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Determination of key sensor locations for non-point pollutant sources management in sewer network

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Abstract−As the importance of watershed management has emerged for water systems, non-point pollutant sources have been blamed as the main problem of water pollution. To control non-point pollutant sources, it is necessary to monitor sewers connected to the watershed and to analyze their effects on the sewer network. As the cost to monitor a sewer network depends on the number of sensors installed, the monitoring stations should be decided with proper guide of the installation location rule. In present paper, a new method to select the proper sensor location is proposed by combining monitoring information with data mining techniques. To estimate the amount of pollutants by wash-off and to find the sensor locations in a sewer network, three scenarios are considered based on rainfall intensity, influent concentrations and flow rate. The optimal locations of the sensor were selected based on the proposed method to facilitate the management of non-point pollutant source in sewer network. The presented approach can be extended to a complex sewer network system to design a minimum number of sensors and optimum locations for the sensors.

Key words: Sewer Network, Non-point Pollutant Sources, Sensor Location, Data Mining, ANOVA

INTRODUCTION

Non-point pollutant sources (NPSs) affect the water system as they flow through sewers, branches, and large watersheds. They are generated by the process of washing off of the pollutants from the surface and their transport mechanism has not been known. Most of the studies reported that NPSs are still the major problem in the watershed, although many efforts have been taken to reduce them [1]. Therefore, in Korea, key measurement points for water monitoring are selected and operated upon recognizing the importance of this but they are just for drinking and stream water and not for sewage. Recently, continuous sewer monitoring has become more important to manage effectively flow rate, water quality, infiltration and inflow (I/I) in sewers and combined sewer overflows (CSOs). As a result, it is necessary to control the NPSs in sewer networks, which flow largely in the watershed via branches, and also their effects need to be analyzed for the overall management of the watershed [2].

However, it is difficult to monitor NPSs in sewers, because the sewer network has a large and complex infrastructure due to expansion and development. The installation of sensors at certain locations is very important. Sensors are common in sewer systems as well as industrial systems for systematic and scientific monitoring. Also, they have been used in a wide range such as monitoring many processes due to advantages and convenience, but they are expensive [3]. Determination of the key sensor location which is to be diagnosed as sensitive points is necessary in view of the number of sensors installed in the sewer network, which determines the minimum cost of the system. This helps to increase the cost-effectiveness of the sensors to be installed by minimizing the number of sensors.

In the present scenario, the sewer system has fewer studies than a water supply system, since it has been paid less attention as compared to the drinking water supply system. There are almost few or no cases that sensors are installed in a sewer system, while it is deemed that installations of sensors in drinking water system are reasonable. As a result, there is a great deal of research on the water supply system in which sensors are installed due to drinking water supply security and health risk management compared to a sewer system [4-6]. Few studies are available on non-point sources studies [7,8]. In the drinking water supply system, some authors [9,10] used genetic algorithms, multiobjective optimization models, and heuristic methods with respect to four objectives consisting of expected time of detection, population affected prior to detection, consumption of contaminant water prior to detection, and the detection likelihood for deciding the sensor locations. In this field, the Battle of the Water Sensor Networks (BWSN) was already done to compare the performance of contributed sensor network designs, as applied to two water distribution system examples using four quantitative design objectives. However, in the literature, attempts can hardly be found regarding selection of sensor location for monitoring water quality in sewage network systems, and there is no quantifiable method and research that determines optimum sensor monitoring locations unlike in a water supply system [9-11]. Hence, there is a strong need for applications to fit the situation of a sewer system, since the sewer system's purpose is different from that of a water supply system.

It can be seen that monitoring of sewer network using sensors in real time to control NPSs has already been used in actual sewage

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treatment plants to control the NPSs flowing through watershed. Hence there is a need for the development of an appropriate method for the determination of sensor location to minimize the monitoring expenses. The objective of the present study is to determine the key optimal sensor locations of a sewer system to monitor the NPSs flow in a watershed. These locations should satisfy the minimum cost of sensor installation and precise monitoring of the distribution of pollutants in the sewer network that occur from runoff and wash-off by storm water. Commercial software, XP-SWMM, based on storm water management model (SWMM), is used for the purpose. The SWMM is a comprehensive mathematical model for simulating flow rate and water quality in the sewer system. It also serves to simulate the runoff occurring from rainfall in the urban area, contaminants on the surface and subsurface, trace of effluence in the sewer network and for estimating the amount of storage [12-15].

In the present paper a model of a sewer network was developed using SWMM, and the effects of various factors such as flow rainfall intensity, flow rate, and the concentration of pollutants on sewer network were presented. Also the key sensor locations using the statistical analysis, which are cluster analysis and analysis of variance (ANOVA), were determined. The threshold value β is selected to verify the results.

THEORETICAL BACKGROUND

1. Evaluation of Runoff from Catchment by SWMM

In SWMM, runoff from catchment is calculated through a runoff block. Fig. 1 shows the cross section of the flow of runoff. The runoff block simulates outflow and variation of water quality as a part conducting initial computation in SWMM. In the runoff block, the fundamental equation at surface runoff is a nonlinear storage equation by approximation of the kinematic wave equation, assuming that friction slope is the same as the basin slope. Water level and flow rate in a subcatchment can be represented by continuity equation and Manning equation. Generally, a waterway is trapezoid and continuity equation and Manning equation in subcatchment can be written as [12]:

$$\frac{\mathbf{d}\forall}{\mathbf{dt}} = \mathbf{A}_s \frac{\mathbf{dd}}{\mathbf{dt}} = \mathbf{A}_s \mathbf{i} - \mathbf{Q} \tag{1}$$

$$\mathbf{Q} = \mathbf{W} \cdot \frac{1}{\mathbf{n}} (\mathbf{d} - \mathbf{d}_p)^{5/3} \mathbf{S}^{1/2} \tag{2}$$

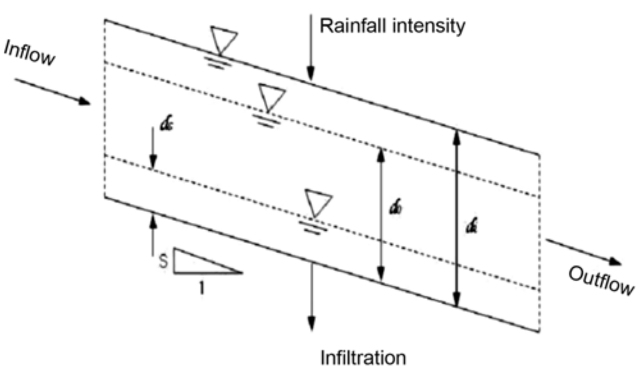

Fig. 1. Cross section of the flow of runoff.

After simplification,

$$\frac{\Delta \mathbf{d}}{\Delta \mathbf{t}} = \mathbf{i} - \frac{\mathbf{W}}{\mathbf{A}_s \cdot \mathbf{n}} (\mathbf{d} - \mathbf{d}_p)^{5/3} \mathbf{S}^{1/2} = \mathbf{i} + \mathbf{R} \cdot (\mathbf{d} - \mathbf{d}_p)^{5/3} \tag{3}$$

where $\mathbf{R} = -((\mathbf{W} \cdot \mathbf{S}^{1/2})/(\mathbf{A}_s \cdot \mathbf{n}))$, $\forall$ is the volume of water, t is the time (s), $\mathbf{A}_s$ is the surface area of water (computed from production of the width of basin and length of drain), **d** is the water level (m), **i** is the rainfall intensity excess (m/s), **Q** is an outflow (m^3/s), **W** is the width of basin (m), **n** is the coefficient of roughness, $\mathbf{d}_p$ is the depth of surface detention storage (m), **S** is slope of subcatchment (m/m), R is a variable which consists of width of basin, slope and coefficient of roughness and so on, and basin characteristic factor changed with basin characteristic. Here it is assumed that the difference between top and bottom width is negligible.

Intensity of excess rainfall was given as the input and average flow rate was calculated by averaging the initial and final flow rate. Eq. (3) is transformed into a nonlinear algebraic equation using semi-implicit forward finite difference method as:

$$\frac{(\mathbf{d}_{n+1} - \mathbf{d}_n)}{\Delta \mathbf{t}} = \mathbf{i} + \mathbf{R} \cdot \left(\mathbf{d}_n + \frac{(\mathbf{d}_{n+1} - \mathbf{d}_n)}{2} - \mathbf{d}_p \right)^{5/3} \tag{4}$$

Eq. (4) is solved by using the Newton-Raphson method to obtain the flow rate from the depth of water for 1 hour time interval. Outflow on surface was interpreted with the initial condition of time and amount of surface storage. It is assumed that the outflow that occurred from the rainfall flow is in the lower watershed and flow rate is not discharged into another watershed.

2. Evaluation of Outflow from Pipe Conduit by SWMM

Discharge through a pipe conduit is calculated in a similar way as the calculation of surface outflow. Manning method is used at each step to carry out integration. Amount of storage used in discharge of pipe conduit can be found by using Manning's mean velocity formula as [12]:

$$\Delta\forall = \Delta \mathbf{t}(\mathbf{Q}_i + \mathbf{Q}_{GW} + \mathbf{Q}_W - \mathbf{Q}) \tag{5}$$

where **Q** is an amount of discharge, $\mathbf{Q}_i$ is an inflow from upstream, $\mathbf{Q}_w$ is an inflow from side of basin and $\mathbf{Q}_{GW}$ is an inflow from underground.

3. Evaluation of Pollutant Load from Catchment by SWMM

The process discharging pollutants in the basin are divided into former process accumulating pollutants and runoff pollutants due to rainfall. The process accumulating pollutants in the basin are influenced by natural and artificial conditions like rainfall pattern, volume, rainfall intensity, antecedent number of dry days, land use, wind, geographic and geologic characteristics of the region, maintenance practices and drainage system configuration.

However, most of the studies suggested the empirical formula disregard physical and chemical countenance as it is difficult to establish a mathematical model incorporating these aspects. In SWMM, the accumulation of pollutants can be calculated by using any one of the equations given in Table 1.

4. Statistical Analysis

The statistical analysis was carried out using analysis of variance (ANOVA) and cluster analysis. ANOVA judges the necessity of sensor installment in the system and cluster analysis shows total emission of pollutants distribution between sewer nodes.

Table 1. Equations of pollutant buildup and washoff

Type	Equation
Build-up	$\mathbf{PSHED}=\mathbf{QFACT(3)}\times \mathbf{t}_a^{QFACT(2)}$ $\mathbf{PSHED}\leq\mathbf{QFACT(1)}$ $\mathbf{PSHED}=\mathbf{QFACT(1)}\times(1-\mathbf{e}^{QFACT(2)\cdot t_a})$ $\mathrm{PSHED}=\dfrac{\mathrm{QFACT(1)}\times \mathrm{t}_a}{\mathrm{QFACT(3)}+\mathrm{t}_a}$
Wash-off	$-\mathbf{POFF(t_r)}=-\mathbf{RCOEF}\times \mathbf{r}^{WASHPO}\times\mathbf{PSHED}$ $\mathbf{POFF(t_r)}=\mathbf{RCOEF}\times\mathbf{WELOW}^{WASHPO}$

Where

PSHED	:	Constituent quantity accumulated (kg/ha)
QFACT(1)	:	Constituent accumulation limit (kg/ha)
QFACT(2)	:	Accumulation rate (-)
QFACT(3)	:	Coefficient of accumulation (-)
$\mathbf{t}_a$	:	Antecedent number of dry days (day)
$\mathbf{t}_r$	:	Time passed after rainfall (hr)
POFF	:	Runoff accumulated (kg)
WASHPO	:	Power of runoff rate (-)
RCOEF	:	Washoff coefficient (mm^{-1})
WELOW	:	Outflow on surface (m^3/s)

4-1. Cluster Analysis

Cluster analysis gives information which notifies characteristics and relation between formed clusters based on their similarity or distance. It is important to understand the characteristics of the clusters as different clusters have considerably different results. To measure the similarity between nodes, Euclidian distance method was used. If the distances between the clusters are closer, similarity is higher. The Euclidian distance between $\mathbf{X}_i$ and $\mathbf{X}_j$ can be calculated as [16]:

$$\mathbf{d}_{ij}=\mathbf{d}(\mathbf{X}_i,\mathbf{X}_j)=[\textstyle\sum_{k=1}^{p}|\mathbf{X}_{ik}-\mathbf{X}_{jk}|^2]^{1/2} \qquad (6)$$

where $\mathbf{X}_i$=[$\mathbf{X}_{i1}$, $\mathbf{X}_{i2}$, …, $\mathbf{X}_{jp}$]^T, $\mathbf{X}_j$=[$\mathbf{X}_{j1}$, $\mathbf{X}_{j2}$, …, $\mathbf{X}_{jk}$]^T are observed vectors in p-dimension.

4-2. Analysis of Variance (ANOVA)

ANOVA is a statistical method in which variability of the parameter is measured and divided into various identifiable sources including the factors (inputs) and the random noise. ANOVA facilitates whether the variability due to a particular factor, or combination of factors, is statistically significant or not as compared to the measured variability due to random sources [17]. In this study, total pollutant emission obtained at each node according to each case is calculated using integral operation. Then the information of sensor location can be found, on examining whether a significant difference between nodes exists using ANOVA or not [18-,19].

MATERIAL AND METHODS

1. Motivation of the Present Study

To control NPSs, which is the main problem in watershed management, it is necessary to monitor a sewer connected watershed. However, in practice, optimal process to monitor water quality in sewer network is not prepared yet for watershed management. Hence it is thought desirable to carry out a study 1) to estimate total amount of NPSs in sewer by its measurement using sensors, and 2) to develop a method that determines optimal key sensor locations for real time monitoring of water quality (NPSs) in sewer.

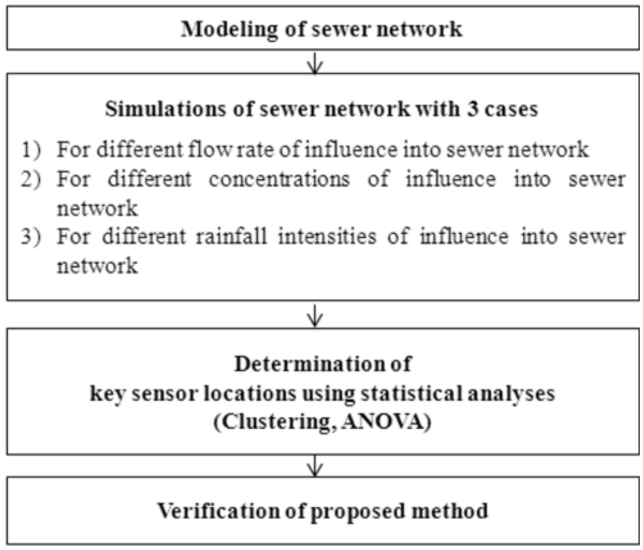

Fig. 2. The scheme of the presented study.

2. Proposed Method

The scheme for the proposed study is presented in Fig. 2. It is divided into four parts: 1) modeling of sewer network, 2) simulation of sewer network with three cases, 3) determination of key sensor locations, and 4) verification of the proposed method.

As a first part, subcatchment data of model sewer network system of city from Korea were obtained at various locations as shown in Fig. 3, which shows a sectional view of the target area. Nodes and links are located underground of this area. The distribution of the number of nodes and links based on target area was determined. Detailed information representing physical structure of nodes and links (like ground and invert elevation, area, slope, width, impermeability, diameter, length, roughness, shape and so on) were collected. In the next step, global data affecting the network such as rainfall data, land use, wash-off, and infiltration capacity were also collected as inputs into the designed network.

The second part is the formulation of model to simulate the designed sewer network using SWMM. A sewer network is known for being affected by the magnitude of the flow rate, pollutant concentrations and the time distribution of different factors including rainfall patterns, volume, intensity and antecedent number of dry days. But we decided to simulate water quality and outflow according to rainfall intensity, concentration and flow rate, as these factors affect the runoff significantly. These three factors were taken as inputs. Three different cases were planned to identify the most sensitive factor for allocation of sensors as shown in Table 2. Each simulation involved the changing of only one factor out of the three chosen factors.

Results of simulation appear in the form of four parameters: biological oxygen demand (BOD), chemical oxygen demand (COD), total nitrogen (TN) and total phosphorus (TP). By integrating the minute data obtained from each node, total emission of pollutants (BOD, COD, TN and TP) in sewer can be calculated and simulation results can be applied for statistical analysis.

In the third part, statistical analysis using cluster analysis and

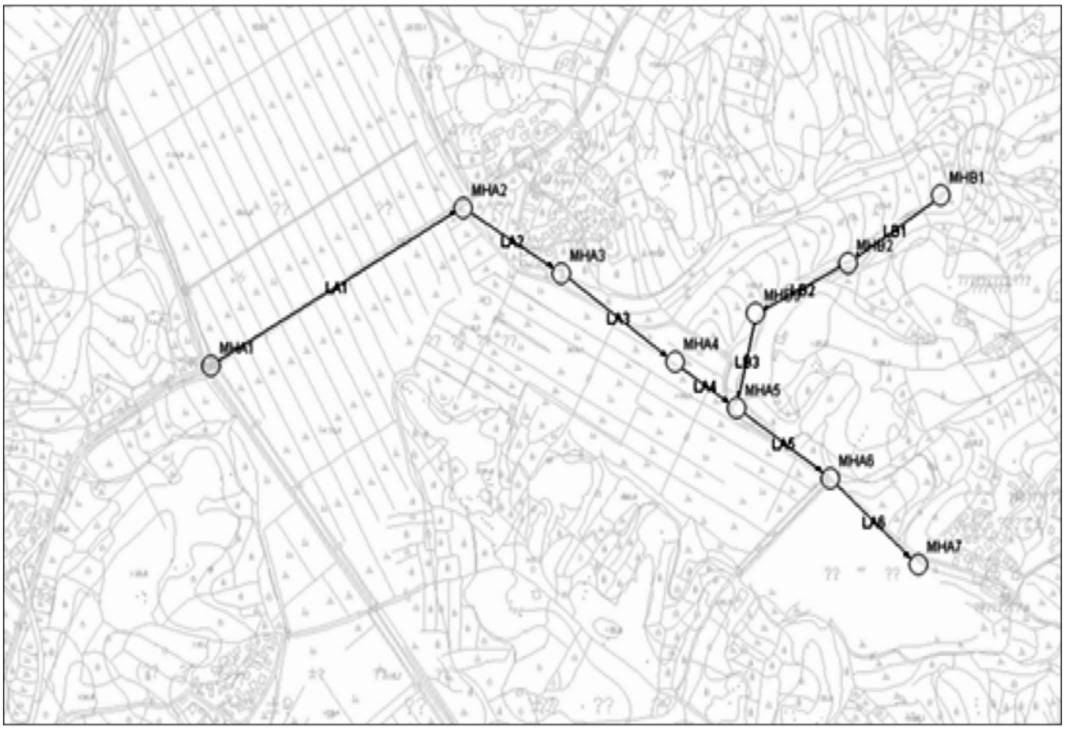

Fig. 3. A sectional view of the target area.

Table 2. Three cases for simulation

Run order	No.	Rainfall	Conc.	Flow rate
Case 1	1-1	100%	100%	100%
- According to variation of rainfall intensity	1-2	200%	100%	100%
	1-3	300%	100%	100%
Case 2	2-1	100%	50%	100%
-According to variation of concentrations	2-2	100%	100%	100%
	2-3	100%	150%	100%
Case 3	3-1	100%	100%	50%
-According to variation of flow rate	3-2	100%	100%	100%
	3-3	100%	100%	150%

ANOVA are applied to determine optimal key sensor locations. To find the number of sensors, cluster analysis is conducted since it separates data into a subgroup called as 'cluster' [20]. For nine monitoring data, it was assumed that the number of clusters equals the number of sensors. For instance, if 10 nodes are divided into two groups, the number of sensors can be considered as two. Then, the sensor locations are determined by ANOVA. If a certain node shows a significant difference among the nodes, that node can be considered as a proper location for sensor installation.

Finally, the proposed method is verified by probability of type II error β testing hypothesis [20]. Based on the results in which amounts of BOD, COD, TN, and TP are evaluated, the increased rate of pollutant amounts entering through the network are compared with previous nodes as calculated. Then, the proportion of pollutants flowing from each node to total pollutants from node and inflow is determined and used to estimate the type II error β of each node according to three cases as:

$$\beta = \Phi\left(z_{\alpha/2} - \frac{\delta\sqrt{n}}{\sigma}\right) - \Phi\left(-z_{\alpha/2} - \frac{\delta\sqrt{n}}{\sigma}\right) \tag{7}$$

At this time, the hypothesis is set as change of pollutant concentration at each node is zero (H_0: μ=0 and H_1: $\mu \neq 0$). β is the probability that the null hypothesis H_0 cannot be rejected when H_0 is false. Therefore, it can be considered a probability that the place becomes a sensor location is higher, as β is lower.

RESULTS AND DISCUSSION

The sewer network system considered for study is presented in Fig. 4. It has total 10 nodes and 9 links. Each node is called MHA 1, 2, 3, 4, 5, 6, 7, MHB 1, 2 and 3 and each link is named as LA 1, 2, 3, 4, 5, 6, 7, LB 1, 2 and 3. Inlets are designated as MHA1, MHB1 and the outlet is MHA7. Rainfall intensities, flow rates and concentrations for MHA1 for different cases are presented in Table 2.

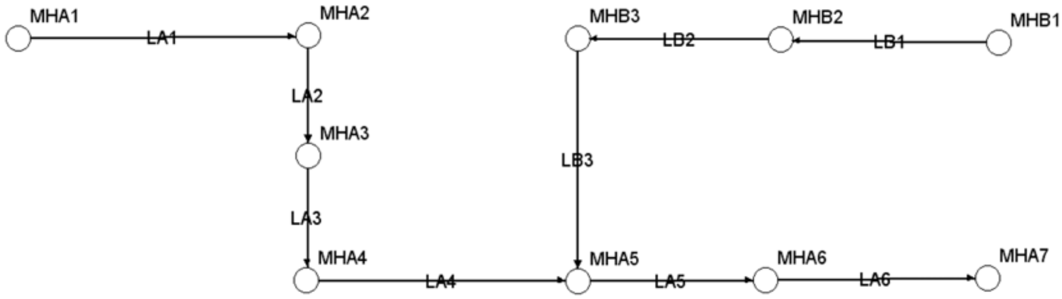

Fig. 4. A piping diagram of the target area.

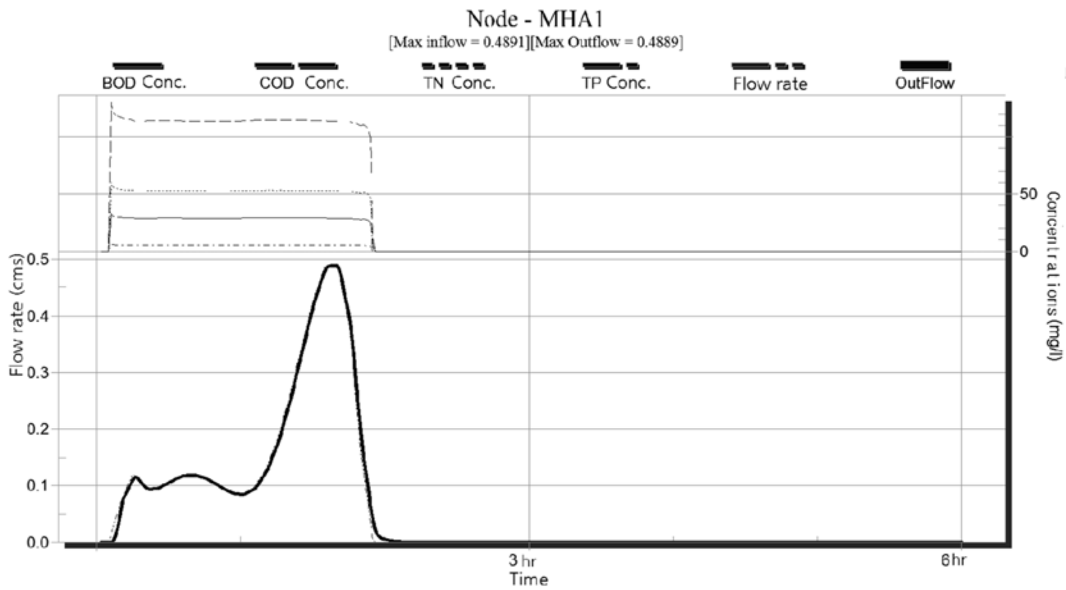

Fig. 5. Node 1 result of simulation of the first experiment.

At MHB1, sewage has constant inflow conditions (constant flow rate of 0.1 m^3/s, BOD of 30 ppm, COD of 50 ppm, TN of 5 ppm, and TP of 0.5 ppm). The simulations were carried out for 6 hours.

The simulation results of the designed network at MHA 1 using data 1-1 (Table 2) are presented in Fig. 5. The change in COD concentration, TN concentration, BOD concentration, and TP concentration with respect to time, can be also observed from Fig. 5. The outflow almost overlapped with the flow rate. Both outflow and flow rate have shown an increase and the peak at around 1.75 hours. It shows the occurrence of heavy rainfall during that period.

Pollutants present in a sewer can be calculated by using integration and estimating the total amount of NPSs. By integrating a minute data obtained at each node, amount of pollutants passing at a node or link can be determined. Similar kinds of results were observed for other experimental data, which shows the validity of the model.

To determine the number of sensors, cluster analysis was applied using data 1-1 (Table 2), and results are presented in Fig. 6. The results of cluster analysis on the simulation results for the other pollutants have shown a similar trend as in Fig. 6, which again shows the qualitative validity of the proposed model. Herein, the numbers from 1 to 7 mean nodes from MHA1 to MHA7 and 8, 9, and 10 correspond to MHB1, MHB2, and MHB3, respectively. This sewer network system has three clusters: C1, C2, and C3. C1 consists of

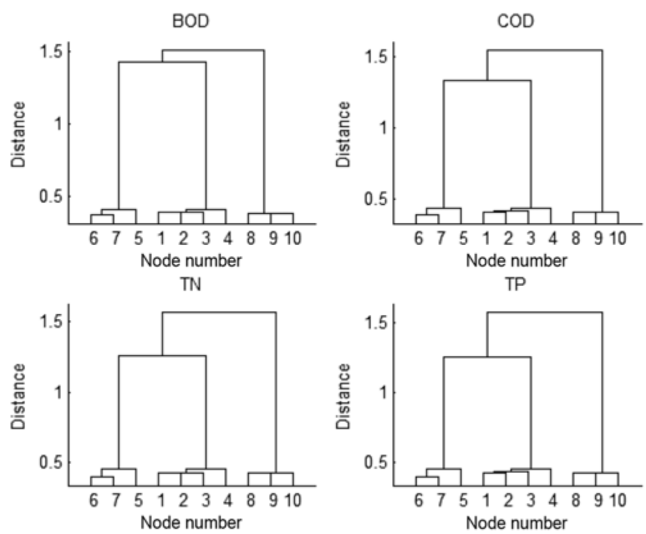

Fig. 6. Cluster analysis among nodes.

MHA 1, 2, 3, and 4; C2 consists of MHA 5, 6, and 7; and C3 consists of MHB 1, 2, and 3. The number of clusters generated from cluster analysis corresponds to the number of sensors which need

Table 3. Simulation result according to variation of rainfall intensity

Case 1		N1	N2	N3	N4	N5	N6	N7	N8	N9	N10	Significant difference
Total	BOD	0	0	0	0	1	0	0	0	0	0	O
Total	COD	0	0	0	0	1	0	0	0	0	0	O
Total	TN	0	0	0	0	1	0	0	0	0	0	O
Total	TP	0	0	0	0	1	0	0	0	0	0	O
Node	BOD	0	0	0	0	0	0	0	0	0	0	X
Node	COD	0	0	0	0	0	0	0	0	0	0	X
Node	TN	0	0	0	0	0	0	0	0	0	0	X
Node	TP	0	0	0	0	0	0	0	0	0	0	X

to be installed, because nodes which belong to the same cluster have similar pollution transports and hydrodynamics characteristics. Thus, sensors can be installed at each cluster (C1, C2, and C3).

Although a cluster decides the number of sensors, ANOVA gave additional information on the determination of specific sensor locations. Table 3 shows the results to check whether a significant difference exists among nodes using data of case 1. In accordance with the simulation results by variation of rainfall intensity, it can recognize the node that has a significant difference. Only the results of case 1 are displayed in Table 3. 'Total' is the total amount of pollutants in the sewer, while 'node' is the amount of pollutants passing from a specific area at each node. Significant differences were observed at MHA 5 in four simulations among eight components for case 1. Cases 2 and 3 (results are not shown) resulted in the existence of significant difference at 16 simulations among the 16 components. It means that installation of a sensor is necessary at MHA 5.

Combining results of cluster analysis and ANOVA, key sensor locations were determined. In C2 including MHA 5, 6, and 7, a sensor should be installed at MHA 5 which represents a significant difference among nodes. From the findings of the study, it is suggested that the inlets and the outlet located in C1 and C2 are the potential sensor locations, because C1 and C2 do not have nodes which appeared with a significant difference. Therefore, MHA 1, MHA 5, MHA 7, MHB 1 can be recommended as final key sensor locations. The results obtained in the simulations of the present studies are as per the typical quantitative and qualitative trends observed in the literature [20]. This is considered to be a numerical validation of the generalized approached presented in this paper.

Table 4. Type error of the three cases for the verification of monitoring points

β	Case 1	Case 2	Case 3
MHA1	4.27×10^{-188}	6.68×10^{-105}	6.23×10^{-101}
MHA2	7.58×10^{-192}	9.37×10^{-107}	1.12×10^{-102}
MHA3	7.64×10^{-219}	2.31×10^{-124}	2.26×10^{-121}
MHA4	7.64×10^{-219}	2.31×10^{-124}	2.26×10^{-121}
MHA5	3.70×10^{-243}	7.40×10^{-141}	3.56×10^{-136}
MHA6	5.29×10^{-219}	1.08×10^{-124}	3.05×10^{-120}
MHA7	1.59×10^{-150}	1.33×10^{-74}	1.19×10^{-71}
MHB1	6.41×10^{-180}	2.22×10^{-101}	2.23×10^{-97}
MHB2	6.41×10^{-180}	2.22×10^{-101}	2.23×10^{-97}
MHB3	7.97×10^{-179}	3.90×10^{-101}	3.85×10^{-97}

Further, Threshold β is used to validate the determined sensor locations. Table 4 shows the values of type II error of each node for three cases. It can be observed that the type II error is the highest at MHA 5 in all cases. MHA1, MHA7, and MHB1 were already determined as sensor locations, since sensors are conventionally installed at the inlet and outlet. Except for these sensor locations, the value of type II error at MHA5 is the lowest in total nodes. It means the probability that a null hypothesis is not rejected when the pollutants change at this node is not zero. Accordingly, it is appropriate to install a sensor at MHA5, which has the lowest the value of type II error. Hence, again it is considered to be a numerical validation of the generalized approached presented in this paper. This study can be very useful for the design of a number of sensors and sensor locations which can be further extended for complex sewer network systems.

CONCLUSSION

Non-point pollutant sources are the main problem in a sewer system. To facilitate the monitoring of NPSs systemically using sensors, a new methodology to determine key sensor locations was presented. Amount of pollutants at each node was calculated for three cases by varying rainfall intensity, influent concentration, and flow rate. The inlets and the outlet located in C1 and C2 are the potential sensor locations, because C1 and C2 do not have nodes which appeared with significant difference. Using ANOVA, MHA 5 was identified as the key optimal sensor location in 20 simulations among 24. MHA 1, MHA 5, MHA 7, and MHB 1 can be considered for the optimal placement of the sensor monitoring stations based on the proposed method using cluster analysis and ANOVA. The results obtained in the simulations of the present studies are as per the typical quantitative and qualitative trends observed in the literature. Also, the presented work was validated using Threshold β approach. Hence, it is considered to be a numerical validation of the generalized approached presented in this paper for sensor location.

This study is expected to help the installation of sensors to monitor NPSs systemically and scientifically for watershed management. The presented approach will be very useful for the design of a number of sensors and sensor locations in various complex sewer network systems.

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NOMENCLATURE

A_s : surface area of water [m^2]
d : water level [m]
d_{ij} : Euclidian distance
d_p : depth of surface detention storage [m]
i : rainfall intensity excess [m/s]
t : time [s]
n : coefficient of roughness [-]
POFF : runoff accumulated [kg]
PSHED : constituent quantity accumulated [kg/ha]
Q : outflow [m^3/s]
Q_{GW} : inflow from underground [m^3/s]
Q_i : inflow from upstream [m^3/s]
Q_w : inflow from side of basin [m^3/s]
QFACT(1) : constituent accumulation limit [kg/ha]
QFACT(2) : accumulation rate [-]
QFACT(3) : coefficient of accumulation [-]
R : variable which consisted of width of basin, slope and coefficient of roughness and so on
RCOEF : washoff coefficient [mm^{-1}]
S : slope of subcatchment [m/m]
t_a : antecedent number of dry days [day]
t_r : time passed after rainfall [hr]
W : width of basin [m]
WASHPO : power of runoff rate[-]
WELOW : outflow on surface [m^3/s]
X_i, X_j : observed vectors in p-dimension[-]

Greek Letters

$\forall$: volume of water[m^3]
β : type II error

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