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Multi-objective optimization of stormwater pipe networks and on-line stormwater treatment devices in an ultra-urban setting

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Abstract. In a highly urbanized area, land availability is limited for the installation of space consuming stormwater systems for best management practices (BMPs), leading to the consideration of underground stormwater treatment devices connected to the stormwater pipe system. The configuration of a stormwater pipe network determines the hydrological and pollutant transport characteristics of the stormwater discharged through the pipe network, and thus should be an important design consideration for effective management of stormwater quantity and quality. This article presents a multi-objective optimization approach for designing a stormwater pipe network with on-line stormwater treatment devices to achieve an optimal trade-off between the total installation cost and the annual removal efficiency of total suspended solids (TSS). The Non-dominated Sorted Genetic Algorithm-II (NSGA-II) was adapted to solve the multi-objective optimization problem. The study site used to demonstrate the developed approach was a commercial area that has an existing pipe network with eight outfalls into an adjacent stream in Yongin City, South Korea. The stormwater management model (SWMM) was calibrated based on the data obtained from a subcatchment within the study area and was further used to simulate the flow rates and TSS discharge rates through a given pipe network for the entire study area. In the simulation, an underground stormwater treatment device was assumed to be installed at each outfall and sized proportional to the average flow rate at the outfall. The total installation cost for the pipes and underground devices was estimated based on empirical formulas using the flow rates and TSS discharge rates simulated by the SWMM. In the demonstration example, the installation cost could be reduced by up to 9% while the annual TSS removal efficiency could be increased by 4% compared to the original pipe network configuration. The annual TSS removal efficiency was relatively insensitive to the total installation cost in the Pareto-optimal solutions of the pipe network design. The results suggested that the installation cost of the pipes and stormwater treatment devices can be substantially reduced without significantly compromising the pollutant removal efficiency when the pipe network is optimally designed.

Keywords: multi-objective optimization, NSGA-II, SWMM, stormwater treatments, pipe network, ultra-urban area

1. Introduction

Urban land use has been a leading cause of many impaired water bodies worldwide due to urban stormwater runoff, characterized by high runoff volume and pollutant loads with toxic anthropogenic chemicals (Elliott and Trowsdale 2007, Roy *et al*. 2008, Xu *et al*. 2017, Eckart *et al*. 2018). Urbanization has progressed rapidly around the world (including South Korea), and is still underway (Meierdiercks *et al*. 2010), underscoring the importance of controlling urban non-point sources among water quality managers.

A common practice to control non-point source pollution caused by stormwater runoff is the installation of structural treatment facilities, known as stormwater best management practices (BMPs) (Lee *et al*. 2010, Liu *et al*. 2015). Stormwater BMPs include detention ponds, infiltration trenches, grass swales, wetlands and underground devices, and use gravitation, infiltration/filtration, evapotranspiration or a combination of the aforementioned mechanisms depending on the type of BMPs required to control the quantity and quality of stormwater runoff (Lee *et al*. 2012). In general, most stormwater BMPs, with the exception of underground devices, are installed on land and thus require large land space, which is not feasible in highly urbanized areas (i.e., ultra-urban areas) due to limited space availability (Zhang and Chui 2018). In light of this situation, installation of underground devices such as underground filters and hydrodynamic separators is generally preferred in ultra-urban areas. Underground devices are non-powered facilities that physically separate pollutants from stormwater runoff using filtration, gravity settling, or swirl actions (US EPA 1999) and require relatively small land-space.

An underground stormwater device is brought on-line within the drainage pipe as a flow-through system (FHWA 2000). Therefore, the design depends on the characteristics of the pipe flow such as flow rate, flow velocity, and the dynamics of pollutant discharge, which are substantially

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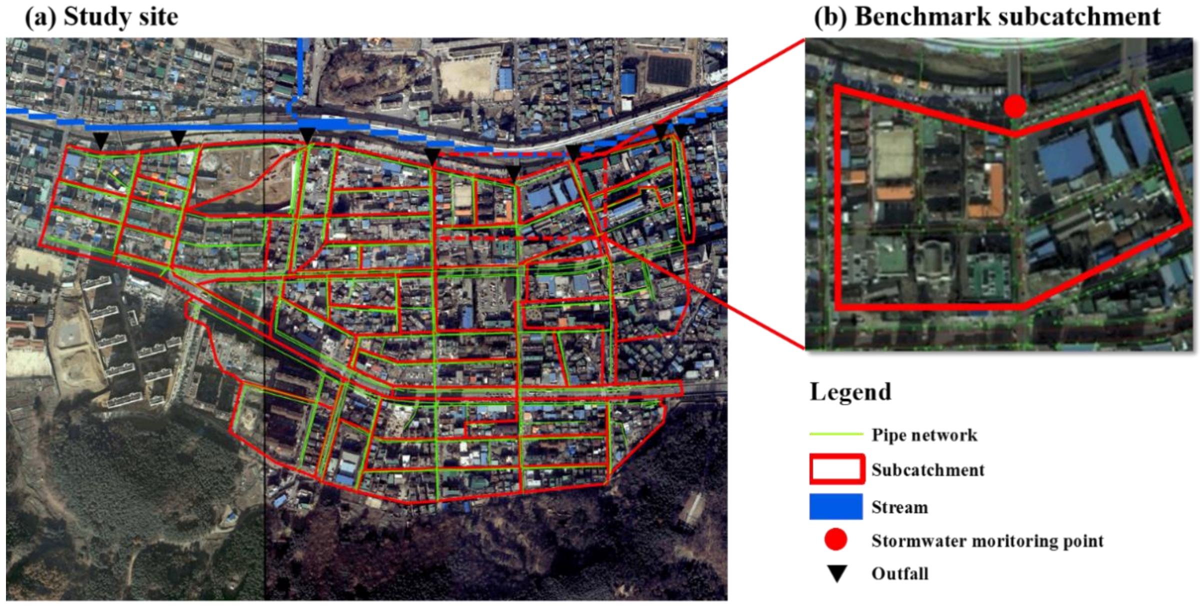


Fig. 1 Map of study site and the benchmark subcatchment for SWMM calibration

influenced by the pipe network configuration in a given catchment (Hatt *et al*. 2004, Afshar *et al*. 2006). Pipe network configurations that can alter the characteristics of the pipe flow include the connectivity, lengths, diameters, and materials of the pipes within the pipe network. Different pipe network configurations can result in different installation costs and stormwater treatment performances and therefore the pipe network design needs to be optimized to cost-effectively manage the stormwater runoff in an urban catchment adapting underground devices.

In this article, a methodology to optimize the pipe network configuration for cost-effective stormwater control in an urban catchment is presented. The total installation costs and annual removal efficiencies of total suspended solids (TSS) were compared among different pipe network configurations with different pipe connectivities and pipe sizes for end-of pipe underground stormwater devices. For this purpose, a multi-objective optimization algorithm, the non-dominated sorting genetic algorithm II (NSGA-II), was applied (Perez-Pedini *et al*. 2005, Zhen *et al*. 2004). Total installation costs for the pipes and underground devices were estimated based on the simulated flow rates and TSS discharge rates for different pipe network scenarios using the United States Environmental Protection Agency's (USEPA) Storm Water Management Model (SWMM).

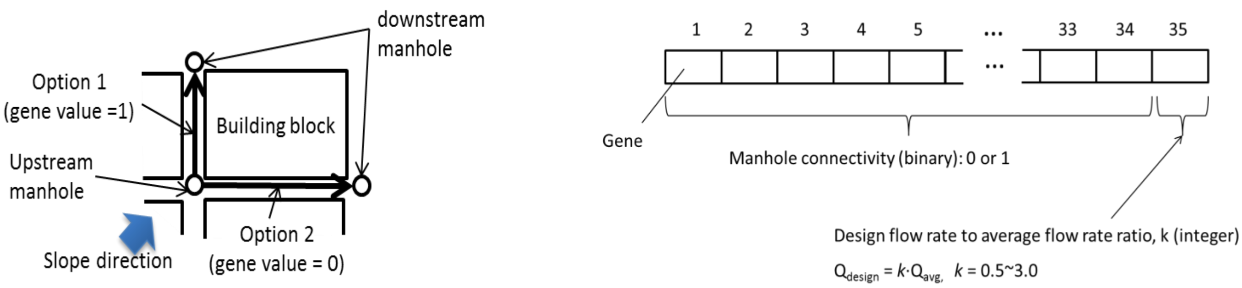
2. Methodology

2.1 Site description and field monitoring

The study site is 100% commercialized area located within the Geumhak watershed in Yongin, Korea. The study site has a total area of 66.18 ha and contains 72 subcatchments and finally discharges to eight outfalls along the Geumhak stream (see Fig. 1(a)). Because the study site was developed as a commercial area, the slope little varies across the area (average slope = 4.51%). A small subcatchment (Area = 2.38 ha) with an outfall to the stream was selected for field monitoring as a "benchmark subcatchment" to characterize the representative characteristics of the stormwater runoff in the study area, and was used for SWMM calibration (Fig. 1(b)). Field monitoring was conducted for six rainfall-runoff events that occurred from June to October in 2012. A portable flow meter (Nivus, Germany) was installed at the outfall to measure flow rate, flow velocity and flow depth during the stormwater runoff. To characterize the water quality of the runoff, grab samples were collected using a first flush-enhanced sampling strategy (Lee *et al*. 2014). That is, samples were taken at the beginning of the runoff, after 5, 10, 15, 30, and 60 minutes, and at intervals of 1 hour after the initial 1 hour until the end of the runoff. A base flow sample was collected if base flow existed before the runoff started. The rainfall data for the study site was obtained using a tipping bucket type portable rainfall gauge (HOBO, USA).

2.2 SWMM setup and calibration

SWMM 5.1 (EPA, Ohio, USA) was used for rainfall-runoff simulation in the study area. A CAD drawing of the existing pipe network of the study area provided by the local agency was used to delineate subcatchments and to obtain drainage system information including the length, invert slope, burial depth, diameter, and material of the pipes as well as the locations of manholes. From the pipe network drawing, 72 polygonal subcatchments were delineated for the model setup. The topographical characteristics of each subcatchment such as the slope, width, elevation, and flow path were extracted from a digital elevation model (DEM) using ArcGIS 10.0 (ESRI, California, USA.). Imperviousness of the subcatchments was estimated using a high resolution satellite image (40cm×40cm) and a land use map of a 5m×5m spatial resolution. Values of pipe roughness, Manning's overland



(a) Binary options for the connectivity of upstream-downstream manholes

(b) Structure of the chromosome consisting of 35 genes that represent the connectivity of the upstream-downstream manholes and the design flow rate

Fig. 2 Generation of the population using the pipe network configuration scenarios and the sizes of the underground stormwater devices

roughness, and depression storage for pervious and impervious areas were estimated based on the ranges given by Rossman (2010). The subcatchment width was calculated based on the method described by Huber and Dickinson (1992).

The model parameters of the SWMM were automatically calibrated by minimizing the difference between the monitored and simulated water quantity and quality data, respectively, for the benchmark subcatchment. For automatic calibration of the model parameters, Box's Complex algorithm (Box 1965) was used. The advantages of this method are that it evaluates the cost function without calculation of derivatives and can manage local optimization problems by simply increasing the number of vertices for evaluating the cost function (Barco *et al*. 2008). For this reason, it has been used in various research fields such as water treatment, computer hardware optimization, and structural optimization (Yuan *et al*. 1993, Haque 1996, Subramanian *et al*. 2005).

The SWMM was calibrated for water quantity and quality in order. The calibrated water quantity parameters included the infiltration parameter (curve number), the evaporation rate, and the subcatchment width factor in the study area. The subcatchment width factor was defined as a multiplication factor to the estimated catchment width calculated as the catchment area divided by the longest flow path. The constraints of the infiltration parameter and evaporation rates for the study area were based on the SWMM manual (U.S. EPA 2010). The lower and upper bounds of the subcatchment width factor were respectively set to 1 and the minimum value for the ratio of the longest side length of the polygonal subcatchment to the estimated catchment width among the 72 subcatchments. The above three water quantity parameters were calibrated by minimizing the sum of the relative errors between the observed and modeled total runoff volume and the peak flow rate as shown in Eq. (1) (Barco *et al*. 2008).

$$\min J = \left(\frac{RV_O - RV_M}{RV_O}\right)^2 + \left(\frac{PF_O - PF_M}{PF_O}\right)^2 \qquad (1)$$

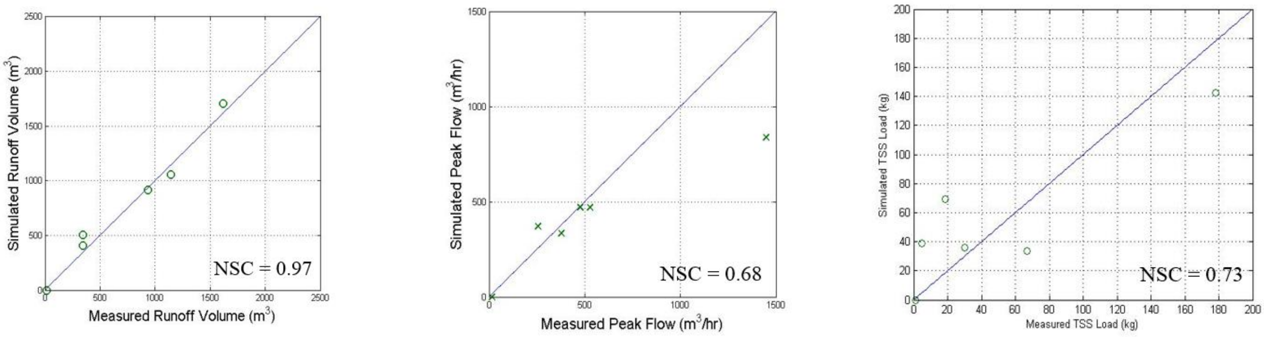
where, RV_O = observed runoff volume (m^3), RV_M = modeled runoff volume (m^3), PF_O = observed peak flow rate (m^3/hr), and PF_M = modeled peak flow rate (m^3/hr). An exponential type equation was used for the functions of pollutant buildup and washoff. The calibrated water quality parameters were the maximum buildup, the rate constant of buildup, and the washoff coefficient. The objective functions for water quality calibration were the sum of the root mean squared error between the observed and modeled TSS mass rates and the root error between the observed and modeled total TSS discharge loads as shown in Eq. (2). The constraints of the maximum buildup, the buildup rate and the washoff coefficient were 30 – 100, 0.122 – 0.382 and 0.1 – 0.2 (Hossain *et al*. 2010).

$$\min J = \frac{1}{2}\left(\sqrt{\frac{\sum_{i=1}^{n}(MR_O - MR_M)^2}{n}}\right) + \frac{1}{2}\left(\left|\sqrt{MD_O - MD_M}\right|\right) \qquad (2)$$

where, MR_O = observed TSS mass rate (g/sec), MR_M = modeled TSS mass rate (g/sec), MD_O = observed TSS discharge (kg), and MD_M = modeled TSS discharge (kg).

2.3 Multi-objective optimization framework

The multi-objective optimization problem in this study was to identify tradeoffs between two conflicting objectives: the annual removal efficiency of TSS and the total installation cost for the pipes and the underground stormwater devices. To solve the multi-objective optimization problem, the Non-dominated Sorted Genetic Algorithm-II (NSGA-II) (Deb *et al*. 2002) was applied. The population in the algorithm was the number of cases for all possible pipe network configuration scenarios and the sizes of the underground stormwater devices installed at the outfalls. For the given locations of 72 manholes, the pipe network configuration could change according to the connectivity between upstream and downstream manholes. Fig. 2(a) illustrates the binary options of the pipe connectivity between the upstream-downstream manholes. Of the 72 manholes, 34 upstream manholes had two connectivity options to downstream manholes whereas the other manholes had only a single connectivity option. In this manner, a total of 2^{34} different pipe network configurations could exist in the study area. It was assumed that an underground stormwater device is installed at each outfall and the design flow rate of each underground device is proportional to the annual average discharge rate of the



(a) Runoff volume (b) Peak flow rate (c) TSS discharge load

Fig. 3 Comparison between measured and calibrated values of runoff volume, peak flow rate and TSS discharge load

Table 1 Summary of water quantity parameter calibration

Evaporation rate (mm/day)		Infiltration parameter (Curve no.)		Percent change in subcatchment width (%)	
Constraint	Calibrated	Constraint	Calibrated	Constraint	Calibrated
1.26-32	32	55-65	55.23	100-155	155%

Table 2 Summary of water quality parameter calibration for each storm event

Event date (mm-dd-yyyy)	Maximum buildup possible (kg/ha)	Buildup rate constant (/day)	Washoff coefficient
06-29-2012	49.81	0.369	0.16
07-18-2012	46.79	0.231	0.19
08-12-2012	99.95	0.38	0.1
09-4-2012	30	0.122	0.1
09-13-2012	92.98	0.122	0.18
10-22-2012	30.13	0.13	0.13
Average	58.16	0.23	0.14

corresponding outfall. The proportionality factor to the annual average discharge rate for the design flow rate of the underground stormwater device was also to be optimized. The chromosome of the NSGA-II algorithm consisted of 35 genes; 34 genes were for the binary connectivity options of the upstream-downstream manholes and the last gene was for the proportionality factor to the annual average discharge rate for the design flow rate of the underground stormwater device. The proportionality factor to the annual average discharge rate was allowed to vary from 0.5 to 3 in the optimization. Fig. 2(b) shows the structure of a chromosome composed of 35 genes with upstream-downstream manhole connectivity and the design flow rate for the underground stormwater devices.

The objective functions (installation cost and annual TSS removal efficiency) were estimated based on the SWMM simulation for different pipe network configuration scenarios. The total installation cost was calculated as the sum of the installation costs of pipes and underground stormwater devices in USD using empirical equations as shown in Eq. (3) (Heaney *et al*. 2002).

$$C_P = (1.38 \times 10^{-3} D^{1.3024})L \tag{3}$$

where, C_P is the pipe construction cost (USD), D is the pipe diameter (m), and L is the total pipe length (m). The diameter of a pipe was derived from the peak flow rate as the design flow rate. The installation cost of an underground stormwater device was calculated using the average installation cost per design flow rate as shown in Eq. (4) (U.S. EPA 1999).

$$C_{SD} = 247{,}000 \times WQF \tag{4}$$

where, C_{SD} is the installation cost for an underground stormwater device (USD) and WQF is the design flow rate (m^3/s). The inflation rate should be reflected on all installation costs calculated based on the year of the referred literature (Weiss *et al.* 2005). In this study, the calculation of the construction costs for the pipe network and the underground stormwater devices was adjusted to the year 2017 by considering the inflation rate (U.S. DOL 2018). The annual TSS removal efficiency for a given pipe network configuration was estimated assuming 40% TSS removal efficiency for each underground stormwater device (Lee *et al.* 2014).

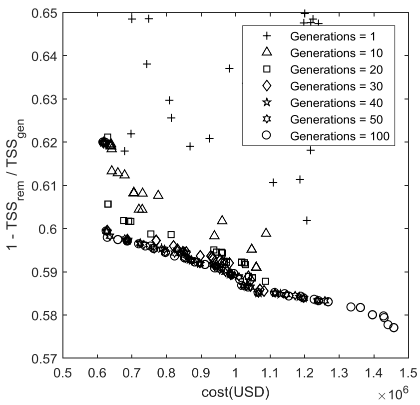
Three population sizes (50, 100 and 200) were used for the optimization, and the maximum evolution number (the number of iterations) varied according to the convergence to the optimal solutions to reduce unnecessary computation (Ishibuchi *et al.* 2009).

3. Results and discussion

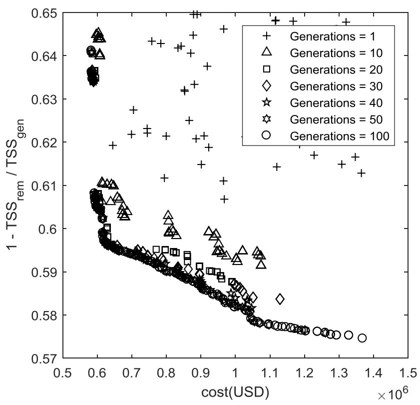
3.1 Water quantity and quality calibration

Table 1 shows the ranges and optimized values of the evaporation rate, the infiltration parameter (Curve number), and the percentage change in subcatchment width, which were 32 mm/d, 55.23, and 155%, respectively. The evaporation rate was relatively high, but this value was accepted in this study to reflect unexpected loss of runoff like infiltration through cracks in impervious areas such as roads and sidewalks (Tobio *et al.* 2015). The pervious fractions of urban sites such as urban green landscapes can be another cause of runoff loss. In addition, there may be leaks in the pipe systems, introducing losses in the runoff (Vale *et al.* 1986).

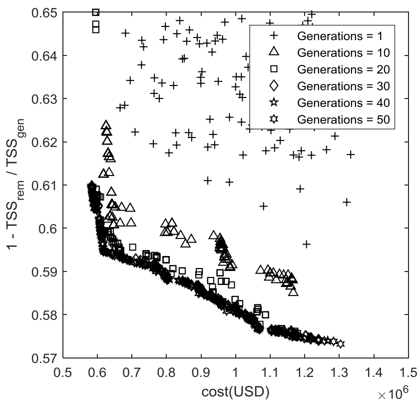
Water quantity simulations of the calibrated SWMM for each of the individual six events were performed.



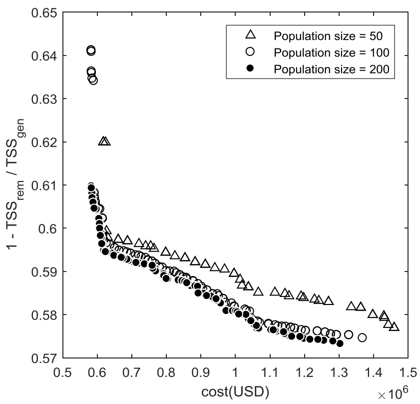
(a) Pareto front evolution at population size = 50 and generation number = 100



(b) Pareto front evolution at population size = 100 and generation number = 100



(c) Pareto front evolution at population size = 200 and generation number = 50



(d) Final Pareto fronts

Fig. 4 Pareto plots for different population sizes and generation numbers

Table 3 Summary of the optimized pipe networks and BMP installations

Cost-efficiency aspect of models	existing pipe network model	Scenario 1	Scenario 2
(1) Cost of BMP installation (USD)	137,460	146,840	169,810
(2) Cost of pipe network installation (USD)	503,980	436,890	447,710
Total cost, (1)+(2) (USD)	641,440	583,730	617,520
Total TSS loading (kg)	50,096	50,096	50,096
Total removal TSS loading (kg)	17,549	19,553	20,297
TSS removal efficiency (%)	35	39	41

Simulations on runoff volume showed a good fit between the measured and simulated data (see Fig. 3(a)). The simulated scenario had a Nash Sutcliffe model efficiency coefficient (NSC) of 0.97, reflecting a satisfactory predicting power for runoff volume. NSC is one of the tools used to assess the predictive power of a hydrological model (Rosa *et al.* 2015). An NSC value close to 1 indicates a more accurate model. Fig. 3(b) shows the measured versus simulated peak flow rates, which have a satisfactory NSC value of 0.68. The calibrated values of the maximum buildup, the buildup rate constant and washoff coefficient were 58.16 kg/ha, 0.226 and 0.074, respectively. Fig. 3(c) compares the simulated and observed TSS loads with an NSC value of 0.73.

The calibrated water quality parameters for each event are summarized in Table 2. The average values of the calibrated parameters were used for the optimization. The number of monitored storm events was just six. Monitoring more rain events, will likely provide a more definitive range of parameter values, and may minimize the differences between parameters calibrated from different storm events. Nevertheless, to attain one value for each parameter to represent all the monitored events, the average values of the calibrated parameters were taken and applied to the entire study site.

3.2 Optimization of pipe network and BMPs

In this study, optimization of the pipe network configuration and underground stormwater devices was performed by setting the population size to 50, 100, and 200 and the corresponding number of generations to 100, 100, and 50, respectively. The results of the optimization are shown in Fig. 4. Fig. 4(a) shows the progression of gradual convergence of the population to the Pareto front as the

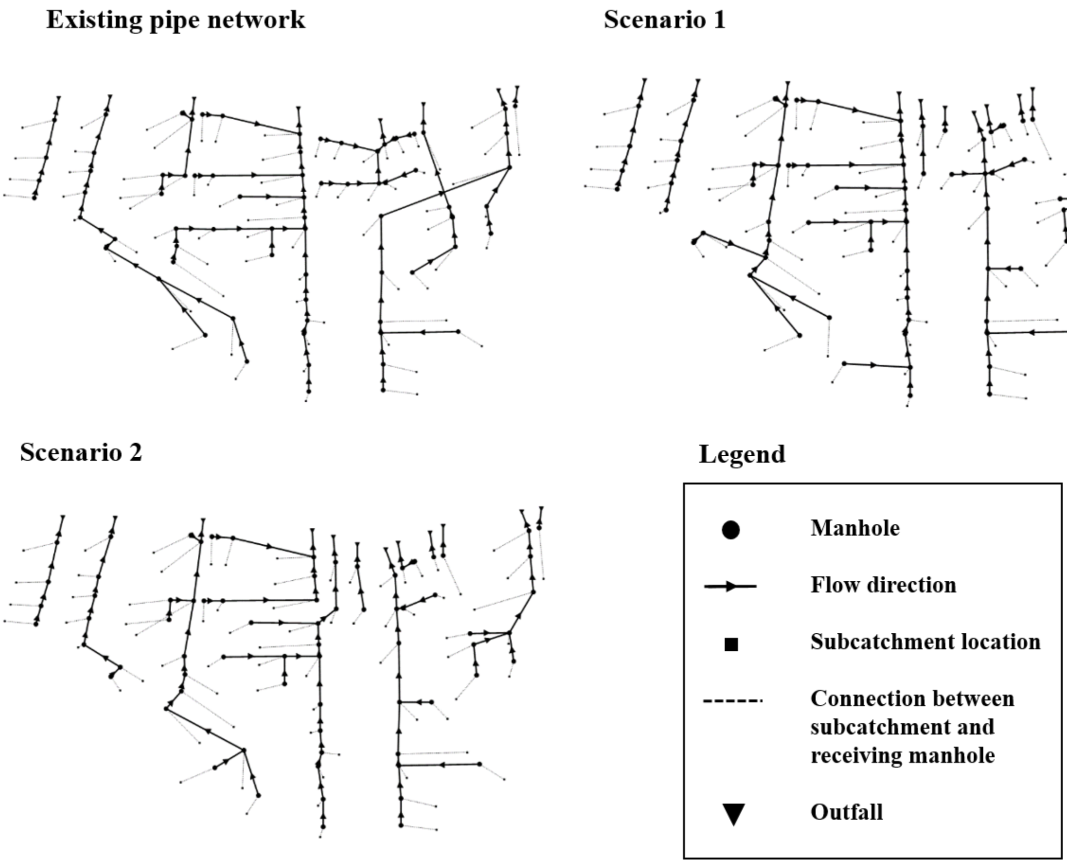


Fig. 5 Comparison of pipe networks for the existing pipe network, scenario 1 and scenario 2

number of generations increased with a population size of 50 and a generation number of 100. Likewise, Figs. 4(b)-(c) show the convergence process when the population size is 100 or 200 and generation number is 100 or 50. Fig. 4(d) compares the final Pareto fronts for different population sizes and generation numbers. The cost-efficiency characteristic common to all Pareto plots is that cost variance is higher than efficiency, which means that the efficiency is relatively insensitive to the change in the cost. Using these results can help decision makers avoid an excessive design for the installation of a pipe network including underground stormwater devices in urban areas and identify optimal conditions for maximum TSS removal efficiency at minimum installation cost.

For further analysis, two optimal cases were selected from the Pareto front for a population size of 200 (Fig. 4(d)). Scenario 1 was the case with the minimum total cost, and Scenario 2 was the case corresponding to the reflection point of the Pareto front. These two scenarios were compared with the existing pipe network for the total installation cost and annual TSS removal efficiency Table 3 summarizes the installation costs and annual TSS removal efficiencies for the existing pipe network model, Scenario 1, and Scenario 2. Scenario 1 was the best in terms of total installation cost and Scenario 2 was the best in terms of TSS removal efficiency.

Fig. 5 shows the pipe configurations for the existing pipe network, Scenario 1, and Scenario 2, respectively. The number of final outfalls increased in Scenarios 1 and 2 compared to the existing pipe network, and the number of pipes was the same in all three scenarios. This is because the manholes installed in the existing study site were always used in the optimization. On the other hand, the total pipe length of Scenario 1 was 4,836 m and that of scenario 2 was 5,090 m, which were both shorter than that of the existing pipe network. Both Scenarios 1 and 2 were better than the existing pipe network model in terms of cost-effectiveness.

4. Conclusion and recommendations

The benchmark subcatchment area in the study area was monitored for six storm events and this data was used to calibrate SWMM with Box's complex method. Simulation results for the calibrated model showed a good fit water quantity and an acceptable fit for water quality. The calibrated parameters were applied to solve the multi-objective optimization problem of the stormwater drainage system including pipe networks and underground stormwater treatment devices at the outfalls. The optimization was performed using NSGA-II, one of the most commonly used multi-objective optimization algorithms, to identify tradeoffs between conflicting objectives such as maximizing annual TSS removal efficiency while minimizing the total installation cost for the pipe network and underground stormwater treatment devices. The following results were confirmed through optimization of the pipe network in this study.

- It is possible to efficiently manage stormwater runoff by re-arrangement (or re-installation) of existing pipe network configurations in urban (or ultra-urban) areas.
- Installation of underground stormwater devices at the outfalls with an optimized pipe network configuration can cost-effectively reduce non-point pollutants into the stream. The location of the installed device, the capacity of the device and the number of devices installed are important cost-effectiveness considerations.
- Two scenarios were derived from the Pareto plots for cost and efficiency for the pipe network configuration and underground stormwater device installation using the NSGA-II multi-objective optimization algorithm, and both scenarios showed more cost-effective results than the existing pipe network.
- The variance of total installation cost was high compared to the TSS removal efficiency in the Pareto plots, which indicates that the increase in pollutant removal efficiency can be obtained with a small increment in cost, and thus an excessive design can be avoided.

Through the series of studies and results described, we demonstrated how a more cost-effective design of storm drainage system can be achieved. This study can be applied before developing new urban areas, before replacing pipe networks in existing urban areas, or when considering areas in which underground stormwater devices will be installed. Additionally, the results of this study can help decision makers to compromise the conflicting purpose of maximizing pollutant removal efficiency with minimal cost in developing or retrofitting urban areas.

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