

Optimization Strategy for Decentralized Water Transport System based on Specific Pollutants Control

Shen Dong^{1,a}, Mou Lv^{1,b*}, Zebin Sheng^{2,c}, H. Gowda^{3,d}

¹Institute of Environmental and Municipal Engineering, Qing Dao University of Technology, Qingdao, Shandong 266033, China

²Shanghai United Design Group Co., Ltd. Qingdao Branch, Qingdao, Shandong 266000, China

³University of Stuttgart, Modelling Hydraulic and Environmental Systems, 70569 Stuttgart, Germany

^adongshends@126.com, ^b35398496@qq.com, ^cszb08xw@qq.com, ^dPHG2003@yahoo.com

Article Info

Volume 83

Page Number: 574 - 585

Publication Issue:

July-August 2020

Abstract

At present, in the research of water resources dispatching technology, while the quality impact of raw water on treatment process as well as pipeline network is usually neglected. In this paper, taking the source wells with poor quality on the upper and middle reaches of the Yellow River as the research object, the dispatching technology of quantity and quality combined optimization based on specific pollutant control is studied. Firstly, according to water quality characteristics of shallow groundwater around Yellow River, plant influent-source water coupling model of specific pollutants is established by combining the Fourier Transform with the Artificial Neural Network (ANN) method. On this basis, an optimization model of decentralized water transport system is constructed considering water quality, supply safety and economy. The optimization strategy is applied to Z city in the middle and upper reaches of the Yellow River, the effectiveness and practicability of decentralized water transport system based on specific pollutants control are verified in the mean while.

Keywords: Dispatching Optimization, Plant Influent-Source Water Coupling Model, Decentralized Water Transport System, Specific Pollutants Control, Middle and Upper Reaches of the Yellow River

Article History

Article Received: 06 June 2020

Revised: 29 June 2020

Accepted: 14 July 2020

Publication: 25 July 2020

1. Introduction

As an essential water source of China, groundwater plays a noteworthy role in drinking water supply, social economy development and eco-environment balance. Additionally, groundwater is an important guarantee of well-balanced water cycling. However, the pollution problems of groundwater are lack of concern for a long time, due to the elusive characteristic and systemic complexity. With the increasing attention to the safety of water source and transport system, there is great significance to study

optimization of groundwater transport system and contaminants control.

In recent years, with the increasing shortage of water resources and the increasing awareness of environmental protection, scholars have carried out a lot of research on the optimal dispatching of water resources at home and abroad. Zhang Yanlan (2014) set up a multi-source joint dispatching model for Beijing under the condition of South-to-North Water Transfer, aiming at ensuring the minimum yield of water supply and discard. Yu Bing (2015) took the

social benefit and supply cost of water supply system as the dispatching objective, constructed the three-layer water supply network structure of "water source-water plant-user in different areas", and established the optimal dispatching model of multi-source supply. Daniel W. (2014) studied the application of multi-objective optimization model for water resources sustainability. Obviously, scholars at home and abroad have paid great attention to water allocation research for multi-source dispatching at present. Many investigations have been carried out primarily with the purpose of water resources security assurance and water supply cost reduction. Nevertheless, there are few studies on quality assurance and pollutant control in the process of water resources dispatching relatively, and the research results are not yet mature.

In this paper, the source wells with poor quality on the upper and middle reaches of the Yellow River are taken as the research object, the relationship of particular pollutants at waterworks and network department is researched. Then, the optimal operation model of source water is established based on the comprehensive consideration of particular pollutants control and operation energy reduction. The research will provide theoretical guidance for water quality guarantee and scientific management of groundwater distribution system on the upper and middle reaches of the Yellow River.

2. Plant Influent-Source Water Coupling Model of Specific Pollutants

It is quite common to fetch water from the wells beside the mainstream beach of Yellow River, because the groundwater level is much higher there due to excellent recharging conditions. Water samples from these well were tested which indicated higher concentrations of As, Fe, Mn and some other contaminants. On-line instruments are not commonly installed for decentralized source water wells due to economic reasons or lack of maintenance. As a result, impact of water quality variation from wells on the influent of plants could

not be detected on time, which brings difficulties to control specific pollutants concentration allocating source water.

The specific pollutants concentration of influent of plants usually correlates with that of wells within water transport systems. However, the correlation cannot be simply explained by polynomials or linear functions. Fortunately, non-mechanism water quality analysis methods became more and more popular, when statistic methods and artificial intelligence algorithm was introduced. This research mainly focus on source water wells in the middle-lower reaches of Yellow River, and employs Fourier transform and artificial neural networks (ANN) to study Plant influent-Source water coupling model of specific pollutants.

2.1 Fourier Transform of Specific Pollutants

Fourier Transform is one of the most important transforms for modern mathematics, which has been commonly applied in digital signal processing. Especially for those complex and elusive function, Fourier transform could transform complex time domain signals into more analysis friendly frequency domain signals.

For arbitrary discrete time series $\{x_n\}$, with Fourier transform we get

$$y(\omega) = \sum_{-\infty}^{+\infty} x_n \exp(-i\omega k) \quad , \quad (1)$$

Relevantly, if $y(\omega)$ is a pericodic function with period length 2π , reverse Fourier transform

$$x_n = \frac{1}{2\pi} \int_{-\pi}^{\pi} y(\omega) \exp(i\omega k) d\omega \quad , \quad (2)$$

Digital filtering was performed via Fourier transform to remove disturbance of specific pollutants data of plant influence and source water wells. Then the frequency domain data was treated as the input and model training data of artificial neural network.

2.2 Plant Influent-Source Water Coupling Model of Specific Pollutants based on Artificial Neural Network

In order to improve the calculation accuracy of the artificial neural network model and avoid the interference of noise data on the simulation accuracy, the Fourier transform was used to pretreat the

specific pollutants monitoring data of plant influent and source wells. After removing the noise data, the plant influent-source well coupling model of specific pollutants based on the artificial neural network was established based on the frequency domain signal, as shown in Figure 1.

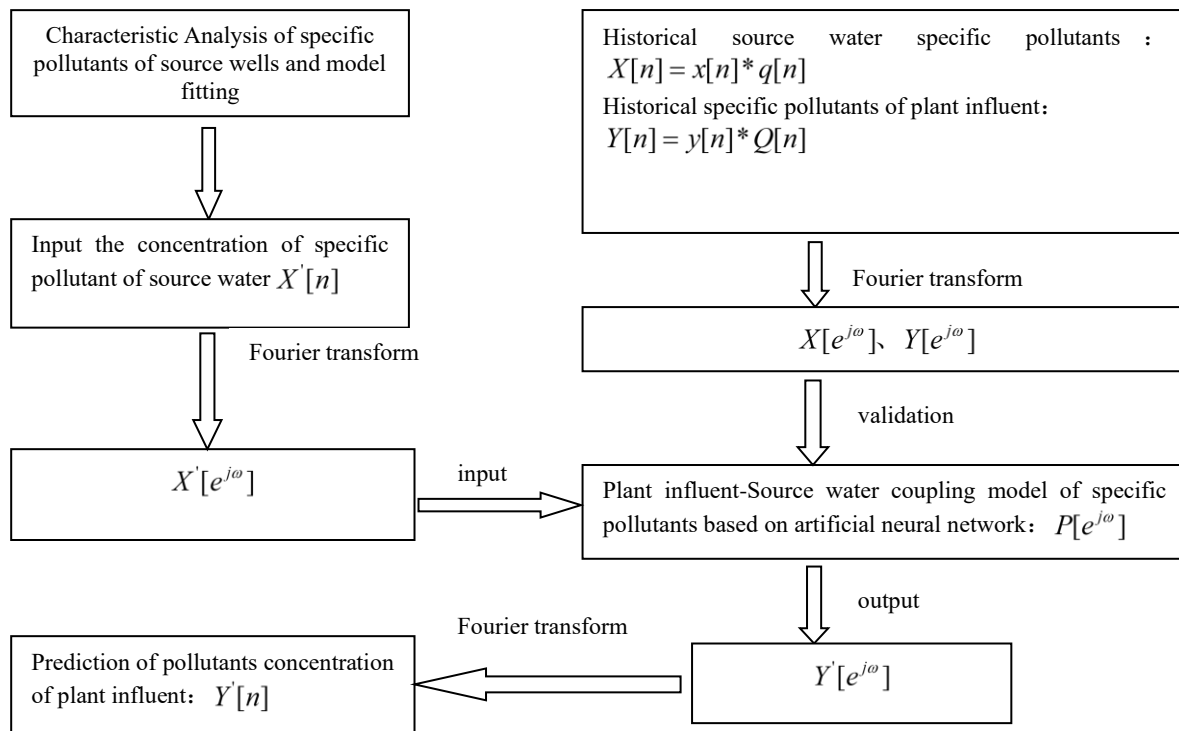


Fig.1. Plant Influent-Source Water Coupling Model of Specific Pollutants

During the construction of ANN model, 240 samples with four indexes of the influent flow, specific pollutants concentration, wells' outlet flow, and wells' specific pollutants concentration were filtered by Fourier transform and used as training parameters. The model was trained by Levenburg-Marquardt function. A BP network model was built later with hidden layers, where the first hidden layer had 14 neuron sand the second hidden layer contains 20 neurons. Logsig function is used as the transfer function between hidden layers. Meanwhile, input layer and hidden layer used tan-sigmoid function, and hidden layer to output layer applied purelin linear function.

3. Construction of Water Transport Optimization Model

In order to guarantee water safety and satisfy water requirement as well as reduce energy consumption, a water transport optimization model was built with consideration of reduce specific pollutants concentration of plant influent. The decision variables of the model are source water well numbers (and decide which wells are suitable to provide water at certain time), flow, and pumping time length.

3.1 Objective Function

$$\min f(F_1, F_2, F_3) , \quad (3)$$

3.1.1 Water quality coupling model F_1

$$F_1 = f_1(x[n], q[n], y[n], Q[n], X'[n], Y'[n]) \quad (4)$$

The methods to build specific pollutants coupling model has already stated in section “Plant Influent-Source Water Coupling Model of Specific Pollutants based on Artificial Neural Network”.

3.1.2 Energy consumption model

Energy is mostly used for pumping water from source wells of decentralized water transport system.

$$F_2 = \sum_{i=1}^I \sum_{j=1}^J SP_{i,j} \frac{C \cdot NP_{i,j} \cdot QP_{i,j} \cdot HP_{i,j}}{\eta_{i,j}} \quad (5)$$

Where, $SP_{i,j}$ -- electricity fee of the i^{th} well at time j^{th} , CNY/kwh;

C -- conversion coefficient;

$NP_{i,j}$ -- operation status of the i^{th} well at time j^{th} . If the pump of this well is on, $NP=1$, otherwise $NP=0$;

$QP_{i,j}$ -- outlet flow of the i^{th} well at time j^{th} , m^3/h

$HP_{i,j}$ -- pump head of the i^{th} well at time j^{th} , m;

$\eta_{i,j}$ -- pump efficiency of the i^{th} well at time j^{th} , which could be calculated from the fitted pump efficiency curve;

I -- total numbers of wells;

J -- total hours, which is equal to 24 for this model.

3.1.3 Water transport safety guarantee model

Source wells usually apply submerged pumps with constant speed, which have smaller scope for flow and head adjustment, compared with secondary pressure pump station. Moreover, there is gaps between outlet flow of wells and the required flow of the transport system under certain conditions. If flow exceed requirement, it not only waste water but also results in higher operation cost. If water flow cannot than the requirement, the water transport system cannot be regarded as a reliable system. Therefore, scientific solution is necessary to allocate well pumps with different rated flow and head optimally.

Theoretically, water quantity balances absolutely, which is denoted as $\sum_{i=1}^I Q_{i,j} = QF_j$. However, in order to guarantee the feasibility of optimization calculation, the restriction could be reduced. As a result, a model to guarantee water transport safety is built as below.

$$F_3 = \sum_{j=1}^J \left| \sum_{i=1}^I Q_{i,j} - QF_j \right| \quad (6)$$

Where, QF_j -- total water requirement at time j^{th} (predicted via water consumption model), m^3/h ;
 $Q_{i,j}$ -- water flow of the i^{th} pump station at time j^{th} , m^3/h .

3.2 Restrictions

3.2.1 Hydraulic conditions

Water transport system should satisfy head loss equation (Darcy–Weisbach equation) and continuity equation.

Head Loss equation:

$$h = SQ^n \quad (7)$$

Continuity equation:

$$A\bar{Q} = \bar{q} \quad (8)$$

3.2.2 Water supply capacity of each well

$$\sum_{j=1}^J Q_{i,j} \leq Q_{\max i} \quad (9)$$

Where, $Q_{i,j}$ -- outlet flow of the i^{th} well at time j^{th} , m^3/s ;

$Q_{\max i}$ -- maximum outlet flow of the i^{th} well, m^3/s .

3.2.3 Running time length of each pump

Overload risk always exists if a certain pump has continuously run for too long time. On the contrast, pumps will get out of order if they have stayed off for too long period. Therefore, the running time length of each pump should be taken into consideration.

$$DUR_{\min i} \leq DUR_i \leq DUR_{\max i} \quad (10)$$

Where, DUR_i -- running length of the i^{th} pump, h;

$DUR_{\min i}$, $DUR_{\max i}$ -- minimum and maximum running length of the i^{th} pump.

3.3 Optimal Solution

The solution of water transport optimization model is a typical multi-objective optimization problem. Therefore, how to find the optimal solution between parallel objective functions and multiple constraints is an important problem to be solved. The inherent

parallelism of hybrid multi-objective evolutionary algorithm (HMOEA) makes it possible to find multiple Pareto optimal solutions in simulation. Compared with traditional optimization algorithm, it can deal with discontinuity, non-differentiability and non-convexity of Pareto frontier better. Therefore, the model in this paper is solved by HMOEA, and the implementation process is shown in Figure 2.

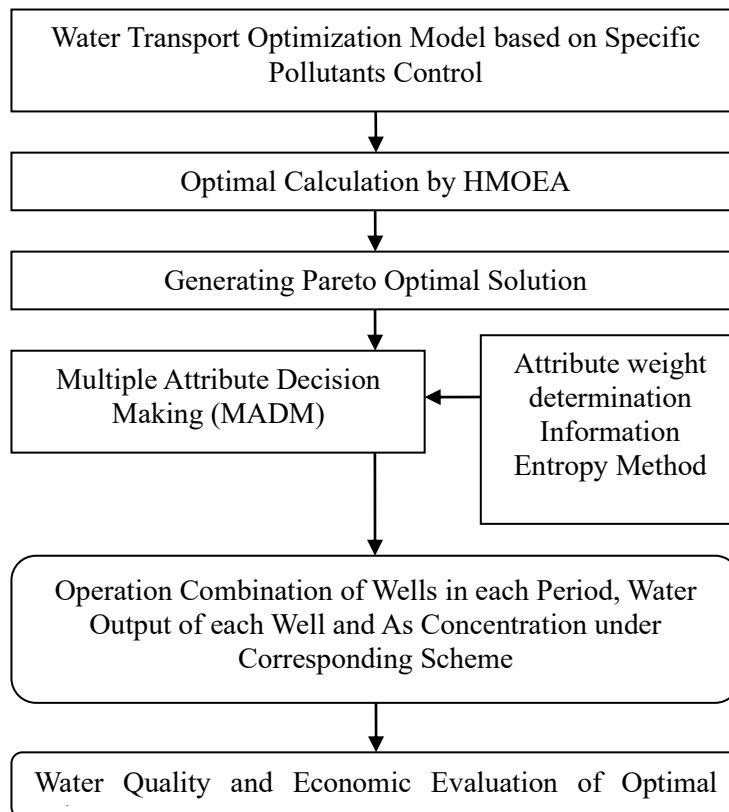


Fig 2. Water Transport Optimization Model Calculation Process

4. Application and Practice

4.1 Project Brief

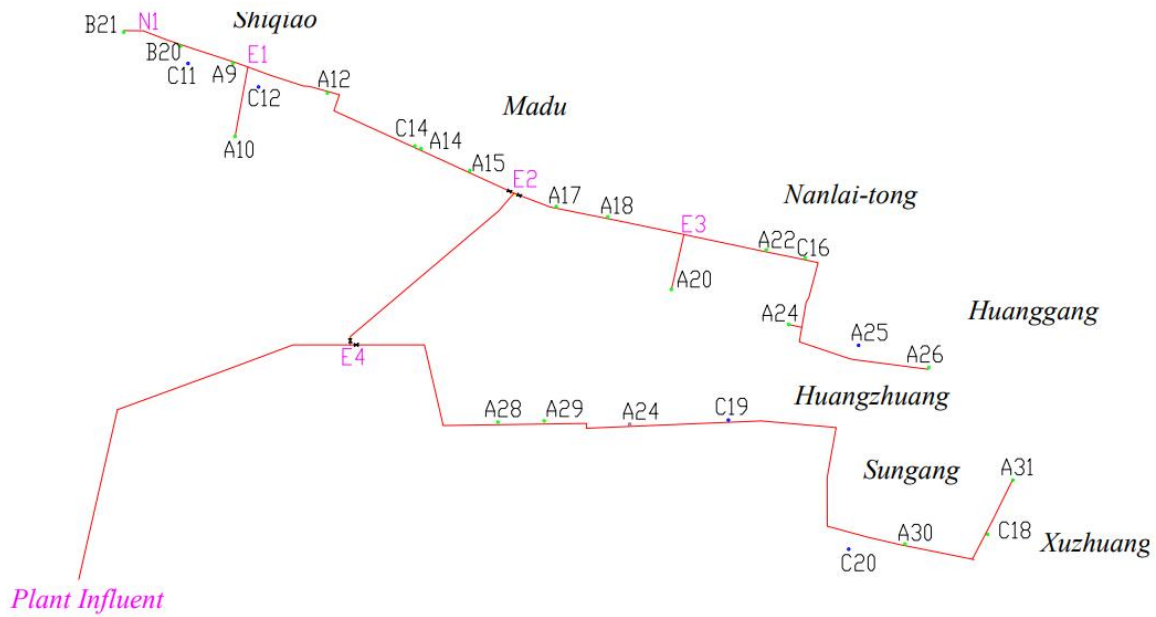


Fig.3. Topology Relation of Source Water Wells and Transport Networks

As is demonstrate previously, supplying water from wells along the beach of Yellow River is quite common in the middle-upper reaches of Yellow River. Groundwater recharged from yellow river constitute 30% water supply of the city Z in the middle-upper reaches of Yellow River. However, specific pollutant such as arsenic, iron, manganese and ammonium of groundwater along the shore of Yellow River exceed national standards quite common. For instance, arsenic concentration of groundwater in “95 Tan” achieves 0.06 mg/L, and iron and manganese concentration is much higher as well. There are 26 groundwater wells in the eastern water source area of Z city, among which 19 wells are shallow wells and 7 wells are middle-deep wells.

The topology relation of wells and water transport networks can be found in Figure 3. In this paper, 16 wells are selected for dispatching optimization.

4.2 Plant Influent-Source Water Coupling Model Validation

20 samples corresponding to different operation status was selected to validate the coupling model of plant influent-source water specific pollutants. The data of outlet flow of wells, fitted arsenic concentration of wells, and plant influent flow are input to the model after Fourier transform. Predicted arsenic concentration of plant influent was the output of the model. Predicted values and measured influent arsenic values are compared to validate the model.

Table 1. Prediction Accuracy Validation Results of 10 Running Conditions

	Operation status	Influent flow(m ³ /h)	Predicted As (µg/l)	Measured As (µg/l)	Relative error (%)
1	0010110111110011	2591	19.36	20.01	3.36
2	0011100111011111	2722	19.14	19.48	1.78
3	0011111111110110	2887	20.76	20.39	1.78

4	0100011111111001	2578	20.55	20.14	2.00
5	0111101101111111	3076	19.83	20.33	2.52
6	0111101111111111	3301	19.77	20.25	2.43
7	111111011111011	2437	19.39	18.72	3.46
8	1001101111011100	2625	20.32	19.93	1.92
9	100111111111011	3112	21.28	20.68	2.82
10	101110110011011	2790	19.83	19.55	1.41

Partial results are shown in Table 1, the maximum relative error among 20 types of operation status is equal to 3.46%, while the average prediction accuracy achieved 97.75%, which is high enough to provide data to support water transport allocate strategy based on specific pollutants control.

4.3 Optimal Dispatching and Economic Technical Analysis

Adaptive intelligent combined algorithm was applied to predicted the required water flow based on on-line data on 14th July 2017. Partial results are shown in Table 2.

Table 2. Hourly Water Usage Prediction of the Selected Area on 14th July 2017

Time	0	1	2	3	4	5	6	7
Predicted flow (m ³ /h)	3145	3059	2982	2966	2955	2930	2918	2908
Measured flow(m ³ /h)	3025	2994	3001	2950	2955	2862	2901	2884
Time	8	9	10	11	12	13	14	15
Predicted flow (m ³ /h)	2889	2888	2824	2805	2799	2773	2639	2588
Measured flow(m ³ /h)	2929	2862	2889	2915	2888	2794	2780	2612

Source water transport from certain groups of wells is performed according to the water transport optimization model mentioned in Section “Construction of Water Transport Optimization Model”, based on the predicted water flow. Then the problem is solved by HMOEA, in which the population part period is 200, the crossover probability is 0.85, and the probability of variation is

0.02. The crossover probability is of off-line water transport results as well as the corresponding evaluating variables are shown in Table 3. Generally, the average energy consumption of 24 hours of this optimization strategy is 344.74 kw, meanwhile average arsenic concentration of the plant influent is 16.91µg/l.

Table 3. Simulated Water Transport Optimization Results of the Selected Area on 14th July 2017

Time	Optimized operation	As (µg/l)	Energy consumption (kw)
0	11001011101111111	16.73	378.83
4	11001011101111111	15.86	380.69
8	11001011101111111	17.74	380.15
12	11001011101110111	17.79	353.64
16	11001011101110111	16.82	349.23
20	11001011101110111	16.09	322.81
23	11001011101111111	15.08	349.38

To test the effectiveness of the proposed strategy, a period of data (January-July, 2017) was employed to perform technology and economic analysis. 14th July 2017, partial results of the real water transport strategy based on manual experience is also measured as is shown in Table 4. The average energy consumption of this strategy is 372.85kw, while arsenic concentration of the plant influent is 18.27µg/l.

Table 4. Measured Water Transport Results based on Experience of the Selected Area on 14th July 2017

Time	Optimized operation	As (µg/l)	Energy consumption (kw)
0	11000111101111111	18.17	401.29
4	11000111101111111	18.38	403.56
8	11000111101111011	17.60	385.93

12	11000111101111011	17.81	386.30
16	11000111101111011	17.47	381.35
20	11000111101111111	18.33	390.92
23	11000111101111111	18.08	394.74

Table 3 and Table 4 shows that optimized water transport strategy could reduce energy consumption and arsenic concentration of the plant influent significantly on 14th July 2017.

Technology and economic analysis was performed to compare the optimized water transport strategy and empirical strategy based the data during January to July 2017. As a result, if the optimization strategy proposed above is adopted, energy consumption could be reduced by 850~1000kw per month, while the average arsenic concentration of the plant influent could be reduced by 1.5~2.3µg/l. What's more, the optimization strategy could control the arsenic concentration always below 20µg/l, which provide guarantee of water safety.

5. Conclusions

(1) In the process of source water optimal dispatching, Fourier transform and artificial neural network (ANN) are used to explain the relation between specific pollutants concentration of groundwater and outlet flow. Plant influent-Source water coupling model of specific pollutants is built which brings water safety into consideration for water transform. Fourier transform is employed to provide frequency domain input to ANN model, which avoids negative influence from disturbance and improves the prediction accuracy.

(2) With the target of minimizing specific pollutants of influent, as well as satisfying water quantity requirement and reducing energy consumption, the water dispatching optimization model is built, in which the operation combination(decide which wells are suitable to provide water at certain time), flow,

and pumping time length are taken as decision variables. The model considers the water quality, security and economy of water supply comprehensively, and realizes the water quality-water quantity joint dispatching optimization technology.

(3) The proposed model is applied to optimize water transport in the city of Z. The prediction accuracy of the specific pollutants coupling model achieves 97.75%, which provide accurate data support for water transport optimization. Compared with manual experience strategy, the proposed optimization solution could reduce specific pollutants concentration of the plant influent significantly as well as reducing the energy consumption, and then guaranteed the safety and economy of water transport system.

Acknowledgements

This work was supported by the National Natural Science Foundation of China (No: 51708312).

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