A neural network prediction of eutrophication index of mainstream discharged tributary flow in a rainstorm

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Abstract. Rivers are the major inland water resources for the survival and health of human and ecosystem. Nonetheless, the water quality of rivers in many places is deteriorating or even eutrophic. As a major external pollution, rainfall runoff has attracted more and more attention. In order to timely know the eutrophication status of mainstream considering tributary flow discharge in a rainstorm period, a neural network prediction method is proposed. The inlet flow of mainstream and rainfall reappearing period are the input variables. The eutrophication index of mainstream control section is the output variable. It’s obtained based on Environmental Fluid Dynamics Code simulation and the universal index formula for eutrophic evaluation using a logarithmic power function. They form the training and testing samples. Then, the back propagation neural network is optimized and well-trained back propagation neural network is obtained. Ten cases are randomly selected and predicted. The results show that the relative error of the predicted eutrophication index is less than 1.5%. It’s demonstrated that this method can timely and accurately predict the eutrophication status of the mainstream in a rainstorm period. It will be helpful for decision makers.

1. Introduction
Rivers are the major inland water resources for the survival and health of human and ecosystem. Nonetheless, the water quality of rivers in many places is deteriorating or even eutrophic. External pollution sources mainly include industrial emissions, domestic sewage, rainfall runoff and agricultural runoff. Among them, people are paying more attention to the impact of rainfall runoff. The water quality of the mainstream deteriorates since because tributary flow discharges in a rainstorm period. Therefore, it’s important to timely and accurately evaluate the eutrophication status of the mainstream in a rainstorm period.

Rainstorm runoff contains a variety of chemical and biological contaminants. They may lead to water quality degradation, disease outbreaks and toxic effects on aquatic organisms [1]. Zong et al. [2] investigated the effects of rainfall runoff on the water quality of Xili Reservoir. The results showed that the pollution indicators of the reservoir increased during the rainfall, and the overall water quality decreased by two levels. Wang et al. [3] found that rainfall runoff could carry non-point source pollutants into the downstream water body and the concentration of pollutants had an obvious relationship with rainfall intensity. Gooré Bi et al. [4] analyzed the correlations between rainfall variables and common indicators of urban water quality. Zhang et al. [5] determined the grain size properties and phosphorus fractions in particulate matter in storm runoff. The overall total phosphorus concentration was high and averaged 298.7mg/kg. The total phosphorus may cause eutrophication of
freshwater systems. The Environmental Fluid Dynamics Code model (EFDC) [6] is an efficient tool to simulate the hydrodynamics and water quality. It’s applied to simulate the hydrodynamics and water quality of rivers [7], lakes [8] and reservoirs [9]. The artificial neural network can realize the mapping relationship from the input parameter to the output parameter [10]. It has been successfully applied in many basins [11-13]. In addition, the back propagation neural network (BPNN) is the most broadly neural network algorithm [14].

However, the previous studies rarely paid attention to the eutrophication status of the mainstream considering tributary flow discharge in a rainstorm period. In this study, a neural network prediction method is proposed to timely know the eutrophication status of the mainstream in a rainstorm period. The database is obtained by EFDC simulation and the universal index formula for eutrophic evaluation. The BPNN is trained, tested and validated. Then, the well-trained BPNN is obtained. It’s demonstrated that the well-trained BPNN can rapidly and accurately predict the eutrophication status of the mainstream in a rainstorm period. This method is helpful for decision makers to formulate the relevant management measures to prevent the deterioration of the water quality of mainstream.

2. Mathematical modeling

2.1 The prediction method

The proposed method is used to predict the eutrophication status of the mainstream in a rainstorm period. The rainfall reappearing period and the inlet flow of the mainstream are defined as the design variables, and the eutrophication index of the mainstream control section is defined as the target variable. The concentration of COD, DO, NH$_3$-N and TP at the mainstream control section is obtained by EFDC simulation. According to the universal index formula for eutrophic evaluation using a logarithmic power function[15], the eutrophication index of the mainstream control section is calculated. The rainfall reappearing period, the inlet flow of the mainstream and the eutrophication index of the mainstream control section constitutes the database. On the basis of the database, the BPNN learns the relationship between the design variables and the target variables.

![Figure 1. The flow chart of calculation procedure.](image)

The database is randomly divided into two parts, one is the training samples and the other is the testing samples. Based on the trainig samples, the BPNN is training. The accuracy of the BPNN is validated by using the testing samples. When the prediction accuracy of BPNN reaches the preset goal, the well-trained BPNN is obtained. Figure 1 shows the flow chart of the calculation procedure. The calculation procedure is broadly explained as follows: (1) The concentration of COD, DO, NH$_3$-N and TP at the mainstream control section are obtained through the EFDC simulation. According to the universal index formula for eutrophic evaluation using a logarithmic power function, the eutrophication indexes of the mainstream control section are calculated. They are the output variables of the BPNN. The input variables of BPNN are the inlet flow of the mainstream and rainfall...
(2) Based on the database, the BPNN is trained, tested and validated. The well-trained BPNN with good prediction function is obtained. The nonlinear relationship between input and output variables can be obtained by the well-trained BPNN.

2.2 Back propagation neural network

The back propagation neural network is predictive and can realize the mapping relationship from the input data to the output data [16]. The topology structure of BPNN is determined by the number of input variables and output variables. The input variables are the rainfall reappearance period and the inlet flow of the mainstream. The output variable is the eutrophication index of the mainstream control section. Therefore, the nodes of the input layer and the node of the output layer are 2 and 1, respectively. As for the nodes of the hidden layer, they are obtained by trial and error method. Firstly, the range of nodes is determined by referring to the formula (1) [17].

\[ l < \sqrt{(m + n) + a} \]  

Where, \( m \) is the number of input layer, \( l \) is the number of hidden layer, \( n \) is the number of output layer, \( a \) is the constant between 0 and 10. After the nodes of hidden layer are optimized, the optimal number is 6. Therefore, the structure of the BPNN is 2-6-1. Figure 2 shows the three-layer back propagation neural network. The nonlinear fitting relationship between the input variables and the output variables is obtained. Figure 3 shows the training behavior of the BPNN.

3. Case studies

The upstream segment of Haihe River is chosen as the research area, which is located in the downtown of Tianjin city. The flow field starts from the Sanchakou (Beiyun River, Ziya River and Xinkai River) and ends at Liulin. There are five main tributary rivers in this area. They are Beijin River, Nanjin River, Hucang River, Yueya River and Fuxing River. Liulin is set up as the water quality control section. The location of the upstream of Haihe River, Sanchakou, Liulin and five main tributary rivers are shown in figure 4.

According to former research [18], the catchments of tributary rivers are divided and their areas are estimated. The catchment area of Beijing River, Nanjin River, Hucang River, Yueya River and Fuxing River is about 31.8km², 16.73km², 11.29km², 46.76km² and 33.82km², respectively. Runoff coefficient is chosen to be 0.5 [19]. The selected rainfall reappearance periods (P) include 0.5a, 1a, 2a, 3a, 5a, 10a and 50a. The selected inlet flows of the mainstream (Q) include 0m³/s, 10m³/s, 20m³/s, 30m³/s, 50m³/s, 60m³/s, 70m³/s, 100m³/s, 150m³/s and 200m³/s. A total of seventy cases are calculated. Ten cases among them are used to verify the well-trained BPNN. They are (0m³/s,3a), (10m³/s,5a), (20m³/s,10a), (30m³/s,2a), (50m³/s,1a), (60,3a), (70m³/s,0.5a), (100m³/s,50a), (150m³/s, 5a) and (200m³/s, 50a). The discharge flow rate of each tributary river is estimated according to daily surface discharge estimation.
formula. Table 1 shows the water quality of the Sanchakou and tributary rivers.

Table 1. The water quality of the Sanchakou and tributary rivers. (unit: mg/L)

| Water quality parameters | Sanchakou Inflow | Beijin River | Nanjin River | Hucang River | Yueya River | Fuxing River |
|-------------------------|------------------|-------------|-------------|-------------|-------------|--------------|
| COD                     | 30.0             | 81.0        | 72.0        | 75.0        | 73.0        | 71.0         |
| DO                      | 5.0              | 3.0         | 3.5         | 3.8         | 4.7         | 4.3          |
| NH3-N                   | 2.0              | 3.1         | 5.0         | 4.0         | 5.8         | 4.2          |
| TP                      | 0.3              | 0.6         | 2           | 0.9         | 3.1         | 1.3          |

Figure 4. The location of the Haihe River and tributary rivers.

4. Results and discussion

Ten cases are randomly selected. Firstly, the concentrations of COD, DO, NH3-N and TP at the mainstream control section are obtained by EFDC simulation. According to the universal index formula for eutrophic evaluation using a logarithmic power function (formulas 2-3), the eutrophication indexes of ten cases are calculated. They are the calculation results. Furthermore, the ten cases are predicted by using the well-trained BPNN. The prediction results are obtained. Figure 5 shows the comparison between the calculation results and the prediction results. It demonstrates that the prediction results are consistent with the calculation results. Regardless of how the inlet flow of the mainstream and the rainfall reappearing period change, the prediction results and the calculation results are almost equal. Table 2 shows the eutrophication index for each standard.

![Figure 4. The location of the Haihe River and tributary rivers.](image)

\[ EI = \sum_{j=1}^{n} W_j 	imes EI_j = 10.77 \times \sum_{j=1}^{n} W_j \times (\ln x_j)^{1.826} \]  \hspace{1cm} (2)

\[ x_j = \begin{cases} 
\left( \frac{c_j}{c_{j0}} \right)^2 & c_j \leq c_{j0}, \text{ DO} \\
1 & c_j > c_{j0}, \text{ DO} \\
1 & c_j < c_{j0}, \text{ COD, NH}_3\text{-N and TP} \\
\frac{c_j}{c_{j0}} & c_j \geq c_{j0}, \text{ COD, NH}_3\text{-N and TP} 
\end{cases} \]  \hspace{1cm} (3)

Where, \( EI \) is the eutrophication index. \( W_j \) is the normalized weight value of index \( j \). The value of \( W_j \) is 0.25. \( c_j \) is the measured value of eutrophication index \( j \). \( c_{j0} \) is the value of very oligotropher. The value of COD, DO, NH3-N and TP is 0.12mg/L, 40mg/L, 0.01mg/L, 0.001mg/L, respectively.
Table 2. The eutrophication index for each standard.

| Grade          | Oligotropher | Mesotropher | Light eutropher | Middle eutropher | Hyper eutropher |
|----------------|--------------|-------------|-----------------|------------------|-----------------|
| EI             | 20           | 39.42       | 61.29           | 76.28            | 99.77           |

In addition, the relative error is used to further evaluate the accuracy of the proposed method. The relative errors of ten cases are shown in Figure 6. It shows that the relative errors are small. These relative errors are less than 1.5%, and most of them are less than 0.6%. It’s clear that the training performance of the BPNN model for all samples is capable of predicting the eutrophication index accurately with a small relative error.

This proposed method is helpful for decision makers to timely adjust the discharge of tributary rivers in a rainstorm period. When the inlet flow of the mainstream and the rainfall reappearing period are known, the eutrophication index of the mainstream control section can be predicted by this method. After the eutrophication index of the mainstream control section is obtained, decision makers can timely formulate governance measures based on the prediction results. For example, the tributary flow can be controlled by sluice gates to prevent the deterioration of the water quality of the mainstream.

5. Conclusions
The present paper proposes a neural network prediction method for eutrophication status of the mainstream considering tributary flow discharge in a rainstorm period. Based on the EFDC simulation and the universal index formula for eutrophic evaluation using a logarithmic power function, the samples are obtained. After being training and testing, the well-trained BPNN is obtained. It demonstrates that the prediction resluts are consistent with the calculation results. The relative errors of ten cases are less than 1.5%. It’s clear that this method is capable of predicting the eutrophication index of the mainstream accurately with small relative error. This method is helpful in preventing the deterioration of water quality of the mainstream in a rainstorm period.

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