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Optimization model for location and operation schedule of chlorine booster stations in water distribution networks

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ABSTRACT

In South Korea, various sensors and smart meters have recently been installed in water distribution networks as a consequence of the Fourth Industrial Revolution and the water supply system modernization project. This study identified consumers' actual water use patterns using hourly automatic meter reading (AMR) data. A genetic algorithm-based model was developed to optimize locations and operation schedules of chlorine booster stations, by minimizing residual chlorine concentration spatiotemporal variation within a water distribution network, and deriving a water quality management plan enabling economical disinfection. The model was applied to one water distribution district of the J water purification plant, and under the worst water quality conditions, three optimal chlorine booster stations locations could satisfy the target residual chlorine concentration of 0.1–0.5 mg/L, at a total cost of 110,991 KRW/d. Moreover, chlorination costs were compared before and after optimizing the chlorine booster stations' operation schedule. Chlorination costs were reduced from 2,554 to 1,576 KRW/d on Day 1, and from 2,232 to 1,319 KRW/d on Day 2, while maintaining 0.5 mg/L residual chlorine concentration. Residual chlorine concentration could be maintained in the range of 0.1–0.5 mg/L at every demand node.

Keywords: Automatic meter reading; Residual chlorine equalization; Genetic algorithm

1. Introduction

As the automatic meter reading (AMR) system and smart meters have been introduced since the late 1990s, water usage data of each house can be collected every minute and even every second. Such detailed water usage data enable a demand model reflecting water use patterns of each consumer to be developed and characteristics of water use to be accurately analyzed according to classification criteria. Accordingly, the smart meter technology is considered to have the potentiality of changing consumers' water use pattern, and the feedback function can be utilized to facilitate water saving and demand management [1].

The monthly analysis of water usage data collected by monthly meter reading and flow data from each water purification plant (WPP), reservoir, and district metered area is effective enough for planning and designing water supply systems. However, as monthly water usage data obtained by meter reading are average values of long-term measurements, such data cannot reflect consumers' water use patterns or other features of daily water usage (weekdays, weekends, and holidays). For this reason, the analysis of water distribution networks on a unit time basis such as extended period simulation (EPS) implies much uncertainty [2]).

Water usage data of each consumer, which are collected on a unit time basis, are the first thing to be considered for evaluating water use patterns in a water distribution district and establishing a management plan. However, because smart meters have not been installed at every service connection yet, water usage cannot be directly measured, which seems to cause the largest uncertainty and dynamic variability [3].

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As local governments have continuously improved water flow rates and built up a block system and as the water distribution system are being modernized, more and more smart meters including automatic reading system and measuring instruments (flowmeter, water pressure gauge, leak sensor, water quality analyzer, etc.) are being installed. This study attempted to develop a model that utilized real-time data collected from those instruments to optimize locations and operation schedule of chlorine booster stations for water use features of the study area, to minimize spatiotemporal variation of residual chlorine concentration and thus to ensure economical chlorination.

Chlorine used in a water treatment process reacts to natural organic matter (NOM) of water, biofilms in a water distribution pipe, tubercles, or pipe material. For this reason, as the retention time increases, chlorine decreases and disinfection by-products increase [4]. The chlorine concentration of clean water can be reduced by the bulk reaction to NOM, the pipe wall reaction to biofilms, tubercles or pipe material, and the loss in a reservoir.

Rossman [5] explained a mechanism of matter loss (or increase) due to reactions occurring while residual chlorine of water passes a pipe network. The reaction mechanism proposed by Rossman [5] simulates the decay of residual chlorine concentration caused by reactions to bulk water or pipe walls by using the first-order dynamic reaction. Fuchigami and Terashima [6] reported that k_b significantly increased at a water temperature of 20°C or above and the logarithm of k_b for the inverse number of water temperature T (absolute temperature °K) could be expressed by the Arrhenius equation [6]. Accordingly, this study investigated water temperatures of the days of the pipe network analysis and applied them to the Arrhenius equation, thereby obtaining k_b. The most conventional method of estimating k_w is the trial-and-error method (systematic analysis method). In this method, a pipe network simulation is conducted by using the bulk decay coefficient determined by a batch experiment for chlorine decay reaction, and k_w is determined when an actual residual chlorine concentration becomes similar to a calculated one [7].

Even if water produced by a WPP satisfies a drinking water quality standard, its quality can decline while reaching consumers through a water supply system. Consumers understand the quality of water produced at a purification plant is different from that of tap water. Accordingly, the quality of water in the distribution system has been less systematically managed. Residual chlorine concentrations in water supply networks are affected by such factors as amount of water supply, retention time, and seasonal variation of water temperature [4]. Thus, in the case of a region, where the length of pipes is large or the demand for water is small, retention time becomes longer, and thus the minimum criterion of residual chlorine concentration cannot often be satisfied. To solve this problem, some local governments still inject an excessive amount of chlorine in a WPP. However, a high residual chlorine concentration in a WPP may increase disinfection by-products, cause more civil complaints about odor, and decrease a drinking rate [8].

Recently, some metropolitan city governments have tightened guidelines for managing residual chlorine at taps, introduced an advanced treatment process, and actively installed chlorine booster stations to solve such problems as the decrease of drinking rate due to chlorine odor, residual chlorine concentration decay due to the increase of retention time, spatiotemporal variation of residual chlorine concentration, and disinfection by-products.

Many studies have derived optimal locations of chlorine booster stations or appropriate rechlorination concentrations to optimize residual chlorine concentrations in a pipe networks through such booster stations.

Boccelli et al. [9], Sert [10], Koker [11], and Ayvaz and Kentel [12] attempted to formulate the optimal scheduling problem of chlorine booster stations by utilizing linear programming, which is a deterministic method. Tryby et al. [13] set the locations of chlorine booster stations by using integer decision variables and determined rechlorination concentrations by formulating the problem by mixed integer linear programming. These studies commonly adopted a deterministic approach to solve problems.

Munavalli and Kumar [14] fixed locations of chlorine booster stations and applied a genetic algorithm (GA) for deriving an objective function that could minimize the total injection of chlorine. Prasad and Park [15] applied a multi-objective genetic algorithm for solving the problem of determining the number of chlorine booster stations. Ostfeld and Salomons [16] also applied a GA to find out the locations of chlorine booster stations, which could minimize the costs of installing and operating those facilities under constraints of chlorine concentration. Ohar and Ostfeld [17] determined the locations of chlorine booster stations and rechlorination concentrations, which could minimize the generation of disinfection by-products along with residual chlorine concentration, in association with EPANET Multi-Species. Chu et al. [18] and Wang and Guo [19] used an immune algorithm and ant colony optimization, respectively, to optimize the locations of chlorine booster stations and rechlorination concentration. These studies adopted a probabilistic approach to find out solutions.

A lot of studies attempt to optimize the locations of chlorine booster stations and rechlorination concentration. However, most of them focus on simply simulated pipe networks or tree-type water distribution networks. In addition, locations of chlorine booster stations, injection and concentrations are determined mainly by considering the decay of residual chlorine concentration according to retention time. Some studies performed a numerical analysis for optimizing rechlorination, but only daily average injection concentration of a chlorine booster station could be determined. This was not sufficient to find out an appropriate residual chlorine concentration for variable water use. Consequently, it seemed to be necessary to develop a model that can derive optimal locations of chlorine booster stations and schedule by considering residual chlorine concentrations and water usage variation based on consumers' water use patterns.

This study developed a hydraulic water quality analysis model by real-time data of flow rate, water pressure, and usage in a water distribution system. The model was validated and calibrated to reproduce the condition of a real water distribution system more accurately. The hydraulic analysis model thus developed was coupled with a genetic algorithm. Thus, the model could be an optimization model for locations of chlorine booster stations and operation of residual chlorine concentration. This model could equalize residual chlorine concentration and enable economical disinfection while satisfying relevant water quality standards, thereby ensuring water quality safety and improving consumers' satisfaction for a water supply block where flow rates, water pressures, and usage could be monitored. The model thus developed was applied to the J water distribution pipe network to simulate residual chlorine concentrations before and after optimization and verify water quality improvement.

2. Study method

2.1. Current status of the study area

The J water distribution district completely established an AMR system and a district metered area system. Accordingly, the water usage of each consumer and the flow rate and water pressure data for each district metered area inflow point could be collected every hour in the area. A total of 2,077 service connections existed in this region, and the daily water supply per person was 374 L in 2015. The study area consisted of four small blocks. Water was supplied to blocks 1–3 directly from the J WPP and indirectly provided to Block 4 through a reservoir. Block 4, to which water was supplied indirectly through a reservoir, had the largest supply area and a tree-type pipe network, because consumers were scattered. In comparison with the other blocks, it had a longer pipe network and the water retention time in the reservoir was long. Accordingly, the residual chlorine concentration was lower than that in the other three blocks. For this reason, the J WPP maintained a high residual chlorine concentration for the entire district to ensure a sufficient level of residual chlorine in Block 4.

2.2. Hydraulic analysis model for the J water distribution district

A water distribution pipe network analysis model was constructed from hourly automatic meter readings, hourly flow rate data (outflow from a clear well, inflow into a reservoir, and inflow into a block), water pressure, depth, and AutoCAD drawing files. The capacity of the J district WPP was 9,000 m^3/d. The direct water supply used two pipe networks, while the indirect water supply used the reservoir. In this study, we skeletonized the pipe networks by focusing on branch points. To reproduce real flow rates, water pressures, and other conditions as closely as possible, each consumers' real water usages and demand patterns, which were collected by AMR data, were applied to demand nodes. In addition, the amount of water leakage, water pressures, and residual chlorine concentrations were calibrated and verified using flowmeters and water pressure gauges that were installed in pipe networks, field measurements of water pressure, and residual chlorine concentration.

2.3. Derivation of residual chlorine decay coefficient and modeling

As water quality for both raw water flowing into the WPP and filtered water seemed to vary with the season. Filtered water was collected at two different times of year from the J WPP to evaluate the residual chlorine bulk decay coefficient (first experiment on September 8, 2017, and second experiment on March 14, 2018). Sodium hypochlorite was put into the filtered water samples to generate the same residual chlorine concentration as that measured on each sampling day. Batch experiments were conducted to derive bulk decay coefficients under different temperature conditions (5°C for winter, 15°C for spring and autumn, and 25°C for summer). The appropriate order and coefficient for the residual chlorine decay reaction in the J water distribution district were derived. The Arrhenius equation was used to express them as a decay coefficient according to water temperature, which was utilized for analyzing water quality.

To estimate the chlorine wall decay coefficient (k_w), residual chlorine concentration data collected by grab sampling at 8 points for the first, and at 17 points for the second experiment within the district, were used in the systematic analysis (that is, trial-and-error) method. The measuring points of residual chlorine concentration in the pipe network were selected by considering retention time in the direct-connected water supply network between the point closest to the WPP and consumers. The correlation coefficient between measured and estimated residual chlorine concentrations was compared with root mean squared error) to determine an appropriate wall decay coefficient. The coefficient thus determined was used for modeling.

2.4. Developing an optimization model for residual chlorine concentration using a genetic algorithm

A model for the locations and operation schedule of chlorine booster stations was developed. This model used a genetic algorithm, to optimize the residual chlorine concentration of the study area. The worst-case water quality conditions for the study area were set using monitoring data of the outflow rate, water temperature, and residual chlorine concentration in the WPP. In other words, a day was selected where the water temperature was high, the residual chlorine concentration quickly declined, and the retention time was longer due to less water usage. Locations of chlorine booster stations and an initial chlorine concentration were determined which could satisfy the target residual chlorine concentration at demand nodes of the pipe network in worst-case water quality conditions, and also minimize the costs of both disinfection at the WPP and installation and operation of the chlorine booster stations.

The distribution of residual chlorine concentration in a water distribution pipe network is affected by water temperature and factors influencing water use such as season, weather, and day of week. Accordingly, to effectively respond to variations in water usage and temperature, and optimally manage the residual chlorine concentration in a water distribution district, it is necessary to develop a model that can determine a 24-h residual chlorine concentration for a chlorine booster station. As shown in Fig. 1, we developed such a model. The objective function of the optimization model for residual chlorine concentration aimed to minimize chlorination cost at the WPP, installation cost of chlorine booster stations, and rechlorination cost at the stations. The objective function can be expressed by Eq. (7) in the following. In this study, the locations to minimize installation and operation costs of chlorine booster stations and disinfection cost

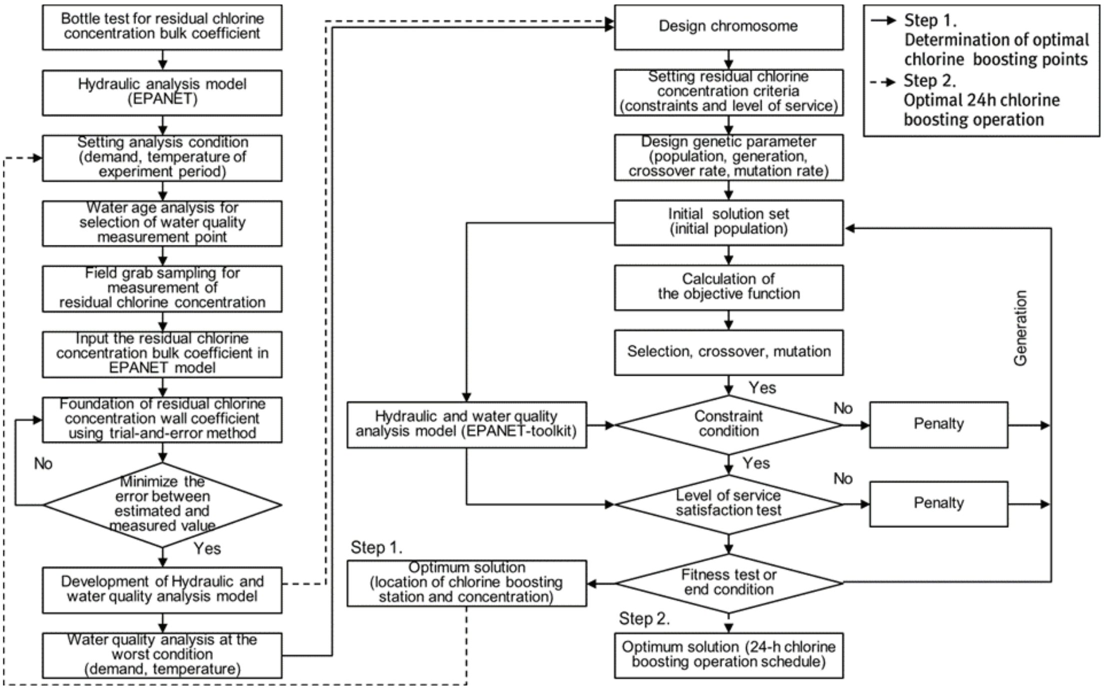


Fig. 1. Flowchart of genetic algorithm optimization model for residual chlorine concentration equalization.

were determined, and the operation schedule was derived for economical disinfection. Because the residual chlorine concentration is a thing that must be strictly observed, the optimization model was developed by setting the residual chlorine concentration range as a constraint, without setting the equalization rate or the satisfaction rate as an objective function. In addition, the disinfection at the WPP and chlorine boosting facilities are not expensive to operate, but installation of chlorine boosting facilities is costly. Therefore, the locations and number of the chlorine booster stations were determined considering both the installation cost and the operating cost.

$$\min B = \min[B^{\mathrm{WPP}} + \sum\nolimits_{i=1}^{n}(B_i^{\mathrm{CBS}} + B_i^{\mathrm{COE}})] \tag{1}$$

$$B^{\mathrm{WPP}} = C^{\mathrm{WPP}} \times Q^{\mathrm{WPP}} \times \rho^{\mathrm{WPP}} \tag{2}$$

$$B_i^{\mathrm{CBS}} = (C_{i,a}^{\mathrm{CBS}} - C_{i,b}^{\mathrm{CBS}}) \times Q_i^{\mathrm{CBS}} \times \rho_i^{\mathrm{CBS}} \tag{3}$$

where B: total cost (KRW/d), B^{WPP}: chlorination cost in WPP (KRW/d); B_i^{CBS}: rechlorination cost in booster station at i node (KRW/d); B_i^{COE}: installation cost of chlorine booster station at i node (KRW/d); C^{WPP}: residual chlorine concentration in WPP (mg/L); $C_{i,a}^{\mathrm{CBS}}$: residual chlorine concentration after rechlorination at i node (mg/L); $C_{i,b}^{\mathrm{CBS}}$: residual chlorine concentration before rechlorination at i node (mg/L); Q^{WPP}: outflow rate in WPP (m^3/d); Q_i^{CBS}: flow rate in chlorine booster station at i node (m^3/d); ρ^{WPP}: the unit price of disinfectant mass in WPP (KRW/kg); and ρ_i^{CBS}: the unit price of disinfectant mass in chlorine booster station (KRW/kg).

The daily cost of installing a chlorine booster station was calculated and applied under the assumption that the service life of the station is 20 years and the total cost is paid on a daily basis. This was because the initial investment cost far exceeded the operation cost, and thus the solutions tended to suggest installing as few stations as possible. As shown in Table 1, this study estimated the installation cost in South Korean won according to the capacity of chlorine booster stations [20].

When liquefied chlorine is used, the chlorination cost at the WPP is the product of unit input price and supply volume. In the case of a chlorine booster station, the chlorination cost is the product of unit input price of sodium hypochlorite and the flow rate at the station. In this study, the unit input price of liquefied chlorine at the WPP was assumed to be 550 KRW/kg [21], and that of sodium hypochlorite at a chlorine booster station was assumed to be 15,000 KRW/kg.

The first constraint of the optimization model for residual chlorine concentration was whether the criterion of residual chlorine concentration at a demand node was satisfied. The management standard of the drinking water supplier, consumers' requirements, and the perception level of an ordinary adult for odor needed to be comprehensively considered to set the constraint. In this study, to determine an appropriate residual chlorine concentration for the study area, we set up a scenario for the upper target concentration that could satisfy the residual chlorine concentration of 0.1 mg/L or above, which is provided by the Water Supply Act to improve the drinking rate and equalize residual chlorine.

The second constraint was the criterion for residual chlorine concentration in the outflow of the WPP. The maximum and minimum values were set by considering the management standard of drinking water supplier and whether chlorine contact time values for each season were satisfied. As the third constraint, the upper and lower limit of residual chlorine concentration at any chlorine booster station was set. This constraint aimed to prevent the installation of an excessive number of chlorine booster stations with too small capacity in consideration of economic aspects and the operation of chlorine booster stations. These constraints can be expressed by the following formulas.

$$\min C_c \le C_c \le \max C_c \tag{4}$$

$$\min C^{\mathrm{WPP}} \le C^{\mathrm{WPP}} \le \max C^{\mathrm{WPP}} \tag{5}$$

$$\min C^{\mathrm{CBS}} \le C^{\mathrm{CBS}} \le \max C^{\mathrm{CBS}} \tag{6}$$

where C_c: residual chlorine concentration at demand node (mg/L); C^{WPP}: residual chlorine concentration at outflow rate in WPP (mg/L); and C^{CBS}: residual chlorine concentration at booster station (mg/L).

Table 1
Installation cost of chlorine boosting station

Study area	Injection range (kg/d)	Installation cost (KRW/d)
J region	0–0.5	36,200
	0.5–1.0	36,700
	1.0–1.5	37,300
	1.5–2.0	37,800
	2.0–2.5	38,400
	2.5–3.0	38,900

To prevent any point where a chlorine booster station could not be installed from being selected, it was necessary to develop a model that could find out solutions at 25 points including the flowmeter chamber, the valve chamber and the pump station, which had been designated in advance. The abovementioned objective function was used for testing the goodness-of-fit and termination condition. A higher goodness-of-fit was given a lower cost. The calculation was set to terminate when reaching a set number of households. When the calculation was completed, any solution obtained at the lowest cost was selected as the optimal solution.

2.5. Optimizing locations of chlorine booster stations in the water distribution network

The highest water temperature and average flow rate of summer were set as the worst-case water quality conditions to optimally locate chlorine booster stations in the water distribution pipe network. A hydraulic and water quality model was constructed from the bulk decay coefficient at the highest water temperature and the average flow rate. In 2017, the annual average outflow rate and the highest water temperature in the clear well were 4,014 m^3/d and 20.9°C, respectively. These values were set as the worst-case conditions. As presented in Table 2, scenarios for optimizing locations of chlorine booster stations were constructed by considering the range of residual chlorine concentration at the WPP, residual chlorine in each junction, range of residual chlorine concentration in boosting stations, and the number of chlorine boosting points.

Table 2
Scenarios for optimization of chlorine boosting stations

Scenario	Range of residual chlorine concentration in water purification plant (mg/L)	Criteria of residual chlorine in each junction	Range of residual chlorine concentration in boosting stations (mg/L)	Number of chlorine boosting points
1-1	0.1–1.0	0.1–0.4	0.1–1.0	1
1-2	0.1–1.0	0.1–0.5	0.1–1.0	1
1-3	0.1–1.0	0.1–0.6	0.1–1.0	1
1-4	0.1–1.0	0.1–0.7	0.1–1.0	1
2-1	0.1–1.0	0.1–0.4	0.1–1.0	2
2-2	0.1–1.0	0.1–0.5	0.1–1.0	2
2-3	0.1–1.0	0.1–0.6	0.1–1.0	2
2-4	0.1–1.0	0.1–0.7	0.1–1.0	2
3-1	0.1–1.0	0.1–0.4	0.1–1.0	3
3-2	0.1–1.0	0.1–0.5	0.1–1.0	3
3-3	0.1–1.0	0.1–0.6	0.1–1.0	3
3-4	0.1–1.0	0.1–0.7	0.1–1.0	3
4-1	0.4	0.1–0.4	0.1–0.4	3
4-2	0.5	0.1–0.5	0.1–0.5	3
4-3	0.6	0.1–0.6	0.1–0.6	3
4-4	0.7	0.1–0.7	0.1–0.7	3
5-1	0.4	0.1–0.4	0.1–0.4	2
5-2	0.5	0.1–0.5	0.1–0.5	2
5-3	0.6	0.1–0.6	0.1–0.6	2
5-4	0.7	0.1–0.7	0.1–0.7	2

2.6. Optimal operation schedule of chlorine booster stations

After optimal locations for chlorine booster stations were determined under the worst-case water quality conditions, that is, at the highest summer water temperature and the average flow rate, scenarios were set up and optimization was conducted to obtain optimal 24-h residual chlorine concentrations at the WPP and the booster stations. The minimum and maximum residual chlorine concentrations had to be 0.1 and 0.5 mg/L, respectively, at every demand node of the water distribution district. Fig. 2 shows the locations of the J WPP and reservoir and the optimal locations of chlorine boosting points. Representative nodes of each block are also shown. These nodes were selected to compare residual chlorine concentrations according to the optimal operation scenarios of chlorine booster stations. To select the boosting points, water flow directions and water age were considered. These points included the WPP, reservoirs, chlorine booster stations, main pumping stations, junctions of small blocks, and pipe ends, thereby enabling variations in residual chlorine concentration to be easily identified.

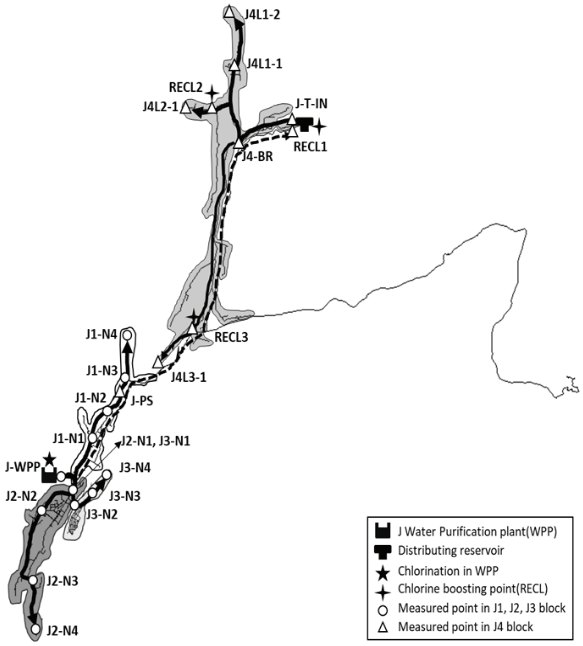


Fig. 2. Chlorine boosting points and residual chlorine concentration observation points.

Two bulk decay coefficient experiments and field measurements of residual chlorine concentration were conducted on September 8, 2017, and March 14, 2018. For those 2 d, operation scheduling of the WPP and the chlorine booster stations was conducted. The results were compared with the real distributions of residual chlorine concentration on the same days, and the scheduling effectiveness was analyzed. Table 3 presents scheduling scenarios for residual chlorine concentration in the chlorine booster stations on the days of the first and second experiments (September 8, 2017, and March 14, 2018, respectively).

3. Results and discussion

3.1. Analysis of water use characteristics of the study area by using AMR data

Water use data of each household, which were collected through the AMR system, were used to derive the annual and seasonal distributions of the daily average water usage at each household. In the study area, the daily average water usage of each service connection was 0.643 m^3/d. However, the actual daily water usage of each service connection ranged from 0 to 4.815 m^3/d, and the standard deviation was 0.588 m^3/d. It turned out that almost 84.9% of all the households consumed water below 1.0 m^3/d. Accordingly, if the average value is uniformly input into every node for a numerical analysis, the actual distribution of water usage could not be accurately identified, and influential factors on water use such as the number of occupants in each household, residence type, and other characteristics of each household as well as water pressure would not be considered. Thus, there would be a gap between reality and the results of numerical analysis.

Table 3
Scenarios for determining optimal operation schedule of chlorine boosting stations

Scenario		Range of residual chlorine concentration in WPP (mg/L)	Criteria of residual chlorine concentration in customer junction (mg/L)	Range of residual chlorine concentration in chlorine boosting point (mg/L)	Number of chlorine boosting points
September 08, 2017	Current operation	1.18	–	–	–
	Opti-ReCl-Point	0.39	0.10–0.50	0.20 0.36 0.11	3
	Opti-ReCl-Oper (WPP: 0.5)	0.50	0.10–0.50	0–0.50	3
March 14, 2018	Current operation	1.05	–	–	–
	Opti-ReCl-Oper (WPP: 0.5)	0.50	0.10–0.50	0–0.50	3
	Opti-ReCl-Oper (WPP: 0.39)	0.39	0.10–0.50	0–0.36	3

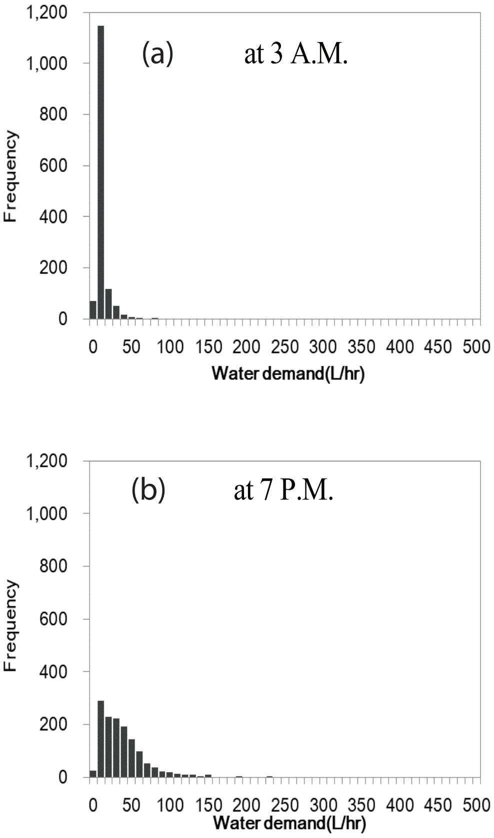


Fig. 3. Histograms of hourly average water demand by households in 2015 at (a) 3 a.m. and (b) 7 p.m.

As shown in Fig. 3, the hourly water usage data of the study area were used to present the frequency distribution of the average water usage of each service connection both at 3 a.m. and 7 p.m. The majority of households recorded water usage of 20 L/h or below at 3 a.m., where the smallest amount of water was used throughout the day. As an hourly water use pattern is the basic input for EPS using a hydraulic analysis model, it is usually estimated based on outflow rates, which are measured at a certain time interval either in a clear well or in a reservoir. In Fig. 3, the minimum flow rate period at night shows that each household consumes a different amount of water even in the same time period. For this reason, if the same hourly pattern is applied to a hydraulic analysis, an error is likely to occur.

3.2. Determining the residual chlorine decay coefficient for analyzing water quality

The residual chlorine bulk decay coefficients (k_b) were obtained from the first experiment by assuming the first-order, second-order, and third-order residual chlorine decay reactions at water temperatures of 5°C, 15°C, and 25°C, respectively. Curve fitting for the linearized Arrhenius equation can be expressed by the following equation:

$$\ln k_b = -8.7397 \times \left(\frac{1000}{T}\right) + 30.512 \quad (R^2 = 0.9118) \tag{7}$$

where T: absolute temperature (K) = 273 + temperature (°C).

In the case of the third-order decay reaction, the decay tendency of residual chlorine concentration measured at each temperature showed the highest correlation and resulted in the closest estimation to measurement. Accordingly, it was assumed that the residual chlorine decay reaction of the J water distribution district follows the third-order reaction. Then, the residual chlorine decay coefficient at the corresponding water temperature was reflected in the modeling of this study.

On March 14, 2018, where the second experiment was performed, the residual chlorine decay reactions in the J WPP were assumed to be the first-order, second-order, and third-order reactions, respectively. The curve fitting for the linearized Arrhenius equation can be expressed by Eq. (8). When the water quality on the day of the second experiment was analyzed, the bulk decay coefficient obtained from the third-order reaction was used.

$$\ln k_b = -5.5815 \times \left(\frac{1000}{T}\right) + 18.826 \quad (R^2 = 0.9894) \tag{8}$$

where T: absolute temperature (K) = 273 + temperature (°C).

To simulate the worst-case water quality conditions in the optimization model of residual chlorine concentration, this study estimated a bulk decay coefficient at the highest water temperature of summer utilizing the residual chlorine decay coefficient obtained from the Arrhenius equation, which was derived from the first experiment with high water temperature conditions, on the basis of the results of the above two experiments.

When the field experiment was performed on September 8, 2017, the water temperature of the J WPP was 17.1°C and the bulk decay coefficient (k_b) was –1.4703 (mg/L)$^{-2}$ d^{-1} under the assumption of the third-order reaction. On the experiment day, the average residual chlorine concentration of outflow of the WPP was 1.18 mg/L. Hourly residual chlorine concentration data were measured at the outflow point of the clear well, and reflected in the water quality analysis model. The pipe wall decay coefficient (k_w) was calculated to be –0.038 m/d. On March 14, 2018, the water temperature of the J WPP was 5.2°C, and the bulk decay coefficient (k_b) was –0.2492 (mg/L)$^{-2}$ d^{-1} under the assumption of the third-order reaction. On the experiment day, the average residual chlorine concentration of outflow of the WPP was measured to be 1.05 mg/L and reflected in the water quality analysis model. The pipe wall decay coefficient (k_w) was calculated to be –0.005 m/d.

3.3. Distribution of residual chlorine concentrations in the water distribution pipe network

The residual chlorine concentration at 5 a.m. (Fig. 4(a)) was analyzed by water quality analysis on the first experiment day (at the water temperature of 17.1°C). The residual chlorine concentration of the outflow at J WPP was 1.18 mg/L, and the average concentration in the water supply network was simulated at 0.64 mg/L for 24 h. It has been simulated that there is a demand node with a residual chlorine concentration less than 0.1 mg/L at the end of the indirect water supply area through the reservoir.

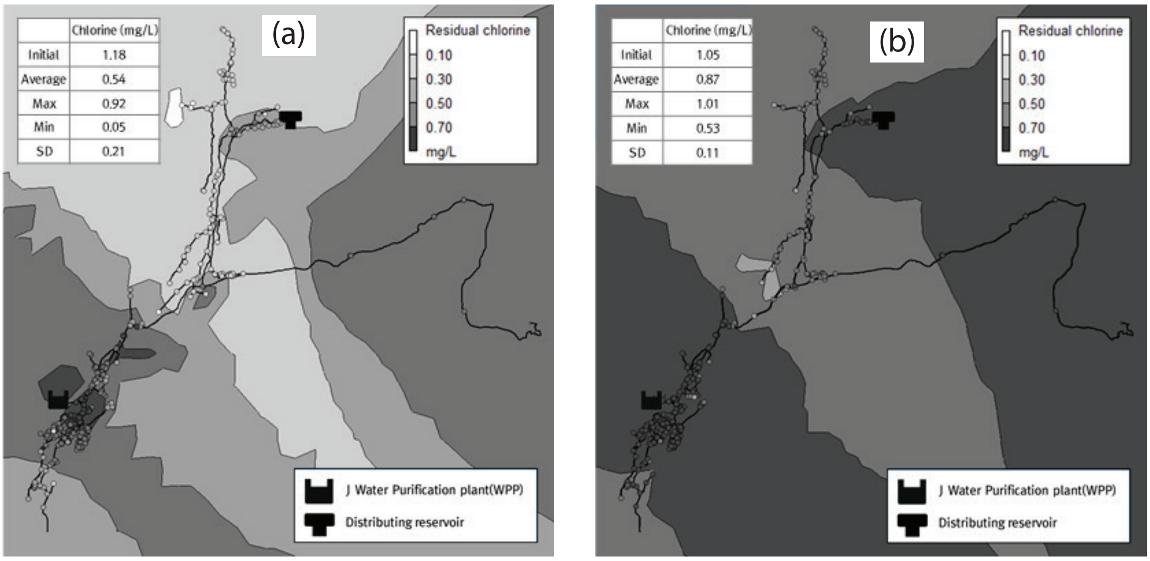


Fig. 4. Contour plot of simulated residual chlorine concentration at 5 a.m. on (a) September 8, 2017, and (b) March 14, 2018.

Table 4
Optimized chlorine boosting station locations and concentrations by scenario

Scenario	Optimization results							
	WPP		Boosting stations				Total cost (KRW/d)	Number of dissatisfied points
	Residual chlorine concentration (mg/L)	Chlorination cost (KRW/d)	Residual chlorine concentration (mg/L)	Chlorine injection dosage (kg/d)	Installation cost (KRW/d)	Operation cost (KRW/d)		
3-1	0.34	766	0.14	0.0046	108,600	1,288	110,654	1
			0.17	0.0809				
			0.37	0.0003				
3-2	**0.39**	**878**	**0.20**	**0.0952**	108,600	**1,512**	**110,991**	0
			0.36	**0.0003**				
			0.11	**0.0053**				
3-3	0.35	788	0.21	0.1000	108,600	1,648	111,037	0
			0.29	0.0003				
			0.20	0.0097				
3-4	0.41	924	0.25	0.0608	108,600	1,774	111,298	0
			0.12	0.0571				
			0.41	0.0003				
4-1	0.40	901	0.12	0.0040	108,600	992	110,493	1
			0.13	0.0619				
			0.36	0.0003				
4-2	0.50	1,126	0.19	0.0905	108,600	1,512	111,238	0
			0.25	0.0002				
			0.21	0.0101				
4-3	0.60	1,351	0.14	0.0667	108,600	1,163	111,115	0
			0.33	0.0003				
			0.22	0.0106				
4-4	0.70	1,577	0.16	0.0762	108,600	1,235	111,411	0
			0.42	0.0003				
			0.12	0.0058				

The bold values of scenario 3-2 was selected the best results for optimized chlorine boosting station locations and concentrations.

The residual chlorine concentration at 5 a.m. (Fig. 4(b)) was analyzed by water quality analysis on the second experiment day (at the water temperature of 5.2°C). The residual chlorine concentration in the effluent of the clear well was 1.05 mg/L, and the average concentration in the water supply network was simulated as 0.90 mg/L for 24 h. Although the effluent concentration of the clear well (1.05 mg/L) was lower than that of the first experiment, k_b was low due to the low water temperature and was supplied at a relatively high concentration.

3.4. Optimization results for the locations of chlorine booster stations

Table 4 presents the optimal locations of chlorine booster stations under each scenario. When a scenario produced a result that could not satisfy the criteria of the range of residual chlorine concentration at demand nodes of the water distribution district, the scenario was dismissed. Fig. 5 illustrates the optimal concentrations and locations of chlorine booster stations derived from the analysis of scenarios. Fig. 6 shows the distributions of residual chlorine concentration at 5 a.m. and 8 p.m., which were obtained by reflecting the optimal concentration and locations of chlorine booster stations in the first experiment.

The residual chlorine concentration in the effluent of the clear well was simulated at 0.39 mg/L. It has been simulated that the residual chlorine concentration was 0.1 mg/L or more at all demand nodes in the water supply area, and the deviation of the residual chlorine concentration was simulated as low as 0.05 mg/L.

The residual chlorine concentration for the consumers is shown in order of water age for 5 a.m. (Fig. 7(a)) and 8 p.m. (Fig. 7(b)) before and after rechlorination. After 24-h water quality analysis, the ratio of residual chlorine concentration of less than 0.1 mg/L was 0.14%, and the ratio of more than 0.5 mg/L was 85.77%. The water quality satisfaction was 100% at all demand nodes through the three chlorine boosting points determined by the developed optimization model.

3.5. Optimal operation schedule for chlorine booster stations

3.5.1. Analysis of the optimization effect for the residual chlorine concentration in the first experiment (September 8, 2017).

In the first experiment, the average residual chlorine concentration of the outflow from the J WPP was 1.18 mg/L. This required a 2,554 KRW/d disinfection cost for the plant. The total disinfection cost was calculated to be 2,267 KRW/d after reflecting the residual chlorine concentration obtained by optimizing the locations of chlorine booster stations. Accordingly, apart from the installation cost, disinfection seemed to be possible at a lower cost than the current operation cost. Because the locations of chlorine booster stations were determined by considering worst-case summer conditions, the residual chlorine concentration at each chlorine booster station was estimated to be too high. For this reason, an appropriate residual chlorine concentration for the WPP and chlorine booster stations on the first experiment day was derived. When the residual chlorine concentration of the outflow from the WPP

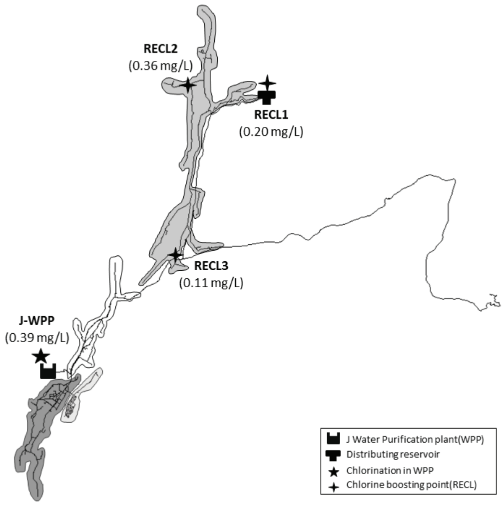
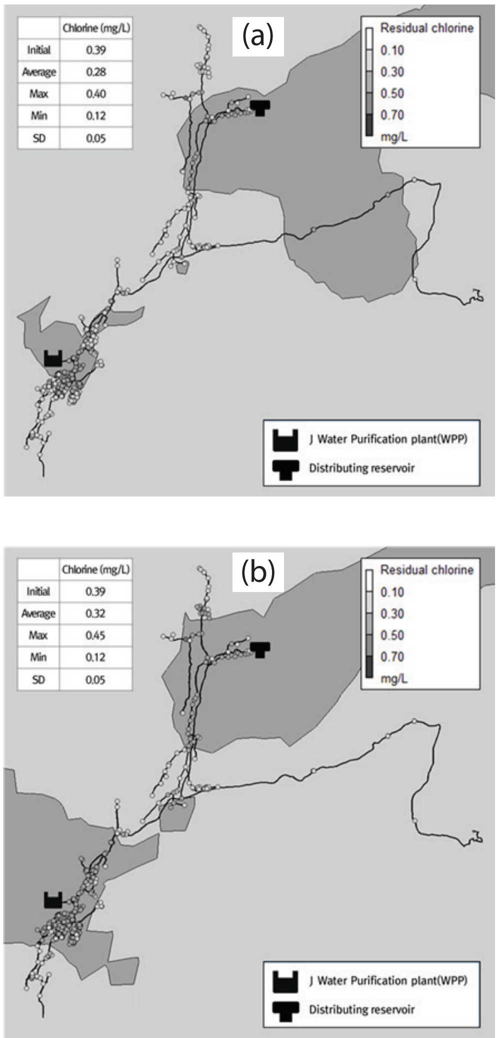


Fig. 5. Residual chlorine concentration after chlorine boosting (Scenario 3-2).



	Chlorine (mg/L)
Initial	0.39
Average	0.28
Max	0.40
Min	0.12
SD	0.05

	Chlorine (mg/L)
Initial	0.39
Average	0.32
Max	0.45
Min	0.12
SD	0.05

Fig. 6. Contour plot of simulated residual chlorine concentration after rechlorination at (a) 5 a.m. and (b) 8 p.m. on September 8, 2017.

was maintained at 0.5 mg/L, the residual chlorine concentration of the chlorine booster station installed at the outflow point of the reservoir could be 0.16 mg/L or below, which lowered the operation cost to 1,576 KRW/d.

Fig. 8 illustrates residual chlorine concentrations at main points of the three small blocks, to which water was supplied directly from the WPP, under each scenario. The water quality standard could be satisfied at all demand nodes of the three blocks even if 0.5 and 0.39 mg/L were supplied at the WPP through operation scheduling in chlorine boosting stations.

The residual chlorine concentration at the representative observing points in the indirect water supply area (Block 4) from the WPP through the pumping station and reservoir is as follows: if the chlorine boosting stations can measure and control residual chlorine concentration in consideration of hourly water consumption, the developed optimization model is expected to enable efficient chlorine boosting operation (Fig. 9).

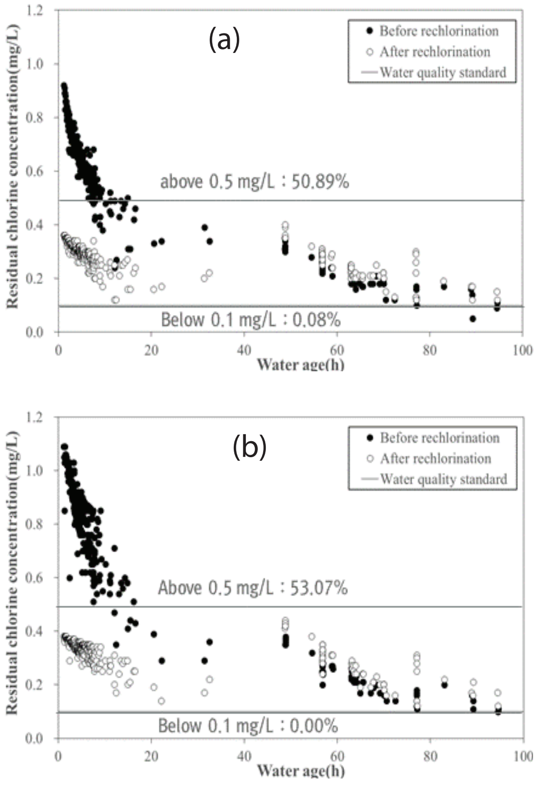


Fig. 7. Variation of residual chlorine concentration before and after rechlorination at (a) 5 a.m. and (b) 8 p.m.

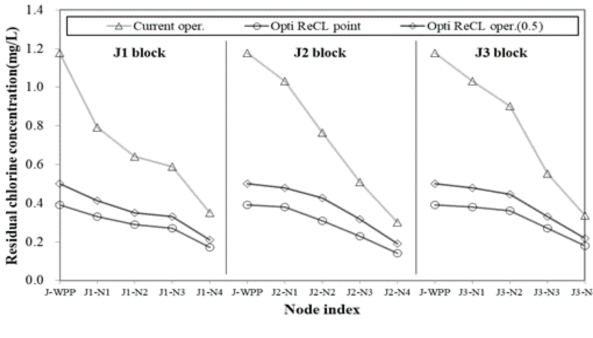


Fig. 8. Variation of average residual chlorine concentration by each block in direct water supply area according to optimal operation on September 8, 2017.

3.5.2. *Analysis of the optimization effect for the residual chlorine concentration in the second experiment (March 14, 2018).*

From the optimization results for residual chlorine concentration under each scenario, the residual chlorine concentrations of the three small blocks, which belonged to the area of direct water supply, were derived as shown in Fig. 10. Because residual chlorine bulk decay coefficients were low due to low water temperatures, the residual chlorine concentration did not change much according to retention time. Even when the existing residual chlorine concentration of 1.05 mg/L at the WPP was decreased to 0.2 mg/L as the chlorine booster stations were operated, all the demand nodes of three blocks met the requirement of 0.1–0.5mg/L.

Fig. 11 shows the optimization results for residual chlorine concentration on March 14, 2018, at the area of indirect water supply under each scenario. When the residual chlorine concentrations at the WPP were maintained at 0.5 and 0.39 mg/L respectively, two out of three chlorine boosting points conducted rechlorination at 0.1 mg/L or below or were hardly operated, and the rechlorination of only Re-chlorination point (ReCl2) was sufficient to satisfy the water quality standard at every demand node.

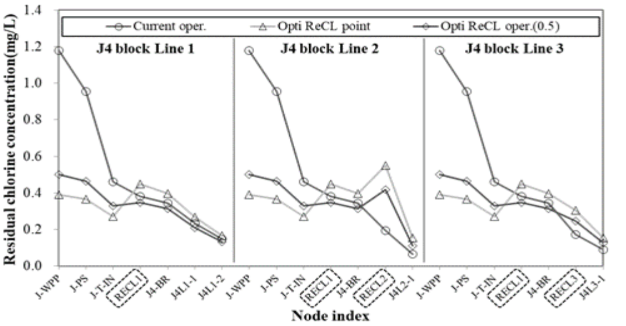


Fig. 9. Variation of average residual chlorine concentration by each block in indirect water supply area according to optimal operation on September 8, 2017.

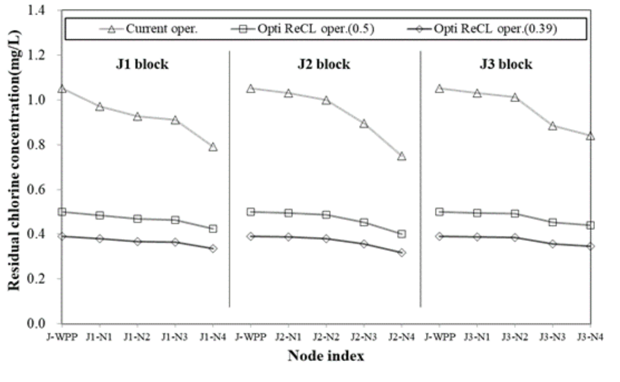


Fig. 10. Variation of average residual chlorine concentration by each block in direct water supply area according to optimal operation on March 14, 2018.

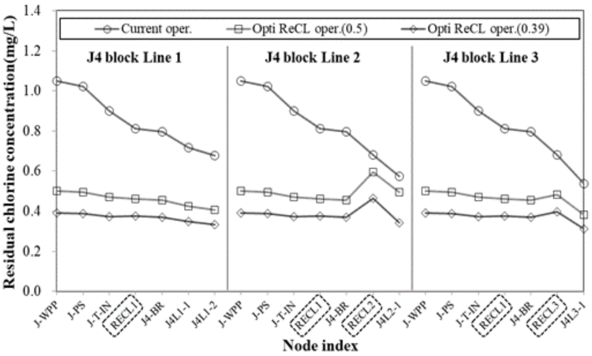


Fig. 11. Variation of average residual chlorine concentration by each block in indirect water supply area according to optimal operation on March 14, 2018.

On the second experiment day, the average residual chlorine concentration of the outflow from the J WPP was 1.05 mg/L. This required 2,232 KRW/d as the disinfection cost for the plant. When the residual chlorine concentration of the WPP was fixed at 0.5 mg/L, a lower disinfection cost (1,319 KRW/d) was derived. In the case of fixing the residual chlorine concentration at 0.39 mg/L, the most economical operation (1,101 KRW/d) seemed to be possible.

Although the optimization model developed in this study could derive the schedule for 24-h residual chlorine concentration at the WPP, as the operational convenience of the plant and the safety issue of chlorination needed to be considered, it seemed to be appropriate that the effluent concentration of the clear well was maintained to be constant.

In this study, we analyzed and optimized water quality of the J water distribution district by performing two bulk decay coefficient experiments and field measurement of residual chlorine concentration. We found that chlorine booster stations need to be installed and operated to reduce high residual chlorine concentrations in the direct water supply area close to the J WPP, and to satisfy the mandatory residual chlorine concentration at the small blocks to which water is indirectly supplied through reservoirs. Moreover, if the operation of residual chlorine concentration in chlorine booster stations is optimized by considering the variation of residual chlorine concentration according to seasonal variations of water temperature and usage and the change of water use pattern within a day, economical operation could be possible within the target range of water quality.

4. Conclusions

This study has developed an optimization model for residual chlorine concentration by utilizing AMR data of water use and adopting a hydraulic analysis method reflecting actual water use characteristics of consumers. The locations and operation schedule of chlorine booster stations were optimized to propose a method for improving the reliability of water quality.

An optimization model for locating and operating chlorine boosting station was developed that can minimize spatial and temporal deviation of residual chlorine concentration, enabling economical disinfection, based on an optimization technique utilizing a genetic algorithm and a water quality analysis model that considers consumer water consumption patterns. The application of the model deduced three optimal boosting points that allow the achievement of the target residual chlorine concentration (0.1–0.5 mg/L) even under the worst-case water quality conditions of the service area. The calculation of the cost for chlorine disinfection at the WPP and for chlorine boosting station installation and operation resulted in 110,991 KRW/d. According to the first experiment, in which measured water temperature was 17.1°C, the average residual chlorine concentration at J WPP was 1.18 mg/L, and disinfection cost was 2,554 KRW/d. The optimal residual chlorine concentration operating schedule satisfying residual chlorine concentration standard for demand nodes was performed at lower cost by fixing residual chlorine concentration at the WPP (1,576 KRW/d). Therefore, if residual chlorine concentration can be measured and controlled at chlorine boosting stations, the utilization of the developed optimization model is expected to enable efficient disinfection according to the hourly change of water consumption and seasonal changes in water temperature. Maintaining the concentration of residual chlorine at the WPP as low as possible within the range satisfying the water quality standards will contribute effectively to reduce the generation of disinfection by-products and to prevent the decrease of the drinking rate due to chlorine odor.

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