1	1	0	1	0	1	0	0
9	1	1	0	0	1	1	1	1	1	1
10	1	1	1	1	0	1	1	1	1	0

industrial, domestic, and agricultural wastewater from various points and lateral sources (tributaries) along the main stream of the Hanjiang River (Zaheer 2000). It is therefore necessary to evaluate the relative effects of various pollution sources on river water quality. Using a back-propagation algorithm of a feed forward neural network, evaluation of the relative effects of pollution sources was carried out for strategic planning of water quality management. The existing water quality of the Hanjiang River was assessed based on Chinese National water quality Standards. Under the present conditions of flow, the water quality at the downstream reaches of the River is categorized as class II. Water quality can satisfy the requirements of water for various uses except in a few places where it falls to class III or IV. Table 1 shows the permissible limits for the various kinds of water quality parameters in five different classes (NWQS 1996).

ANN Methodology

A typical neural network is composed of a number of elements called nodes and the connected pathways linking these nodes. The nodes are the computational element of the network and are usually referred to as neurons, thus reflecting the origin of the neural network methodology in modeling the biological neural network in the human brain. A neural network is described as a linear relationship between a set of input patterns (waste characteristics or pollution sources) and the network output (appearance of chemical pollutants). Assume that C_p chemical pollutants or water quality parameters, which are detected in the river. Specific chemical pollutants that exceed the permissible limits of water quality standards on a daily basis determine the pollution of the river. The pollution of a river during the k_{th} days can be described by a pollution pattern as *Cpk=[p1k,p2k,..pnk],* where each element of *Cpk* is defined by *pik*, for which the value is taken as 1 if the *ith* C_p exceeds the permissible limit during k_{th} days otherwise 0 (Table 2). Similarly, assume that the river receive the waste of *Ws* pollution sources. The contribution of pollution source is determined by the presence of chemical pollutants in the waste, which can be described by waste pattern as *Wsj=[w1j, w2j,…wnpj]* where each element of *Wsj* is defined by *Wsij,* for which the value is taken as 1 if *ith Cp* is detected in the *jth* pollution source otherwise 0 (Table 3). Using this input and output pattern, the neural network is used to simulate the daily appearance of pollutants exceeding the permissible limits. The pollution pattern of each corresponding day is formed by the combination of pollution patterns of the previous day plus waste patterns for all sources. This implies the formation of an input-output pattern used for training of the neural network with respect to set (x_k, y_k), (k as no. of days), where input patterns *xk* are, $x_k = \left[x_k^0 x_k^1 x_k^2 \ldots x_k^{wns}\right], k = 1,2\ldots,m-1$, and

Table 2 Presences of chemical pollutants released from different pollution sources

Pollution Sources		Chemical Pollutants									
		BOD_5	COD_{mn}	NH_3-N	NO_3-N	SS	TP	Cl	F	CN	S_2
		1	2	3	4	5	6	7	8	9	10
Pulp & paper	PP	1	1	1	1	1	0	1	0	0	1
Fertilizers	FL	1	1	1	1	1	1	0	0	0	1
Dyes & Chemicals	DC	0	0	0	0	0	1	1	1	1	1
Metals	MET	0	0	0	0	1	0	0	0	1	0
Domestic Sources	DS	1	1	1	1	0	0	1	0	0	0

Table 3 Characteristics matrix for the pollution of the river by five pollution sources

Pollution sources	PP	FL	DC	MET	DS
PP	3	1	1	1	0
FL	2	4	0	1	2
DC	1	1	2	1	1
MET	0	2	1	3	1
DS	1	1	0	2	1

similarly the yk patterns are $yk = Cpk + 1, k = 1,2..., m - 1$. After training, the network is able to simulate the daily appearance of pollutants in the river. With this network, the relative effects of pollution sources are evaluated by the simple formation of outputs when various combinations of pollution sources are active. The input pattern formation for the neural network provides the rules for decision-making. Based on the daily input of waste patterns into the neural network, the training of the neural network will assign a set of weights to each of the pollution sources, which then determines the relative effects of the pollution sources. Performance of the neural network is achieved by getting the output while considering the contribution of a single pollution source under the assumption that all the other pollution sources are inactive. This output is generally distributed to a number of linked pathways to provide input to the other neurons, with each of these linked pathways transmitting all information from the contributing neuron output.

In the present study, the neural network contained one layer of a hidden unit. Therefore, a feed forward neural network a used. However, a multi-layer feed forward neural network may also be used though it requires not only a large amount of computational time but also results over training, which is due to the availability of less amount of input data . The performance of an over-trained neural network is generally poor compared with a well-trained neural network (Masters 1993). Each neuron has a state or activity level that is determined by the input received from the other unit in the network. Each input signal is weighted, i.e. it is multiplied by a weight value of the corresponding input line. In the hidden and output layer, the net input to unit i is written in the following form:

$$x_i = \sum_{j=1}^{n} y_i w_{ji} + b_i \tag{1}$$

where b_i is the bias of the unit, y_j is the output from unit j, ($w_{1i}, w_{2i} ..... w_{ni}$) is the synaptic weight vector of unit I, and n is the number of neurons in the layer preceding the layer including unit i. The bias of units describes the systematic distortion in the results that arises from neglecting certain factors. The weight sum x_i, which is referred to as the incoming signals of unit i, is passed through a nonlinear activation function or transfer function to produce the output signals, y_i. The most commonly used activation function in construction of the ANN is the sigmoid function, whereas the sigmoid function is assumed as a continuous range of values from 0 to 1 while considering the unit value of the shape factor, defined by

$$y_i = \frac{1}{1 + \exp(-x_i)} \tag{2}$$

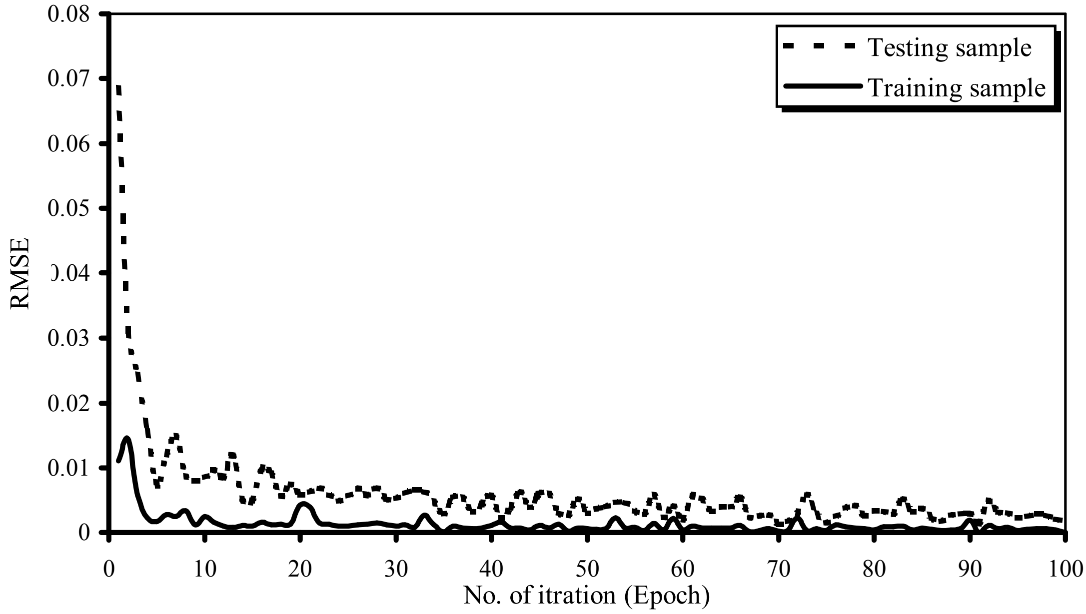

Fig. 3 Root mean square error (RMSE) in back propagation learning

Moreover, it is evident from Equation 2 that the output from the neural network model is always between 0 and 1. Before training, the synaptic weights w_{ji} are initialized by a small real number obtained from a random number generator. Training is performed using a back-propagation algorithm (Rumelhart et al. 1986). During training of the network by the back-propagation algorithm, the error function is calculated to produce the desired output y_k when starting with input x_k. Approximately 100 epochs are tried for the systematic changes in the synaptic weight since the desired output is achieved within a given tolerance. The error function is calculated as the sum of individual RMS error for each pattern to modify the weights accordingly before the next iteration by

$$RMS(k) = \frac{1}{2}(\hat{y}(k) - y(k))^2 \qquad (3)$$

where $\hat{y}(k)$ is the actual state of the output in response to the state of input, $x(k)$, while $y(k)$ is the desired output unit. The size of the step taken down the error surface is determined by the learning rate, α. Learning is thus reduced to a minimization procedure of error measurement. After the presentation of $(k+1)th$ inputs, each weight is computed using the following equation:

$$\Delta w_{ji}(k+1) = -\eta \frac{\partial E}{\partial w} - \alpha \Delta w_{ji}(k) \qquad (4)$$

where η is a learning rate, i.e. the fraction by which the global error is minimized during each iteration, and α is a constant (momentum term) that determines the effect of previous weight change on the current weight change. Much iteration of data is required to guarantee the convergence of known values towards their desired values. The initial connection of synaptic weights and the biasing threshold of the neural network are generated to be randomly distributed over the interval (-0.4 to +0.4). After 100 cycles (no. of iteration), the root mean square training error is reduced to below 0.01 and the estimated values converge towards their desired values. The appearance of chemical pollutants in the river is simulated by a feed forward neural network with $n_i = n_p(1+n_s)$ inputs, $n_h = n_i = n_p(1+n_s)$ hidden units and, $n_o=n_p$ output units because the number of input and output units are specified by the application and because the number of hidden units is free choice allowed by neural network structure. Figure 3 shows the monotonic decrease in the RMS training error. This trained neural network is used for evaluation of the relative effects of pollution sources in the river system. The computational program was created in a FORTRAN environment and computed with an Intel Pentium processor.

RESULT AND DISCUSSION

The performance of the neural network in the Hanjiang River was evaluated assuming that the contribution of one-pollution sources was active, while all other were eliminated. Such an input pattern is called a pseudo-input pattern that results when one of the *jth* pollution sources is active. The contribution of any particular pollution source is evaluated by observing the difference between its corresponding pseudo-pollution pattern and the real one. A characteristics number is assigned to each pollution source, i.e. *Nj,* which is obtained by counting the outputs $y_k(j)$ and the expected output y_k. If D_k *(j)* is the distance between y_k *(j)* and y_k, then the characteristic numbers, N_i, are equivalent to the number of D_k *(j)* that are nonzero. Clearly, *0 <.* N_j *< m-1 for all j=1,2,……..,ns.* The relative effects of each pollution source can be determined by comparing the characteristic number of pollution sources N_j, *j=1,2, ……..*n_s, which indicates that the smaller the characteristic number, the stronger the effects of the corresponding pollution source (Table 4). In the resulting characteristics matrix, the diagonal element provides the basis for evaluation of the pollution sources under the condition where one pollution source is active. According to Table 3, *DS > DC > MET = PP > FL,* which indicates that *DS* is more responsible for river pollution then *DC*, while *MET* and *PP* are equally responsible for river pollution. The pollution source *FL* shows the least effects on river pollution compared with the other sources. Moreover, a comparison of the results obtained from the artificial neural network and those of actual observed data source of the Hanjiang River show the relative effects of various pollution sources. From the results obtained, the artificial neural network model appears to be a useful tool in the decision-making process in water environmental pollution control. The greatest difficulty is in determining the appropriate model input and the reliability of data for problems of a similar nature. The basic idea for using the information source of the Hanjiang River basin in this study was to explore the usefulness of an artificial neural network in a water environmental application.

CONCLUSIONS

In the present study, a new approach to an artificial neural network was applied to water quality management for environmental pollution control. The obtained results suggest that ANN is a useful tool for evaluating the relative effects of pollutants in a river system during the decision-making process. Data for the Hanjiang River basin were used based on the hypothetical assumption of finding a new approach for an artificial neural network application. In the curve RMS error versus the number of iterations, a temporary minimum can be recognized as a phase in which an error is virtually constant for a long training time after initial learning. Although ANN techniques involve a data-driven approach, it is important to find the dominant model inputs that help to reduce the network size and ultimately reduce the training time and increase the generalization ability of a neural network for a given set of data. Moreover, this study may also provide guidelines for evaluating the relative effects of tributary discharges into the main stream for river basin planning and water pollution control. The neural network simulation outcomes show the relative effects of pollutants while considering two active pollution sources . This work may lead to the future application of a artificial neural network requiring a more complex back-propagation learning algorithm and even more training time. It is highly recommended that further resources be invested in such an artificial neural network application so as to develop a promising decision-making system for water quality management.

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REFERENCES

Chakraborty, K., Mehrotra, K., Mohan, C. K, and Ranka S. (1992). Forecasting the behavior of multivariate time series using neural network. Neural Networks. 5: 961-970.

Ching, G. W. and Chih, S. L. (1998). A neural network approach to multi-objective optimization for water quality management in a River Basin. Wat. Res. Res.. 34(3): 427-436.

James, A. (ed.) (1984). An introduction to water quality modeling. John Willy and Sons, NY.

Holger, R. M. and Graeme, C. D. (1996). The use of artificial neural networks for the prediction of water quality parameters. Wat. Res. Res.. 32 (4): 1013-1022.

Karayiannis, N. B. and Venetasanopoulos, A. N. (1990a). Artificial Neural Network: Learning Algorithm, performance Evaluation and Application. Kluwer Academic Publishers, London.

Karayiannis, N. B. and Venetasanopoulos, A. N. (1990b). Application of neural network to environmental protection. Proceeding of International Neural Network Conference, Paris, France, 334-337.

Karayiannis, N. B. and Venetasanopoulos, A. N. (1991). Fast learning algorithm for neural network (ed). 1141-1144 Elesvier Publishers, Holland.

Lachtermacher, G. and Fuller, J. D. (1994). Back propagation in hydrological time series forecasting in stochastic and statistical methods in hydrology and environmental engineering. 3: 229-242 Kluwer academy, Norwell Mass.

Masters, T. (1993). Practical neural network recipes in C++, Academic press Inc. San Diego, CA.

Miller, J. E. and Jennings, M. E. (1979). Modeling nitrogen oxygen of Chattahoochee River. Journal of Environ. Engn. Div., ASCE. 105: 641-653.

NWQS (1996). National Water Quality (GB 3838-88) and Integrated Waste Water Discharge (GB 8978) standard. Environmnetal Protection Bureu of China.

O'Connor, D. J., Thomson, R. V. and Ditoro, D. M. (1973). Dynamic water quality forecasting and management, EPA 660/373-009, Proj. No. R 800369, USA.

Rumelhart, D. E., Hinton, G. E. and William, R. J. (1986). Learning representation by back-propagating error. Nature. 323: 533-536.

Schizas, C. N., Patticjis, C. S. and Michaclides, S. C. (1994). Forecasting minimum temperature with short time length data using artificial neural network, Neural Network World, 4 (2): 209-219.

Sovan, L G., Maritxu A. and Giraudel, J. (1999). Prediction of stream nitrogen concentration from watershed features using neural network, Wat. Res.. 33(16): 3469-3478.

Thayer, R. P. and Krutschkof, G. (1967). Stochastic model for BOD and DO in stream. J. Sani. Engn. Div., Proc. Am. Soc. Civ. Eng.. 93: 59-72.

Wen, C. G and Lee, C. S (1998). A neural network approach to multi-objective optimization for water quality management in a river basin. Wat. Resources Res.. 34(3): 427-436.

Windsor, C. G. and Hacker, A. H (1990). Multivariate financial index prediction-A neural network study, in International Neural Network Conference, Vol 1, Kluwer academy, Norwell Mass.

Zaheer, I. (2000). Development of One–dimensional water environmental pollution control model using numerical solution of advection dispersion equation (a case study of Hanjiang river basin), M.Sc thesis, Hohai University Nanjing, China.

Zaheer, I. and Cui, G. B. (2002). Simulation of pollutants in the River system using finite difference method. Journal of Sediment Research, 17(2): 114-123.