Article

Robust Placement of Water Quality Sensor for Long-Distance Water Transfer Projects Based on Multi-Objective Optimization and Uncertainty Analysis

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Abstract: It is important to place water quality sensors along open channels in long-distance water transfer projects optimally for rapid source identification and efficient management of sudden water contamination. A new framework which considers multiple objectives, including earliest detection time, lowest missing detection rate and lowest sensor cost, and combines the randomness of injected contaminant type and contaminant incident consisting of contaminant intrusion location, time and mass, was established to obtain optimal placement of water quality sensor with better robustness in this paper. The middle route of the South-to-North Water Diversion Project in China was chosen as a case study, and it was found that both missing detection rate and detection time decrease with sensor cost gradually; furthermore, given the higher detecting precision, the detection accuracy and efficiency would be improved, a smaller number of water quality sensors would be needed, and the ten key placement positions where sensor with different detecting precision placed could be identified. Under the constraints of the allowable maximum missing detection rate, 1.00%, and detection time, 120.00 min, the detecting precision of 0.20 mg/L and 38 sensors placed could be selected as the optimal sensor placement scheme. Finally, with the consideration of contaminant uncertainty, the sensor placement scheme with better robustness could be constructed. The proposed framework would be helpful in solving the problem of water quality sensor placement with high practicality and efficiency in long-distance water transfer projects.

Keywords: long-distance water transfer project; sudden water contamination incident; water quality sensor placement; optimization; robustness

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1. Introduction

Long-distance water transfer projects are constructed to alleviate the shortage of water resource and meet the increasing demands. However, these projects are threatened by sudden water contamination incidents, i.e., an accidental or malicious intrusion of contaminant, sewage or polluted underground water infiltration. As indicated by Timothy Liptrot [1], the influence of water contamination on water transfer would be reflected in political and social dimensions to a great extent. Therefore, in order to identify the contamination source rapidly and accurately after a sudden water contamination incident and balance between the efficiency and cost of its effective monitoring, it is highly necessary to optimize the amount and position of water sensors placed along an open channel in long-distance water transfer projects. Water quality sensor placement is an optimization problem, focusing on objectives such as missing detection rate, detection time, the population affected, and water quality sensor placement cost and so on. Among these objectives,

the cost is the most concerned target; therefore, the traditional intention of placing water quality sensors is to monitor water quality with limited sensors [2–5]. Chen et al. (2012) [6] optimized the fifteen placed sensors monitoring the Heilongjiang river water quality based on a matter-element analysis approach, and found that the three water quality sensors could be removed. Besides, there is a competitive or synergistic relationship among objectives, which need to be traded off to find the Pareto-optimal placements [7–11]. Zhao et al. (2016) [12] considered minimizing detection time and maximizing detection likelihood as the objectives, and obtained the optimal Pareto front solution through a trading-off relationship between these competitive objectives.

Additionally, the optimal sensor placement problem naturally involves uncertainty, including the type of injected contaminant related to contaminant degradation coefficient, intrusion location and time, and duration. Pareto-optimal placements' performance in the base scenario with a fixed condition is quite different from the performance impacted by various uncertain factors. Perelman et al. (2013) [13] showed that the mean detection accuracy and detection time with more sensors deployed are better than involve a small number of sensors; however, the performance of more sensors would be influenced by many uncertain factors related to contaminant incident. Therefore, these uncertain factors should be considered for optimal sensor placement. The simulation-optimization method based on uncertain scenarios can be adopted [14–18]. These uncertain scenarios are usually generated through coarse enumeration [19–21] or sampling of a relatively small subset of the time and location of the injection with Markov Chain Monte Carlo (MCMC) methods, assuming a uniform probability distribution [22–25].

The middle route of the South-to-North Water Diversion Project in China is 1277 km long with 88 water diversions. Unlike closed pipe network systems for urban water distribution, the project would pass through more than 100 cities and more than 1000 traffic bridges, long-distance water transfer through open channel would suffer more external interference, i.e., an accidental or malicious intrusion of dangerous chemicals and pesticides carried by vehicles from rollover accident on traffic bridges, sewage discharge from chemical plants, polluted underground water intrusion from aquifer through broken concrete lining along both sides of the open channel would happen inevitably, however, only 11 water quality sensors have been built to monitor water quality automatically up to now, which could not meet the water quality monitoring requirement obviously. Therefore, the optimal amount and position of water sensors and the impact of various uncertain factors on optimal sensor placement need to be considered and discussed comprehensively.

This paper takes a typical long-distance water transfer project through an open channel, i.e., the middle route of the South-to-North Water Diversion Project in China, as a case study, and focuses on the issue of optimal sensor placement. The earliest detection time, lowest missing detection rate, and lowest sensor cost were taken to optimize the sensor placing number and location with the non-dominated sorting genetic algorithm (NSGAI) and find Pareto optimal front. With the consideration of contaminant mass, intrusion location and time, and sensor detecting precision uncertainty, the trade-offs and their changing characteristics among different objectives were analyzed to explore the Pareto optimal boundary. Then optimal Pareto solution under the requirement of missing detection rate and detection time would be obtained. Meanwhile, combined the analysis on the probability distribution of sensor placement location and impact of injected contaminant type uncertainty on the optimal solution, the critical sensor placement location and recommending placement scheme were determined to improve the robustness of the sensor placement solution. The results can be helpful to develop mitigation and adaptation strategies for sensor placement and water quality management in long-distance water transfer projects.

2. Materials and Methods

Because of the concrete lining along both sides of the open channel, the requirement of power supply and maintenance, and the highest probability of sudden water contamination

incidents happening on the traffic bridges built across the open channel, it would be most realistic for water quality sensors to be equipped on these bridges.

In water transfer projects, sudden water contamination incidents could be detected rapidly and accurately if each bridge built across the open channel, i.e., every key node of the project, was equipped with a water quality sensor; however, the cost is prohibitively high. While fewer nodes of the project are equipped with water quality sensor, sudden water contamination incidents in water transfer projects could not be detected rapidly and accurately. A new framework concerning optimal sensor placement could be constructed to achieve high efficiency, high accuracy and low-cost objectives for sensor placements in long-distance water transfer projects, as shown in Figure 1.

Figure 1. Framework concerning optimal sensor placement in long-distance water transfer projects.

The optimization model includes decision variables and multiple optimal objectives. For each intrusion scenario, multiple objectives could be calculated with the water quality simulation model. Based on the results of simultaneous simulations with a water quality simulation model, optimization algorithms could be used to find optimal decision variables, i.e., the optimal sensor placement strategy. Finally, the relationship between different

objectives and robustness of sensor placements related to different injected contaminant types could be analyzed with the Pareto optimal solution set.

2.1. Water Quality Sensor Placement Optimization Model

2.1.1. Basic Assumptions

Assume that the length of one channel in a water transfer project is L kilometers, and n bridges are built across the channel, i.e., a maximum of n nodes (bridges) where water quality sensors could be equipped. The sudden water contamination incidents resulting from the accidental introduction of a contaminant, i.e., transport accidents, happen on each bridge with the same probability. Let us assume that contamination would be spilled into the channel instantly, and after a period, the downstream monitoring station could detect a series of pollutant concentration data.

2.1.2. Decision Variables

The sensor placement optimization is to optimize the number of water quality sensors placed and their instrumented locations within the n nodes to detect such intrusions rapidly and accurately with the lowest cost. Therefore, decision variables could be represented by

$$x_i = \begin{cases} 1 & \text{water sensor placed on node/bridge } b_i \\ 0 & \text{no water sensor placed on node/bridge } b_i \end{cases} \quad 1 \leq i \leq n \quad (1)$$

2.1.3. Objective Functions

The objective is to detect sudden water contamination incidents in channels of water transfer projects rapidly and accurately by applying water quality sensors on key nodes, this paper considers three objectives: (1) lowest missing detection rate, (2) earliest detection time and (3) lowest sensor cost.

(1) Lowest missing detection rate

Missing detection rate refers to the proportion of detected contamination incident in all happened contamination incident. Assume $L_{max}(i, j)$ represents the longest diffusion distance of the contamination referred to the j th sudden water contamination incident happened on node b_i , i.e., the distance between the contamination source location b_i and the downstream location where contamination concentration could reach water quality sensor detecting precision C_{dp} . As shown in Figure 2, when there exists the nearest downstream bridge from node b_i and it is equipped with water quality sensor, i.e., $b_{i,1}$, and the distance between b_i and $b_{i,1}$ is less than $L_{max}(i, j)$, i.e., $d(b_{i,1}, b_i) \leq L_{max}(i, j)$, the j th sudden water contamination incident could be detected; otherwise, it could not be detected and misdetection happens. $L_{max}(i, j)$ could be calculated iteratively with a one-dimensional water quality simulation model.

Lowest missing detection rate could be calculated by

$$\min F_1 = \min \left\{ \frac{\sum_{i=1}^n m_i - \sum_{i=1}^n \sum_{j=1}^{m_i} f(e_{i,j})}{\sum_{i=1}^n m_i} \right\} \quad (2)$$

where n is the number of bridges/nodes across an open channel, m_i is the amount of sudden water contamination incidents which happened on bridge/node b_i , $e_{i,j}$ is the j th sudden water contamination incident which happened on node b_i , $f(e_{i,j})$ is the function which value indicates whether $e_{i,j}$ would be detected or not with the current placement strategy of water quality sensor. $f(e_{i,j})$ could be calculated by

$$f(e_{i,j}) = \begin{cases} 1 & d(b_{i,1}, b_i) \leq L_{max}(i, j) \\ 0 & d(b_{i,1}, b_i) > L_{max}(i, j) \end{cases} \quad 1 \leq i \leq n, 1 \leq j \leq m_i \quad (3)$$

Figure 2. Layout of bridges across open channel and water quality sensor placement for sudden water contamination incident detection in long-distance water transfer projects.

(2) Earliest detection time

Given the sudden water contamination incident $e_{i,j}$ could be detected, i.e., $d(b_{i,1}, b_i) \leq L_{max}(i, j)$, the time required for concentration at $b_{i,1}$ increasing to water quality sensor detecting precision is detection time $Td_{i,j}$. Earliest detection time could be calculated by

$$\min F_2 = \min \left\{ \frac{\sum_{i=1}^n \sum_{j=1}^{m_i} Td_{i,j}}{\sum_{i=1}^n m_i} \right\} \quad (4)$$

(3) Lowest sensor cost

The costs of water quality sensor placement involve the number of water quality sensors equipped on bridges/nodes mostly. The smaller the number of water quality sensors equipped on nodes, the better the costs of water quality sensor placement. In this paper, the minimum number of water quality sensors equipped on nodes would be taken as the objective for the lowest sensor cost. Lowest sensor cost could be calculated by

$$\min F_3 = \min \left\{ \sum_{i=1}^n x_i \right\} \quad (5)$$

2.2. Water Quality Simulation Model

For the long-distance water transfer project, channel length exceeds flow width and depth to a great extent, and the variation of contamination concentration in the direction of water flow is far more significant than its variation in the horizontal and vertical directions, e.g., convection and diffusion. Therefore, a one-dimensional water quality simulation model that describes the flow lengthwise could be used to simulate pollutant transport along the open channel. Assume that the biochemical degradation of contaminant conforms with the first-order dynamic attenuation pattern and water flow uniformly, the contamination source location is set as the original point, i.e., $x(m) = 0$, $c_0(\text{mg/L})$ and

c_x (mg/L) are the contamination concentration at the original point and the location which is x (m) away from the original point downstream, respectively, and the fundamental differential equation of the one-dimensional steady-state water quality simulation model could be described as

$$u \frac{dc_x}{dx} = E_x \frac{d^2c_x}{dx^2} - Kc_x \quad (6)$$

where u (m/s) is average velocity in the longitudinal direction, E_x (m²/s) is dispersion coefficient in the longitudinal direction, K (s⁻¹) is degradation coefficient of contaminant. Then, the analytical expression of above equation could be described as

$$c_x = c_0 \exp \left[\frac{u}{2E_x} \left(1 - \sqrt{1 + \frac{4KE_x}{u^2}} \right) x \right] \quad (7)$$

At time t , contamination concentration at the location which is x (m) away from the original point downstream, i.e., $c(x, t)$, could be calculated as

$$c(x, t) = \frac{M}{A\sqrt{4\pi E_x t}} \exp \left\{ -\frac{(x - ut)^2}{4E_x t} \right\} \exp(-Kt) \quad (8)$$

where M (g) is contaminant mass, A (m²) is cross-section area of channel.

2.3. Optimization Method

Evolutionary algorithms have emerged as a widely used method for solving problems in complex engineering systems characterized by conflicting objectives. Popular multi-objective algorithms include NSGAII [26], MOEA/D [27], ABYSS [28], and ϵ -NSGAII [29]. The NSGAII was selected in this study as it has been tested in a wide variety of applications and shown to be very efficient and effective for complex optimization problems.

2.4. Visual Analytics

This paper used a highly interactive visualization software named DecisionVis which is capable of taking extremely complex spaces of design possibilities and translating them into meaningful visual representations [30–32]. This tool can handle many objectives explicitly and show the changing trend of each objective and keenly identify inflection points, which are unimaginable in traditional decision-making analytical methods. This tool can help decision makers to understand where performance tradeoffs exist, their severity, and their shape. Seeking to understand these relationships provides a more informed and data driven approach to decision making.

3. Case Description

The middle route of the South-to-North Water Diversion Project is chosen as a case study. The project transfers water from Danjiangkou reservoir in Hubei province and crosses the Yangtze River, Huaihe River, Haihe River, Yellow River basins and finally arrives at Beijing Tuancheng Lake. The total length of the project is 1277 km, crossing nearly 150 cities and 151,000 hectares of land via open channels, culverts and pipes. In addition, the span of the project is very large, and 936 different types of structures, including 44 railways and more than 1000 bridges across the channel, have been built.

The last section of the project is from Shijiazhuang city to Beijing Tuancheng Lake, i.e., Jing-Shi section. The length of Jing-Shi section is 307 km. Due to the rapid development in economy and society in the regions along Jing-Shi section, 241 bridges have been built across the open channel within the section where many factories have been built near. Therefore, there is a high probability of sudden water contamination incident happening in Jing-Shi section especially. Above all, the Jing-Shi section is taken as an example to optimize water quality sensor placement, as shown in Figure 3.

Figure 3. Location of Jing-Shi section of the middle route of South-to-North Water Transfer Project.

The water quality sensor placement optimization model would be constructed as described in Section 2.1. Water quality contamination evaluation indexes include NH₃N, TP, TN, COD and BOD mostly. Corresponding to different contamination type, optimal sensor placement solution could be obtained with the same methodology, as shown in Section 2.1, the example of NH₃N is taken to illustrate the acquirement of optimal sensor placement solution accordingly. Based on the field experiment and existing research, degradation coefficient intervals of all contaminations and the water quality model parameters corresponding to NH₃N could be obtained, as listed in Tables 1 and 2, respectively.

Table 1. Contamination degradation coefficient intervals.

Evaluation Index	Interval for Degradation Coefficient ($K/(s^{-1})$)
NH ₃ N	$[0.122 \times 10^{-5}, 0.405 \times 10^{-5}]$
TP	$[0.002 \times 10^{-5}, 0.684 \times 10^{-5}]$
TN	$[0.013 \times 10^{-5}, 0.911 \times 10^{-5}]$
COD	$[0.010 \times 10^{-5}, 0.544 \times 10^{-5}]$
BOD	$[0.028 \times 10^{-5}, 0.063 \times 10^{-5}]$

Table 2. Water quality model parameters.

Parameter	Default Value
$E_x / (m^2 \cdot s^{-1})$	20.417
$K / (s^{-1})$ for NH ₃ N	0.231×10^{-5}
u (m/s)	0.360

Additionally, a large number of sudden water contamination incident scenarios would be constructed to optimize water quality sensor placement solution for NH₃N as follows. Assume that detecting precision of water quality sensor C_{dp} is 0.10×10^{-3} g/L, contamination incidents would happen on each bridge across the channel with the same probability, and contaminant mass for NH₃N M (g) is identified from the range [2000, 2,000,000]g successively with the interval of 2000 g for each incident. 241 bridges have been built across open channel along Jing-Shi section, the total number of incident scenarios is up to 241,000.

Because of the random nature of optimization method based on evolutionary algorithms, ten random seed runs are used to solve the optimal sensor placement problem in Jing-Shi section. For each random seed, 500 thousand model evaluations are carried out, the population size is 200. The Pareto approximate set analyzed in this study would be generated across all ten random seed optimization runs. Visual analysis would show that beyond one million evaluations there would be little improvement in the Pareto approximate sets attained.

4. Results and Discussion

4.1. Synergistic and Competitive Relationship Analysis on Pareto Front

The water quality sensor placement optimization model could be solved with the non-dominated sorting genetic algorithm (NSGAI) to find the Pareto optimal solution set. The approximate Pareto front pair of objective functions could be found by non-dominated sorting Pareto optimal solution set limited to the corresponding pair of objective functions, as shown in Figure 4.

Figure 4. Pareto front pair of objective functions: (a) missing detection rate and sensor cost; (b) detection time and sensor cost.

Clear tradeoff curves for two pairs of objective functions, i.e., missing detection rate vs. sensor cost and detection time vs. sensor cost, could be observed in Figure 4. Accordingly, there exists an obvious competitive relationship in each pair. It could be indicated that both missing detection rate and detection time decrease with sensor cost gradually.

Additionally, given the fewer water quality sensors placed yet, both missing detection rate and detection time would decrease by a wide margin with the increase in sensor cost; otherwise, there would be less influence of sensor cost on both missing detection rate and detection time given that more water quality sensors had been placed already, i.e., a threshold value for sensor cost existed. It could be indicated that when the number of sensors/sensor cost reached 50 or more, missing detection rate and detection time would be lower than 0.5% and 60 min respectively; however, given a continuous increase in sensor cost, the decrease in missing detection rate and detection time would not be obvious.

Furthermore, sensor cost, missing detection rate, and detection time would be influenced by detecting precision of water quality sensors actually, e.g., for the same placement scheme, given the higher detecting precision, the detection accuracy and efficiency would be improved, and then a smaller number of water quality sensor would be needed. According to the investigation of NH₃N monitoring sensors sold in the market currently, except the assumed detecting precision of water quality sensor in Section 3, 0.10×10^{-3} g/L, four detecting precisions of water quality sensor would be adopted additionally, including 0.02×10^{-3} g/L, 0.05×10^{-3} g/L, 0.20×10^{-3} g/L, 0.50×10^{-3} g/L. Based on the constructed sudden water contamination incident scenarios, Pareto optimal solution set and approximate Pareto front pair of objective functions could be obtained corresponding to different detecting precisions, as shown in Figure 5.

Figure 5a indicated that missing detection rate decreases gradually with the increase of detecting precision from 0.50 mg/L to 0.02 mg/L given the same sensor cost. Threshold values for sensor cost exist for each detecting precision, i.e., missing detection rate would increase obviously with one sensor added if fewer water quality sensors have already been placed. Missing detection rate would not change almost if sensor cost has exceeded the corresponding threshold value.

Figure 5. Pareto front pair of objective functions with different detecting precision: (a) missing detection rate and sensor cost; (b) detection time and sensor cost.

Additionally, it could be observed from Figure 5b that detection time would be less influenced by detecting precision given the same sensor cost. Within the framework, sudden water contamination incidents could be detected by water quality sensors placed with different precision. Due to the obvious competitive relationship between detection time vs. sensor cost, no matter what precision sensor used, the detection time would change in a wide range. Therefore, detection time would be influenced by sensor cost instead of its detecting precision.

4.2. Optimal Sensor Placement Scheme Based on Cost–Benefit Analysis

Pareto optimal solution set for sensor placement could be found by the water quality sensor placement optimization model's solution with monitoring benefit, i.e., missing detection rate and detection time, and cost objectives, i.e., sensor cost (number of sensors). An Optimal sensor placement scheme should be formulated through the balance among different objectives according to their Pareto front solutions and actual demand. Moreover, referring to the actual monitoring demand, water quality sensor placement cost includes both sensor cost and water quality sensor prices for different detecting precision. The prices of NH₃N monitoring sensors with different detecting precision sold in the market currently are listed in Table 3.

Table 3. Prices of NH₃N monitoring sensors with different detecting precision.

Detection Precision ($\text{mg}\cdot\text{L}^{-1}$)	Price of NH ₃ N Monitoring Sensor (ten thousand RMB)
0.02	4.60
0.05	4.20
0.10	3.90
0.20	2.50
0.50	1.50

Table 3 indicates that the NH₃N monitoring sensor's price would be increased with the raise of detecting precision from 0.50 mg/L to 0.02 mg/L. Taking the allowable maximum missing detection rate of 1.00% combined with the allowable maximum detection time of 120 min as control standards for monitoring benefit, the variation of placement cost and number of sensors with different detecting precisions would be analyzed to formulate the optimal sensor placement scheme in this section.

The relationship curves among detecting precision, placement cost and number of sensors under the constraint of the above-mentioned control standards are shown in Figure 6.

Figure 6. Relationship curves among detecting precision, placement cost and number of sensors under the constraints of the control standards for missing detection rate, 1.00%, and detection time, 120 min.

Figure 6 indicates that under the constraints of the control standards for missing detection rate, 1.00%, and detection time, 120 min, with the decline of detection precision from 0.02 mg/L to 0.20 mg/L, the number of sensors would vary slightly between 33 and 38, and then the water quality sensor prices for different detecting precision have a dominant impact on placement cost, which decreases gradually from 150.80×10^4 RMB to 95.00×10^4 RMB. Furthermore, with the continuous decline of detection precision from 0.20 mg/L to 0.50 mg/L, the number of sensors would increase substantially from 38 to 77, i.e., the number of sensors with detection precision of 0.50 mg/L would be over two times as much as that with detection precision of 0.20 mg/L, and then the number of sensors for different detecting precision play dominant impact on placement cost, which increase substantially from 95.00×10^4 RMB to 169.40×10^4 RMB.

Therefore, based on the above cost–benefit analysis on Pareto optimal solution set for sensor placement scheme, the detection precision value of 0.20 mg/L is the point of inflection, i.e., the detecting precision of 0.20 mg/L and 38 sensors placed could be selected as the optimal sensor placement scheme under the constraints of the control standards for missing detection rate, 1.00%, and detection time, 120 min. The missing detection rate and detection time are 0.71% and 117.44 min, respectively, and the placement cost is 95.00×10^4 RMB which is only related to the cost of NH₃N monitoring sensors in the optimal sensor placement scheme.

4.3. Distribution of Water Quality Sensor Placement Position

Placement position is also an important part of water quality sensor placement scheme, especially the identification of the key positions where a sensor placed could assist in formulating sensor placement scheme for safety management department of long-distance water transfer projects.

The cumulative probability of each bridge where water quality sensor of different detecting precision would be placed across open channel along Jing-Shi section could be adopted to present the significance of its position and be calculated by

$$P_i = \sum_{l=1}^m \frac{n_{l,i}}{N_l} \quad (9)$$

where P_i is the cumulative probability of bridge b_i , l is the l th detecting precision of water quality sensor, N_l is the number of solutions in the Pareto optimal solution set for sensor placement scheme responding to the l th detecting precision of water quality sensor, $n_{l,i}$ is

the number of solutions including bridge b_i in the Pareto optimal solution set for sensor placement scheme responding to the l th detecting precision of water quality sensor.

It could be indicated for Equation (9) that the maximum value of the cumulative probability is 500% for each bridge due to five different detection precisions which need to be considered, the larger cumulative probability of one bridge means that if water quality sensor with any detection precision places on the bridge, both missing detection rate and detection time of sudden water contamination incident would be decreased, and the location of this bridge is the key position where a sensor is placed and needs to be considered dominantly when formulating sensor placement scheme.

Based on the statistical analysis of Pareto optimal solution set for sensor placement scheme with different detecting precision, it could be found that there are ten bridges built across open channel along Jing-Shi section which have the cumulative probability exceeding 250% each, i.e., water quality sensor with the detection precision which is in more than half the amount of the five different detecting precisions which need to be placed on the ten bridges, and the ten key placement positions where sensor placed, as shown in Figure 7 and Table 4. Additionally, placement positions in an optimal water quality sensor placement scheme could also be as shown in Figure 7, and the rationality of optimal scheme could be examined because of the ten key positions and the other positions with higher cumulative probability included.

Figure 7. Cumulative probability of each bridge with water quality sensor of different detecting precision being placed across open channel along Jing-Shi section.

Table 4. Ten bridges on the key placement positions where sensors were placed.

Number	Name	Location
9	Xibotang South Bridge	Zhengding Country, Shijiazhuang City
51	Chizhi South Bridge	Xinle Country, Shijiazhuang City
82	Xinzhuang North Bridge	Dingzhou Country, Baoding City
122	Xichaoyang Bridge	Shunping Country, Baoding City
141	Weigong Bridge	Mancheng Country, Baoding City
150	Dalouxi Bridge	Mancheng Country, Baoding City
152	Baibao Bridge	Mancheng Country, Baoding City
164	Xifushan West Bridge	Xushui Country, Baoding City
166	Dongloushan South Bridge	Yi Country, Baoding City
171	Nanlin Bridge	Yi Country, Baoding City

4.4. Robustness of Sensor Placements Based on Uncertainty Analysis

Contamination incidents happening on each bridge across the channel would involve other contaminant types except NH_3N , e.g., TP, TN, COD and BOD. As shown in Table 1, the degradation coefficient interval of any contaminant type, which reflects contaminant degradation rate in water, differs from another type. Therefore, the impact of contaminant

uncertainty, i.e., different contaminant degradation characteristic, on detection accuracy and efficiency, should be analyzed to keep a higher detection accuracy and efficiency for any contaminant type and then improve robustness of sensor placements. In this section, according to degradation coefficient interval of each contaminant listed in Table 1, the impact of contaminant uncertainty on missing detection rate and detection time of optimal sensor placement scheme would be analyzed to improve its robustness further.

Assume contaminant degradation coefficients of 0.001 d^{-1} , 0.100 d^{-1} , 0.200 d^{-1} , 0.300 d^{-1} , 0.400 d^{-1} , 0.500 d^{-1} , 0.600 d^{-1} , 0.700 d^{-1} and 0.800 d^{-1} , and then present the variation of missing detection rate and detection time with different degradation coefficient based on the optimal sensor placement scheme, as shown in Figure 8.

Figure 8. Variation of missing detection rate and detection time with different degradation coefficient based on the optimal sensor placement scheme and the optimal sensor placement scheme after eight water quality sensors being added.

It could be noted from Figure 8 that based on the optimal sensor placement scheme within the control standards for monitoring benefit, i.e., allowable maximum missing detection rate of 1.00% and allowable maximum detection time of 120.00 min, missing detection rate could be more sensitive to degradation coefficient than detection time, and missing detection rate would increase linearly by 11.10% with the increase of degradation coefficient. Missing detection rate, detection time and their sensitivity to degradation coefficient would be declined with the increase of the number of water quality sensors placed. By experiment, with eight water quality sensors being added, missing detection rate and detection time could be declined to a large extent and changed less. As shown in Figure 8, the impact of degradation coefficient variation on both missing detection rate and detection time would be extremely low, e.g., missing detection rate and detection time would increase only by 0.78% and 0.01% respectively, and the robustness of optimal water quality sensor placement scheme would be improved largely.

Additionally, the rationality of water quality sensor increase could be examined due to cumulative probability of all the eight positions higher than 120.00%. The eight added positions and their cumulative probability could be shown in Figure 9.

Figure 9. Cumulative probability of each bridge with water quality sensor of different detecting precision being placed across open channel along Jing-Shi section after eight water quality sensors being added.

5. Conclusions

Placing water quality sensors along open channel has been the dominant measure and tendency to detect and manage sudden water contamination in long-distance water diversion project rapidly and accurately. However, the key to place water quality sensors efficiently lies in the optimal water quality sensor placement based on the trade-off analysis among sudden water contamination detection accuracy, sudden water contamination detection efficiency and water quality sensor placement cost. This paper takes a typical long-distance water transfer project through open channel, i.e., the middle route of the South-to-North Water Diversion Project in China, as a case study, and focuses on the issue of its optimal water quality sensor placement. The results could be helpful in developing mitigation and adaptation strategies for sensor placement and water quality management in long-distance water transfer projects.

- (1) The main source of water contamination and feasibility of water quality sensor placement were analyzed, and based on the main contradiction analysis between cost and effectiveness, lowest missing detection rate, earliest detection time and lowest sensor cost were taken as objectives to optimize the sensor placing number and location with the non-dominated sorting genetic algorithm (NSGAI) and find Pareto optimal front. Meanwhile, considering the wide distribution of bridges and the difficulty in acquiring their traffic information, we assume that the sudden water contamination incidents resulting from the accidental introduction of a contaminant, i.e., transport accidents, happen on each bridge with the same probability without the consideration of their importance. It could be found that there exists an obvious competitive relationship in each pair of objective functions, i.e., missing detection rate vs. sensor cost and detection time vs. sensor cost, and there would be extremely reduced influence of sensor cost on both missing detection rate and detection time given the number of water quality sensors placed more than its threshold value. Additionally, missing detection rate decreases gradually with the raise of detecting precision, and detection time would be less influenced by detecting precision.
- (2) Based on the cost–benefit analysis on Pareto optimal solution set for sensor placement scheme, under the constraints of the control standards for missing detection rate, 1.00%, and detection time, 120 min, it would be found that the detection precision value of 0.20 mg/L is the point of inflection, i.e., the water quality sensor prices for different detecting precision and the number of sensors for different detecting precision play dominant impact on placement cost with the decline of detection precision higher and lower than 0.20 mg/L, respectively, and the detecting precision of 0.20 mg/L and 38 sensors placed could be selected as the optimal sensor placement scheme.
- (3) Uncertain influence of contaminant monitoring on optimal solution for sensor placement scheme were analyzed. Based on the statistical analysis of Pareto optimal solution set for sensor placement scheme with different detecting precision, it could

be found that there are ten key bridges where water quality sensor with the detection precision in more than half the amount of the five different detecting precisions which need to be placed. Missing detection rate, detection time and their sensitivity to degradation coefficient would be declined with the increase of the number of water quality sensors placed, and with eight water quality sensors being added, missing detection rate and detection time could be declined to a large extent and changed less, i.e., the robustness of optimal water quality sensor placement scheme would be improved greatly.

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