An inverse design method for determining the optimal tributary flow into main stream in a rainstorm period

Lei Liu, Huimin Chen and Xue-Yi You

ABSTRACT

To ensure water quality at the control cross-section of main stream (CCMS) in a rainstorm period, an inverse design method was proposed to determine the optimal discharge flow of tributary rivers. The design variables are tributary discharges and the target variables are the required concentrations of chemical oxygen demand (COD), dissolved oxygen (DO) and ammonia nitrogen (NH₃-N) at CCMS. The relationship between target variables and design variables was identified using artificial neural network (ANN). The database was obtained by Environmental Fluid Dynamics Code (EFDC) and the optimal tributary discharges were obtained by genetic algorithm (GA) coupled with well-trained ANN. The results showed the following results: (a) The relative prediction errors of ANN are mostly less than 5%. (b) When the inlet flow rate is 0 m³/s, 30 m³/s, 50 m³/s, 100 m³/s and 200 m³/s, the optimization total discharges of tributaries are 5.7 m³/s, 12.5 m³/s, 18.6 m³/s, 33.4 m³/s and 61.8 m³/s, respectively. (c) Most of optimization plans satisfy entirely the water quality requirements at CCMS except a few plans, which the relative errors between optimized results and required values of COD and DO are less than 0.4% and 0.1%, respectively. The study showed that the inverse design method is efficient for determining the optimal discharges of multiple tributaries.

Key words | artificial neural network, genetic algorithm, inverse design method, optimization, stormwater, tributary flow

HIGHLIGHTS

- An inverse design method of Environmental Fluid Dynamics Code, artificial neural network and genetic algorithm is proposed.
- The optimal discharge of multiple tributaries into mainstream is obtained.
- The optimal discharge schemes satisfy the water quality requirement of main stream.
- The inverse design method is proved to be highly efficient.
INTRODUCTION

Rivers are major inland water resources for municipal, industrial and irrigational purposes. However, the water quality of rivers in many regions has been deteriorated because of artificial pollution such as industrial wastewater, domestic sewage and urban and agricultural runoff. Simultaneously, rainfall runoff including numerous pollutants has become an important pollution source (Wijesiri et al. 2018). Particularly, these pollutants are transported to main stream via tributaries in a rainstorm period and lead to the deterioration of water quality. To ensure the water quality requirements of main stream, the rainfall runoff pollution via tributaries needs to be controlled.

Some studies showed that stormwater runoff contained large amounts of heavy metal, organic matter and suspended substance (Helmreich et al. 2010; Zhao et al. 2021). Meanwhile, stormwater was also found to be a significant source of labile organic matter to receiving waters, especially during the first flush of runoff (McCabe et al. 2021). Furthermore, it was reported that suspended substance was an important carrier of chemical oxygen demand and total phosphorus. In stormwater runoff, the average particulate phosphorus concentration was high and organic phosphorus was in the majority (Zhang et al. 2018a, 2018b; Hu et al. 2021). These pollutants lead to the eutrophication of receiving waters. It is very important control the discharge of stormwater runoff into receiving waters.

Artificial intelligence algorithm has been successfully applied in many fields including water engineering, ecological and environmental sciences. ANN is successfully used for predicting water quality because it’s characterized to model the complex pattern and nonlinear processes without any advance knowledge of the relationship between the data of input and output (Salari et al. 2018; Jahan & Pradhanang 2021). The parameters of transient storage model were well predicted by using the symbiotic organism search algorithm and improved moth-swarm algorithm, respectively (Madadi et al. 2020a, 2020b). To solve optimization problem, the GA is usually used. For instance, it’s used for optimizing the structural best management practices to improve water quality goals and assess water quality in parameter optimization (Kaini et al. 2012; Sotomayor et al. 2018). Recently, the inverse design method has caught attention due to its high efficiency and wide applications. Zhai et al. (2014) proposed an inverse design method to research the air flow of a three-dimensional aircraft cabin. It’s based on multi-objective GA and computational fluid dynamics was used. Xu et al. (2020) used the GA to propose a new optimization approach for reservoir operation to balance hydropower generation and plant diversity conservation in downstream wetlands. However, to our best knowledge, the discharge rate of all tributary rivers into main stream to ensure the water quality at CCMS has rarely been optimized in a rainstorm period based on reverse design principle.
The aim of this study was to determine the optimal tributary discharge to meet the water quality requirements at CCMS in a rainstorm period. To realize this purpose, an inverse design method was proposed based on the combination of EFDC, ANN and GA. Tributary discharges are design variables and the required concentrations of COD, DO and NH₃-N at CCMS are target variables. The database of 25 samples was obtained by EFDC for training the ANN in order to establish the relationship between the variables of design and target. Subsequently, the GA was applied to find optimization plans. Finally, the obtained optimization plans were verified by EFDC. With the optimization plans, the control strategies were carried out to prevent the water quality deterioration of main stream in a rainstorm period.

**MATHEMATICAL MODELING**

**Inverse design method**

The inverse design method was used to find the optimal conditions to satisfy the required objectives. It’s operating in an inverse way of forward method used commonly. In this method, the discharges of multiple tributaries were put as design variables, and the concentrations of COD, DO and NH₃-N at the CCMS were set as target variables. The target variables were obtained through EFDC simulation under different typical cases. Based on results of EFDC simulation, the BPNN (Back Propagation Neural Network) learned the relationship between the variables of design and target. With the requirement of water quality of main stream at CCMS, the GA and well-trained BPNN were combined to obtain the optimal discharges of tributaries.

Establishing the EFDC database is the primary step. Different cases were generated by orthogonal design method. The concentrations of water quality parameters at the CCMS under different cases were obtained by EFDC. The values of main parameters of EFDC were shown in Table 1. The boundary conditions were set up according to Table 2.

Secondly, the EFDC database was separated into the training samples and testing ones. The BPNN was trained by training samples while testing samples were used to validate accuracy of the BPNN. The well-trained BPNN was obtained and its accuracy was validated by the mean squared errors of predicting testing samples.

In inverse design step, the GA and the well-trained BPNN were combined to obtain the optimal discharge of each tributary by satisfy the requirement of water quality of main stream at CCMS. In this method, the well-trained BPNN was used to predict target variables of new individuals. The GA was to find the optimal solutions. The individuals with high fitness were selected and the selected

| Parameters                  | Value       | Parameters                  | Value       |
|-----------------------------|-------------|-----------------------------|-------------|
| Grids                       | 2,642       | Initial value of NH₃-N      | 2 mg/L      |
| Initial water level         | 1.5 m       | Degradation rate of COD     | 0.1 day⁻¹   |
| Bottom roughness            | 0.02        | Re-nutrition coefficient    | 1.1 day⁻¹   |
| Temperature of water        | 27 °C       | Maximum nitrification rate  | 0.1 day⁻¹   |
| Initial value of COD        | 30 mg/L     | Initial value of DO         | 5 mg/L      |
| Release rate of NH₃-N by sediment | 0.2 g/m²/day | Oxygen consumption rate of sediment | 6 g/m²/day |

| 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         | 3.3          |
| NH₃-N                       | 2.0              | 3.1         | 5.0          | 4.0          | 5.8         | 4.2          |
individuals were then used in next iteration of the algorithm (Ayvaz & Elci 2018). When the maximum generation size was reached, the iteration stops and the optimal discharges of tributaries were obtained. Finally, the optimal discharges of tributaries were verified by EFDC to assure the optimal discharges satisfying the requirement of water quality of main stream at CCMS. The flow chart of calculation was explained in Figure 1.

Artificial neural network

The BPNN was used to realize the mapping relationship of input data and output ones. The discharges of five tributary rivers are input variables and the concentrations of COD, DO or NH$_3$-N at CCMS are output ones. Therefore, the input layer and output layer have 5 nodes and 1 node, respectively. As for the hidden layer, the number range of nodes was firstly determined as:

$$l < \sqrt{m+n} + a$$  \hspace{1cm} (1)

where, $l$, $m$ and $n$ are the number of nodes of hidden, input and output layers, respectively. $a$ is a constant between 0 and 10. The optimal number of hidden nodes was determined by trial and error method and it was 6 at first. Finally, three single-output BPNNs of COD, DO or

![Figure 1](http://iwaponline.com/ws/article-pdf/doi/10.2166/ws.2021.089/862839/ws2021089.pdf)
NH3-N were established separately. The structure of three-layer BPNN was shown in Figure 2.

Other parameters used for BPNN were mainly based on previous study (Zhang et al. 2018a, 2018b). Meanwhile, their values were determined through multiple debugging. The transfer functions selected for the neurons of hidden layer and output layer were Tansig function (S-type hyperbolic tangent function) and Purelin function (linear transfer function), respectively. The Levenberg-Marquardt algorithm was used to train the network in training function. The learning rate and the goal of mean squared error were set as 0.02 and 0.01, respectively. When the predicted results of COD could reach the target accuracy, the well-trained BPNN for COD was obtained. Similarly, the well-trained BPNN for DO and NH3-N was also obtained.

In order to evaluate the prediction performance of the trained BPNN, root mean square error (RMSE) was used. The RMSE between predicted results of BPNN and target output was expressed as:

\[
RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (C_P - C_T)^2}
\]  

where, \( C_P \) is the predicted concentration of COD, DO or NH3-N; \( C_T \) is target concentration of COD, DO or NH3-N; \( n \) is number of samples. The case that the inlet flow rate of main stream is 50 m\(^3\)/s was taken as an example. Table 3 showed the values of RMSE varying with the learning rate, number of hidden nodes and number of training samples. A small learning rate ensures the stability of training, but too small learning rate reduces the speed of training. Therefore, the learning rate was chosen as 0.02.

**Genetic algorithm**

Coupled with the BPNN, the GA was used to find the optimal discharges of tributaries. It includes population initialization, fitness function, selection operator, crossover operator and mutation operator. Real number encoding was chosen for individual coding because real number coding could indirectly and naturally express the continuous parameter optimization. Furthermore, it can improve the operational accuracy and speed. The roulette wheel selection was used for selection operator. The cross point was selected randomly for each pairing and the crossover operator was the single point crossover operator. The mutated gene was obtained by using the stochastic method. Based on previous studies (Lei et al. 2014) and multiple debugging, the values of the parameters were determined. The population size, maximum genetic algebra, crossover probability and mutation probability were 50, 200, 0.8 and 0.1, respectively.

**Hydrodynamic and water quality model**

The EFDC model is an efficient tool for understanding the hydrodynamics and water quality responses in surface water systems such as rivers, stream networks and lakes (Quijano et al. 2017; Saharia et al. 2019; Zhao et al. 2020). The Boussinesq approximation and hydrostatic assumption are assumed in EFDC. This EFDC consists of hydrodynamic module, water quality module, sediment module and so forth. It uses horizontal Cartesian and vertical sigma coordinates. Because the horizontal magnitude of main stream is much greater than the vertical one, a two-dimensional EFDC model was used to simulate the hydrodynamic and water quality of main stream. To accommodate realistic horizontal boundaries, it’s convenient to formulate the control equations with curvilinear orthogonal coordinates in the \( x \) and \( y \) directions.
In water quality model, the governing mass-balance equation for each state variable is expressed as:

$$\frac{\partial C}{\partial t} + \frac{\partial(uC)}{\partial x} + \frac{\partial(vC)}{\partial y} = \frac{\partial}{\partial x}(K_x \frac{\partial C}{\partial x}) + \frac{\partial}{\partial y}(K_y \frac{\partial C}{\partial y}) + S_C$$  \hspace{1cm} (3)

where, $C$ is the concentration of state variable; $u$ and $v$ are velocity components in the $x$ and $y$ directions, respectively; $K_x$ and $K_y$ are turbulent diffusivity coefficients in the $x$ and $y$ directions, respectively; $S_C$ is internal and external sources and sinks per unit volume.

Equation (3) shows the dispersion and transportation of COD, DO and NH$_3$-N. According to the variables of water quality and their relationship, the structure chart of state variables and interactions were shown in Figure 3 (Huang et al. 2018).

### CASE STUDIES

The upstream segment of Haihe River located in the downtown of Tianjin city was chosen to investigate the
applicability and reliability of the proposed method. The flow field is between Sanchakou (Beyun River, Ziya River and Xinkai River) and Liulin. Liulin was set up as the cross-section of water quality control. There are five main tributary rivers including Beijin River, Nanjin River, Hucang River, Yueya River and Fuxing River. Figure 4 showed the location of the upstream of Haihe River, Sanchakou, Liulin and tributary rivers. The annual average rainfall and road evaporation are 539 and 470 mm, respectively (Bai et al. 2020). In addition, concentrations of nitrogen and phosphorus were seriously high in Haihe River during the study period.

The catchments of tributary rivers were divided and their areas were estimated according to earlier research (Xu et al. 2015). The catchment areas of Beijin River, Nanjin River, Hucang River, Yueya River and Fuxing River were about 31.8 km², 16.73 km², 11.29 km², 46.76 km² and 33.82 km², respectively. According to the rainstorm analysis in this region (Hao & Wang 2008), fifty years of rainfall recurrence period was selected as the extreme rainfall scenario. The rainfall was estimated by the following equation.

\[ i = \frac{22.95(1 + 0.85 \lg P)}{(t + 17)^{0.85}} \]  

where, \( i \) is the rainstorm intensity (mm/min); \( P \) is the rainfall recurrence period (a); \( t \) is the duration time (min).

Here, the runoff coefficient was chosen to be 0.5 (Zhang 2005). Based on the surface runoff, the maximum discharge of Beijin River, Nanjin River, Hucang River, Yueya River and Fuxing River were chosen as 18 m³/s, 10 m³/s, 7.0 m³/s, 27 m³/s and 20 m³/s, respectively. Four scenarios were chosen for the inlet flow rate of main stream \((Q)\) at Sanchakou boundary (Zhang 2005). They were 30 m³/s, 50 m³/s, 100 m³/s and 200 m³/s. In addition, the case that \( Q = 0 \) m³/s was also chosen, which was taken as the benchmark calculation.

The simulation cases of EFDC model were generated using orthogonal experiment design method. The range of each tributary’s discharge was divided into five levels for one inlet flow rate of main stream. Table 4 showed the flow of each tributary river under different inlet flow rate of main stream. For each inlet flow rate of main stream, five factors and five levels orthogonal experiment schemes shown in Table 5 was adopted for establishing the database of inverse design method. Twenty-five simulation cases were set up for each inlet flow rate of main stream. In addition, two more cases were added to ensure the completeness of database. One case was zero discharge of each tributary river \((0, 0, 0, 0, 0)\), and the other was the maximum discharge of each

Figure 4 | Location of the Haihe River and tributary rivers.
tributary river. When Q was 0 m$^3$/s, 30 m$^3$/s, 50 m$^3$/s, 100 m$^3$/s and 200 m$^3$/s, the cases of the maximum discharge of each tributary river were (5, 1, 1, 0.5, 0.5), (8, 4, 4, 3.5, 3.5), (10, 7, 5, 5, 5), (14, 10, 7, 10, 10) and (18, 10, 7, 27, 20), respectively. Therefore, there were 27 simulation cases for each inlet flow rate of main stream. Finally, the database of flow field and water quality was obtained by EFDC model.

The flow rate of tributary rivers can be controlled by discharge gates to main stream (Zhang 2005). The inlet flow rate at Sanchakou input boundary was changed by the upstream condition during a rainstorm. The optimal flow rate of tributary rivers was determined by the inverse design method under different inlet flow rates at Sanchakou during a rainstorm. When the tributary rivers discharged during a rainstorm period, the concentrations of COD, DO and NH$_3$-N at Liulin cross-section were required to satisfy water quality requirements, which the maximum values of COD and NH$_3$-N and the minimum value of DO are 40 mg/L, 3 mg/L and 4 mg/L, respectively.

**RESULTS AND DISCUSSION**

**Optimized design**

After the database was obtained, the BPNN was trained and tested. When the inlet flow rate of main stream was 0 m$^3$/s,
30 m$^3$/s, 50 m$^3$/s, 100 m$^3$/s and 200 m$^3$/s, two testing samples were selected to evaluate the well-trained BPNN, respectively.

In order to verify the reliability of the prediction, the predicted results of BPNN and simulated ones of EFDC were compared in detail and the relative errors between the above results were calculated by the following equation:

$$RE = \frac{|B - S|}{S} \times 100$$  

(5)

where, $RE$ is the relative error; $B$ and $S$ are predicted results of BPNN and simulated results of EFDC, respectively.

The results in Table 6 showed that the relative errors between above two methods are small. Therefore, the water quality of main stream at CCMS can be predicted by well-trained BPNN.

The discharges of tributary rivers were optimized by GA coupled with well-trained BPNN. When the inlet flow rate of main stream was 0 m$^3$/s, four optimization plans were obtained. They were shown in Figure 5(a). The four optimization plans were defined as Plan-1 to Plan-4. The total discharges of five tributary rivers were almost the same in different plans. In each plan, the discharge of Beijin River accounts for 70% of total discharge. The reason is because Beijin River is closest to Sanchakou and there is a long distance between Beijin River and the second tributary. The self-purification capacity of main stream permits more discharge from Beijin River.

When the inlet flow rate of main stream was 30 m$^3$/s, 50 m$^3$/s, 100 m$^3$/s or 200 m$^3$/s, four optimization plans were also obtained, respectively. They were shown in Figure 5(b)–5(e). Similarly, the discharge of each tributary river was different for each inlet flow rate, but the total discharges of five tributary rivers were almost the same. For example, when the inlet flow rate of main stream was 30 m$^3$/s, the total discharge of five tributary rivers was between 12.1 m$^3$/s and 12.6 m$^3$/s. The total discharge 12.6 m$^3$/s of Plan-1 was the maximum.

When the inlet flow rate of main stream was 50 m$^3$/s, the total discharge of five tributary rivers was between 18 m$^3$/s and 18.7 m$^3$/s. The total discharge 18.7 m$^3$/s of Plan-2 was the maximum. When the inlet flow rate of main stream was 100 m$^3$/s, the total discharge of five tributary rivers was between 31.1 m$^3$/s and 33.5 m$^3$/s. The total discharge 33.5 m$^3$/s of Plan-4 was the maximum. When the inlet flow rate of main stream was 200 m$^3$/s, the total discharge of five tributary rivers was between 59.8 m$^3$/s and 61.8 m$^3$/s. The total discharge 61.8 m$^3$/s of Plan-1 was the maximum.

From the above results, it was found that the total discharge of five tributary rivers increases when the inlet flow rate of main stream increases because the dilution capacity of main stream is enhanced. However, the self-purification capacity of main stream is becoming weak due to the decrease of water retention time of main stream. Therefore, the dilution of input water plays dominant role in the reduction of pollutants concentration of main stream at this time. When the inlet flow rate of main stream increases, the pollutants from tributary rivers are discharged downstream out of the controlled upstream segment of Haihe River.

### Verification of water quality at the control cross-section

In order to check the performance of the proposed inverse design method, the optimized plans were validated by comparing with the water quality requirements at CCMS. The comparison were shown in Table 7. For the index of COD, DO and NH$_3$-N, the negative difference indicates that it not only meets the water quality requirement, but also has
abundant environmental capacity for the corresponding index. Conversely, the positive difference implies that the optimized results don't satisfy the water quality requirements for the corresponding index.

From Table 7, it was found that the optimized results of the inverse design satisfied the water quality requirements at CCMS well. When the inlet flow rate of mainstream was 0 m³/s, the concentrations of COD and NH₃-N at CCMS...
were better than those of water quality requirements. For the Plan-1, the concentration of DO exceeded the water quality requirement. For the Plan-2 to Plan-4, the concentrations of DO were less than the water quality requirement. However, the relative error between the optimized result and the required DO value at CCMS was very small and it was only 0.2%, 0.4% and 0.01%, respectively. It means this method can reliably obtain the optimal flow rate of tributary discharged into the main stream. It also showed that DO is the limiting factor for this discharge case.

When the inlet flow rate of main stream was 30 m$^3$/s, 50 m$^3$/s, 100 m$^3$/s or 200 m$^3$/s, the optimized concentration of DO at CCMS was more than that of water quality requirement. The concentration of NH$_3$-N was less than the required value of water quality requirement. When the inlet flow rate of main stream was 30 m$^3$/s, the concentration of COD of Plan-2 slightly exceeded that of required value of water quality requirement. Furthermore, when the inlet flow rate of main stream was 200 m$^3$/s, the optimized concentrations of COD of Plan-1 and Plan-2 were more than those of the required value of water quality requirement. However, the relative errors between the result of the inverse design method and the required COD value at CCMS was very small and it was only 0.03%, 0.008% and 0.1%, respectively. This means the inverse design method can give reliable optimal flow rate of tributary rivers discharged into the main stream.

From the above optimized results, the absolute difference of NH$_3$-N was the largest and it was more than 0.3 mg/L in all plans. This means that NH$_3$-N was not the limiting factor for all plans in this approach. The optimized concentration of DO was more than that of water quality requirement for most plans. With the increase of the inlet flow rate of main stream, the difference of DO between the optimized results and the required value increases gradually in four plans. This is because the pollutant degradation ability and DO concentration of main stream increase with the increase of the inlet flow rate of main stream. In addition, the positive relative errors of COD between the calculated results and the required water quality values were small. It illustrates that the discharges of tributary rivers to the main stream were mainly limited by the concentration of COD for many plans in this study.

| Q (m$^3$/s) | COD (mg/L) | NH$_3$-N (mg/L) | DO (mg/L) |
|-------------|-------------|-----------------|----------|
| 0           | 40          | 3               | 4        |
|             | -0.7        | -0.5            | +0.02    |
| 30          | 40          | 3               | 4        |
|             | -0.04       | -0.3            | +0.07    |
| 50          | 40          | 3               | 4        |
|             | -0.1        | -0.4            | +0.1     |
| 100         | 40          | 3               | 4        |
|             | -0.5        | -0.4            | +0.3     |
| 200         | 40          | 3               | 4        |
|             | +0.003      | -0.4            | +0.4     |

Note: Positive value represents that optimized results are more than required datum. Negative value represents that optimized results are less than required datum.
CONCLUSIONS

An inverse design method was proposed by integrating the methods of BPNN, GA and EFDC to determine the optimal discharge flow rate of tributary rivers to ensure the required water quality condition at CCMS. This method was applied to design maximum discharge of tributary rivers in a rainstorm period. The reliability of the method was verified by an example studied for the water quality control problem in Haihe River (main stream). The optimal discharges of tributary rivers were obtained by the inverse design method and verified by EFDC simulation. The main conclusions were shown in the following.

While the inlet flow rate of main stream increases, the total discharge of tributary rivers into main stream increases in a rainstorm period. The results revealed that the optimization plans ensured the water quality requirements at CCMS. For the present example, the concentration of COD was the limiting factor. For the fifty years recurrence period, when the inlet flow rate of main stream was 0 m$^3$/s, 30 m$^3$/s, 50 m$^3$/s, 100 m$^3$/s and 200 m$^3$/s, the total optimal discharge of tributary rivers was 5.7 m$^3$/s, 12.5 m$^3$/s, 18.6 m$^3$/s, 33.4 m$^3$/s and 61.8 m$^3$/s, respectively. And the detail discharge rate of each tributary river was found in the above Section 4 for brief. The discharges of tributary rivers should be controlled by sluice gates according to the optimized results. The present method was proved to be highly efficient for determining the optimal discharges of tributary rivers into main stream in a rainstorm period. Meanwhile, the required water quality condition at CCMS was satisfied. In addition, the limiting factors of each plan were found out by the proposed inverse design method. The results showed that the present inverse design method has important application value for the main stream water quality control and management.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

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