Development of a new method to optimize storage units in urban drainage systems

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Abstract

Flood severity and frequency have grown over the years as a result of urban development and climate change. Floods in cities cause major challenges such as property and infrastructure damage, transportation congestion, loss of life, environmental threats, and health concerns. To relieve the load on the urban drainage system and prevent flooding, effective measures to strengthen its resilience are required. Traditional design methods, which rely on past performance trends and long lifespans, usually result in infrastructure that is inflexible and unable to adapt to changing situations. Those traditional studies focused on drainage design, such as pipe slope and diameter optimization, coupling design cost limitation. Furthermore, various terminologies for the overall concept of green/grey infrastructure have been proposed in the literature. Some studies have been focused on the optimization of the suitable locations for storage tanks, which would be one of the most efficient approaches. Building storage facilities such as retention or detention basins are a cost-effective and efficient structural option to improve the resilience of urban sewerage system, reducing peak runoff in existing drainage systems in urban areas, especially compared to traditional methodologies such as increasing pipe diameter or slope providing sufficient hydraulic capacity. The basic concept is to create an optimization framework using Non-dominated Sorting Genetic Algorithm II (NSGA II), coupling with hydraulic model SWMM, and use it to change a number of drainage system-related variables such pipe diameter, slope, and storage unit size. The main idea of the optimization framework in thesis is to combine different methods into one framework, which is a challenge in a complex system due to the dilemma between the resilience objective and financial limitation. Literature review would shows that the recent research in terms of sewerage system resilience optimization utilizing different methodologies. Application of the system would shows that optimization model has the capability to improve the resiliency of urban sewerage system.

The main objective of the thesis are (i) develop a new framework to optimize volume and location of storage units in urban drainage systems; (ii) develop a two-stage multi-objective optimization framework; (iii) develop the new index to make the optimization process feasible.

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List of Symbols

C	Cost of storage tank
$volume_i$	Storage volume (m^3) of the i tank
C_T	Total rehabilitation costs
L_i	Length of ith Auxiliary
H_i	Height of ith Culvert
W_i	Width of ith Bridge
h_i	Height of ith Side Weir
L_{Wi}	Length of ith Side Weir
M	Number of discrete values
$V_{f;N}$	Flood volume exceeded from the N^{th} channel of the drainage network(m^3)
f_2	Total flood volume exceeded from the whole of the network.
Q	Peak runoff rate for a design return period (frequency) in cubic feet per second (cfs)
Ci	Runoff coefficient for a design return period expressed as the dimensionless ratio of rainfall excess to total rainfall
I	Rainfall intensity in inches per hour during a period of time equal to the time of concentration for the design return period.
Tc	Time of concentration for the longest flow path in the contributing watershed area, in minutes.
Ai	Contributing watershed drainage area, in acres, tributary to the design point
S	Overland slope in ft/ft.
n	Roughness coefficient.
L_o	Length of overland flow in feet.
V	Cross-sectional average velocity (L/T; ft/s, m/s);
ω	Gauckler–Manning coefficient. Units of ω are often omitted, having units of: ($T/[L^{1/3}]$; $s/[ft^{1/3}]$; $s/[m^{1/3}]$).

Rh	Hydraulic radius (L; ft, m);
S	Slope of the hydraulic grade line or the linear hydraulic head loss (L/L)
k	Conversion factor between SI and English units.
C_S,	Construction cost of sewers
C_L	Construction cost of pump stations
C_M	Construction cost of manholes
Np	Number of sewer pipes
P	Unity if a pump station exists at the upstream end of the pipe
S_i	Detention size (m^2)
f_1	Peak flow function of the downstream specific location
f_2	Number function of the waterlog node
i	Precipitation intensity rate in mm/h
A	Coefficients for each return period (T) in years
B	Coefficients for each return period (T) in years
t0	Coefficients for each return period (T) in years
t	The time (duration) of the precipitation event in hours (h)
i	Average rainfall intensity (mm/hr or inch/hr)
t_d	Storm duration (minutes)
a	Rainfall intensity coefficients
b	Rainfall intensity coefficients
c	Rainfall intensity coefficients
i_a	Rainfall intensity after the peak (mm/hr or inch/hr);
r	Peaking-Time-Ratio
t_p	The time of peak intensity;
i_b	Rainfall intensity before the peak (mm/hr or inch/hr);
I1	Sensitivity index used to evaluate the sensitivity of sub-catchment J in the drainage system based on the flooding volume
I2	Sensitivity index used to assess junctions in the drainage system based on flooding time

ΔV_F	Reduction in flooding volume of the drainage system after implementing a storage unit at sub-catchment J (10^3 m^3)
MV_S	Actual maximum storage volume of the storage units at specific nodes (10^6 ltr).
ΔT_F	Reduction in flooding time of the drainage system after implementing storage unit
α	Over-flooding volume reduction
β	Flooding time reduction.
V_i	Flood volume (m^3) of the ith node of original sewerage system;
V_j	Flood volume (m^3) of the jth node of optimized sewerage system;
n	Flooding nodes number of original sewerage system;
N	Flooding nodes number of optimized sewerage system.
T_i	Flood time (hrs) of the ith node of original sewerage system;
T_j	Flood time (hrs) of the jth node of optimized sewerage system;
C_1	Cost of storage units;
$Volume_s$	Actual maximum storage volume
S	Total number of storage unit
ε_{sc}	Location cost coefficient
W_1	Weighting coefficient
C_2	Flood cost as a penalty function;
γ_{sc}	Location cost coefficient associated with flood volume;
$\emptyset_{sc}$	Location cost coefficient associated with flood time;
V_{fst}	Overflow (m^3) with storage units replacement at flow location f;
V_{fallow}	Maximum allowable overflow (m^3) at flow location f;
T_{st}	Overflow duration (hours) with storage units replacement at flow location f;
W_2	Flooding volume weighting coefficient;
W_3	Flooding duration weighting coefficient;
T	Total flooding time of the sewerage system
V	Total over-flooding volume of the sewerage system

List of Acronyms

Analytical hierarchal process	AHP
Low impact development	LID
Best management practices	BMPs
Urban drainage systems	UDSs
Multi-criteria decision-making	MCDM
Geographic Information System	GIS
Simulated Annealing	SA
Non-dominated Sorting Genetic Algorithm II	NSGA II
Genetic Algorithm	GA
Multi objective particle swarm optimization	MOPSO
Multi objective evolutionary algorithms	MOEAs
Sustainable urban drainage systems	SUDS
Water sensitive urban design	WSUD
Dynamic programming	DP
Hydrologic Engineering Center - Hydrologic Modeling System	HEC-HMS

Chapter 1: Introduction

1.1 Background

Urbanization and climate change have increased the intensity and frequency of floods in recent years, which has resulted in the lack of municipal sewerage system's capability not being able to accommodate the volume of surface runoff (Yazdi et al. 2014; O'Sullivan et al., 2015). To mitigate the pressure of urban sewerage system and prevent urban flooding, efficient measures are required to improve its resilience (Mailhot et al. 2008; Sheng and Wilson, 2009).

Building storage facilities such as retention or detention basins would be one of the most efficient approaches (Kessler and Diskin, 1991). Storage units are a cost-effective and efficient structural option to achieve this goal, reducing peak runoff in existing drainage systems in urban areas, especially compared to traditional methodologies such as increasing pipe diameter or slope providing sufficient hydraulic capacity (Bellu et al., 2016; Woods-Ballard et al., 2007).

Determining the volume of storage units is difficult due to a dilemma between sewerage system resilience and economic concerns. The position of storage units in a watershed also has an impact on its efficiency (Weiss et al., 2006; Wicke et al., 2012). In a complicated system, considering both the optimal size of storage units and searching for the suitable locations is a difficult problem, meaning that combining different methods into one framework is a demanding practice. Based on the conflict that maximizing resilience and minimizing costs, the multi-objective optimization methodology could help find the “near” optimal solution.

1.2 Sewerage systems and storage units

Despite considerable research on river floods, urban flooding has received little attention and is still being explored (Chen, Hill, and Urbano 2009).

Fig. 1.1 Urban Flooding in Toronto, Canada in July 2013(Adapted from activehistory.ca)

Traditional approaches to urban flood planning and management, such as channelization (discharging rainfall into a channel network), are frequently used without considering novel techniques for the source control (Ebrahim et al., 2016). Therefore, in developing and developed countries, it is vital to investigate the capabilities of novel storm water techniques such as retention basins for urban flood management. In recent years, new strategies such as low-impact development (LID) and best management practices (BMPs) have been introduced into storm water management (Young et al. 2009). Figure 1.2 shows the analytical hierarchal process (AHP) as a methodological tool for BMP selection, using prioritized list of storm water regulatory requirements and BMP performance measures as an example. The AHP helps the user to convert the challenge of numerous criterion decision making into a methodical algorithmic approach, which has four steps including modelling the problem as a hierarchy, evaluating the hierarchy, establishing priorities, making decisions. In Figure 1.2, the right boxes shows the steps for AHP, then BMP selection criteria in the left side simulate the usage for AHP to further establish the selection process in this research. The effectiveness of these solutions is determined by their geographic location, and their haphazard implementation may exacerbate an existing problem (McCuen 1974; Emerson, Welty, and Traver 2005; Gilroy and McCuen 2009; Fang et al. 2010). There has been no attempt to incorporate the results of hydraulic modelling into the site selection of BMPs, such as storage units (Ebrahim et al., 2016). The traditional BMP site selection technique comprises two key steps: (1) an assessment of the current pipe network using a hydrologic-hydraulic modelling tool, and (2) the placement of BMPs in the areas of concern while considering project limitations and case study restrictions into account (Ebrahim et al., 2016). The results of the hydraulic modelling, on the other hand, are not immediately employed in the framework for site selection.

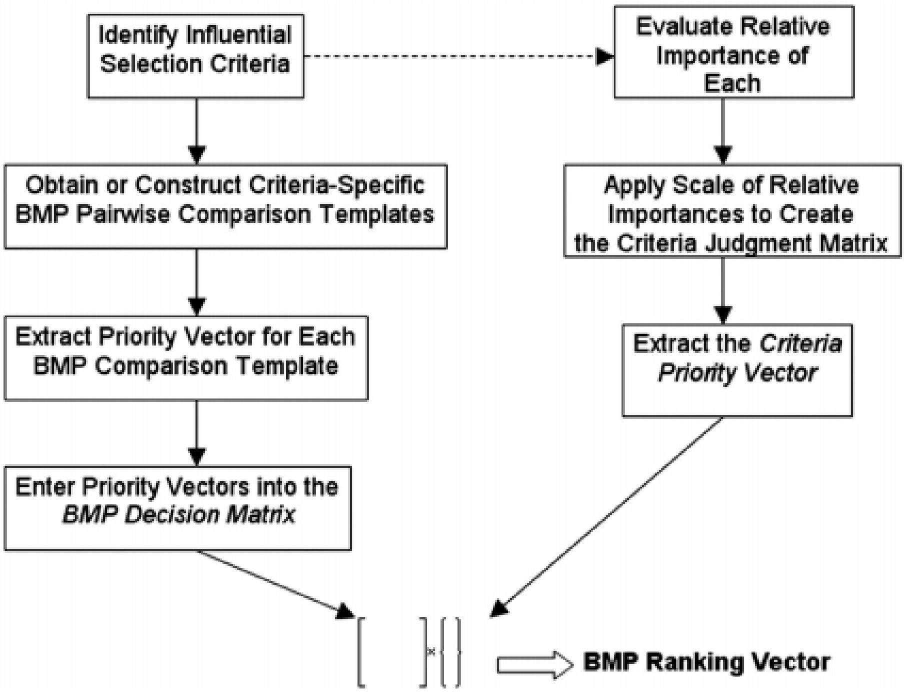


Figure 1.2 The usage of the AHP algorithm as a BMP selection criterion is depicted in this diagram. (Young et al. 2009)

The site selection is multi-objective problem, requiring the integration of multiple methodologies into a single framework. Multi-criteria decision-making (MCDM) procedures, for example, are important tools that can give a systematic framework for dealing with multi-disciplinary challenges that are difficult to analyze (Fattahi and Fayyaz 2010). Figure 1.3 shows one method for optimizing the dimensioning and site selection of a flood mitigation system based on detention basins by combining MCDM with Geographic

Information System (GIS).

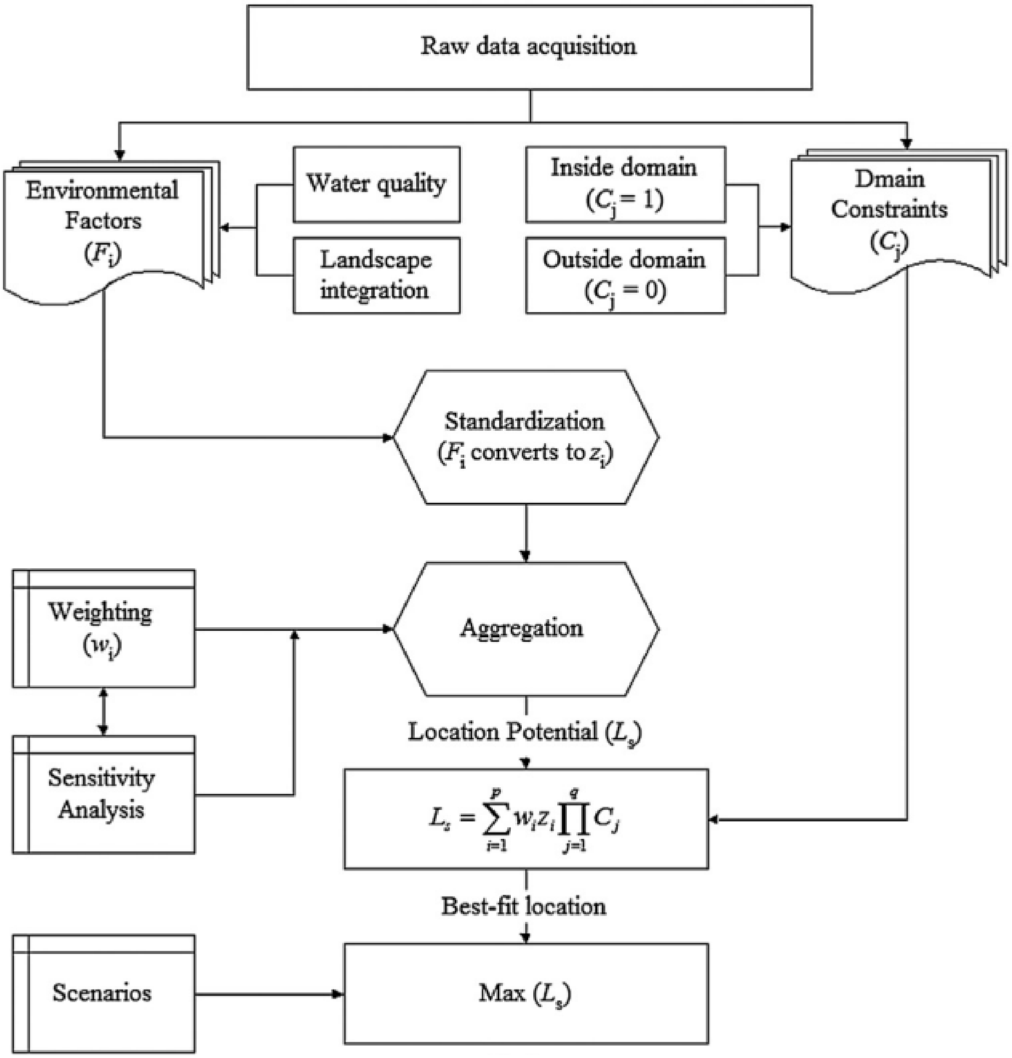


Figure 1.3 A flowchart for developing a GIS-MCDA (Bellu et al., 2016)

Therefore, the major goal of our research is to use a spatial MCDM-based framework to integrate hydraulic modelling results into detention basin site selection, coupling SWMM with site selection optimization model. Except for the location consideration, it is more reasonable to take tank size into account, which would affect both financial concern and system resilience. Based on the climate change in future, it is necessary to consider future climate condition into the framework, which would make the system tends to be more resilient.

1.3 Research Objectives

The main objective of the thesis are:

- Development of a new framework to optimize volume and location of storage units in urban drainage systems.
- Develop a two-stage multi-objective optimization framework combining the SWMM model and Non-dominated Sorting Genetic Algorithm II (NSGA II).
- Develop the new index to make the optimization process feasible for complex problems.

1.4 Novelty of the study

- The adoption of a multi-objective methodology coupled with SWMM model in this context has not been done before. Although the SWMM model and NSGA II method have been used in some cases, the majority of the cases focused on drainage design (Moussavi et al. 2017; Shao et al. 2017). For some relevant studies focusing on the optimization of storage tank volume and/or location, they adopted different methodologies (Oxley and Mays, 2014), or focused on single storage tank location section (Wang et al. 2017). However, in this study, we consider site selection, storage tank size, with constraints of flooding volume and flooding time, which is more comprehensive.
- To the best knowledge obtained from the literature scan, the temporal variation index has not been considered in this context so far. In this study, we consider flooding time reduction efficiency as an indicator of flood resilience, which can result on flood resilience improvement for the urban drainage system.
- A two-component cost function has not been employed in this set-up before. For the cost objective function, we not only consider the storage cost based on tank volume, but also consider the cost of penalties associated with location constraint and future climate change.

- Add the indices for prioritizing sub-catchments and improving the performance of optimization. In this study, we add two indices, sensitivity index and node criticality index to further select the variables, which can improve the working performance of proposed system.

1.5 Thesis Outline

This document is organized as follows. Chapter 1 presents an introduction where objectives and novelty of the research is presented. Chapter 2 deals with a literature review in which relevant studies on resilient urban drainage system are discussed, and the comparison between traditional replacement method and storage unit implementation will be summarized. Moreover, this chapter summarizes the main methodologies and relevant hydrological model.

Chapter 3 includes a technical paper. In this paper, the objective is to find optimal strategies to integrate storage units within the drainage network in order to increase, resilience, redundancy and flexibility in the system. Developing a two-stage multi-objective optimization framework combining the SWMM model and Non-dominated Sorting Genetic Algorithm II (NSGA II); developing a new method to determine optimal volume, locations and number of storage units in urban sewerage systems; devising three different indexes for prioritizing candidate locations, and comparing the performance of the framework with different methods via various synthetic test cases. Chapter 4 focuses on the future climate change. In this study, we also consider the impact of future climate change, and our system was designed for the future, which improve the resilience of urban drainage system.

Chapter 5 presents conclusions and recommendations for future work.

Chapter 2: Literature Review

2.1 Introduction

In recent years, computational models have been employed in urban planning, including the design of subsurface infrastructure and pipe rehabilitation (Ogidan et al., 2016; Yazdi et al., 2017). The primary idea is to use the Non-dominated Sorting Genetic Algorithm II (NSGA II) to construct an optimization framework that can be used to adjust a variety of drainage system-related variables such pipe size, slope, and storage unit size (Delelegn et al. 2011).

In this study, we incorporate a hydraulic simulation module using SWMM into the Non-dominated Sorting Genetic Algorithm II (NSGA II), and consider storage units size and location as well as the number of storage units to be implemented in the system. In addition, to improve the climate resilience the impact of climate change is taken into account through using projected IDF curves. There are several tools and studies, focused on the future IDF curves. In this study, we combined the IDF-CC tool and multi-objective framework to design the system for future, to consider the impact of future climate change (Andre et al. 2021).

According to a review of the relevant literature, the majority of past research on the design/rehabilitation of urban drainage systems is based on hydraulic capacity, with the goal of improving the drainage system's hydraulic performance. However, those studies lead to a lack of consideration to other economic and efficient structural practice, such as detention basins for urban flood control. Therefore, detention basins are widely used for delaying peak flow and controlling urban flooding. For storage unit application in improving sewerage system resilience, both storage unit location and volume should be considered. To reduce runoff, the storage tank should provide sufficient capacity and ensure that it could accommodate the flooding volume. However, the size of storage unit should not too large due to the economic limitation, meaning that he cost of storage will rise as the size of detention tanks increases. Meanwhile, the sites of storage units in a watershed will influence efficiency, and different location would also affect the cost of system. Moreover, except for tank consideration in network, considering future climate change is extremely important in terms of reducing the vulnerability of sewerage system. The term "resiliency" refers to "the state of the system that allows it to restrict the duration and magnitude of any threat" (Mugume et al. 2015). The approach proposed in this research is an optimal improvement of resilience, redundancy and flexibility on the system by implementing storage units within the network, considering volume and location of tank with financial limitation, and future climate change. This optimization framework is more efficiently mitigate urban flooding with the combination of those consideration. To find this optimal intervention, simulation and optimization models are needed.

2.2 Main Methodologies and Terminologies

2.2.1 Hydraulic simulation module

The Storm Water Management Model (SWMM) is a dynamic rainfall–runoff simulation model that is used to simulate runoff amount and quality from mostly metropolitan regions in a single event or over time (Yazdi et al., 2015).

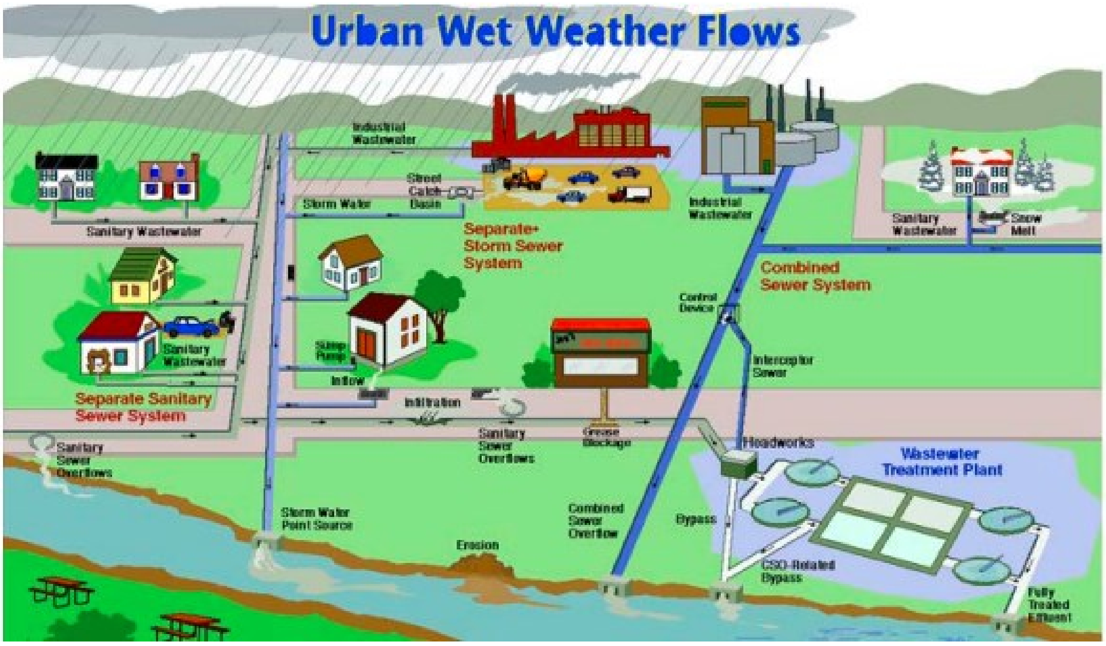


Figure 2.1 The EPA Storm Water Management Model (SWMM) (Rossman 2015)

SWMM was first released in 1971 and has subsequently undergone multiple major revisions, which divides the study area into several sub-catchments, with each sub-catchments averaging precipitation, then surface runoff can be produced in sub-catchments as well. The runoff component of SWMM works with a group of sub-catchment sites that receive precipitation and produce runoff and pollutant loads. Surface runoff in a sub-catchment is presumed to reach the corresponding junction before being delivered in storm sewer conduits to the area exit, therefore only pipeline runoff flow is analyzed, with no consideration for surface runoff routing (Rossman 2015). Runoff is routed through a network of pipes, channels, storage/treatment devices, pumps, and regulators by SWMM's routing component.

SWMM tracks the quantity and quality of runoff generated within each sub-catchment, as well as the flowrate, flow depth, and quality of water in each pipe and channel, during the course of a simulation period made up of several time steps (Rossman 2015). Then the result would show the node flooding summary and water elevation profile, which could be used in the flowing optimization step.

2.2.2 Multi-objective optimization module

One of the objectives of system management is to provide maximum security at the lowest possible cost (Yazdi et al., 2018). Numerous research have proven that optimization approaches can significantly aid in the discovery of effective flood control system design/rehabilitation procedures. In optimization step in the framework, the main tool is basically NSGA-II, SA algorithm (Simulated Annealing) or AHP.

In this research, we adopt GA to conduct the optimization. A variant of NSGA-II, known as the “gamultiobj” is a regulated and elitist algorithm. Individuals with higher fitness values are always favored by an elitist GA (rank). Individuals who can help promote population diversity, even if they have a lower fitness value, are favored in a controlled elitist GA (Deb 2001). Genetic algorithm (GA) is currently the most widely used technology for better storm water management planning. GA is basically a random search program, uses probability rather than deterministic search rules, and is based on the principle of "survival of the fittest" (Zhen et al. 2004). Because the magnitude of the objective function is employed directly in the search rather than derivative information, GAs can be used to solve nonconvex, highly nonlinear, and complicated problems (Goldberg 1989).

The optimization module contains two or more objective functions, and a set of constraint functions for green/grey infrastructure, hydraulics performance, and risk mitigation, and budget constraints, climate change, ageing problems, urbanization. Equation 2-1 demonstrates one example of objective functions in optimization module in terms of minimizing total cost based of storage tank volume (Wang et al., 2017):

$$\mathrm{C} = \sum_{i=1}^{n}(2768 \times volume_i^{0.773}) \qquad (2\text{-}1)$$

Where C is the cost of storage tank (*10^4 CNY, Chinese currency unit); $\mathrm{volume}_\mathrm{i}$ is the storage volume (m^3) of the *i* tank; n is the storage tank number.

Equation 2-2 and 2-3 demonstrates the objective functions to optimize size of auxiliary tunnels, detention ponds and control structures, with cost limits and resiliency consideration (Yazdi et al., 2018):

$$\min f_1 = C_T = (1+\alpha) \cdot \Big(\sum_{i=1}^{n}\big[C_i L_i f(H_i, W_i) + C_i^l L_{wi} h_i\big] + \sum_{j=1}^{m}\big[C_j^n A_j H_{D,j}\big] +$$

$$\sum_{k=1}^{K} C_k^m L_k D_k\Big) \qquad (2\text{-}2)$$

$$\min f_2 = \begin{Bmatrix} \sum_{N=1}^{N_T}\big(Q_{f,N} - Q_{C_r,f,N}\big) \times t_{f,N} = \sum_{N=1}^{N_T} V_{f,N}; & Q_{f,N} > Q_{C_r,f,N} \\ 0 & Q_{f,N} \le Q_{C_r,f,N} \end{Bmatrix} \qquad (2\text{-}3)$$

where $\mathrm{C_T}$ is total rehabilitation costs, The length, height, and breadth of the ith auxiliary culvert/bridge are $\mathrm{L_i}$, $\mathrm{H_i}$, and $\mathrm{W_i}$, respectively; the height and length of the ith side weir are hi and $\mathrm{L_{Wi}}$, respectively. $\mathrm{L_i}$, $\mathrm{H_i}$, $\mathrm{W_i}$, $\mathrm{h_i}$, and $\mathrm{L_{Wi}}$ can each take an infinite number of discrete values. $\mathrm{V_{f,N}}$ (m^3) is the total flood volume surpassed from the drainage network's Nth channel, while $\mathrm{f_2}$ is the total flood volume exceeded from the entire network.

Secondly, after setting the objective functions and reasonable constraints under GA, the next step is to incorporate the simulation results under hydraulic model into optimization functions. Figure 2.2 demonstrates the framework to calculate the hydraulic performance, risk, and maintenance cost of a drainage system, using the Hydraulics and Risk Combined

Model (HRCM) (Cai et al 2020).

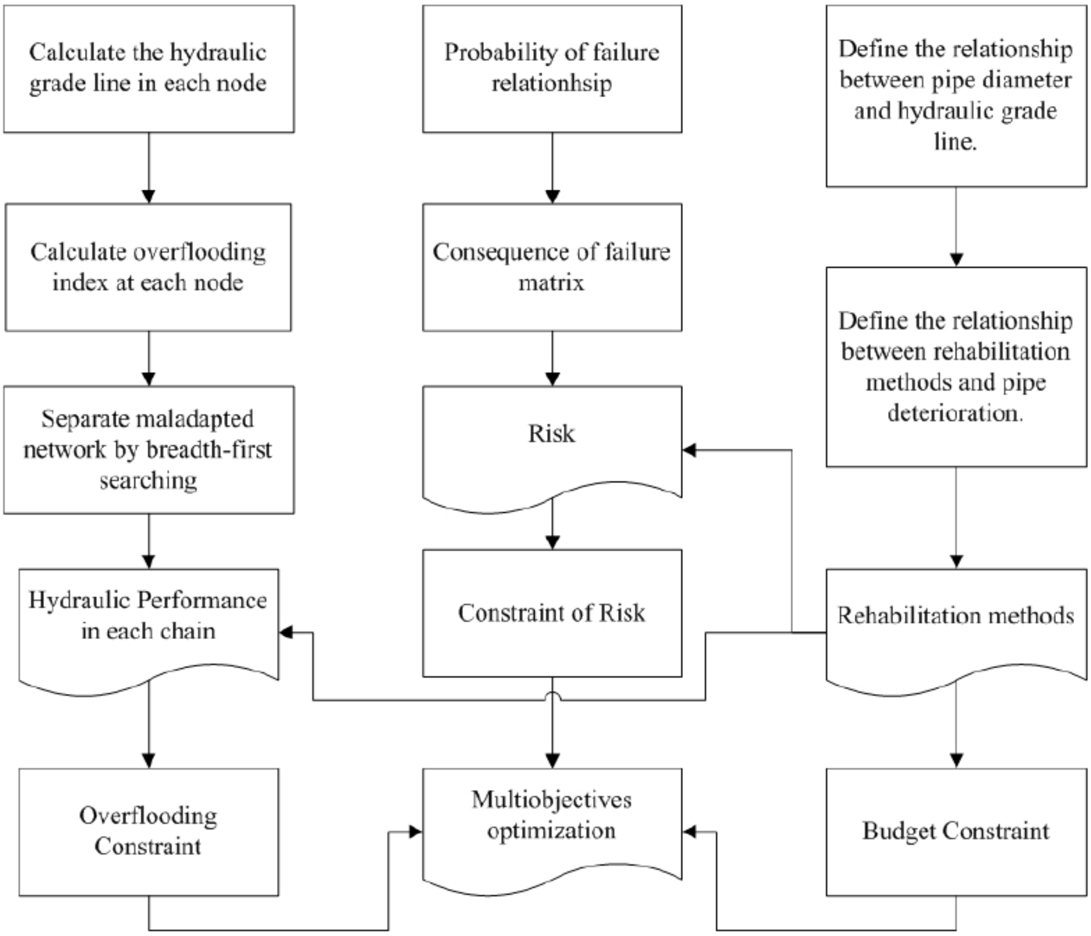


Figure 2.2 Structure of the HRCM model (Cai et al 2020).

In this study, optimization algorithms are used to identify the ideal size and position of a grey infrastructure storage unit to improve the efficiency of an urban flood management system while taking into account two or more variables at the same time: climatic change and economic constraints. Minimizing expenses and boosting the robustness index are two opposing objective functions in this case. Flooding duration and severity of discharges above the system capacity, or flooding volume, are resiliency metrics in urban drainage systems. Figure 2.3 illustrates the calculation flow in terms of the combination of hydraulic model and GA process. The NSGA-II algorithm incorporates the calling module, SWMM model to create the programming language for the layout model of storage unit optimization.

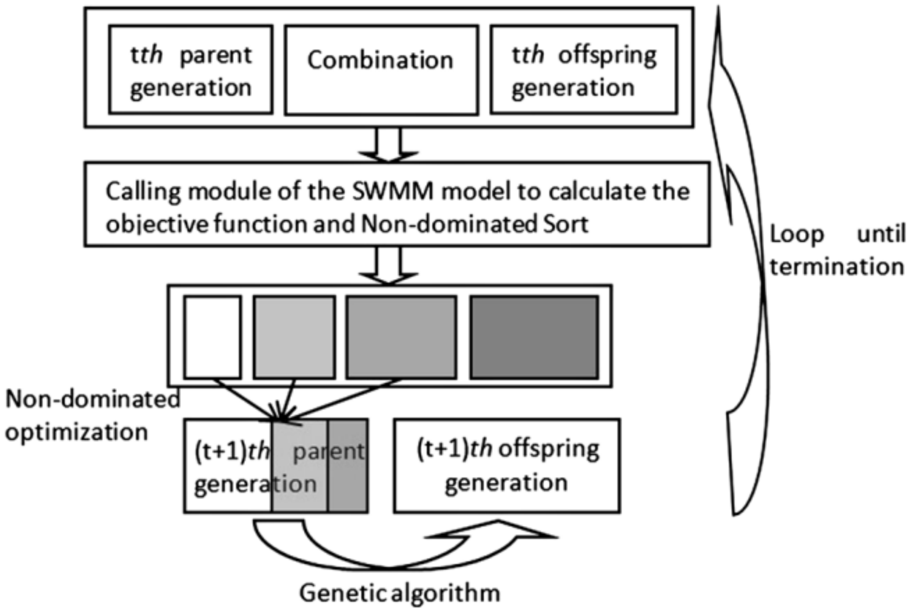


Figure 2.3 The calculation flow chart (Tao et al. 2014)

2.2.3 Storm Sewer Design Overview

A well-designed, well-functioning storm sewer system is an essential component of any storm water drainage system and is critical to effective storm water management. The proper hydraulic design determines the diameter, slope, and depth of a storm sewer line, ensuring that it drains storm water and does not back up (Carter 2010). Minimal storm water runoff movement, minimum depth, and adequate size to carry the design storm water runoff rate are the requirements for determining the proper diameter, slope, and depth for a storm sewage pipe (calculated using the Manning equation) (determined by the rational method). All of this is dependent on the design storm's rainfall intensity.

The rational technique is used to establish the design storm water runoff flow rate for a specific segment of storm sewer as the first step in this storm water system design. The Rational Method, which is described in the equation2-4, is commonly used to investigate system hydrology. (Carter 2010):

$\mathrm{Q} = \mathrm{C}_i \mathrm{\ x\ I\ x\ A}_i$ (2-4)

Where:

Q= the peak runoff rate in cubic feet per second for a design return period (frequency) (cfs)

C_i = Runoff coefficient stated as the dimensionless ratio of rainfall excess to total rainfall over a design return time.

I = Rainfall intensity in inches per hour for a period of time equal to the design return period's concentration time. This number can be calculated using an equation derived from an Intensity-Duration-Frequency (IDF) curve for the location being studied. $\mathrm{I} = \mathrm{AT}_C{}^B$,

A, B are the coefficient derived from real IDF curve.

Tc = the time of concentration in minutes for the longest flow path in the contributing watershed region, which is used to calculate I.

A_i = Contributing watershed drainage area, in acres, tributary to the design point

For natural drainage distances of less than 500 feet and greater than 300 feet, Kerby (1959) derived an equation for determining the period of concentration, equation 2-5:

$$t_c = \left(\frac{0.67 * n * L_o}{\sqrt{S}}\right)^{0.467} \qquad (2\text{-}5)$$

Where:

t_c = time of concentration in minutes.

S = overland slope in ft/ft.

n = roughness coefficient.

L_o = length of overland flow in feet.

The following is a table of recommended n values:

Table 2.1 Recommended surface roughness values (Kerby 1959)

Surface Description	***n***
Surface that is smooth and impervious	0.02
bare dirt that is smooth and compacted	0.1
Poor grass, cultivated row crops, and barren soil that is moderately rough	0.2
Pasture or a typical grass	0.4
Forested area with a mix of deciduous and coniferous trees	0.6
Forestland with a lot of deep forest debris or a lot of dense grass	0.8

The next step is to use the Manning Equation 2-6 to calculate the pipe diameter and slope for that stretch of storm drain (Robert 1891):

$$\mathrm{V} = \frac{k}{\omega} {R_h}^{2/3} S^{1/2} \quad \text{(2-6)}$$

Where:

V is the cross-sectional average velocity (L/T; ft/s, m/s); ω is the Gauckler–Manning coefficient. The units of ω are frequently ignored, however ω is not dimensionless, with units such as (T/[$L^{1/3}$]; s/[$ft^{1/3}$]; s/[$m^{1/3}$]). The hydraulic radius (L; ft, m) is Rh. When the water depth is constant, S is the slope of the hydraulic grade line or the linear hydraulic head loss (L/L), which is the same as the channel bed slope ($S = h_f/L$).

The conversion factor k is used to convert between SI and English units. It can be omitted as long as the units in ω are noted and corrected. If you leave ω in SI units, k is simply the dimensional analysis to convert to English. k = 1 for SI units, and k = 1.49 for English units. (Note: $(1\ \mathrm{m})^{1/3}/\mathrm{s} = (3.2808399\ \mathrm{ft})^{1/3}/\mathrm{s} = 1.4859\ \mathrm{ft/s}$)

The following are the factors used to determine the design diameter and slope of a sewer pipe section: 1) The pipe must be capable of carrying the storm water runoff rate specified in the design. 2) The sewer pipe flow velocity must be larger than or equal to the design V_{min} (usually 3 ft/s)

2.2.4 IDF_CC Tool

Climate change over the last few decades is thought to be the cause of major changes in the severity and frequency of extreme occurrences. According to the Intergovernmental Panel on Climate Change's Fifth Assessment Report (AR5), global surface temperatures would rise by 0.3 to 4.8 degrees Celsius by 2100, relative to the 1986-2005 reference period, with higher changes in the tropics and subtropics than in the mid-latitudes. Rising temperatures are likely to have a significant impact on the severity and frequency of extreme precipitation occurrences in some areas (Barnett et al., 2006; Wilcox et al., 2007; Allan et al., 2008, Solaiman et al. 2011). Implementing a generic and simple web-based tool that allows users to readily assess the impact of climate change in the form of upgraded IDF curves for stormwater drainage design and management is thought to be a viable technique for increasing Canada's climate change adaptation capacity (Sandink et al., 2016). The IDF CC tool was created to help with this work, and it has been in use since March 2015. (Schardong et al., 2020).

This application combines a user-friendly web-based user interface with a robust database structure, as well as an efficient and smart approach for IDF curve updates (Andre et al. 2021). The web-based IDF CC program version 5.0 is implemented as a Decisions Support System (DSS) with three primary components (User Interface, Mathematical models, Datebase) for IDF update with different climatic conditions. Figure 2.4 shows the example IDF maps for gauged locations, Ottawa, which is the study area in this thesis.

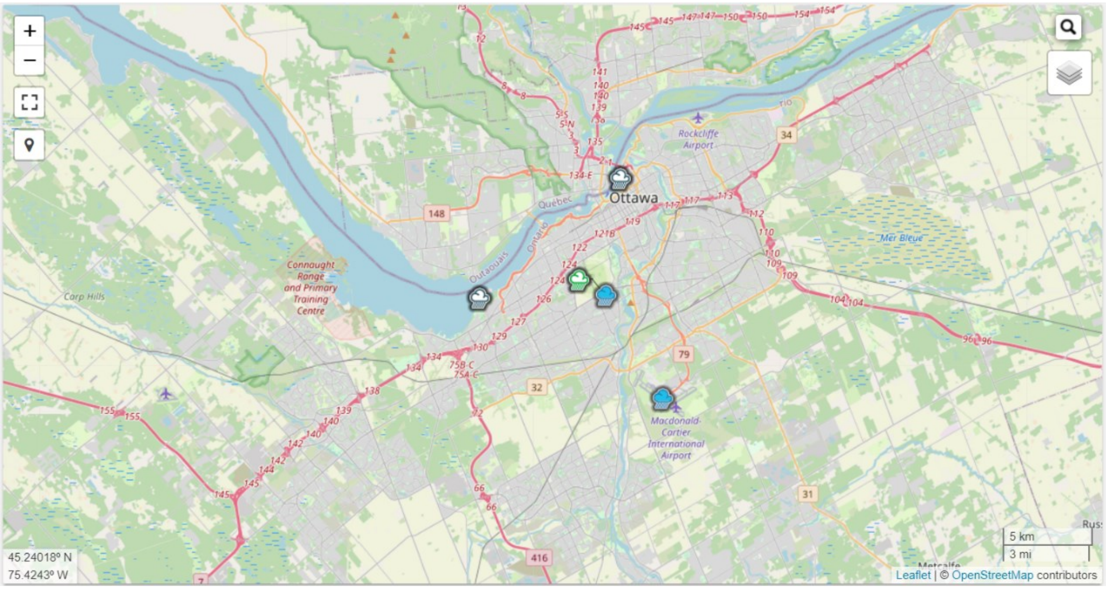


Figure 2.4 User interface in IDF_CC (Andre et al. 2021)

The user interface is created as a Leaflet™-based GIS component, allowing for a clear spatial depiction of hydro-meteorological stations. The database system for the IDF CC tool stores user data, station data, and Global Circulation Model (GCM) results (Andre et al.

2021). The tool's model foundation is made up of mathematical models and algorithms. The table providing the coefficients for interpolated equations for future scenarios fitted to the average IDF would be calculated in IDF_CC tool. Table 2.2 shows one example of the coefficients for future climate change rainfall data in year 2050.

Table 2.2 The coefficients for the interpolated equations fitted to the average IDF for future scenario RCP 4.5 (Andre et al. 2021)

T (years)	Coefficient A	Coefficient B	Coefficient t_0
2	26.9	-0.797	0.074
5	35.1	-0.795	0.084
10	41.1	-0.791	0.097
20	47.2	-0.782	0.110
25	49.4	-0.779	0.116
50	56.2	-0.774	0.134
100	64.2	-0.770	0.164

Equation 2-7 displays the estimated equations suited to the average IDF for the future situation, using the coefficients given in the table above and the equation below (Andre et al. 2021):

$$\mathrm{i}\left(\frac{mm}{h}\right) = A \cdot (t + t_0)^B \qquad (2\text{-}7)$$

Where:

i is the precipitation intensity rate in mm/h

A, B and t_0, are the coefficients for each return period (T) in years

t, the time (duration) of the precipitation event in hours (h).

2.2.5 Summary of Terminologies in urban drainage system

Urban drainage is an ancient field that dates back to at least 3000 BC (Burian & Edwards, 2002), with a main focus on water transfer away from urban centers. Low impact development (LID) (Department of Environmental Resources, 1999), sustainable urban drainage systems (SUDS) (CIRIA, 2000), water sensitive urban design (WSUD) (Whelans et al., 1994; Wong, 2007), best management practices (BMPs) (Schueler, 1987), and alternative techniques have all gained popularity in recent years (Azzout et al., 1994).

The term low impact development (LID) has been most commonly used in North America and New Zealand (Fletcher et al. 2015). By using a "design with nature" approach, the strategy aims to reduce the cost of storm water management (Barlow et al., 1977). LID was created with the goal of achieving "natural" hydrology through site design and integrated control methods. The balance of pre-development runoff, infiltration, and evapotranspiration sites achieved by a "functionally similar hydrological landscape" is referred to as natural hydrology (US Environmental Protection Agency, 2000). LID opposed the large watershed solution that was generally adopted at that time because it could not meet the hydrological restoration within the watershed (Fletcher et al. 2015). Moreover, the term LID was coined to differentiate the site-design and catchment-wide strategy from the standard watershed management approach at the time, which entailed conveyance to huge end-of-pipe detention facilities. Smaller scale storm water treatment devices, such as bio-retention systems, green roofs, and swales, were used in LID and were positioned at or near the source of runoff. The most recent Low Impact Development guides (NC State University, 2009) reintroduce hydrologic targets for both retrofit and new urban developments, as well as design solutions for meeting and maintaining these goals. Nowadays, the use of LID was coded in legislation throughout North America, and become the mainstream in urban storm water management (United States of America, 2007; Toronto Region Conservation Authority, 2010).

- The phrase "water sensitive urban design" (WSUD) initially appeared in Australia in the 1990s, with Mouritz (1992) being the first to use it, followed by Whelans et al. in a report for the Western Australian government shortly after (1994). The following are the goals outlined by Whelans et al. (1994):
- Manage the water balance (consider groundwater and streams, as well as damage from floods and erosion of water courses),
- Maintain and improve water quality (including sediments, protect riparian vegetation,

and minimize export to pollutants from surface and groundwater) as much as feasible,

- Encourage water saving (by storing water and reusing wastewater, as well as lowering the demand for irrigation, minimizing the importation of supplies of drinking water),
- Maintain water-related environments and recreation opportunities.

Storm water management is a part of WSUD that focuses on flood prevention, flow management, water quality enhancement, and storm water harvesting to augment mains water for non-potable use" (Fletcher et al. 2015).

Best Management Practices (BMP) is a term used to define a systematic strategy or method for preventing pollution in North America (mostly the United States and Canada) (Fletcher et al. 2015). Non-structural (operational or procedural techniques; for example, reducing fertilizer and pesticide use) and structural practices are both included in this phrase (engineering or built infrastructure). The performance of urban storm water BMPs was measured by the national urban runoff program, which was divided into four categories (detention devices, recharge devices, housekeeping practices, and other) (Fletcher et al. 2015). Storm water BMPs are used in practice to identify management strategies that address one or both sources of water volume pressure and water quality produced by storm water.

Early storm water management planning literature in North America (American Public Works Association, 1981; Whipple et al., 1983) focused on detention to mitigate increased runoff, treating on-site (or source control) practices as a subset of detention techniques, with essentially only quantity control as the goal (Fletcher et al. 2015). The Urban Drainage Design Guidelines produced by Ontario and Vancouver in Canada at the time focused on source management as a phrase (Metro Vancouver, 2012).

2.3 Resilience sewerage systems

Urban flooding is a major issue around the world, having far-reaching implications for the economy, culture, and ecology. Floods in cities cause major challenges such as property and infrastructure damage, transportation congestion, loss of life, environmental threats, and health concerns (Yazdi 2018; Girones et al. 2010). Recent challenges, such as increased surface imperviousness and rainfall intensities, have put existing storm water infrastructure, which are primarily piped, under strain. Therefore, efficient practices are needed to improve the resiliency of sewerage system. The studies mainly focus on drainage design, green/blue infrastructure, ageing problem, urbanization trend, and climate change.

Traditional design methods, which depend on historical performance trends and long lifespans, usually result in infrastructure that is rigid and unable to adapt to changing situations (Ashley et al. 2005). The consideration of novel techniques for urban flood control draw more attention in recent years, and accordingly in this section, the literature review below would give the summary of terminology in urban storm water management and comparison of related research.

2.4 Comparison with the previous research on drainage design

Some studies focused on drainage design, such as pipe slope and diameter optimization (Moussavi et al. 2017; Shao et al. 2017), coupling design cost limitation (Maharjan et al. 2009). Figure 2.5 demonstrates the proposed model in terms of traditional design for improving hydraulic performance of drainage system. And equation 2-8 shows the cost objective functions in this framework ((Moussavi et al. 2017).

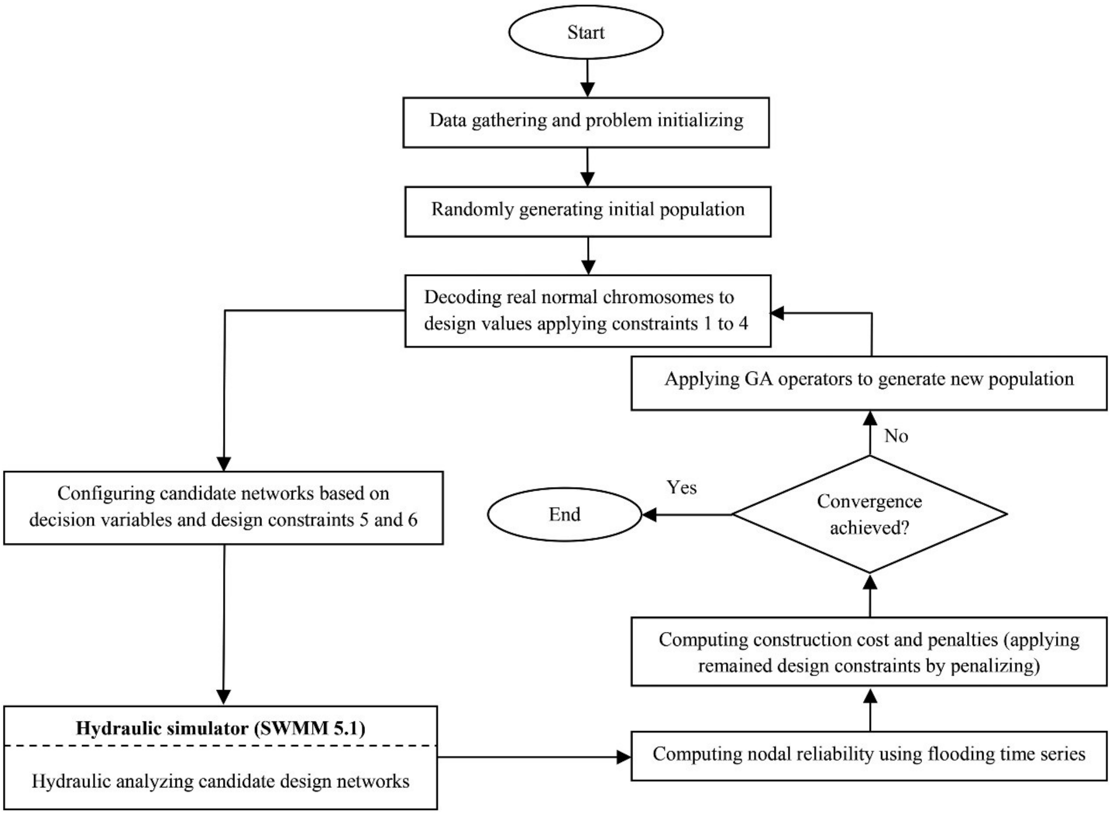


Figure 2.5 The framework of the optimal reliability-based storm sewer network design (Moussavi et al. 2017)

$$\mathrm{C}(D,S,P) = \sum_{I=1}^{N_P}(C_{Si} + P_i C_{Ii}) + \sum_{i=1}^{N_P+1} C_{Mi} \quad (2\text{-}8)$$

where P is unity if a pump station exists at the upstream end of the pipe; otherwise, it is zero. C is the cost function; C_S, C_L, and C_M are the construction costs of sewerage, pump stations, and manholes, respectively; N_p is the number of sewage pipes; and N_p is the number of sewer pipes.

This proposed framework has several limitations, such as using a single, fixed-duration design storm to evaluate network performance, and only investigating the system reliability of network nodes. Furthermore, the reliability index is unable to characterize the degree of network flooding or its potential implications. Criteria like resilience and vulnerability can best represent the potential severity of network flooding. It is required to further the research by using multi-objective optimization models and taking into account performance criteria such as rainwater pipe network design flexibility and fragility. (Moussavi et al. 2017).

Using a risk-based approach, Sun et al. (2011) used a genetic algorithm to discover the appropriate pipe sizes and slopes in an urban drainage system (GA). Oraei Zare et al. (2012) use three factors to optimize the site of low impact development (LID) practices in Tehran: pricing, quality indices improvement, and surface runoff volume. They examined NSGA-II and multi objective particle swarm optimization (MOPSO), two commonly used multi objective evolutionary algorithms (MOEAs), and discovered that NSGA-II outperforms MOPSO (see Figure 2.6). Yazdi et al. (2015) optimize the renewal pipe size of a sewerage system under a fixed design storm by combining the EPA-SWMM hydraulic model with three various MOEAs, including NSGA-II, MOPSO, MOPSO-II and NSHS.

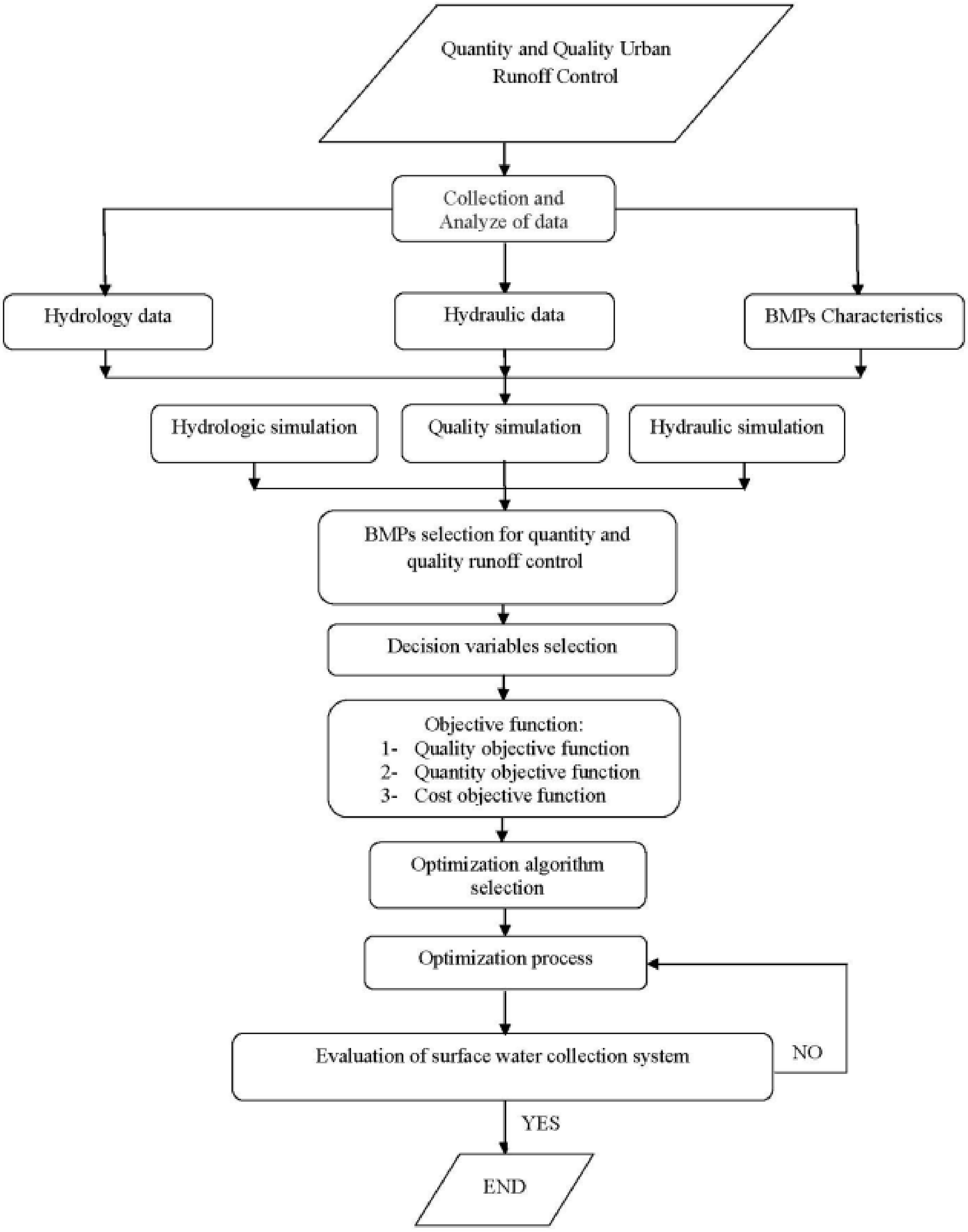


Figure 2.6 The overall view of the methodology (Oraei Zare et al. 2012)

Cai et al. (2020) present a new framework for dynamically combining drainage system hydraulic performance with the probability of failure to produce efficient rehabilitation approaches utilizing multi-objective optimization. The HRCM is made up of five different modules: (1) hydraulic performance, (2) risk assessment, (3) optimization, (4) rehabilitation, and (5) post-processing. This framework has three flaws: (1) the computational speed is slow, (2) the model's cost-effectiveness needs to be addressed, and (3) each component in the model is simplified without sacrificing generality (Cai et al. 2020).

2.5 Comparison with the previous Detention Optimization Research

Some studies have been focused on the optimization of the suitable locations for detention basin, such as storage tanks, or green infrastructure detention pond. Doyle (1976) devised a mixed integer linear optimization model to assess various storm water detentions in a sub-catchment, which was one of the first attempts to quantify and optimize detention basin site challenges. Behera et al. (1999) employed dynamic programming (DP) to expand optimization methodology for a multiple parallel catchment system targeted at mitigating the negative effects of urban drainage, and storm-water detention ponds are often used in watersheds experiencing urban growth. Figure 2.7 depicts a network of parallel catchment areas, each with its own detention pond for regulating the quantity and quality of overflow from its watershed.

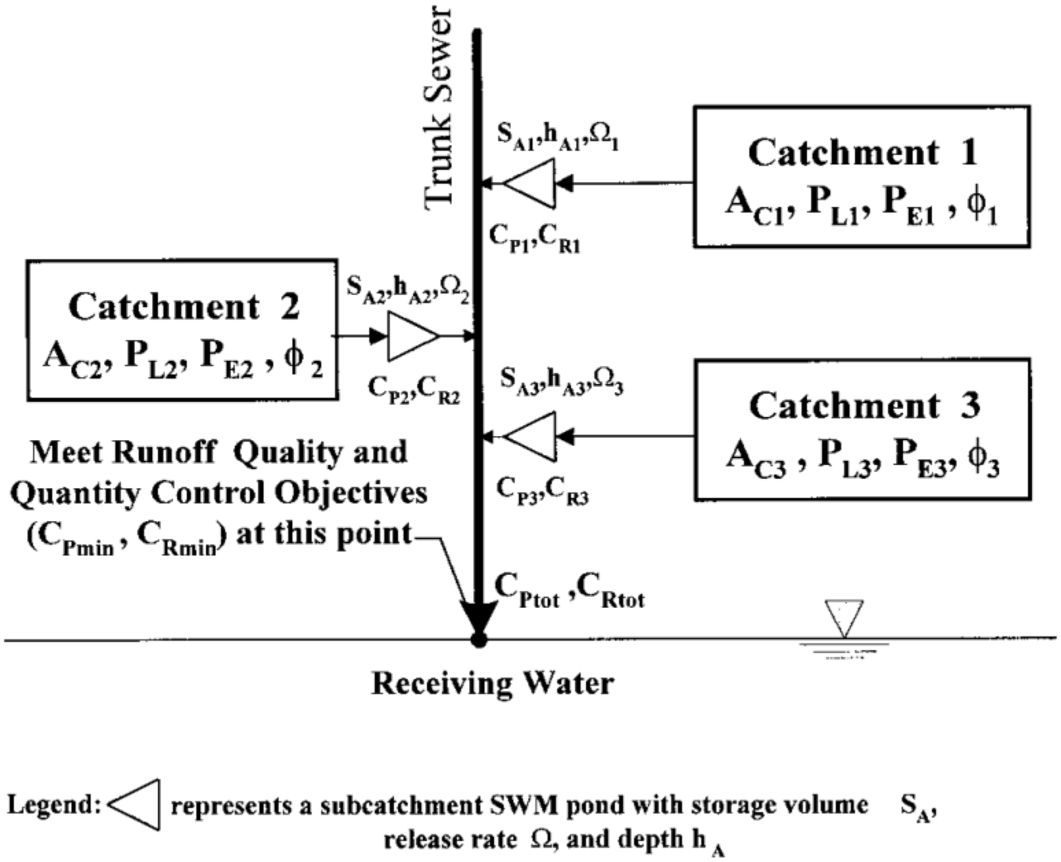


Figure 2.7 Schematic Representation of Example Problem (Behera et al. 1999)

To optimize and construct the storm water retention system in a real watershed, Yeh and Labadie (1997) designed and used successive reaching dynamic programming (SRDP). Zhen et al. (2004) investigated the problem with the help of many simulation models, heuristic optimization methodologies, and a scatter search algorithm. The structure of optimization framework consists of three functional components, the initialization run of AnnAGNPS (continuous-simulation surface runoff computer model for estimating nonpoint source pollution loads), the system evaluator, and the optimizer are all shown in Figure 2.8.

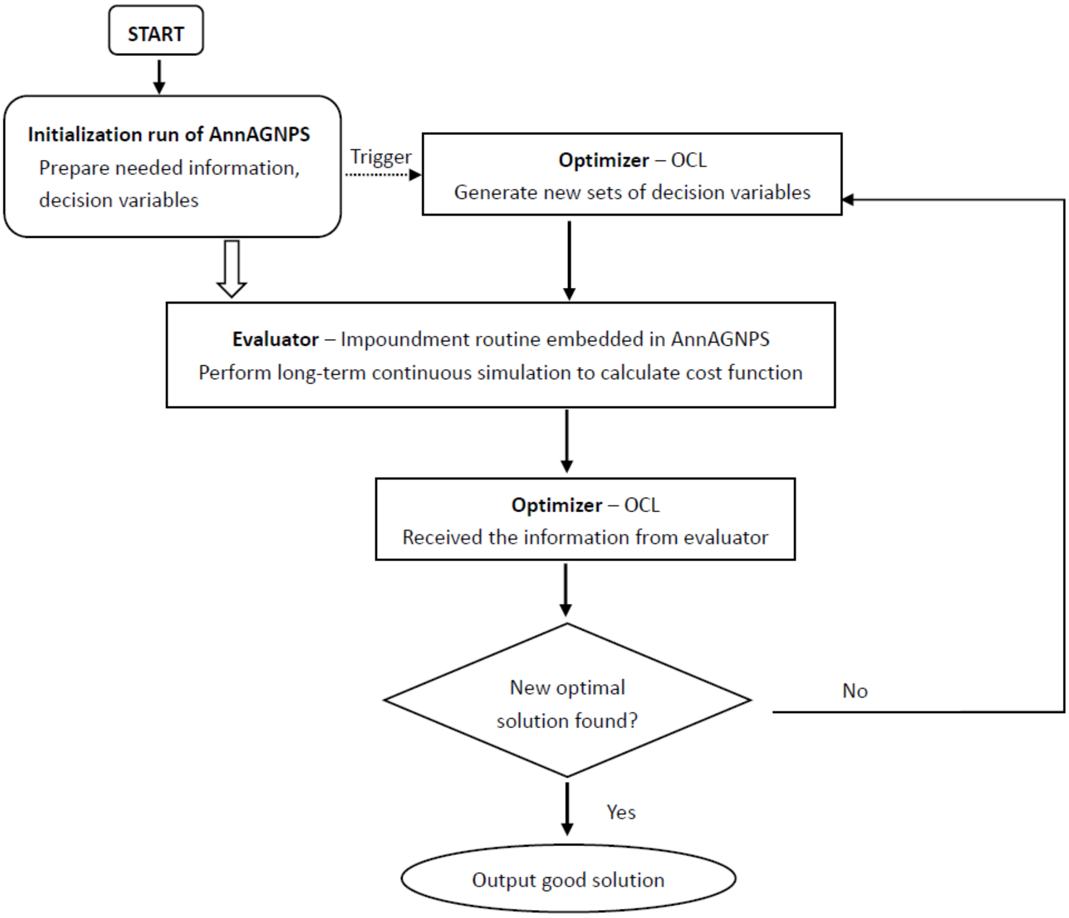


Figure 2.8 Conceptual design of optimization framework (Zhen et al. 2004)

Travis and Mays (2008) developed a discrete dynamic programming-based design process for identifying the appropriate position and sizing of a network of retention basins, as well as the sizing of the outlet structures. Retention basins, unlike detention basins, often use infiltration as their principal means of storm-water disposal, according to Travis and Mays (2008), and are consequently referred to as infiltration ponds. Dynamic programming (DP) was utilized to improve the system in terms of cost reduction and successful flood management, as shown in Figure 2.9.

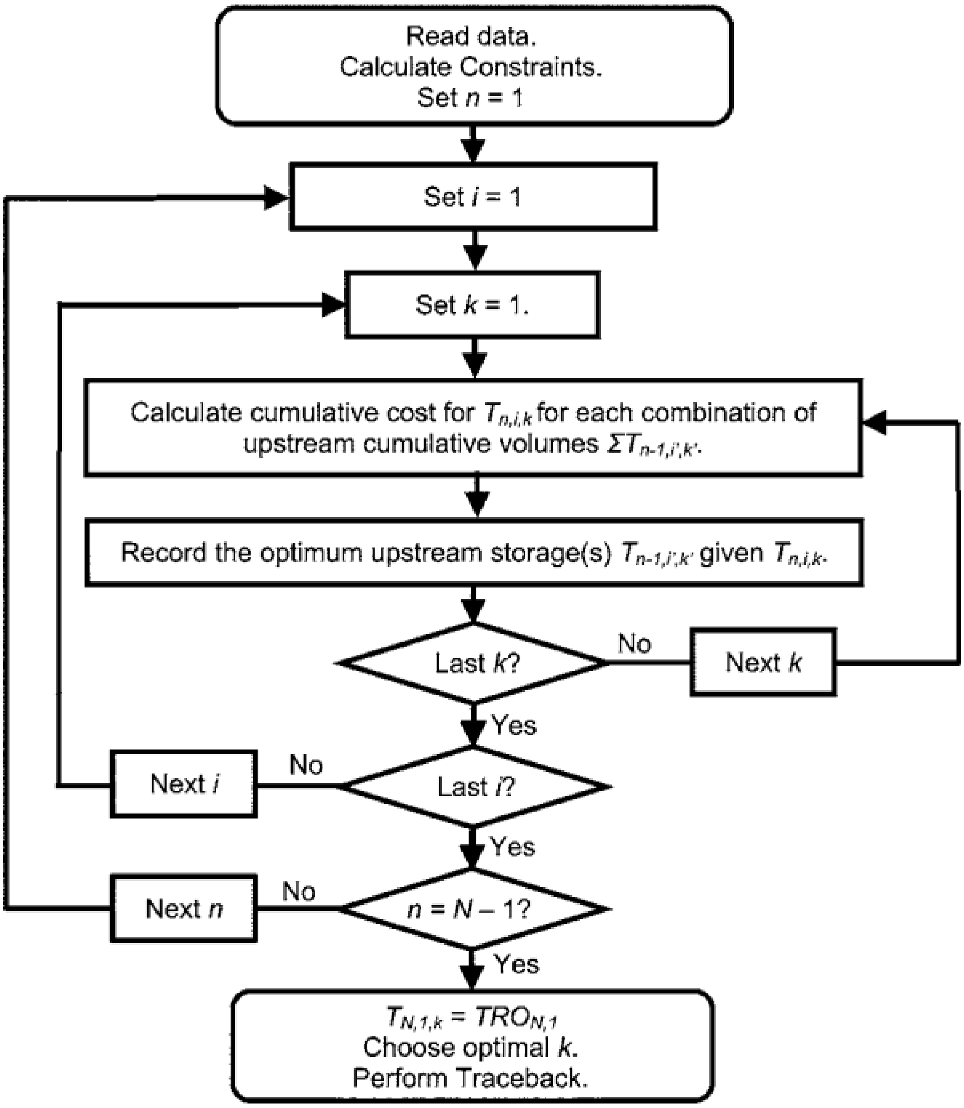


Figure 2.9 Dynamic programming method flowchart (Travis and Mays 2008)

None of the earlier detention basin optimization models included a thorough hydrologic simulation model like the Hydrologic Modeling System (HMS) or another more comprehensive Hydraulic Simulation Model (SWMM) (Oxley and Mays, 2014). For the optimization model, it is necessary to incorporate the hydraulic design result into optimization process. Oxley and Mays (2014) optimized the location and size of a storage basin network, including the discharge components in a separate storage basin system and numerous detention basin systems, using the simulated annealing approach. Figure 2.10 illustrates one example proposed by Oxley and Mays (2014), which incorporates Hydrologic Engineering Center - Hydrologic Modeling System (HEC-HMS) in the overall optimization procedure. In this research, it contains two basic components: the control interface and the HEC-HMS model. However, in this study, the hydrologic model could not present the detailed hydraulic sections in the urban sewerage network, including links and nodes, and accordingly the next section would focus on the detention optimization model incorporates hydraulic section.

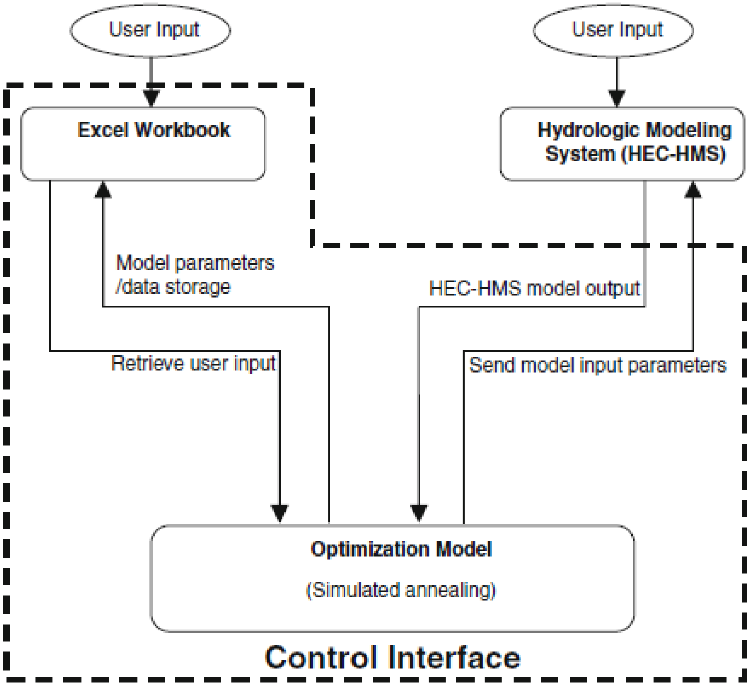


Figure 2.10 General model structure showing data flow (Oxley and Mays 2014)

2.6 Comparison with the recent Detention Optimization Research

In recent years, the rapid development of computer programming has resulted in a growth in the modern optimization approach, which gives new methods for optimizing the structure of storage tanks (Wang et al. 2017). Wang et al. (2017) use a two-stage optimization framework to discover the best storage tank scheme utilizing the storm water management model (SWMM), with the goals of reducing floods, total suspended solids (TSS) load, and storage costs. Figure 2.11 demonstrates the combination of the AHP and GPS methods for the multi-objective optimization framework. However, in this research, authors focus on optimization of storage tank location, without consideration of storage tank size and future climate change, which would overestimate the resiliency of urban sewerage system.

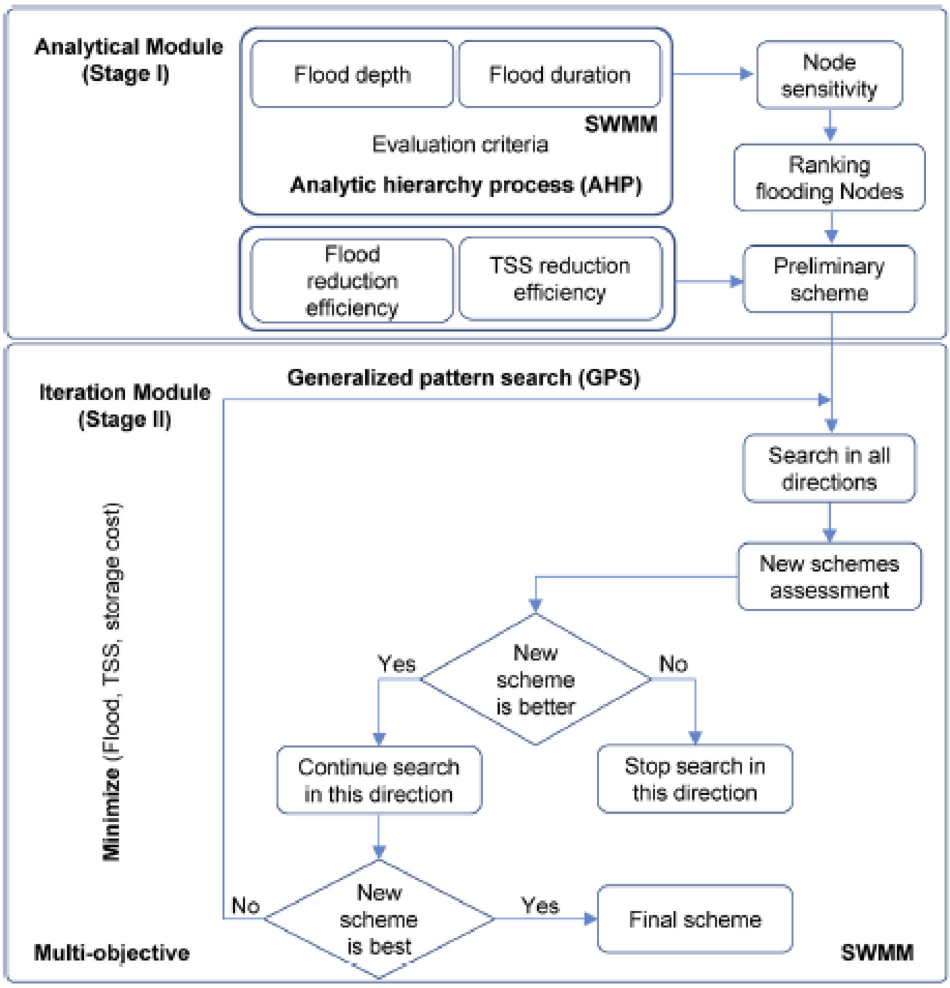


Figure 2.11 Framework of multi-objective optimization for storage tanks (Wang et al. 2017)

Tao et al. (2014) used the NSGA-II computer programming methodology to build an optimization framework of decentralized detention, coupling SWMM model and considering flood disaster control, peak flow reduction and investment cost as the main constraints. Equation 2-9, 2-10 demonstrate the objective functions and constraints in optimization model.

$$\begin{gathered}\text{Min Cost}\\ \text{Min Peakflow} = f_1(S_1, S_2, \ldots S_n)\end{gathered} \quad \text{(2-9)}$$

$$\begin{gathered}0 \le S_i \le 800\\ f_2(S_1, S_2, \ldots S_n) = 0, variables: S_i(i - 1,2,3, \ldots n)\end{gathered} \quad \text{(2-10)}$$

Where S_i is the detention size (m^2) of I ($S_i = 0$ indicates no detention layout), n is the detention number, f_1 () is the downstream particular location peak flow function used in SWMM calculations, and f_2 () is the waterlog node number function used in SWMM calculations. Only two ideal objectives of flood mitigation effect and cost of peak flow detentions were explored in this article. Many academics have been studying multi-purpose storage tanks in recent years with the goal of managing the peak flow of rainstorms (Tao et al. 2014)

Delelegn et al. (2011) combined the Non-dominated Sorting Genetic Algorithm II (NSGA II) and a 1D-2D hydraulic model to create detention ponds in metropolitan areas using the return period approach. Park et al. (2012) adopted GA methodology to optimize storage capacity, outlet structure diameter, and the quantity of detention ponds in an urban area. After defining the size and location of a detention basin, Park et al. (2012) calculate the outflow hydrograph (see Figure 2.12) using the existing inflow hydrograph, initial condition, and pond parameters. Weir flow, orifice flow, pipe flow with free outfall, and pipe flow with submerged tail water are the different types of flow circumstances (Figure 2.13). Figure 2.14 shows the entire technique for determining the ideal pipe size and detention pond size using the suggested GA algorithm-based method.

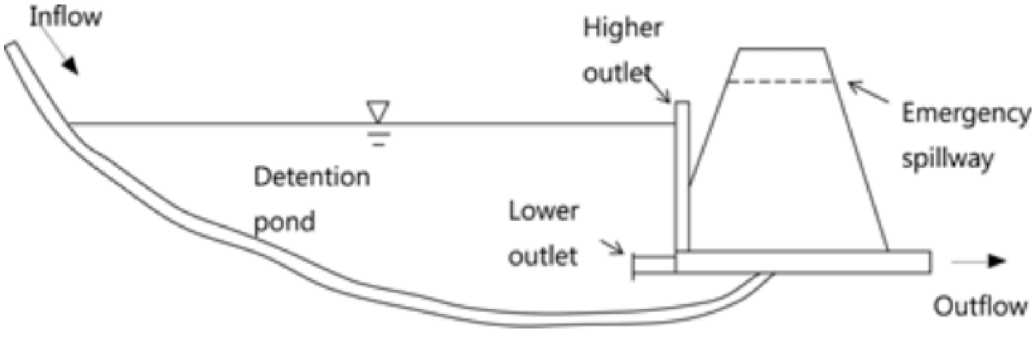


Figure 2.12 Figure of a Detention Basin (Park et al. 2012)

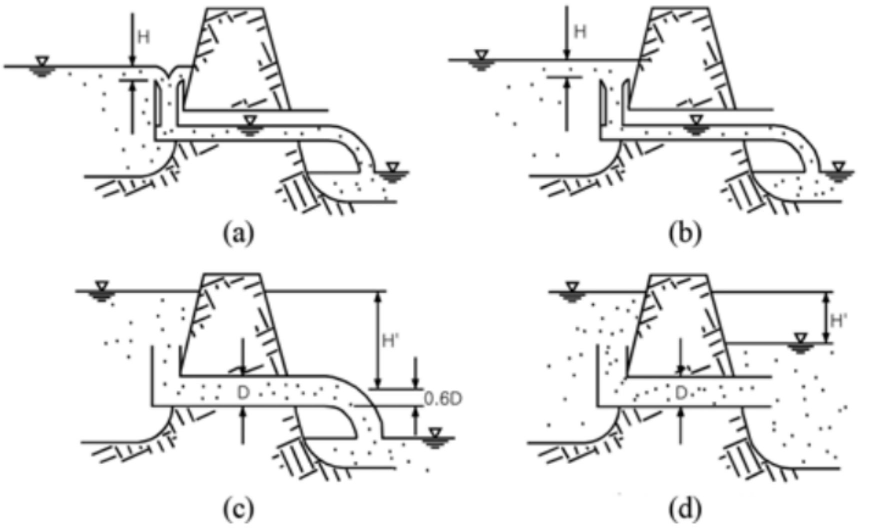


Figure 2.13 Flow Classification of Riser-pipe in a Detention Basin (Park et al. 2012): (a) Weir Control, (b) Orifice Control, (c) Pipe Flow with Free Outfall, (d) Pipe Flow with Tailwater Control

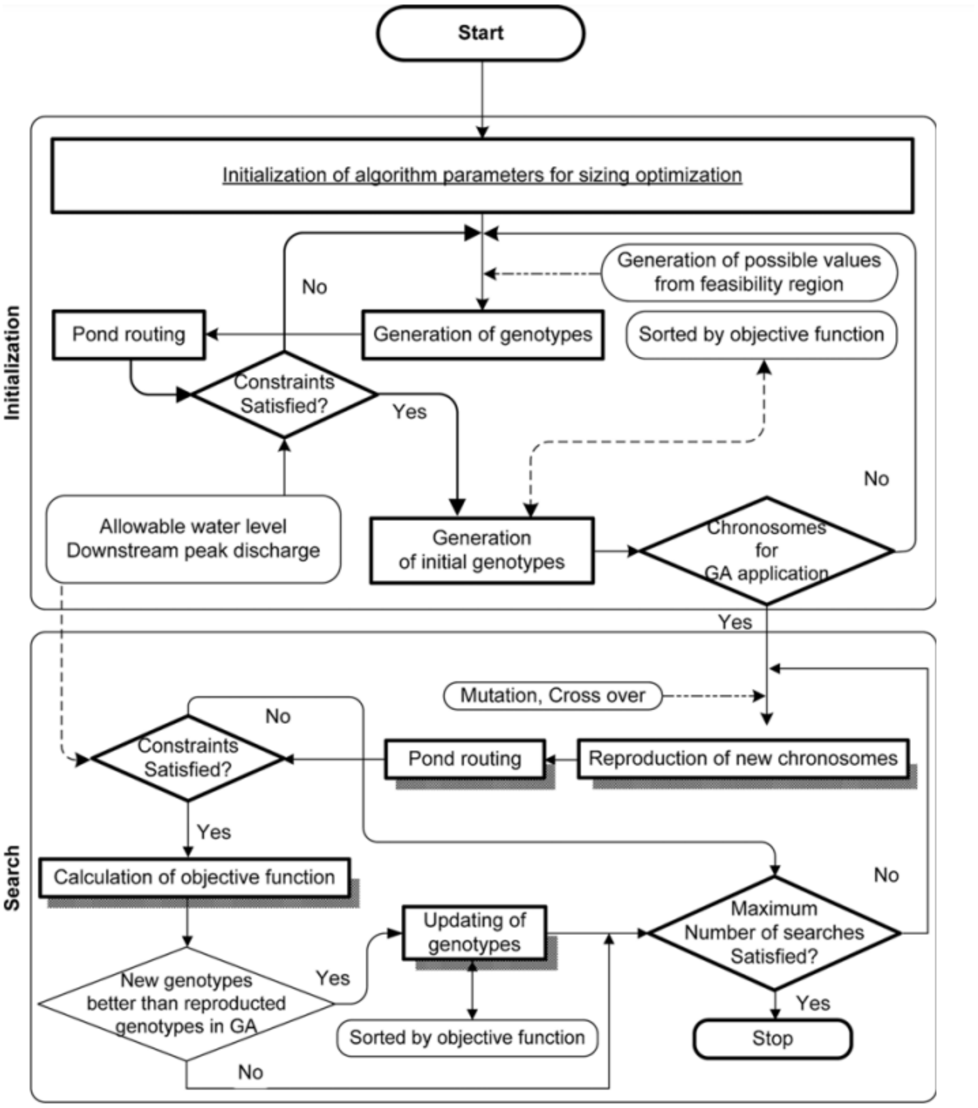


Figure 2.14 GA Algorithm for Optimal Storm water Detention Basin Design Procedure (Park et al. 2012)

Cunha et al. (2016) employed hydraulic controls and a Simulated Annealing (SA) technique to predict the best size of detention tanks. Figure 2.15 illustrates the variables in this research, including the number of storage units, their location, size and the orifice dimensions. In this study, it combines hydraulic model with SA method, which is different from GA method, and Figure 2.16 demonstrates the framework of this optimization practice. In this study, variables related to climate change and urbanization and variables related to cost cannot be estimated without some degree of uncertainty (Cunha et al. 2016).

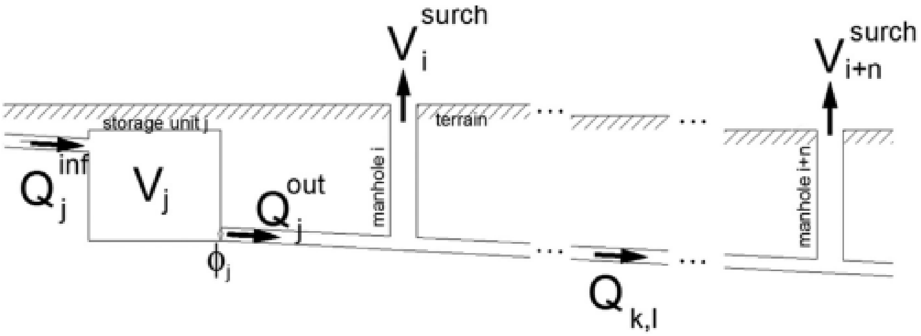


Figure 2.15 Schematic figure of variables and parameters (Cunha et al. 2016)

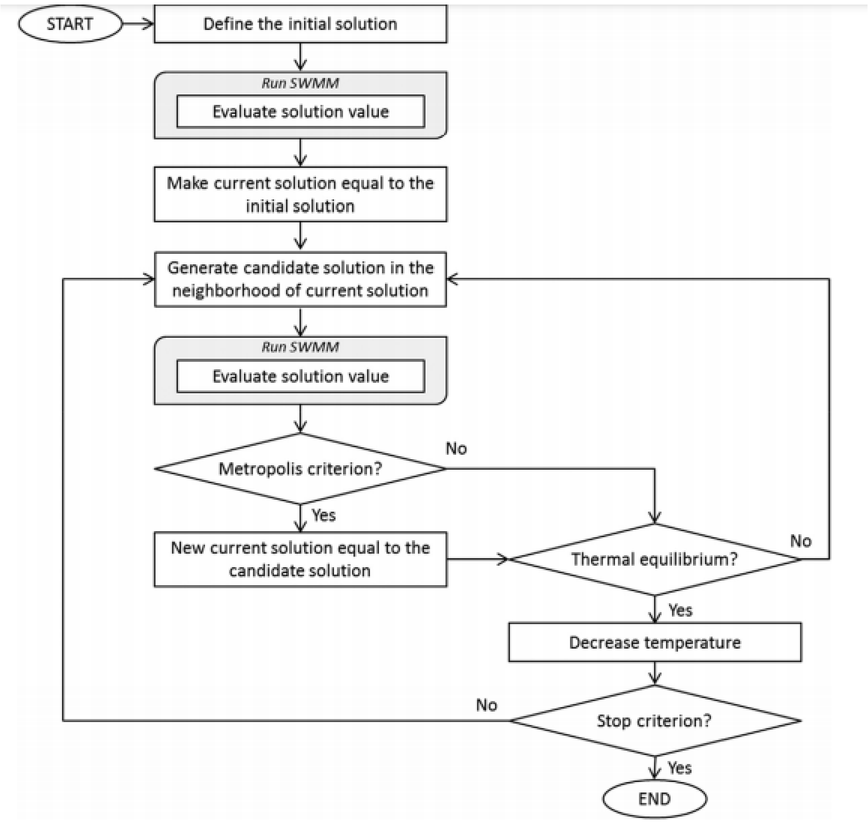


Figure 2.16 Basic steps of the model solution (Cunha et al. 2016)

Heitz et al. (2000) looked into the design of detention basins from the perspective of pond sizing for better water quality. Bach et al. (2013b) developed the 'UrbanBEATS' decision support tool, which uses a multi-criteria assessment algorithm to find optimal places for WSUD placement based on parameters such as land development, population size, topological and geological features, and urban heat islands. Kuller et al. (2016) assessed biophysical (e.g. natural rivers) and socio-demographic characteristics to determine the best green/blue infrastructure choice and location (e.g. income in certain districts). To determine the optimum green infrastructure option, Anas et al. (2016) construct an optimization model for best management practice (BMP) selection and deployment at the watershed level. Bellu et al. (2016) constructed a framework model to determine the appropriate position and size for the storage basin system, with three goals in mind: to reduce diffuse pollution, reduce point-source pollution, and improve landscape integration (by minimizing the dam height). Figure 2.17 depicts the study framework, referred to as a Multi-Criteria Decision Analysis (MCDA), which consists of three distinct but interrelated modules: (i) hydrologic; (ii) geomorphologic; and (iii) environmental.

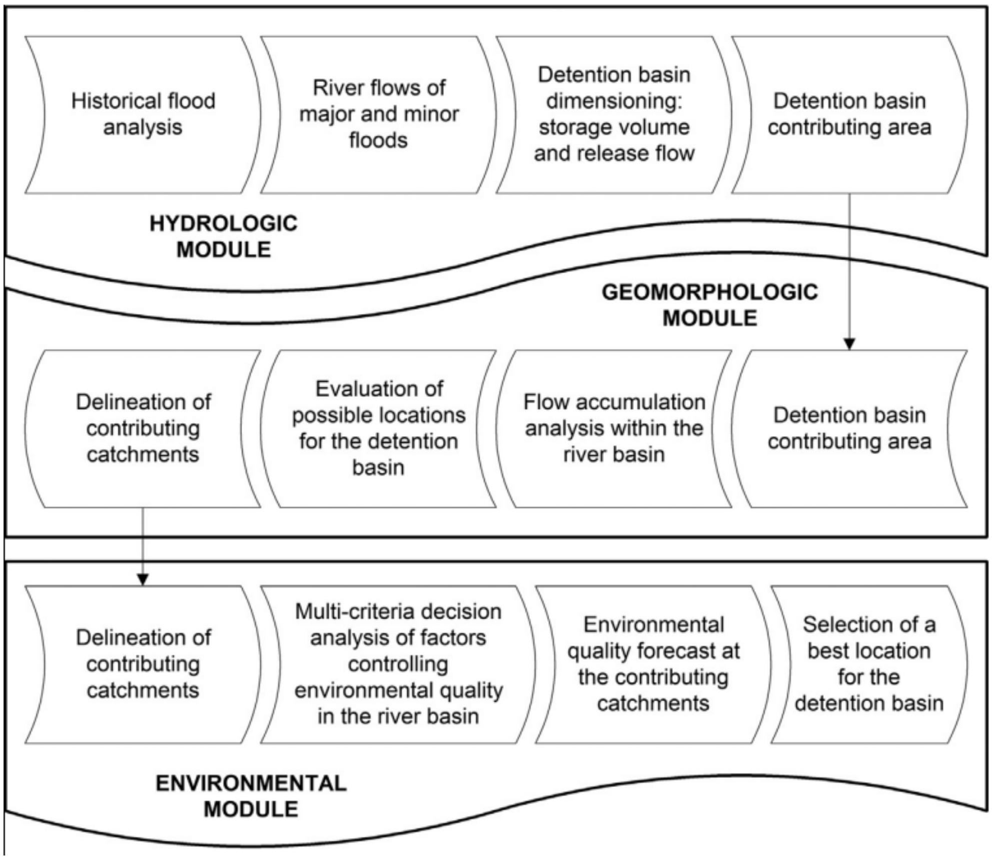


Figure 2.17 Modules and procedures for locating and sizing a detention basin in a watershed are depicted in this flowchart (Bellu et al. 2016)

Chapter 3: Technical Paper - A new framework to optimize storage units in urban drainage systems

Abstract - In order to mitigate over-flooding situation in urban areas, the adoption of storage units may be a cost-effective and efficient alternative for lowering peak runoff in existing drainage systems in urban areas. This paper proposes a two-stage multi-objective optimization framework to find near optimal solutions for storage units in urban drainage systems. The proposed multi-objective framework aims to maximize flood reduction efficiency and minimize the total cost. The EPA-SWMM model was employed for hydraulic simulation of the system while the optimization was performed using Non-dominated Sorting Genetic Algorithm II (NSGA II). The output of SWMM model is used to estimate two over-flooding indexes based on the flood volume and duration, which can in turn determine the flood reduction efficiency. The optimization model considers location, volume and number of storage units in the drainage system, and generates near optimal solutions based on the specified objectives on cost and flood reduction. The optimization model was tested for dependency on population size and results showed that the population size in genetic algorithm (GA) can affect the final selection of optimal solutions. To evaluate the capability of the framework, the proposed system was applied to a real sewerage system and examined through various synthetic test cases. In addition, we proposed and examined different methods based on the flood reduction sensitivity as well as flooding volume and node depth to prioritize the sub-catchments for storage unit implementation when the problem in hand is very complex and the optimization solution domain is large. The results indicated that the framework has the capacity to find different strategies for near optimal implementation of storage units that can improve the resiliency of existing urban drainage infrastructure systems.

Keywords: Over-flooding, Storage units, Resiliency, Multi-objective, Real sewerage system

3.1 Introduction

Despite considerable studies on river flooding, urban flooding has received little attention and has received little attention from scholars (Chen, Hill, and Urbano 2009). Urbanization and climate change have increased the intensity and frequency of floods in recent years, which has reduced the ability of municipal sewerage systems to accommodate the volume of surface runoff (Yazdi et al. 2014; O'Sullivan et al., 2015; Cai et al., 2021). To mitigate the pressure on urban sewerage system and prevent urban flooding, efficient measures are required to improve their resilience (Mailhot et al. 2008; Sheng and Wilson, 2009).

Building storage facilities such as retention or detention basins may be one of the most efficient approaches (Kessler and Diskin, 1991; Ebrahim et al., 2016). Storage units are a cost-effective and efficient structural option to reduce peak runoff in existing drainage systems in urban areas, especially compared to traditional methodologies such as increasing pipe diameter or slope to provide sufficient hydraulic capacity (Bellu et al., 2016; Woods-Ballard et al., 2007; Ogidan et al., 2016; Yazdi et al., 2017; Cai et al., 2020).

In recent years, the rapid advancements in computer programming have resulted in growth in the modern optimization approach, which provides new methods for optimizing the structure of storage tanks (Wang et al., 2017). Using the storm water management model (SWMM), Wang et al. (2017) proposed a two-stage (analytical and iteration) optimization method to discover an ideal scheme for storage tanks, with the purpose of decreasing flooding, total suspended solids (TSS), load, and storage costs. Tao et al. (2014) used the NSGA-II computer programming methodology to build an optimization framework of decentralized detention, coupling the SWMM model with optimization method while considering flood disaster control, peak flow reduction and investment cost as the main constraints. Cunha et al. (2016) employed hydraulic controls and a Simulated Annealing (SA) technique to predict the optimal size of detention tanks. Kuller et al. (2016) assessed biophysical (e.g. natural rivers) and socio-demographic characteristics to determine the best green/blue infrastructure choice and location (e.g., cost limitations in certain districts). To determine the optimum green infrastructure option, Anas et al. (2016) developed an optimization model for best management practice (BMP) selection and deployment at the watershed level. Bellu et al. (2016) created a framework model to determine the appropriate location(s) and size for the storage basin system, with three goals in mind: reduce diffuse pollution, reduce point-source pollution, and improve landscape integration (by minimizing dam height). Delelegn et al. (2011) combined the NSGA II with a 1D-2D hydraulic model to create detention ponds in metropolitan areas using the return period approach. Park et al. (2012) adopted GA methodology to optimize storage capacity, outlet structure diameter, and the quantity of detention ponds in an urban area. Heitz et al. (2000) investigated the construction of detention basins from the standpoint of pond sizing for improved water quality. Bach et al. (2013b) created the 'UrbanBEATS' decision support tool, which examines suitable locations for Water Sensitive Urban Design (WSUD) placement based on a multi-criteria assessment algorithm.

The majority of previous research for optimizing urban sewerage systems have been based on hydraulic capacity and have focused on how to increase a drainage system's hydraulic performance (Bellu et al., 2016; Woods-Ballard et al., 2007). However, these studies lead to a lack of consideration of other economic and efficient structural practices, such as detention basins, for urban flood control. Therefore, storage units are widely used for delaying peak flow and controlling urban flooding. For storage unit application in improving sewerage system resiliency, storage unit locations, volume and number should be considered. To reduce runoff, the storage units should provide sufficient capacity and ensure that they can accommodate the flooding volume. However, the size of the storage unit should not be too large due to the prohibitive cost. The location and number of detention units in a watershed will influence the efficiency of flood reduction. In addition, the cost of the storage unites may vary with their locations given the space limitation in sub-watersheds. The integration of storage units within existing urban drainage system can improve their resilience. Resiliency here refers to “the state of the system that enables it to limit failure duration and magnitude to any threat” (Mugume et al. 2015). Reduction of flooding time and flooding volume can improve resiliency, as shorter flooding time and smaller flooding volume are beneficial for absorbing the impact of the threat and improve the recoverability.

The proposed framework in this research context is designed for future and to find optimal strategies to integrate storage units within the drainage network in order to increase redundancy and flexibility in the system. The proposed method helps determine the volume, location and number of units while considering financial limitations. The proposed optimization framework can help mitigate urban flooding more efficiently through reduction of flooding time and volume. To find the optimal intervention strategies to integrate the storage units, both hydraulic and optimization models are required to be coupled.

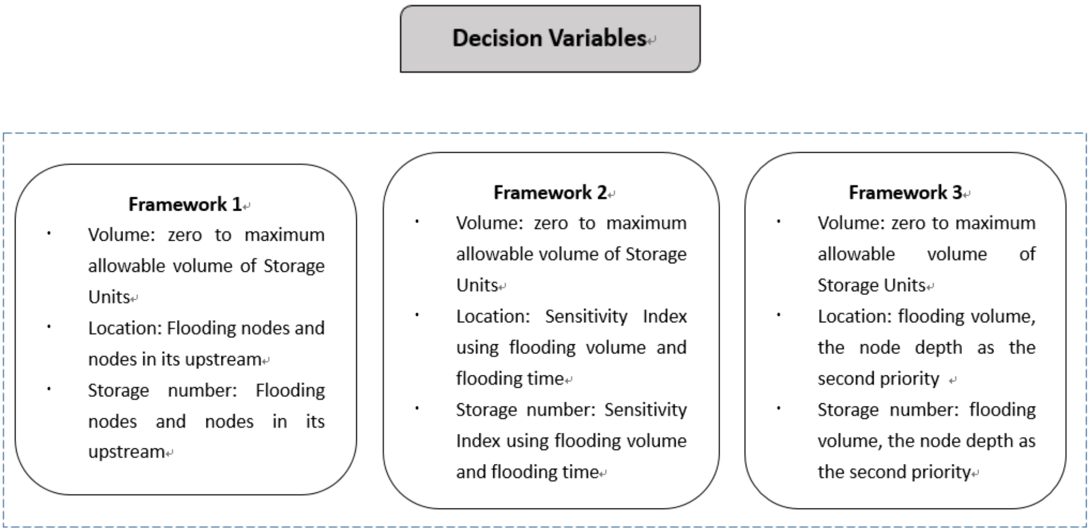
Determining the near optimal volume, location and number of storage units is difficult due to a conflict between sewerage system resilience and economic concerns. The position of storage units in a watershed also has an impact on efficiency (Weiss et al., 2006; Wicke et al., 2012). In a complicated system, considering both the optimal size and number of storage units and searching for suitable locations is a difficult problem. That is, combining different methods into one framework is a demanding practice. Based on the need to maximize resilience and minimize costs, the multi-objective optimization methodology may help uncover the best solution.

Main objectives of this paper include developing a two-stage multi-objective optimization framework combining the SWMM model and Non-dominated Sorting Genetic Algorithm II (NSGA II); developing a new method to determine optimal volume, locations and number of storage units in urban sewerage systems; devising three different indexes for prioritizing candidate locations, and comparing the performance of the framework with different methods via various synthetic test cases. To the best knowledge of the authors, in this context, multi-objective optimization approaches were barely coupled with the SWMM model (i.e. to take into account the dynamic response of the system to the intervention strategies). Although the SWMM model and NSGA II method have been used in some cases, the majority of the cases focused on drainage system design (Moussavi et al. 2017; Shao et al. 2017). For some related studies focusing on the optimization of storage tank volume and/or location, they adopted different methodologies or focused on single storage tank location (Oxley et al., 2014; Wang et al. 2017). However, in this study, we consider location, size, and the number of storage units while taking into account reduction of the flooding volume and time. In addition, a two-component cost function including the direct cost of storage unit as well as the cost of penalties associated with flooding based on the location has been considered which was not considered in this context in previous studies. Moreover, in addition to the flood volume, we considered reduction of flood duration as an objective function in the proposed framework, which can improve the urban flood resilience.

3.2 Methodology

3.2.1 Multi-objective Optimization Framework

The multi-objective optimization framework proposed in this paper includes two main models (Figure 3.1): (1) hydraulic model and, (2) optimization model. This framework considers two objective functions i.e., flooding reduction efficiency and total cost of storage units. In addition, it has three decision variables, i.e., the storage unit size, and the number and location of storage units. In this context, we incorporate a hydraulic simulation model using SWMM into Non-dominated Sorting Genetic Algorithm II (NSGA II); this framework can change size, location selection, and number of storage units.



Decision Variables

Framework 1

- Volume: zero to maximum allowable volume of Storage Units
- Location: Flooding nodes and nodes in its upstream
- Storage number: Flooding nodes and nodes in its upstream

Framework 2

- Volume: zero to maximum allowable volume of Storage Units
- Location: Sensitivity Index using flooding volume and flooding time
- Storage number: Sensitivity Index using flooding volume and flooding time

Framework 3

- Volume: zero to maximum allowable volume of Storage Units
- Location: flooding volume, the node depth as the second priority
- Storage number: flooding volume, the node depth as the second priority

Figure 3.1.a. Decision Variables of Multi-objective Optimization Framework

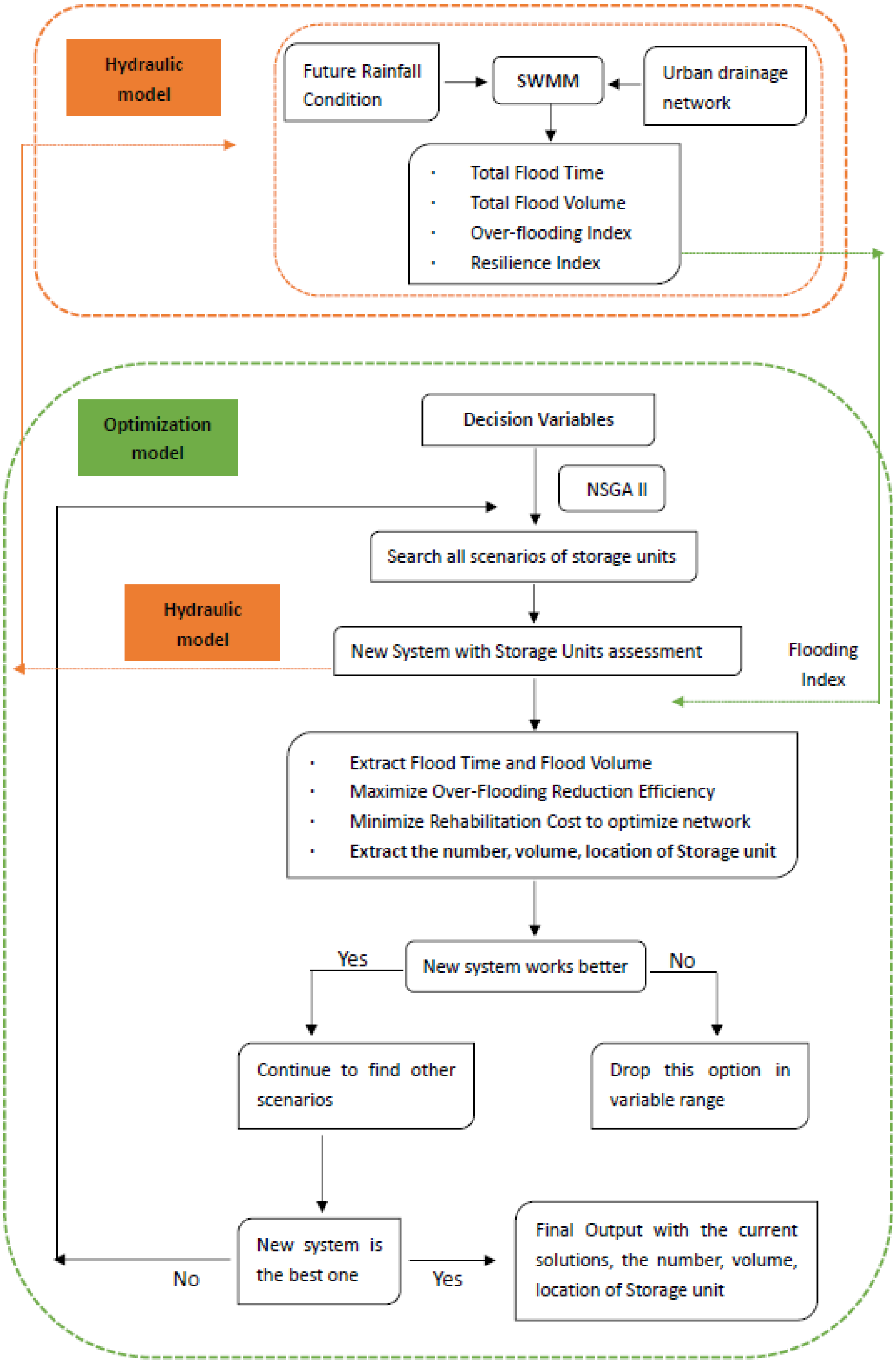


Figure 3.1.b. Structure of Multi-objective Optimization Framework

3.2.2 Hydraulic Simulation Model

To build a hydraulic model for drainage systems, the most efficient tool is the Storm Water Management Model (SWMM) developed by the U.S. Environmental Protection Agency (USEPA), which is widely utilized around the world for storm water management. The EPA SWMM is a dynamic rainfall-runoff simulation model that may be used to simulate runoff quantity and quality in metropolitan areas for single-event or long-term (continuous) simulations (Rossman 2015; Yazdi et al., 2015). In this framework, we utilized SWMM as a tool to simulate the hydraulic state of the sewerage system, which in turn will allow for calculation of over-flooding indexes (i.e. total flood time and total flood volume) that are required in the optimization model. In addition, the hydraulic information required for prioritizing sub-catchments for storage unit implementation is obtained from SWMM output.

3.2.2.1 Designed Rainfall

The Chicago designed storm is a popular approach for design and evaluation of drainage systems, and has been utilized in a number of studies (Bennis et al. 2003). Keifer and Chu (1957) created the "Chicago Design Storm" or "Chicago Method" to estimate design rainfalls for urban storm water systems. Chicago method can be utilized in future prediction and combined with proposed framework, which is designed for future. In this case the Sherman I-D equation is used to calculate the average intensity is as follows:

$$i = \frac{a}{(t_d+b)^c} \qquad (3\text{-}1)$$

Where i is the average rainfall intensity (mm/hr or inch/hr),

t_d is the storm duration (minutes),

a, b, c are coefficients.

For those coefficients, use real rainfall data and solver function in Excel to match the proper values.

The time distribution of rainfall intensity can then be defined in terms of time after the peak t_a and time before the peak t_b using the following two equations:

$$i_a = \frac{a\left[\frac{(1-c)t_a}{(1-r)}+b\right]}{\left(\frac{t_a}{(1-r)}+b\right)^{1+c}} \quad (3\text{-}2)$$

Where i_a is the rainfall intensity after the peak (mm/hr or inch/hr);

r is Peaking-Time-Ratio, $r=t_p/t_d$ (when the peak is expected within the total duration);

t_p is the peak time;

$t_a = t-t_p$, t is time.

$$i_b = \frac{a\left[\frac{(1-c)t_b}{r}+b\right]}{\left(\frac{t_b}{r}+b\right)^{1+c}} \quad (3\text{-}3)$$

Where i_b is the rainfall intensity before the peak (mm/hr or inch/hr);

r is Peaking-Time-Ratio, $r=t_p/t_d$ (when the peak is expected within the total duration);

t_p is the time of peak intensity;

$t_b = t_p-t$, t is time.

3.2.3 Optimization Model

One of the objectives of stormwater management is to give optimal security at the lowest possible cost. (Yazdi et al., 2018; Girones et al. 2010). Numerous research have proven that optimization approaches can significantly aid in the discovery of effective flood control system design/rehabilitation procedures. In the optimization step in the proposed framework, we adopted GA to conduct the optimization process through the multi-objective optimization tool of non-dominated sorting genetic algorithm II (NSGA-II) in MATLAB version R2019b. GA could work well on mixed discrete and continuous problems. The multi-objective algorithm applied in the optimization tool is regulated (a variant of NSGA-II) (Zhen et al. 2004). Because the magnitude of the objective function is employed directly in the search rather than derivative information, GAs can be used to solve nonconvex, highly nonlinear, and complicated problems (Goldberg 1989). The mixed-integer problem in multi-objective GA provided by MathWorks has been solved in this framework to ensure that the location variable works properly (MathWorks Support Team 2018).

The optimization model was used to find the optimal volume and location of storage units as well as the number of storage units using two objective functions. Two opposing objective functions were determined to be flood reduction efficiency maximization and total cost minimization. The decision variables include volume, locations and number of storage units. In this study, three variants of the framework were developed based on different methods used for the selection of candidate sub-catchments for storage unit implementation (see Table 3.1). The candidate locations for storage unit implementation in general depend on the hydraulic state of the system under the design storm obtained from the SWMM model. However, three different selection process used in three different variants of the framework based on: (i) flooding nodes (ii) a sensitivity index (Equation 3-4), and (iii) flooding volume and node depth for the three frameworks, respectively. The range of volume for the storage unit is from zero to maximum allowable volume of storage unit. The number for storage unit is linked to the candidate locations, which is obtained from the different methods based on the hydraulic state of the system under the design storm obtained from the SWMM model. The sensitivity index is estimated as shown in Equation 1:

$$\boldsymbol{I} = \boldsymbol{I_1} + \boldsymbol{I_2} \qquad (3\text{-}4)$$

$$I_1 = \left(-\frac{\Delta V_F}{\Delta MV_S}\right)_J \qquad (3\text{-}5)$$

$$I_2 = \left(-\frac{\Delta T_F}{\Delta MV_S}\right)_J \qquad (3\text{-}6)$$

Where I_1 is the sensitivity index used to evaluate the sensitivity of sub-catchment J in the drainage system based on the flooding volume, and I_2 is the sensitivity index used to assess junctions in the drainage system based on flooding time. ΔV_F is the reduction in flooding volume of the drainage system after implementing a storage unit at sub-catchment J (10^3 m^3).MV_S is the actual maximum storage volume of the storage units at specific nodes (10^6 ltr). ΔT_F is the reduction in flooding time of the drainage system after implementing a storage unit at sub-catchment J (hrs);

Table 3.1 Indexes of three Frameworks

Decision Variables[1]	Framework 1	Framework 2	Framework 3
Candidate Locations for Storage Unit Implementation	All flooding nodes (sub-catchments) and upstream nodes	Based on a Sensitivity Index using flooding volume and flooding time	Based on the flooding volume (first priority) and node depth (second priority)

[1] Decision variables for Frameworks 2 and 3 were further selected based on the variables (flooding nodes) in Framework 1.

3.2.3.1 Flood reduction efficiency

The over-flooding reduction efficiency is determined by Equation 3-7. This objective function R aims to maximize the sum of flooding time reduction and over-flooding volume reduction associated with different storage unit implementation strategies:

$$\text{Maximize: } \mathrm{R} = 0.5\alpha + 0.5\beta \qquad (3\text{-}7)$$

In which α is the over-flooding volume reduction and β is flooding time reduction.

$$\alpha = \frac{\sum_{i=1}^{n} V_i - \sum_{j=1}^{N} V_j}{\sum_{i=1}^{n} V_i} \qquad (3\text{-}8)$$

Where V_i is the flood volume (m^3) of the ith node of original sewerage system;

V_j is the flood volume (m^3) of the jth node of optimized sewerage system;

n is the flooding nodes number of original sewerage system;

N is the flooding nodes number of optimized sewerage system.

$$\beta = \frac{\sum_{i=1}^{n} T_i - \sum_{j=1}^{N} T_j}{\sum_{i=1}^{n} T_i} \qquad (3\text{-}9)$$

Where T_i is the flood time (hrs) of the ith node of original sewerage system;

T_j is the flood time (hrs) of the jth node of optimized sewerage system;

n is the flooding nodes number of original sewerage system;

N is the flooding nodes number of optimized sewerage system.

3.2.3.2 Total Cost

The total cost considers both the direct cost for storage unit implementation and the indirect cost for flooding as a penalty function. This objective function takes into account the location in the cost estimation as the costs are dependent on location as the storage unit implementation and flooding costs vary from one sub-catchment to another (Equation 3-10). For storage unit cost, we consider two assumptions to ensure the framework can appropriately respond to various situations: (i) the storage unit cost is not expensive (relative to the flooding cost), see Equation 3-11 and (ii) storage unit is expensive (Equation 3-12).

$$\text{Minimize}: \ \mathrm{C} = C_1 + C_2 \qquad (3\text{-}10)$$

$$Storage\ \ Unit\ Cost\ \mathrm{C}_1 = \sum_{s=1}^{S} \varepsilon_{sc} \times Volume_s^{W_1} \quad (3\text{-}11)$$

$$Storage\ Unit\ \ Cost\ \mathrm{C}_1 = S \times \mathrm{B} + \sum_{s=1}^{S} \varepsilon_{sc} \times Volume_s^{W_1} \quad (3\text{-}12)$$

Where C_1 is the cost of storage units;

$Volume_s$ is the actual maximum storage volume;

S is the total number of storage unit;

B is the construction cost for storage units;

ε_{sc} is the location cost coefficient (different region has different value);

W_1 is the exponent/weighting coefficient.

$$Flood\ Cost\ C_2 = \begin{Bmatrix} \sum_{f=1}^{F} \gamma_{sc} \times {V_{f,st}}^{W_2} + \emptyset_{sc} \times {T_{f,st}}^{W_3} & ;\ (V_{f,st} > V_{f,allow}) \\ 0 & ;\ (V_{f,st} \leq V_{f,allow}) \end{Bmatrix} \quad (3\text{-}13)$$

Where C_2 is the flood cost as a penalty function;

γ_{sc} is the location cost coefficient associated with flood volume;

$\emptyset_{sc}$ is the location cost coefficient associated with flood time;

$V_{f,st}$ is the overflow (m^3) with storage units replacement at flow location f;

$V_{f,allow}$ is the maximum allowable overflow (m^3) at flow location f;

$T_{f,st}$ is the overflow duration (hours) with storage units replacement at flow location f;

W_2 is the flooding volume weighting coefficient;

W_3 is the flooding duration weighting coefficient;

3.3 Test Cases

3.3.1 Hydraulic Model

The proposed framework was tested in a real sewerage system. The drainage area was 196.72 ha, with an average slope of 1.3%, 54.24% impervious area that accounts for the total area. The drainage system consisted of 40 sub-catchments and 41 main pipes (Figures 3.2 and 3.3). To establish the hydraulic model using SWMM, urban drainage system including hydrologic and hydraulic state, and rainfall condition are required. The layout of the drainage system used for the test case in this study is obtained from Jiang et al. 2015, and the size and slope of the pipes are designed based on the historical design rainfall for Ottawa (See Table A1).

The original system was designed for the 5-year 3-hour Chicago designed rainfall, with Peaking-Time-Ratio r=0.488 (see Figure 3.2), and other parameters has presented in Equation 3-14.

$$i = 459.7(t - 0.005)^{-0.699} \quad (3\text{-}14)$$

Where *i* is the average rainfall intensity (mm/hr) and t is the storm duration (minutes). The SWMM hydraulic model output provides the flooding time and volume required to calculate the system overflow (see Equations 3-15 and 3-16), which are finally used to calculate the flood reduction efficiency.

$$\mathrm{T} = T_1 + T_2 + \cdots + T_n \qquad (3\text{-}15)$$

$$\mathrm{V} = V_1 + V_2 + \cdots + V_n \qquad (3\text{-}16)$$

Where T is the total flooding time of the sewerage system and V is the total over-flooding volume of the sewerage system, with n be the total number of flooding nodes (sub-catchments).

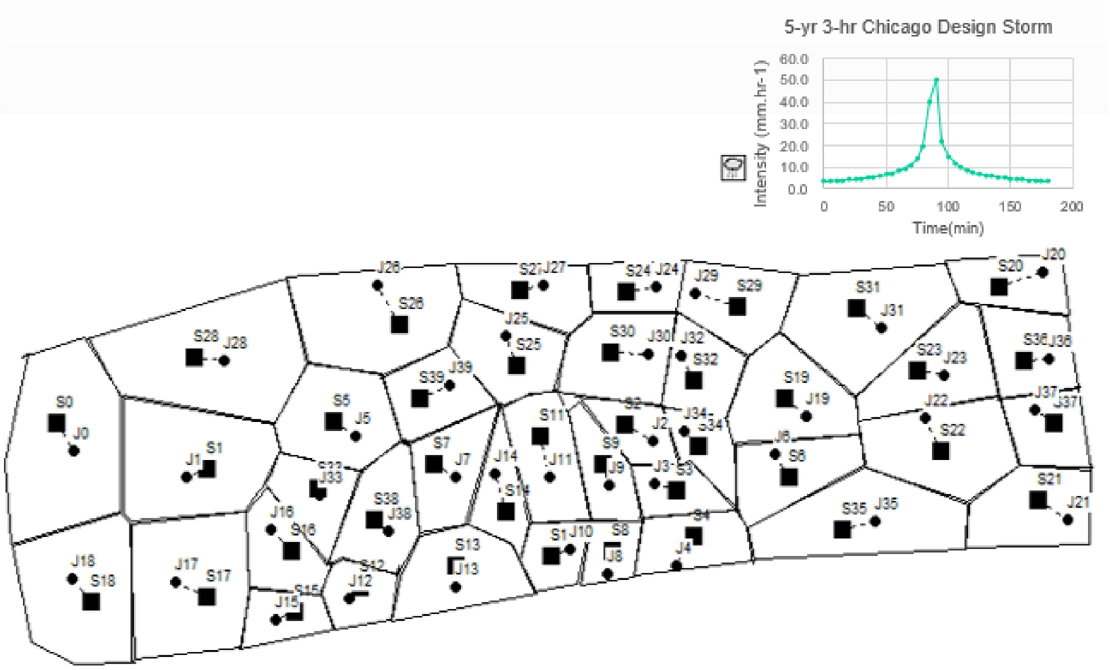


Figure 3.2. Layout of sub-catchments and Chicago design storm in study area (S: Sub-catchments; J: Junctions)

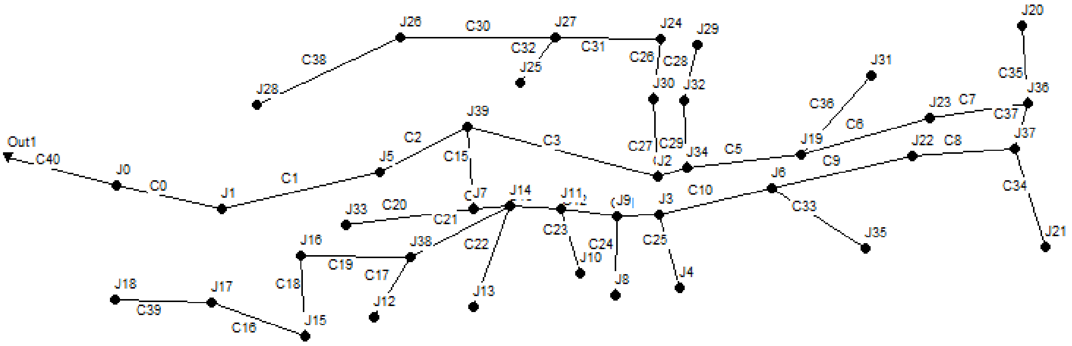


Figure 3.3 Drainage network of study area (C: Conduits)

3.3.2 Optimization Model

To test the framework properly, we designed three synthetic test cases with narrow pipes in the network in order to assess the “optimal” storage unit implementation strategies provided by various variants of the proposed framework. The details of test cases are summarized in Table 3.2. In Case 1 we test the framework fundamentals with the simplest test case. For Case 2, we made two narrow pipes in the proposed drainage network and simply tested the optimization model, and gave special configuration for storage unit cost for selected locations, and tested whether the framework would avoid an extremely high cost strategy via choosing other optimal strategies. Then, For Case 3, we made a narrow pipe further downstream in order to generate more flooding nodes. This case provides a good test case when the number of decision variables grow significantly, which in turn makes the optimization process more challenging and time consuming. Adopting this case allows to test the proposed framework with a more complex situation that enable us to examine the performance of different methods for selecting candidate sub-catchments for storage unit implementation. In addition, we conducted sensitivity analysis considering different population sizes, which allowed us to test whether higher population size can generate more accurate and optimal strategies.

To take into account the regional variation of sub-catchments that can affect the cost function, the study area was divided into five regions (Figure 3.4).Region E was set to have higher costs associated with the storage unit implementation and flooding (e.g. due to the space limitation and profound adverse flooding consequences). The “optimal” strategy that includes the size, location and number of storage units is determined by the proposed framework, which generates a Pareto front containing optimal solutions for the drainage network. Figures 3.5 to 3.7 illustrate the details for the three test cases with narrow pipes and show the flooding nodes. Table 3.3 summarizes the decision variables that must be considered after selecting based on three indices. Case 1 is the simplest case where all framework variants are expected to work the same. This test case is designed to examine the fundamentals of the framework. Case 2 is designed to show that considering all flooding nodes and upstream nodes in the optimization process is not feasible, and that is why this paper proposed different selection methods to reduce the solution space by removing non-effective solutions (Framework 2 and 3). The comparison for Framework 2 and 3 shows that in complex cases with several decision variables, the selection process based on a sensitivity index can be more effective than one base on flooding volume/depth, given that Framework 3 need one more step to select the flooding nodes. Based on the selection method, Framework 2 and 3 focus on optimizing the implementation of storage units that are effective for improving the flood resiliency. Therefore, Frameworks 2 and 3 are flexible and more feasible in providing storage units implementation strategies for various scenarios with different number of storage units. After selection process for Framework 2 and 3, Case 2 and 3, which tend to be more complex, can be briefly test by the system under less number of flooding nodes, and the selected nodes are located in critical junctions, which can show that the selection method for Framework 2 and 3 is rational. Test cases will be further discussed in the following sections.

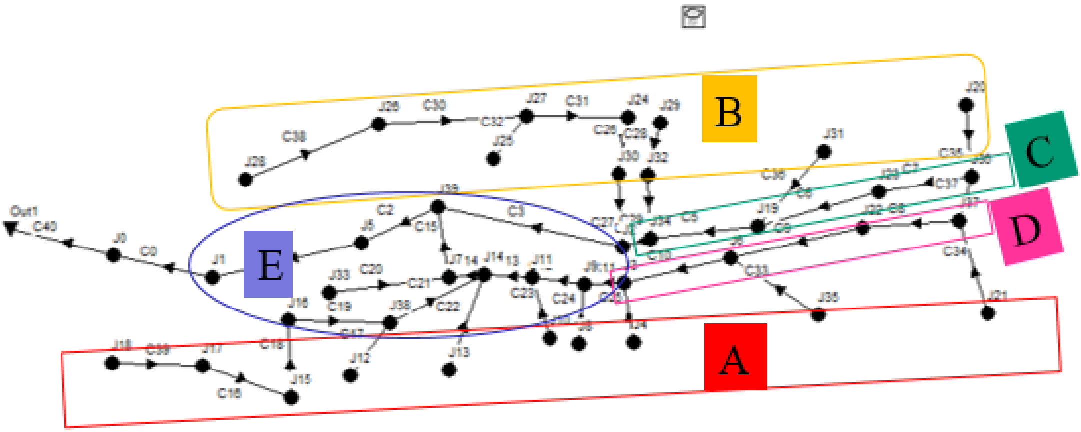


Figure 3.4 Zone for Location Cost Coefficients

Table 3.2 Details of test cases

Classification	Case name	Description	Function
System and Cost function	Case 1	Drainage system with one narrow pipe and set extremely high storage	Test the model as to whether it works properly when we know the solution for only one decision variable.

Testing		cost	
Hydraulic	Case 2	Drainage system with two narrow pipes	Simple system used to test whether it could select the proper scenario of storage unit, and do sensitivity analysis[1]. And test whether it could avoid the scenario with extremely high storage cost and find another proper scenario for the storage unit.
Multiple flooding nodes	Case 3	Drainage system with one narrow pipe very far downstream (many flooding nodes)	More complex system used to test whether it could select the proper storage unit scenario, and perform sensitivity analysis[1].

[1] Sensitivity analysis is used to test the impact of population size in the optimization model.

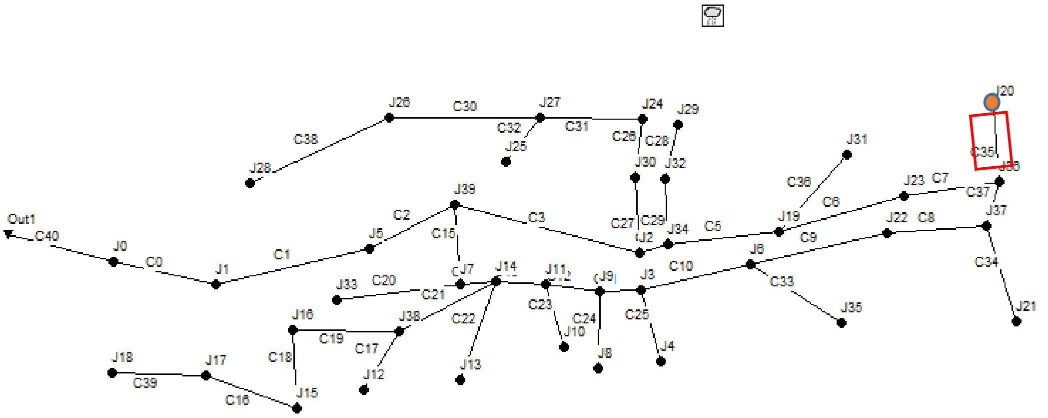


Figure 3.5 Narrow pipe C35 and flooding nodes demonstration for Case 1.

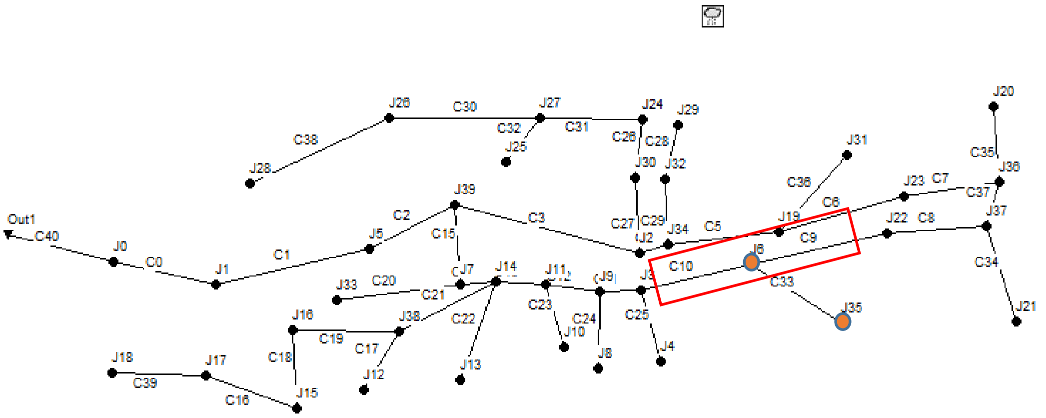


Figure 3.6 Narrow pipes C9 and C10, and flooding nodes demonstration for Case 2.

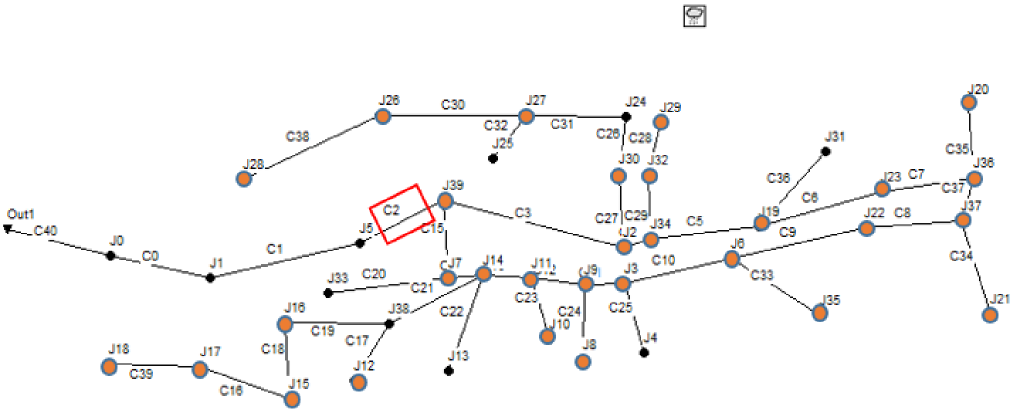


Figure 3.7 Narrow pipe C2 and flooding nodes demonstration for Case 3.

Table 3.3 Decision variables for 3 Cases in 3 Frameworks

	Framework 1	Framework 2	Framework 3
Case1	J20	J20	J20
Case2	J6 J35 J22 J37 J21	1 Storage unit (J6) 2 Storage units (J6 J35) 3 Storage units (J6 J35 J22)	1 Storage unit (J6) 2 Storage units (J6 J35) 3 Storage units (J6 J35 J22)
Case3	J2 J3 J4 J6 J7 J8 J9 J10 J11 J12 J13 J14 J15 J16 J17 J18 J19 J20 J21 J22 J23 J24 J25	1 Storage unit (J39) 2 Storage units (J39 J14) 3 Storage units (J39 J14 J19) 4 Storage units (J39 J14 J19 J38)	1 Storage units (J39) 2 Storage units (J39 J14) 3 Storage units (J39 J14 J7) 4 Storage units (J39 J14 J7 J17)

	J26 J27 J28 J29 J30 J31 J32 J33 J34 J35 J36 J37 J38 J39	5 Storage units (J39 J14 J19 J38 J6) 6 Storage units (J39 J14 J19 J38 J6 J16)	5 Storage units (J39 J14 J7 J17 J15) 6 Storage units (J39 J14 J7 J17 J15 J18)

3.4 Results and Discussion

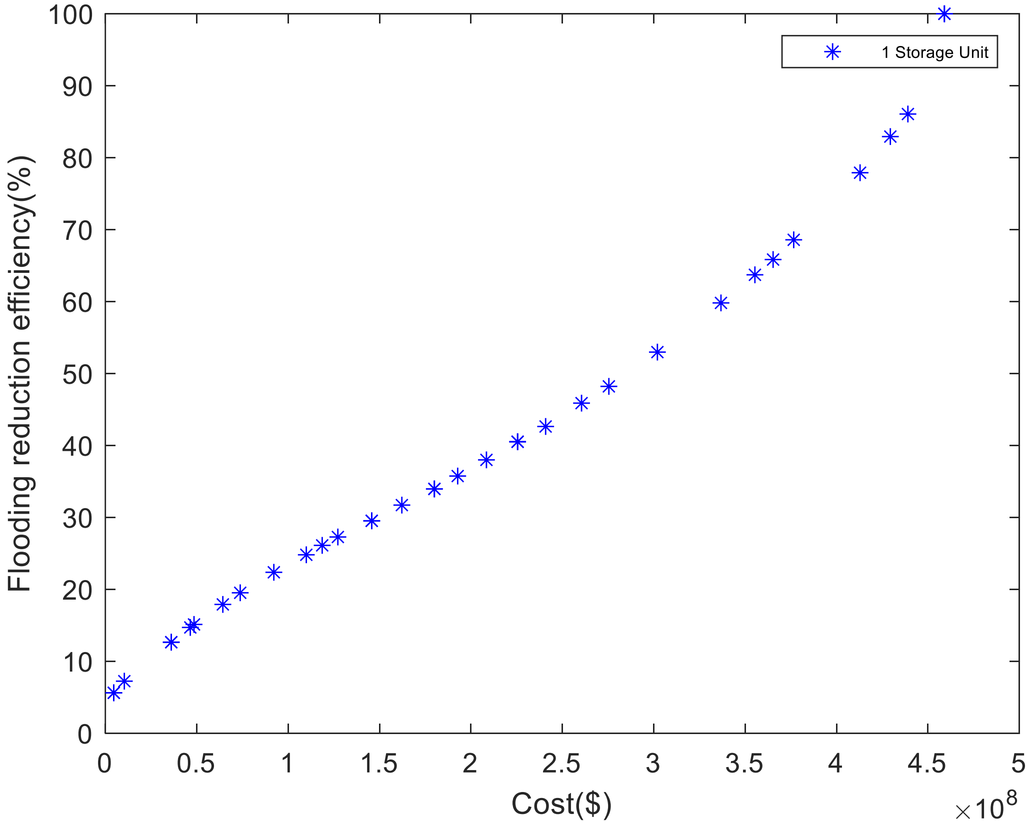
The proposed multi-objective optimization framework is developed to provide optimal strategies for implementation of storage units in urban drainage networks that can enhance the system resiliency. Three variants of the framework were developed. Framework 1 considered flooding nodes and nodes upstream as potential location for implementation of storage unites. This can result in large number of decision variables for complex cases where the solution space can become very large. In order to make the optimization process more feasible Framework 2 and Framework 3 were developed by adding a selection method, which selected the candidate nodes for storage unit implementation based on a sensitivity index and node criticality index, respectively. The selection method in Framework 3 is based on flooding volume and time, while in Framework 2 the proposed method selected candidate nodes based on the sensitivity of the nodes to the reduction of the flood after implementing a storage unit. The proposed framework was applied to three test cases to examine the performance of different variants of the framework.

3.4.1 Case 1: System and Cost function Testing

The objective of Case 1 was to test the framework fundamentals with the simplest test case. Case 1 only includes one narrow pipe at one of the most upstream sub-catchments whose surcharge result in only one flooding node (i.e. one decision variable). As there is only one potential candidate for storage unit implementation, all variants of the framework will hold the same results. We tested the proposed framework under two assumptions to ensure it can appropriately respond to various situations: (i) the storage unit cost is not expensive (relative to the flooding cost) and (ii) storage unit is expensive.

The solution for Case 1 under low storage cost showed that the implementation of a storage unit at J20 could achieve 100% reduction efficiency, with storage unit area of 985 m^3, and computational cost (CPU time) of 38 minutes. In this case, the model identified the flooding node, then implemented a storage unit, and determined the proper storage volume. The proposed model provided strategies to replace the flooding node and accommodated more runoff successfully. It should be noted that despite having two objective functions, due to the relatively low storage unit cost, the solutions on Pareto front converges to a single solution.

The result for Case1 under relatively high storage unit cost assumption is presented in Figure 3.8. As can be seen, the model is capable of finding more solutions on the Pareto front as the prohibitive storage cost can results in solutions where flooding is allowed. The results indicated that the model worked properly and found reasonable solutions with trade-off between the economic concerns and resiliency.



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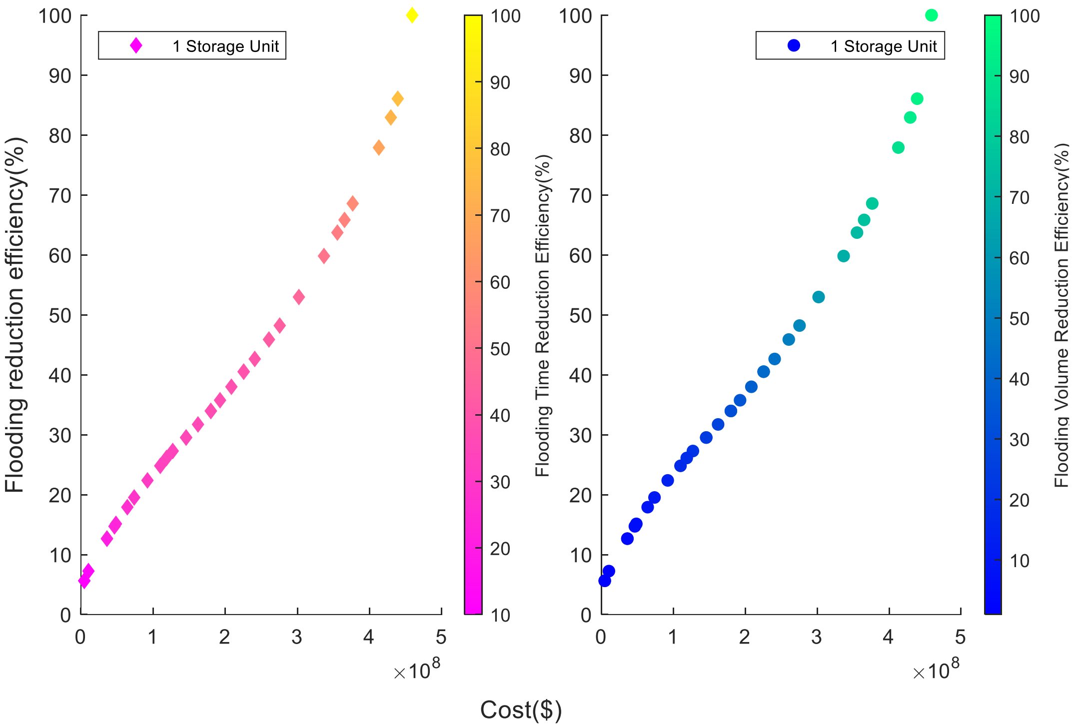

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Figure 3.8. (a) Solutions for Case 1 in Framework 1. (b) The flooding time and flooding volume reduction efficiency, respectively.

3.4.2 Case 2: Hydraulic Scenario

The objective of Case 2 test was to test the proposed methodology to a case that closer to reality but is still relatively simple. This test case includes more potential locations for implementation of storage units at the upstream of the flooded nodes, which can present a challenging situation for the optimization model as the solution space becomes very large. Therefore, in addition to the original framework (Framework 1) we apply new variants of the framework (i.e. Frameworks 2 and 3) to overcome this issue. Similar to Case 1 we tested the frameworks under two assumptions where (i) the storage unit cost is not expensive (relative to the flooding cost) and (ii) storage unit is expensive.

Case 2 in Framework 1 has five sub-catchments (J6 J35 J22 J37 J21) as candidates for implementation of storage units including flooding nodes and nodes upstream. The results of Framework 1 with low storage cost are presented in Table 3.4, where five storage units among the five candidates are selected with storage unit maximum volume summarized in the table. When we set low storage unit cost, similar to Case 1, Framework 1 converges to a single solution with 100% flood reduction. The results of Case 2 in Framework 1 with high storage cost are shown in Figure 3.9. The comparison between low and high storage costs shows that, when storage cost increased, the proposed model could reasonably provide a wider range of solutions.

Table 3.4 Framework 1 Results for Case 2 under low storage cost assumption - (five locations as candidate: J6 J35 J22 J37 J21)

	Storage unit Maximum Volume($1000m^3$)	Final Locations	Number of Storage units
Solution	0.988/1.905/ 1.410/0.724 /1.394	J6 J35 J22 J37 J21	5
Flooding reduction (%)	100%		
Total Cost ($)	1.35×10^6		

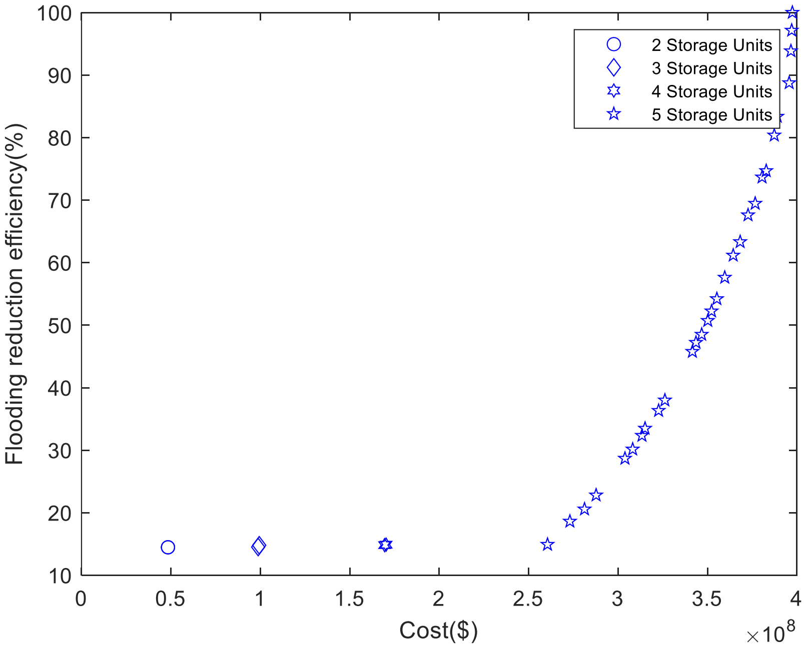

Figure 3.9. Framework 1 Results for Case 2 with five candidate locations under high storage unit cost assumption.

Frameworks 2 and 3 were applied to Case 2. Framework 2 employed the sensitivity index to sort the nodes and determine decision variables (candidate locations), while Framework 3 used the flooding volume to sort the nodes, with the node depth as the second priority when the flooding volume was zero at the node (see Tables 3.5 and 3.6). As can be inferred from these tables, if up to three storage units are to be implemented, the candidate locations will be the same between the two frameworks. Unlike Framework 3, if more than three storage units are to be implemented, Framework 2 does not provide any further priority. We ran the multi objective optimization with the assumption of having different number of storage unites implemented in the network.

Table 3.5 Sensitivity Indexes for Case 2 - Framework 2

Node	Sensitivity Index
J6	187.7
J35	97.3
J22	0
J37	0
J21	0

Table 3.6 Node criticality indexes for Case 2 - Framework 3

Node	Total Flood volume(10^6 L)	Node depth if flooding is zero(m)
J6	2.589	-
J35	0	5.85
J22	0	3.28
J37	0	2.88
J21	0	2.41

Table 3.7 and Figure 3.10 present the results for Case 2 obtained from Framework 2 and 3. With considering only 1 storage unit under low storage unit cost assumption, Framework 2 and 3 converged into a single solution with implementing a storage unit at J6 with the storage unit maximum volume of 2614 m^3 and total cost of \$5.4×10^5 while

achieving 100% reduction efficiency. As for two decision variables (i.e. considering two potential storage units to be implemented) under low storage cost, the framework produced solutions with two storage units implemented at J6 J35 with the total cost CAD \$5.7×10^5 (see Table 3.7). When the model used a default population size 100, chose a smaller storage volume for J6 and achieved 100% reduction efficiency. After increasing population size, the model chose 2 storage units at J6 and J35 with smaller volume and higher cost efficiency. The results for Case 2 considering 1 storage unit and 2 storage units in Framework 2 & 3 with high storage cost have summarized in Figure 3.10 and Figure 3.11 respectively, which generate more solutions than frameworks with low storage cost. And higher flooding reduction efficiency means higher total cost for storage unit replacement. The advantage of the Pareto front with larger number of solutions is that decision maker could have more choices based on different conditions, like some cities make have different economic limitations, allowable flooding volume and time.

This results indicated that Framework 2 and 3 produced more reasonable solutions with higher cost efficiency. Framework 1 that considered all flooded nodes and upstream nodes as candidate locations was unable to identify the solution effectively, and failed to find reasonable feasible solutions, due to the large number of decision variables and large solution space. The computational cost for Framework 1 and Framework 2 & 3 - with the same population size - was 40 minutes, but Framework 2 & 3 generated better solutions with lower total cost and smaller storage number, which tend to be more reasonable. The comparison between the results obtained from Framework 1, 2 and 3 for Case 2 under high storage unit cost assumption are presented in Figure 3.12. The results show that Framework 1 have larger total cost than Framework 2&3, especially for Framework 1 with 5 storage units implemented. However, Framework 1 has lower flooding reduction efficiency under similar cost efficiency with Framework 2&3, which could show that Frameworks 2&3 work more effectively.

Table 3.7 Framework 2 and 3 Results for Case 2 under low storage cost assumption - (one and two Candidate locations: J6, J6 J35)

Storage unit Maximum Volume($1000m^3$)	1 Candidate Sub-catchment		2 Candidate Sub-catchments	
	(Population 100)	(Population 500)	(Population 100)	(Population 500)
J6	2.614	2.562	0.637	0.096
J35	NA	NA	2.318	2.820
Candidate Locations	J6	J6	J6 J35	J6 J35
Number of Storage units	1	1	2	2
Flooding reduction (%)	100%	100%	100%	100%
Total Cost ($)	5.4×10^5	5.3×10^5	5.7×10^5	5.2×10^5

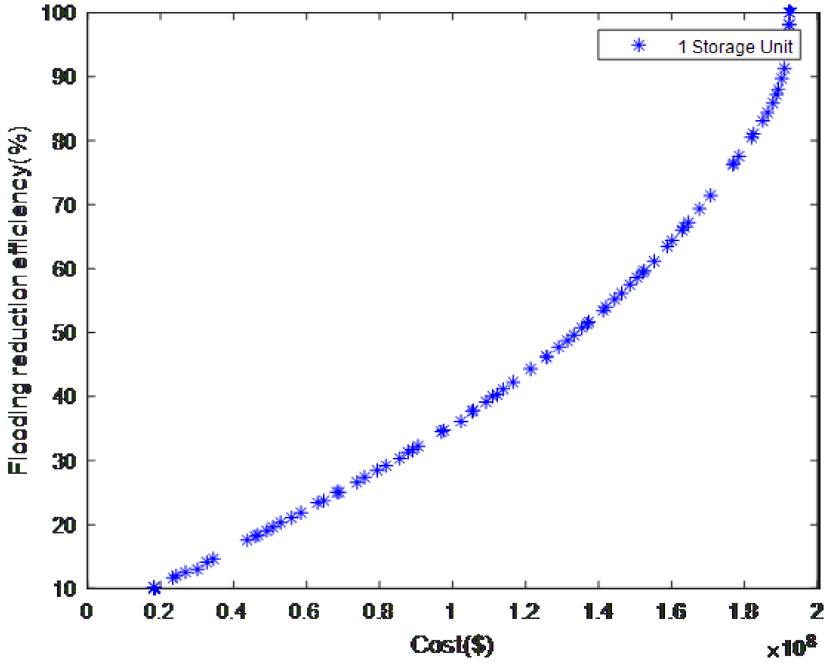

Figure 3.10. Framework 2 and 3 Results for Case 2 with one candidate location under high storage unit cost assumption.

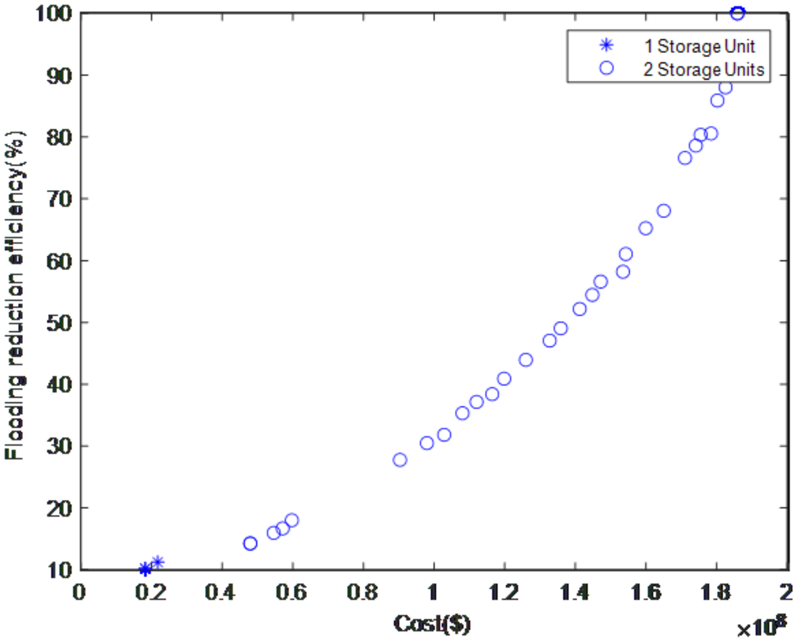

Figure 3.11. Framework 2 and 3 Results for Case 2 with two candidate locations under high storage unit cost assumption.

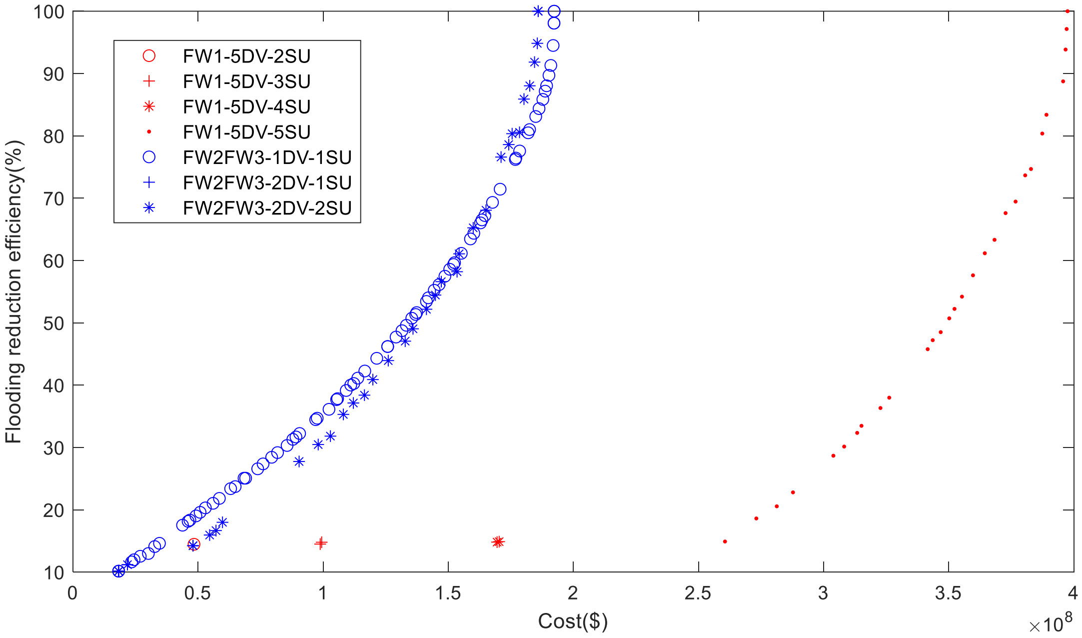

Figure 3.12. Framework 1, 2 and 3 Results for Case 2 with different number of candidate locations under high storage unit cost assumption.

In this test case, we further tested the framework by significantly increasing the storage cost unit to a prohibitive cost for a specific sub-catchment (J35), which was one of the locations selected by the model for a storage unit implementation in a normal cost scenario. With this test, we examine whether the model can choose other solutions by avoiding sub-catchments with prohibitive costs. The results (Table 3.8) show that the model tends to reduce the storage volume for sub-catchment J35, with lowest storage unit maximum volume under default population size, and achieve 100% reduction efficiency. The comparison between Case 2 under 2 candidate locations without prohibitive cost for any locations and with prohibitive cost for J35 shows that framework is capable of selecting lowest storage unit volume for J35 to avoid higher total cost. We also tested the effect that the population size may have on the results.

Table 3.8 Frameworks 2 and 3 Results for Case 2 under prohibitive storage cost assumption for J35 - (two Candidate locations: J6 J35)

Storage unit Maximum Volume($1000m^3$)	2 Candidate Sub-catchments	2 Candidate Sub-catchments
	(Population 100)	(Population 500)
J6	2.678	2.670
J35 (prohibitive cost)	0.001	0.001
Candidate Locations	J6 J35	J6 J35
Number of Storage units	2	2
Flooding reduction (%)	100%	100%
Total Cost (CAD)	39.75×10^7	39.70×10^7

3.4.3 Case 3: Multiple flooding nodes Scenario

The objective of Case 3 was to apply the developed framework to a more complex case and see how the system responds to a large number of decision variables. Since Case 3 includes one narrow pipe far downstream in the network, there are 37 candidate locations for storage unit implementing. Similar to previous cases, we tested frameworks under two conditions (i) the storage unit is not expensive (relative to the flooding cost) and (ii) storage unit is expensive.

Framework 1 for Case 3 had 37 candidate locations (decision variables) with a large solution space. The results under low storage cost assumption shows that final solution could achieve 100% flood reduction efficiency, with the total cost of 8.9×10^6 while 37 storage units implemented. Framework 1 considered all flooding nodes and upstream nodes, and it resulted in a high number of decision variables and resulted in a large solution space, which in turn was not beneficial for the optimization process.

In order to address the issue of large number of decision variables in Framework 1, Frameworks 2 and 3 were applied to case 3, that select decision variables based on proposed indexes. Tables D1 and D2 present the sensitivity index and node criticality index, respectively. As these tables show, for the specific number of storage units to be implemented, Frameworks 2 and 3 select different decision variables (i.e. candidate locations).

Table 3.9 shows the results for Case 3 obtained from Framework 2 under low storage unit cost assumption. The final solutions for Case 3 achieved high reduction efficiency, and total cost, storage volume and storage number were lower than Framework 1. The comparison between Frameworks 1 and 2 under low storage cost showed that Framework 2, with reducing the number of decision variables through the proposed sensitivity index, worked effectively and produced more reasonable solutions, close to an optimal solution.

Table 3.10 shows the results for Case 3 obtained from Framework 3 under low storage cost. The comparison between Frameworks 1 and 3 under low storage cost shows that Framework 3 worked effectively and produced more reasonable solutions. Framework 1 failed to identify feasible solutions, and chose 37 storage units within 37 location candidates. The comparison between Frameworks 2 and 3 will be discussed further.

Table 3.9. Case3 (J39 J14 J19 J38 J6 J16) storage unit maximum volume ($1000m^3$) in Framework 2 under low storage cost assumption

Candidate Sub-catchment	1	2	3	4	5	6
Population	100	100	100	100	100	200
J39	24.547	7.411	2.246	1.203	3.077	2.576
J14		14.559	0.544	24.806	9.540	16.259
J19			25.152	8.167	8.007	8.102
J38				2.866	8.469	1.886
J6					5.149	0.319
J16						6.282
Total Cost (CAD)	3.824×10^6	3.832×10^6	4.164×10^6	5.812×10^6	6.206×10^6	6.322×10^6

Table 3.10. Case3 (J39 J14 J7 J17 J15 J18) Storage unit Maximum Volume ($1000m^3$) in Framework 3 under low storage cost assumption

Candidate Sub-catchment	1	2	3	4	5	6
Population	100	100	100	100	100	200
J39	24.547	7.411	9.120	10.567	1.074	5.235
J14		14.559	9.976	10.020	20.878	1.310
J7			2.701	4.514	2.793	17.608
J17				5.549	4.906	2.193
J15					1.310	2.476
J18						2.693
Total Cost (CAD)	3.824×10^6	3.832×10^6	4.005×10^6	5.420×10^6	5.235×10^6	5.524×10^6

The comparison between Frameworks 2 and 3 under low storage cost is presented in Table 3.11. For 1 and 2 decision variables, Framework 2 and Framework 3 have the same nodes and led to the same results. From 3 decision variables to 6 decision variables, Framework 3 generated more optimal solutions than Framework 2 under the same conditions, with lower total cost and the same reduction efficiency (100%). Table 3.11 summarizes the solutions from Frameworks 2 and 3, including corresponding volume, locations and number of storage units.

Table 3.11. Case3 Storage unit Maximum Volume ($1000m^3$) in Frameworks 2 and 3

Number of Candidate Sub-catchments	1	2		3	4	5	6
Population size	100	100	500	100	100	100	200
F2/F3	F2/F3	F2/F3	F2/F3	F2/F3	F2/F3	F2/F3	F2/F3
J39	24.547/24.547	7.411/7.411	2.316/2.316	2.246/9.120	1.203/10.567	3.077/1.074	2.576/5.235
J14		14.559/14.559	19.458/19.458	0.544/9.976	24.806/10.020	9.540/20.878	16.259/1.310
J19 /J7				25.152/2.701	8.167/4.514	8.007/2.793	8.102/17.608
J38 /J17					2.866/5.549	8.469/4.906	1.886/2.193
J6 /J15						5.149/1.310	0.319/2.476
J16 /J18							6.282/2.693
Total Cost (CAD)	3.824×10^6	3.832×10^6	3.618×10^6	4.164×10^6 /4.005×10^6	5.812×10^6 /5.420×10^6	6.206×10^6 /5.235×10^6	6.322×10^6 /5.524×10^6

For another condition, high storage cost, Case 3 in Framework 1, 2 and 3 has been presented in Figure 3.13. Framework 2 and 3 under 1 and 2 candidate locations generate same location selections. The results show that Framework 2 and 3 have similar cost efficiency, and Framework 1 generate solutions with significantly higher cost efficiency. Framework 1 has large number of candidate locations (37 storage units) under high storage cost have lower cost efficiency among three frameworks, and the number of final storage units implemented is larger than Framework 2 and 3. The comparison among Framework 1, 2 and 3 shows that Framework 2 and 3 would generate proper and reasonable solutions with proper number of storage units, total cost. The detailed comparison between Frameworks 2 and 3 in Figure 3.13.b. shows that Framework 3 would generate relatively reasonable solutions with higher cost efficiency when it has four final storage unit implemented.

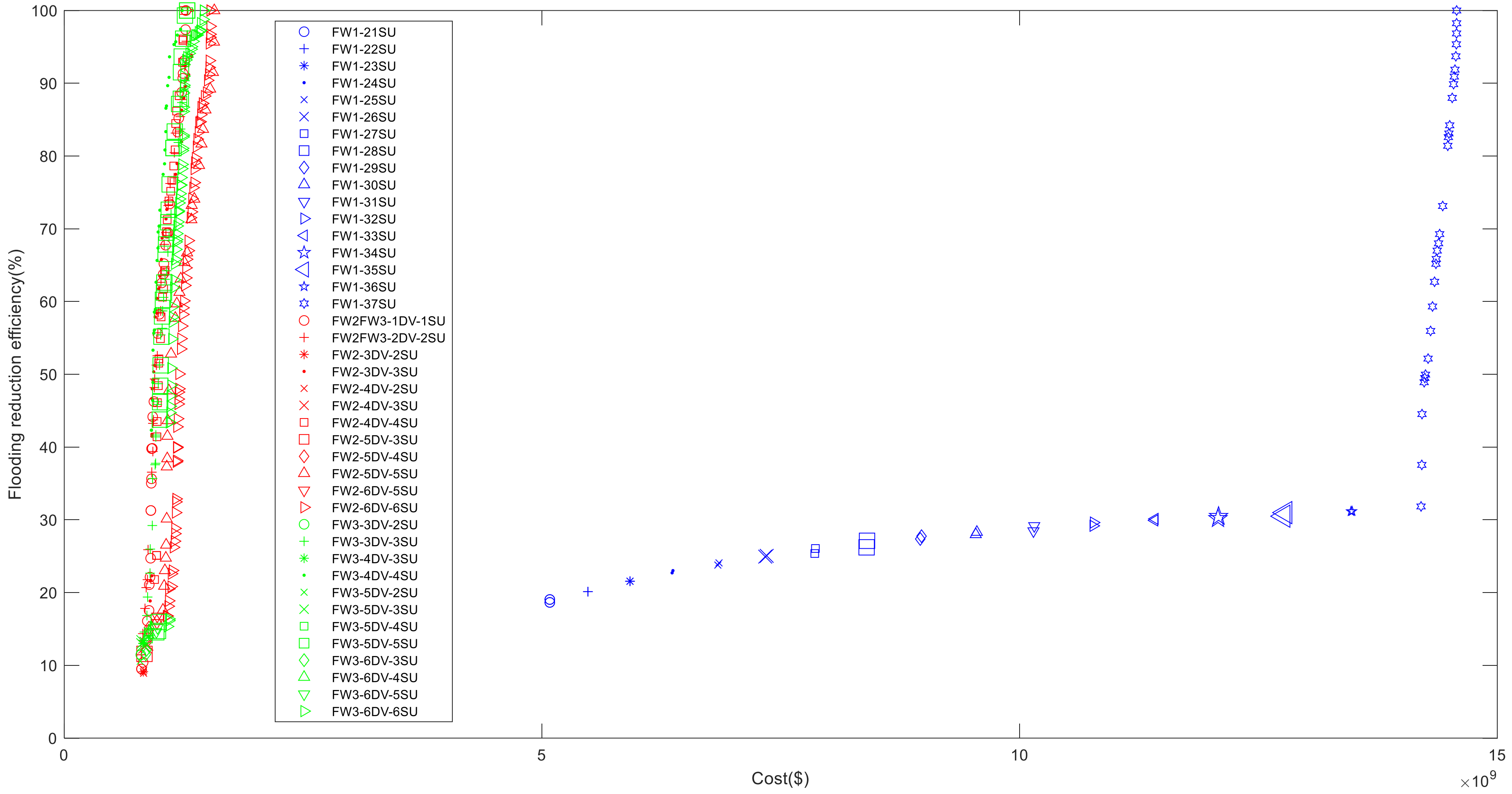

Figure 3.13.a. Framework 1, 2 and 3 Results for Case 3 with different number of candidate locations under high storage unit cost assumption.

(FW: frameworks; DV: decision variables; SU: storage units implemented).

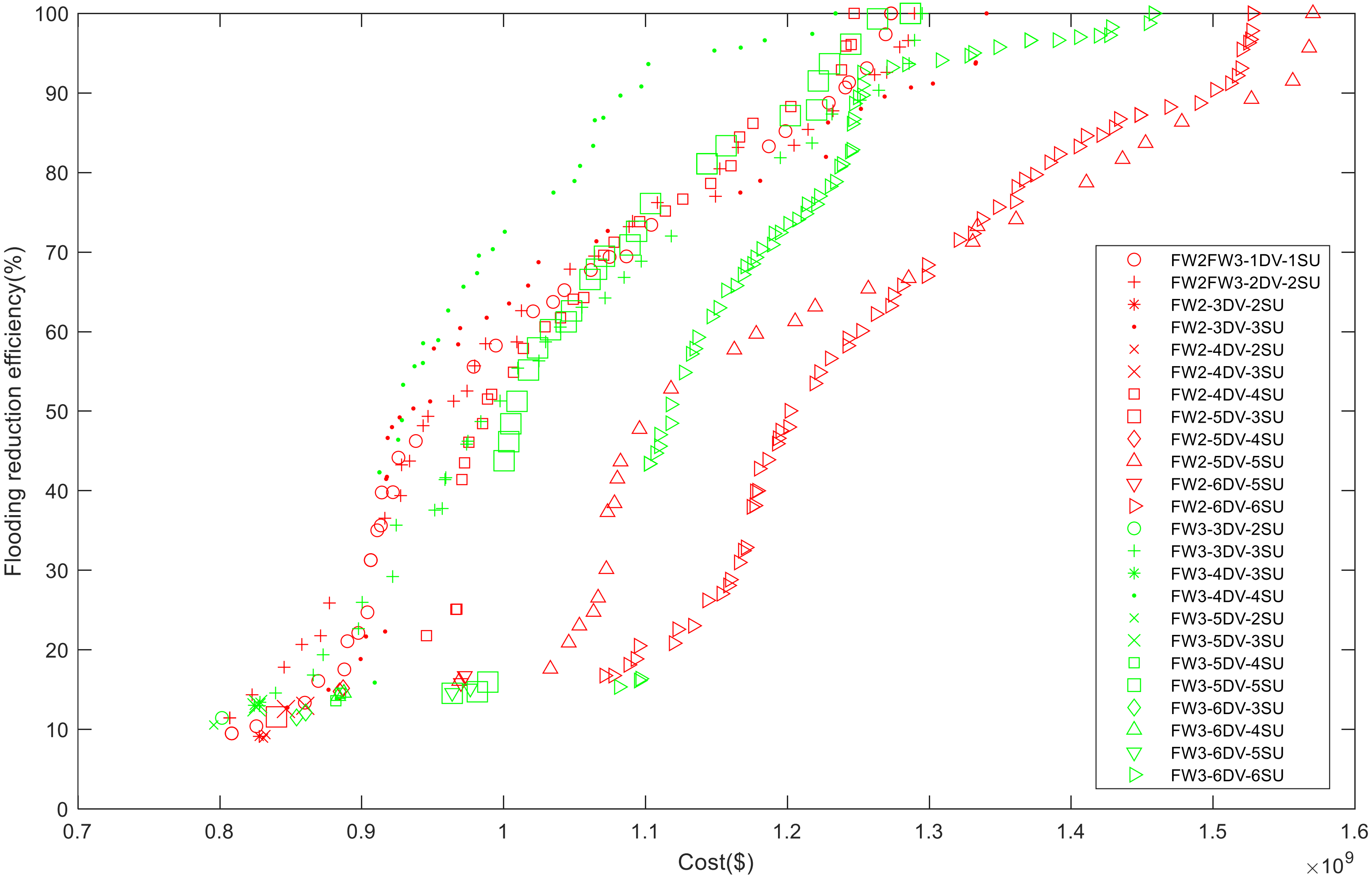

Figure 3.13.b. Framework 2 and 3 Results for Case 3 with different number of candidate locations under high storage unit cost assumption.

(FW: frameworks; DV: decision variables; SU: storage units implemented).

3.4.4 Sensitivity Analysis

We conduct a sensitivity analysis to assess the response of the optimization model to the change in the population size. We applied the framework to Case 2 and 3 for the sensitivity analysis (see Figures 3.14 and 3.15; Tables 3.12 and 3.13). For both cases, the results indicated that by increasing population size the optimization model generated strategies with lower total cost with the same flood reduction efficiency. The flooding reduction efficiency for Case 2 in Framework 1 is 100% for all solutions (Figure 3.14), and the cost efficiency tends to converge when population size over 1000. In addition, the results indicated that using larger population size results in the implementation of lower number of storage units at the candidate locations with lower volume for storage units. Figure 3.16 illustrates the computational cost for different population sizes for Case 2 and 3. The figure shows the population size in genetic algorithm versus calculation time, and as can be observed, the computation time did not converge. The run time is calculated via an 11th Gen Intel(R) Core(TM) i7-11800H CPU at 2.30GHz and with 16.0 GB (RAM).

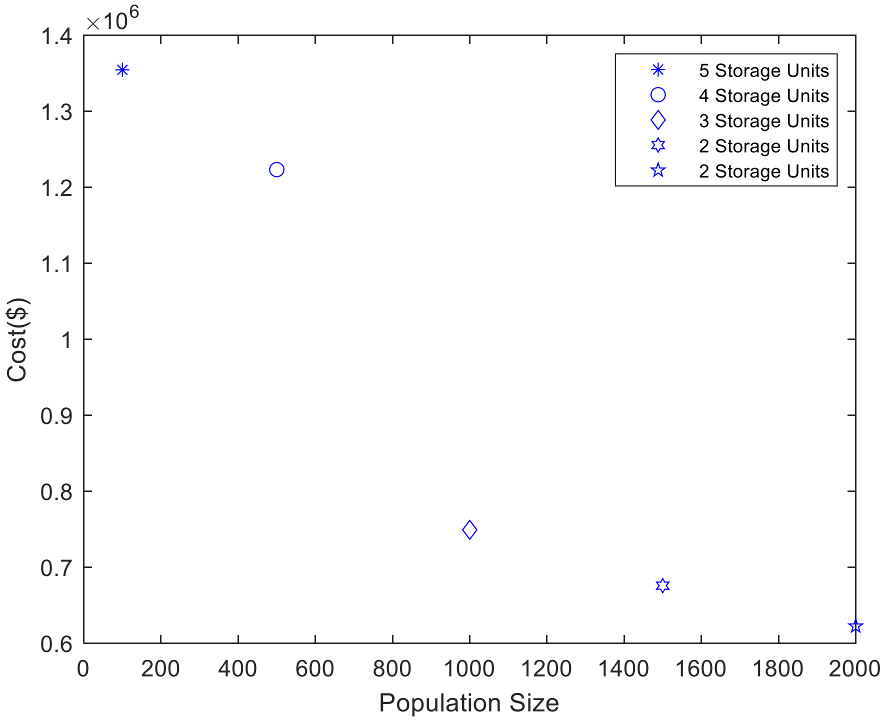

Figure 3.14. Cost Efficiency with different Population sizes for Case 2 in Framework 1 under low storage unit cost assumption (5 candidate locations).

Table 3.12. Framework 1 Sensitivity Analysis Results for Case 2 under low storage

unit cost assumption - (five candidate locations - J6 J35 J22 J37 J21)

	Population 100	Population 500	Population 1000	Population 1500	Population 2000
Storage unit Maximum Volume ($(1000m^3)$)	0.988/1.905/1.410/0.724/1.394	1.035/2.283/1.270/1.459	0.738/1.391/1.278	1.927/1.094	1.152/1.580
Location of Implemented storage units	J6 J35 J22 J37 J21	J6 J35 J22 J21	J6 J22 J21	J6 J22	J6 J37
Number of storage units	5	4	3	2	2

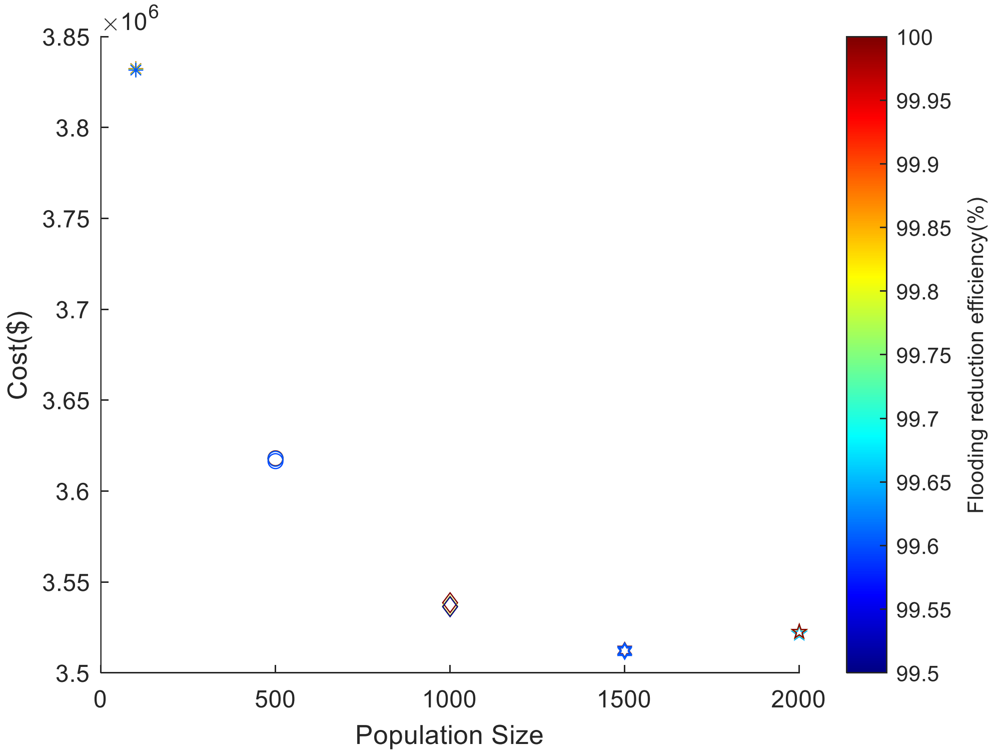

Figure 3.15. Cost Efficiency with different Population size for Case 3 (2 candidate locations) in Frameworks 2 & 3 under low storage unit cost assumption.

Table 3.13. Framework 2 and 3 Sensitivity Analysis Results for Case 3 under low storage unit cost assumption - (two candidate locations - J39 J14)

	Population 100	Population 500	Population 1000	Population 1500	Population 2000
Storage unit Maximum Volume $(1000m^3)$	7.411/14.559	2.316/19.458	0.347/7.923	0.200/8.191	0.267/7.951
Location of Implemented storage units	J39 J14	J39 J14	J39 J14	J39 J14	J39 J14
Number of storage units	2	2	2	2	2

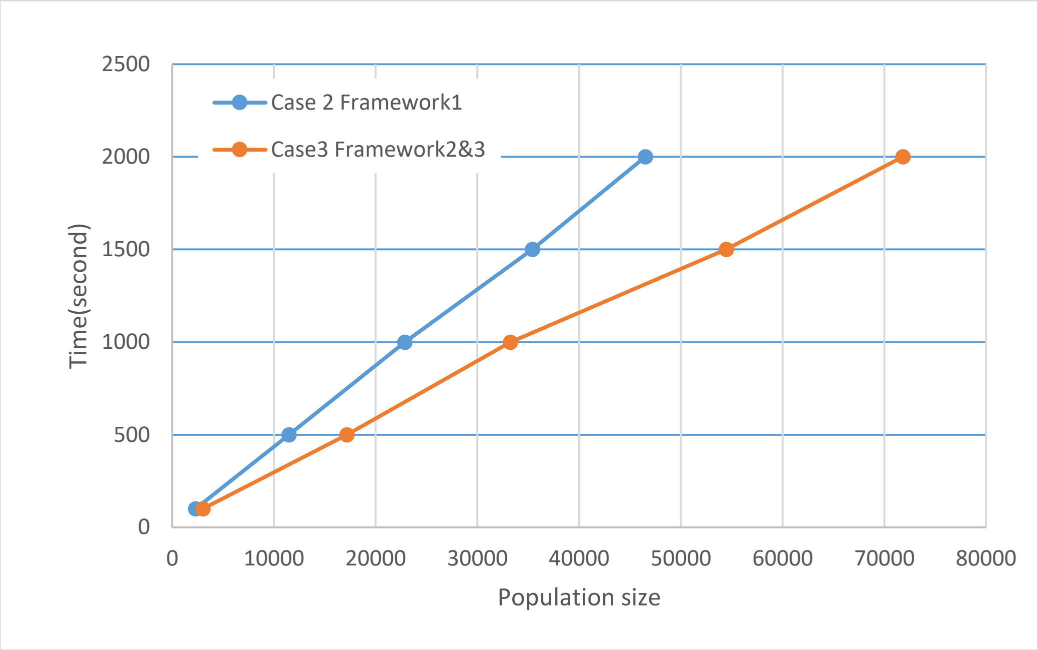

Figure 3.16. Computational cost for sensitivity analysis.

3.5 Conclusions

The proposed optimization system includes three frameworks with three different selection process used in three different variants of the framework based on: (i) flooding nodes (ii) a sensitivity index, and (iii) flooding volume and node depth for the three frameworks, respectively. For complex test cases with large number of DVs, Framework 2 and 3 with further selection processes have better performance than Framework 1. Framework 2 and 3 both can be considered in real cases which have the capability to find more accurate flooding nodes, replace the flooding nodes with storage units under different cases, and determine reasonable solutions. The final decision making for frameworks and solutions, based on the detailed consideration for decision maker, like computational cost, economic limitation, expectation for the final performance.

Chapter 4: Consideration of climate change in the framework

4.1 Introduction

Climate change is assumed to be the source of significant variations in the severity and frequency of extreme events over the previous several decades. In some locations, rising temperatures are expected to have a major impact on the severity and frequency of extreme precipitation events (Barnett et al., 2006; Wilcox et al., 2007). Future climate change may affect the urban drainage system significantly, and this factor will also be considered in the model to improve resilience. IDF CC tool allows users to quickly analyze the impact of climate change in the form of upgraded IDF curves for storm water drainage design and management (Schardong et al., 2020; Sandink et al., 2016). This chapter combining IDF CC tool with multi-objective framework 3 to test the model when we consider future climate change. As we tested three frameworks in previous chapter, Framework 3, which bases on node critically index considering flooding volume (first priority) and node depth (second priority), has better performance especially when system has large decision variables.

4.2 Test Case

This chapter was tested in a real sewerage system as Chapter 3. The drainage area was 196.72 ha, with an average slope of 1.3%, 54.24% impervious area that accounts for the total area. The drainage system consisted of 40 sub-catchments and 41 main pipes (see Figures 3.2 and 3.3).

The drainage system was designed for the future climate condition year 2050 under 5-year 3-hour Chicago designed rainfall. For future rainfall time series, we considered two scenarios, SSP1.26 and SSP5.85. After the simulation from SWMM, the result for hydraulic model shows the flooding nodes for the case with future climate condition under SSP1.26 scenario and SSP5.85 scenario (Figure 4.1 and 4.2). Figure 4.3 shows the different between historical and future rainfall time series. For SSP1.26, total flooding volume is 4.128 (10^6ltr) and total flooding time is 1.170 hours. For SSP5.85, total flooding volume is 6.271 (10^6ltr) and total flooding time is 1.640 hours. This case was applied in Framework 3 which based on the flooding volume (first priority) and node depth (second priority). Table D3 and D4 summarized the nodes criticality index of Case with future climate condition under different emission scenarios in Framework 3. The decision variables after selecting based on the index of Framework 3 for the case in this chapter has been summarized in Table 4.1, which include more detailed information for future climate scenario.

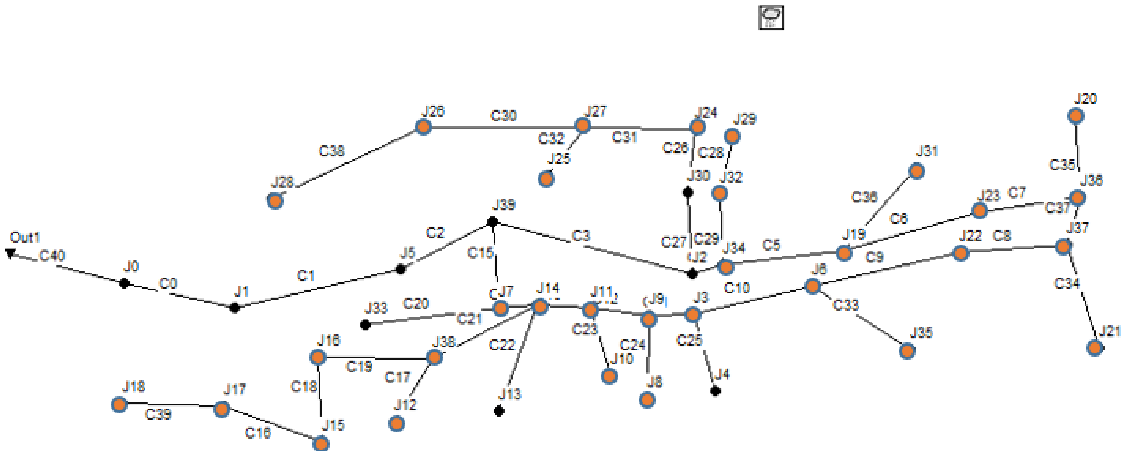

Figure 4.1 Flooding nodes demonstration for Case with future climate condition SSP1.26 (C: Conduits; J: Junctions)

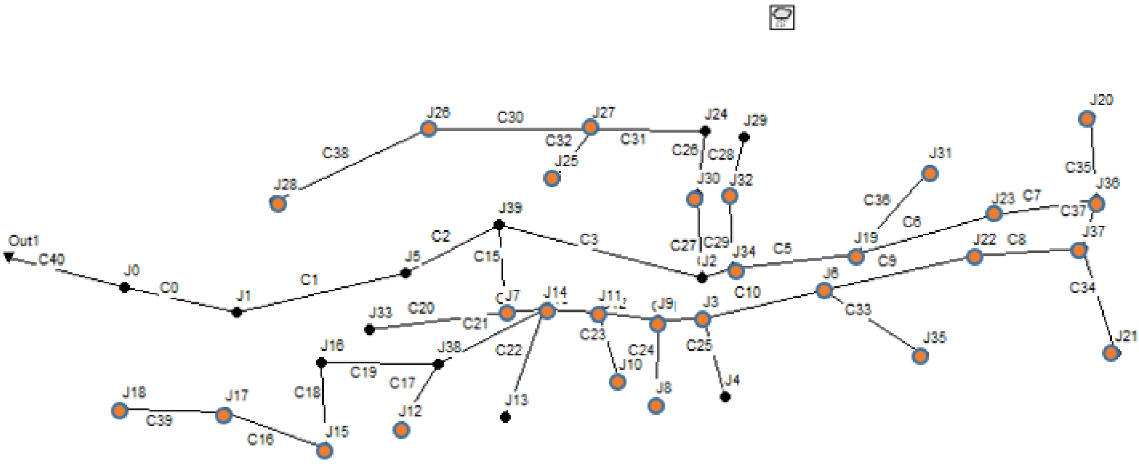

Figure 4.2 Flooding nodes demonstration for Case with future climate condition SSP5.85 (C: Conduits; J: Junctions)

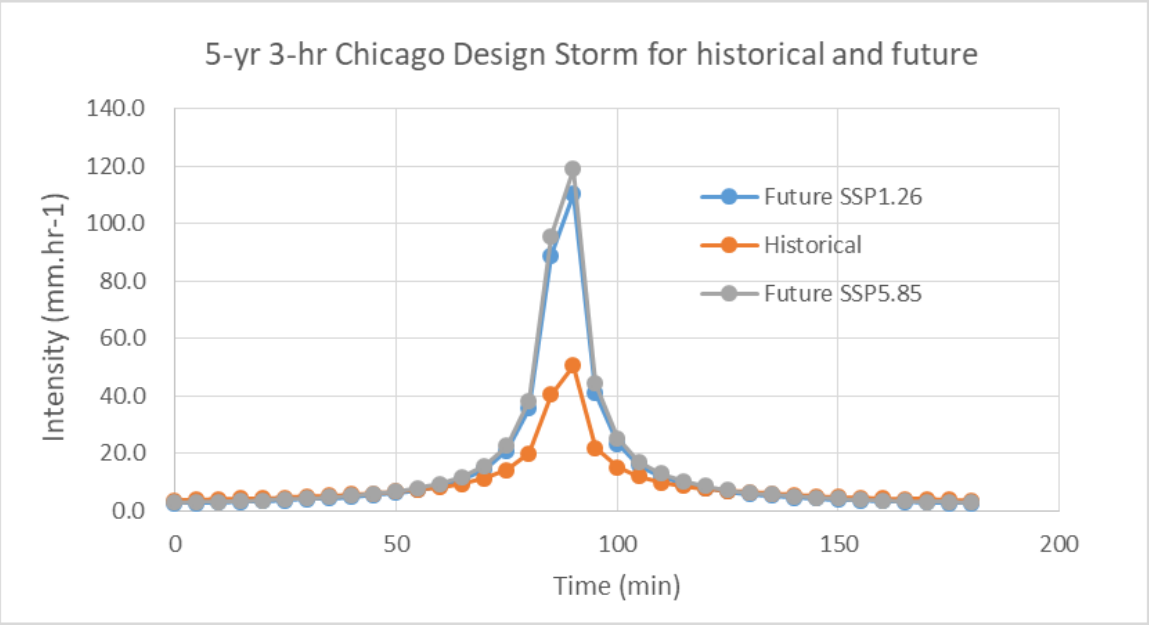

Figure 4.3 Chicago Design Storm for historical and future climate condition

Table 4.1 Future climate condition and Decision variables for test Case in Framework 3

	Future climate scenarios	Framework 3
Case with future climate condition	Station Information: OTTAWA CDA RCS Projection year: year 2050; Climate Model: ACCESS-CM2, SSP1.26; Rainfall time series: the synthetic hyetograph computed by the Chicago method.	1 Storage unit (J14) 2 Storage units (J14 J18) 3 Storage units (J14 J18 J11)
	Station Information: OTTAWA CDA RCS Projection year: year 2050; Climate Model: ACCESS-CM2, SSP5.85; Rainfall time series: the synthetic hyetograph computed by the Chicago method.	1 Storage unit (J14) 2 Storage units (J14 J11) 3 Storage units (J14 J11 J6)

4.3 Results and Discussion

The proposed multi-objective optimization framework 3 is developed to provide optimal strategies for implementation of storage units in urban drainage networks that can enhance the system resiliency. The variants of the framework were developed to enhance the working performance of original framework structure.

The objective of case considering future climate was to test the framework fundamentals with the real test case and predicted future Chicago rainfall data. The results for case with future climate condition SSP1.26 scenario under high storage cost, which can generate more feasible solutions, have summarized in Figure 4.4. The results show that Framework 3 would generate relatively reasonable solutions with higher cost efficiency when we consider future climate condition. The final selection for different number of candidate locations have similar cost efficiency and similar flooding reduction efficiency. The final solution for two candidate locations with two final storage unit implemented has comparatively higher cost efficiency than other selection. The results for case with future climate condition SSP1.26 scenario under high storage cost have summarized in Figure 4.5. The majority of the final selection have similar cost efficiency, while the final solution for three candidate locations with three final storage unit implemented has comparatively higher cost efficiency than other selection. The comparison between two scenarios, SSP1.26 and SSP5.85 has summarized in Figure 4.6. The total cost for high-emission scenario SSP5.85 is comparatively higher than SSP1.26 under same climate model. This result means that comparatively sever climate change due to high-emission greenhouse gas will lead to higher total cost of recovery and rehabilitation in the future.

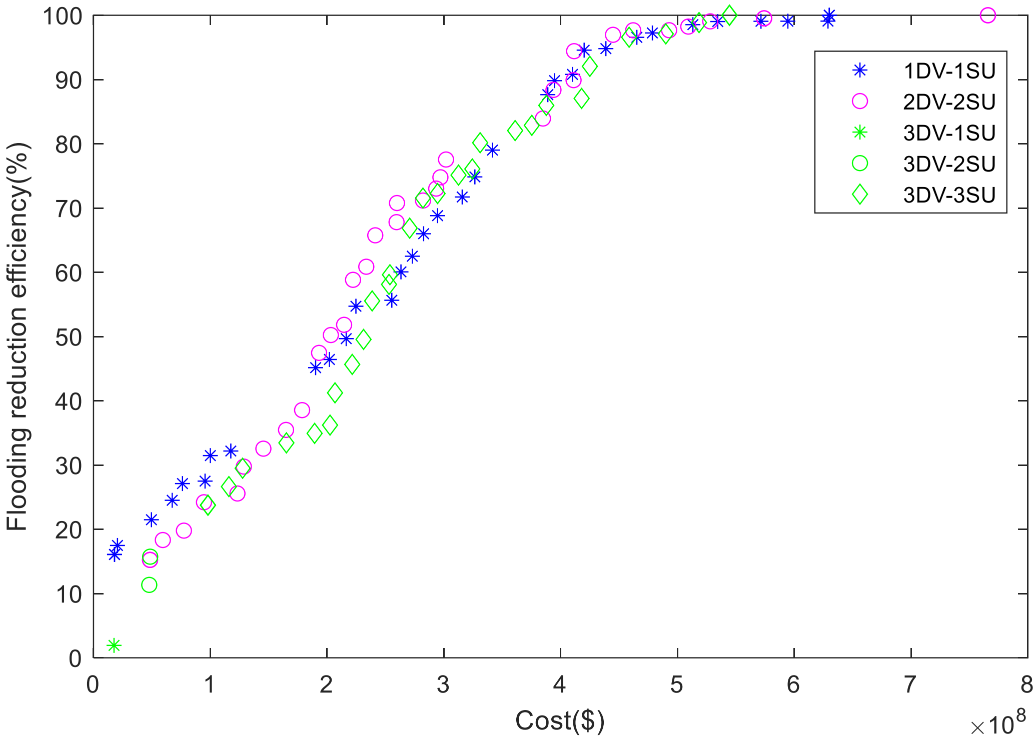

Figure 4.4. Framework 3 Results for Case with future climate condition SSP1.26 scenario with different number of candidate locations under high storage unit cost assumption (DV: decision variables; SU: storage units implemented).

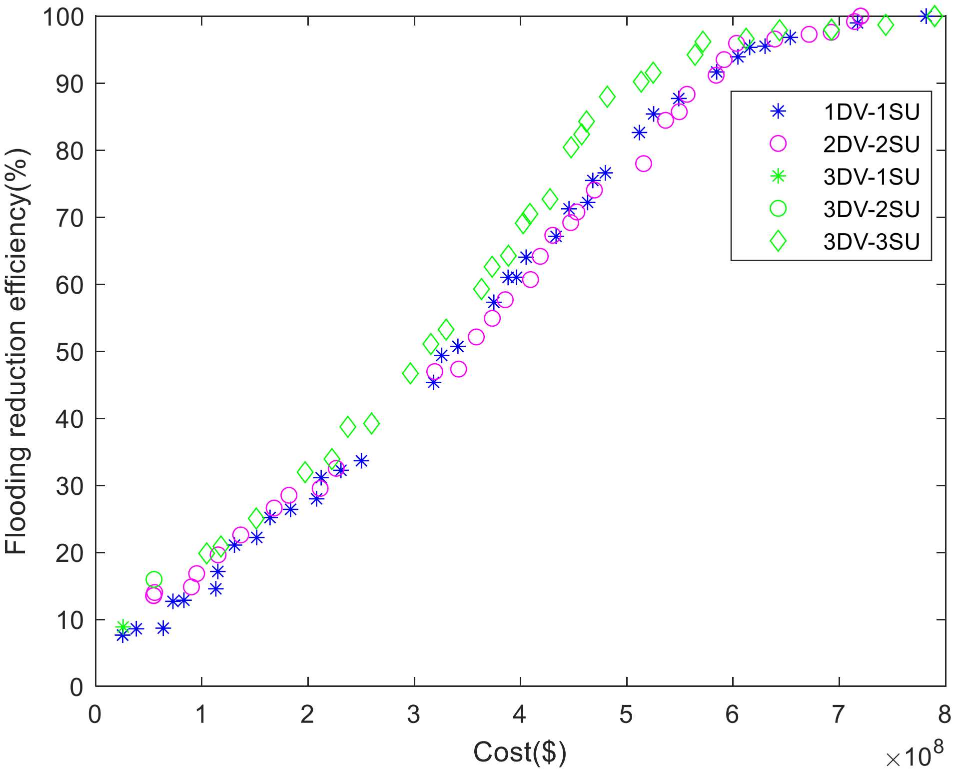

Figure 4.5. Framework 3 Results for Case with future climate condition SSP5.85 scenario with different number of candidate locations under high storage unit cost assumption (DV: decision variables; SU: storage units implemented).

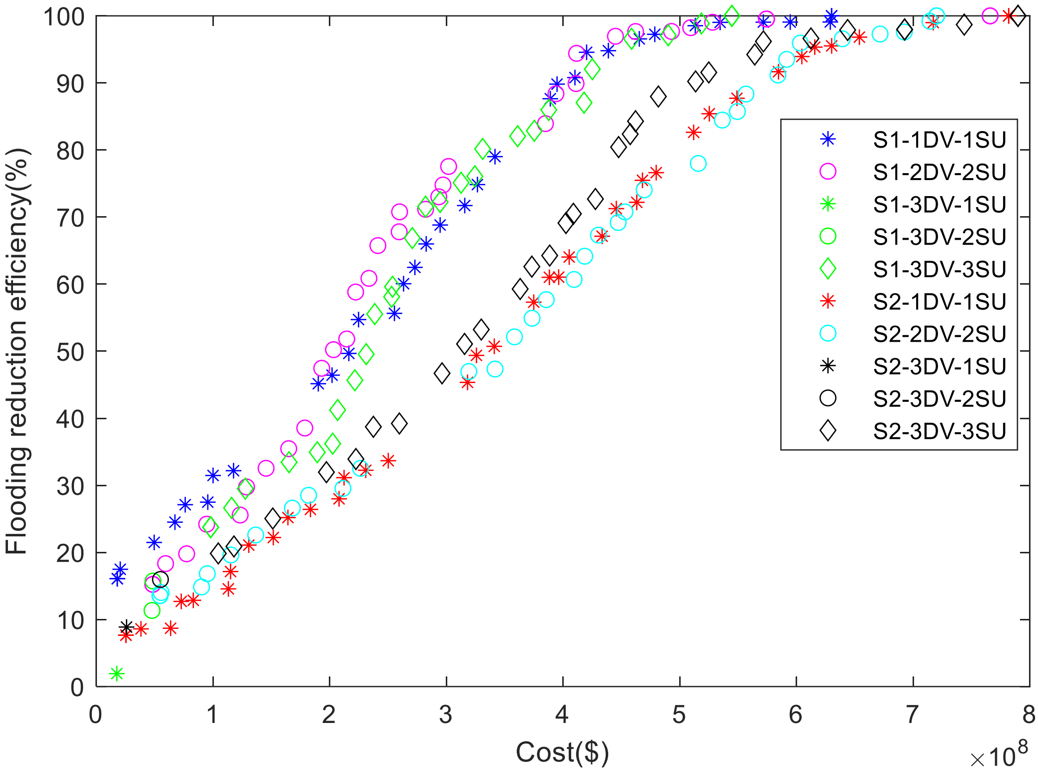

Figure 4.6. Framework 3 Results for Case with future climate condition under two scenarios with different number of candidate locations under high storage unit cost assumption (S1: SSP1.26; S2: SSP5.85; DV: decision variables; SU: storage units implemented).

Chapter 5: Conclusions and Future Work

5.1 Conclusion

To build the optimization framework, the Non-dominated Sorting Genetic Algorithm II (NSGA II) and the Storm Water Management Model (SWMM) were the main methodologies utilized. Despite the numerous previous research studies on detention tank design, the majority of the methodologies demand computational optimization using hydrologic models (Wang et al., 2017). However, for a complicated sewerage system, combining several methodologies into a single framework is difficult. Furthermore, there are few studies that attempted to optimize storage units, and the majority of the studies focus on drainage design. The present study develops a two-stage (hydraulic model and optimization model) multi-objective optimization framework combining the SWMM model and Non-dominated Sorting Genetic Algorithm II (NSGA II) to optimize the volume, locations and number of storage units in an urban sewerage system, with maximizing flooding reduction efficiency and minimizing total cost. The framework consisted of two modules: hydraulic module and the optimization module. The hydraulic model generated a preliminary design for the urban sewerage network and flooding index used in the simulation process. The optimization module combined the initial hydraulic module and optimization method, considered climate change and temporal variation, then generated the optimized solution of storage unit volume, locations and quantity. The propose framework also consider the impact of future climate change under two scenarios (SSP1.26 and SSP5.85), and framework designed for future can generate flexible solutions to improve the resilience of urban drainage system.

The sensitivity analysis of the population size of the genetic algorithm showed that (1) recovery solutions tended to be more reasonable with increasing population size; (2) various kinds of recovery solutions generated the same objective function values on the Pareto front, which shows that frameworks can find the near optimal solutions effectively; (3) the Pareto front showed a convergence trend after the population size exceeded 1000; (4) solutions were independent of increasing population size.

Several case studies were used to test the ability of the proposed multi-objective optimization framework to solve problems under different scenarios. Case 1, with the simplest scenario was used to verify whether the model worked properly and tested the cost functions. Case 2 was comparatively complex, and was used to test the model and analyze the solutions generated by the model. Case 3, with large decision variables, demonstrated the performance of the 3 frameworks, and showed the differences amongst frameworks. We tested the proposed frameworks under two assumptions to ensure it can appropriately respond to various situations: (i) the storage unit cost is not expensive (relative to the flooding cost) and (ii) storage unit is expensive. All 3 frameworks had the capacity to find flooding nodes and replace the nodes with storage units, then calculate the rehabilitation index to determine solutions. Framework 1, which considered both flooding nodes and upstream nodes, had the capacity to find solutions to reduce flooding, but it need large computational coat to find near optimal solutions, especially for larger decision variables. Regarding the selection process, Framework 2 and Framework 3 used the sensitivity index and node criticality index, respectively, which produced better performance. The solutions generated by these two frameworks tended to be more reasonable, with lower total cost, smaller number of storage units, and higher reduction efficiency. After the selection process, Framework 2 and 3 generated different decision variables, and Framework 3 produced better solutions than Framework 2.

The results showed that a two-stage multi-objective optimization framework can mitigate the urban flooding problem, minimize system failure risk and improve drainage system resiliency. This decision support framework can provide effective and proper rehabilitation plans that can assist in decision-making for efficient drainage system rehabilitation.

Even though this model can provide optimal rehabilitation plans, several limitations of this framework can be mentioned: (1) the calculation speed is slow, particularly for larger decision variables, (2) lack of life cycle cost consideration, (3) the uncertainty of climate change was not considered.

5.2 Future Work

The following suggestions are proposed for using GA and SWMM in resiliency improvement of urban sewerage system:

- In this proposed research, genetic algorithm (GA) have been used to couple with storm water management model (SWMM). There are several algorithms in relevant studies such as SA algorithm (Simulated Annealing), multi objective particle swarm optimization (MOPSO), dynamic programming (DP). The comparison between those algorithm, the performance and the impact they would have on the system could be a future study field.
- Future climate change and the rainfall prediction could be used in the proposed optimization system to further improve the resiliency of urban drainage system.
- Other application for combination of GA and SWMM in urban drainage system could be study and include in the research, like aging problem for network, urbanization.

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Appendix A: Hydraulics Calculations Storm water

Table A1: Properties for urban drainage system used in test case

PIPE	Selected diameter (mm)	Upstream	Downstream	Length		Junction name	Maximum water depth (m)
C0	2250	7.63	5.69	200		J0	6
C1	2250	8.43	6.13	250		J1	6
C2	2250	8.32	6.73	150		J2	6
C3	2250	9.4	7.12	250		J3	6
C4	1650	8.37	7.7	70		J4	6
C5	1650	9.72	7.77	200		J5	6
C6	1500	10.19	8.22	200		J6	6
C7	1050	10.66	8.69	200		J7	6
C8	1050	10.8	8.92	200		J8	6
C9	1200	10.42	8.45	200		J9	6
C10	1350	9.95	8.01	200		J10	6
C11	1650	8.91	7.85	100		J11	6
C12	1650	8.75	7.66	100		J12	6
C13	1650	8.56	7.47	100		J13	6
C14	1650	8.07	7.35	70		J14	6
C15	1650	9.05	7.12	200		J15	6
C16	1500	10.32	8.44	200		J16	6
C17	1050	9.9	7.99	200		J17	6
C18	1650	10.14	8.24	200		J18	6
C19	1650	9.94	7.99	200		J19	6
C20	900	9.33	7.35	200		J20	6
C21	1650	9.49	7.47	200		J21	6
C22	1050	9.29	7.47	200		J22	6
C23	900	9.5	7.66	200		J23	6
C24	675	9.78	7.85	200		J24	6
C25	1050	10	8.01	200		J25	6
C26	1800	9.1	8.05	100		J26	6
C27	1800	9.05	7.7	150		J27	6
C28	1050	9.02	8.02	100		J28	6
C29	1050	9.22	7.77	150		J29	6
C30	1500	11.18	8.89	250		J30	6
C31	1500	10.39	8.32	200		J31	6

C32	1050	10.32	8.89	150		J32	6
C33	1050	10.41	8.45	200		J33	6
C34	1050	11.31	9.3	200		J34	6
C35	750	10.7	9.16	150		J35	6
C36	1200	10.12	8.22	200		J36	6
C37	675	10.2	9.16	100		J37	6
C38	1500	11.76	9.38	250		J38	6
C39	1500	10.69	8.82	200		J39	6
C40	2400	7.19	5.2	200			

Appendix B: Tables of Rainfall Data for Test Cases

Table B1: Coefficient for 5-yr return period rainfall data

Duration (min)	Intensity (mm/hr)	Intensity (IDF)	sum of s
5	149.4	149.3982686	2.9976E-06
10	92	92.00830472	6.8968E-05
15	69.3	69.29812671	3.5092E-06
30	42.7	42.68828321	0.00013728
60	26.3	26.29797443	4.1029E-06
120	16.2	16.20127201	1.618E-06
360	7.5	7.518438103	0.00033996
720	4.6	4.631966889	0.00102188
1440	2.9	2.853674038	0.00214609
			0.00372642
a	459.694483		
b	-0.0052203		
c	0.69880073		

Table B2: Coefficient for 50-yr return period rainfall data

Duration (min)	Intensity (mm/hr)	Intensity (IDF)	sum of s
5	227.2	227.2341093	0.00116344
10	140	139.9346348	0.0042726
15	105.4	105.3907047	8.6403E-05
30	64.9	64.91720778	0.00029611
60	40	39.98929929	0.00011451
120	24.6	24.63434243	0.0011794
360	11.4	11.43069219	0.00094201
720	7	7.041751948	0.00174323
1440	4.3	4.338004683	0.00144436
			0.01124206
a	699.303565		
b	-0.0052244		
c	0.69889914		

Table B3: Chicago Design Storm for 5-yr return period 3-hr duration rainfall data

Time (min)	Intensity (mm.hr-1)	value (mm)
0	3.7	11.02651
5	3.8	11.48743
10	4.0	11.99817
15	4.2	12.56788
20	4.4	13.20815
25	4.6	13.93396
30	4.9	14.76504
35	5.2	15.72789
40	5.6	16.85913
45	6.1	18.21095
50	6.6	19.86055
55	7.3	21.92773
60	8.2	24.61
65	9.4	28.26022
70	11.2	33.58426
75	14.1	42.25773
80	19.9	59.63954
85	40.4	121.1434
90	50.5	151.5972
95	21.9	65.70601
100	15.1	45.39153
105	11.9	35.68542
110	9.9	29.84778
115	8.6	25.89295
120	7.7	23.00965
125	6.9	20.79991
130	6.3	19.04389
135	5.9	17.60952
140	5.5	16.41229
145	5.1	15.39543
150	4.8	14.51928
155	4.6	13.75523
160	4.4	13.08209
165	4.2	12.4838
170	4.0	11.94794
175	3.8	11.46477
180	3.7	11.02651

a	459.6945	
b	-0.00522	
c	0.698801	
peak time	87.84	min
r	0.488	
Duration	180	min

Table B4: Chicago Design Storm for 50-yr return period 3-hr duration rainfall data

Time (min)	Intensity (mm.hr-1)	value (mm)
0	5.6	16.75987
5	5.8	17.46055
10	6.1	18.23697
15	6.4	19.10304
20	6.7	20.07639
25	7.1	21.17979
30	7.5	22.44321
35	8.0	23.90698
40	8.5	25.62676
45	9.2	27.68189
50	10.1	30.18976
55	11.1	33.33253
60	12.5	37.41048
65	14.3	42.96014
70	17.0	51.05478
75	21.4	64.24225
80	30.2	90.6713
85	61.4	184.1951
90	76.8	230.5064
95	33.3	99.89565
100	23.0	69.0071
105	18.1	54.24942
110	15.1	45.37383
115	13.1	39.36102
120	11.7	34.9774
125	10.5	31.61788
130	9.6	28.94821

135	8.9	26.76756
140	8.3	24.94745
145	7.8	23.40156
150	7.4	22.0696
155	7.0	20.90807
160	6.6	19.88475
165	6.3	18.97522
170	6.1	18.16062
175	5.8	17.42611
180	5.6	16.75987
a	699.3036	
b	-0.00522	
c	0.698899	
peak time	87.84	min
r	0.488	
Duration	180	min

Table B5: Future Chicago Design Storm under SSP1.26 for 5-yr return period

3-hr duration rainfall data

Time (min)	Intensity (mm.hr-1)	value (mm)
0	2.6	3.752335
5	2.7	3.980246
10	2.9	4.239186
15	3.1	4.535951
20	3.3	4.879461
25	3.6	5.281645
30	3.9	5.758812
35	4.3	6.333827
40	4.8	7.039716
45	5.4	7.925894
50	6.2	9.069506
55	7.2	10.59747
60	8.7	12.73286
65	10.9	15.90298
70	14.4	21.02801
75	20.8	30.45524
80	35.5	52.03183
85	88.8	130.0059
90	110.3	161.4545

95	41.0	60.01538
100	23.3	34.12919
105	15.8	23.1989
110	11.9	17.37163
115	9.4	13.81325
120	7.8	11.43837
125	6.7	9.750894
130	5.8	8.494857
135	5.1	7.525924
140	4.6	6.75699
145	4.2	6.132596
150	3.8	5.615856
155	3.5	5.181345
160	3.3	4.810993
165	3.1	4.491626
170	2.9	4.213422
175	2.7	3.968916
180	2.6	3.752335
a	1296.911	
b	7.0889998	
c	0.8572607	
peak time	87.84	min
r	0.488	
Duration	180	min

Table B6: Future Chicago Design Storm under SSP5.85 for 5-yr return period

3-hr duration rainfall data

Time (min)	Intensity (mm.hr-1)	value (mm)
0	2.8	4.125283
5	3.0	4.373822
10	3.2	4.656036
15	3.4	4.979277
20	3.7	5.353188
25	4.0	5.790658
30	4.3	6.309295
35	4.7	6.933771
40	5.3	7.699698
45	5.9	8.660318
50	6.8	9.898697

55	7.9	11.55139
60	9.5	13.85823
65	11.8	17.27831
70	15.6	22.79977
75	22.5	32.94251
80	38.3	56.13505
85	95.7	140.053
90	118.8	173.9853
95	44.2	64.71618
100	25.2	36.89272
105	17.2	25.13663
110	12.9	18.86138
115	10.3	15.02434
120	8.5	12.46016
125	7.3	10.63595
130	6.3	9.276597
135	5.6	8.226867
140	5.0	7.393009
145	4.6	6.715291
150	4.2	6.153958
155	3.9	5.681588
160	3.6	5.278681
165	3.4	4.93101
170	3.2	4.627964
175	3.0	4.36147
180	2.8	4.125283
a	1380.808	
b	7.010112	
c	0.854108	
peak time	87.84	min
r	0.488	
Duration	180	min

Appendix C: Figures of Rainfall Data for Test Cases

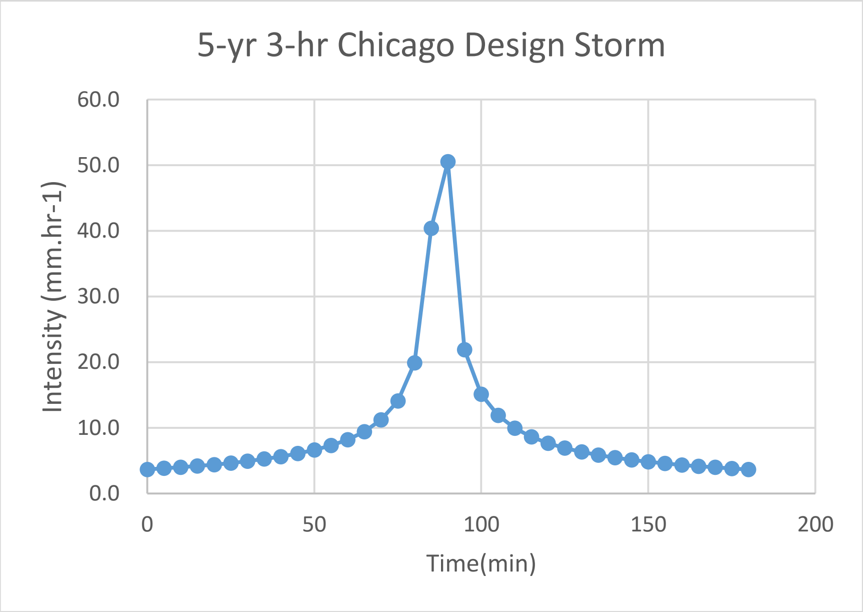

Figure C1: 5-yr 3-hr Chicago Design Storm

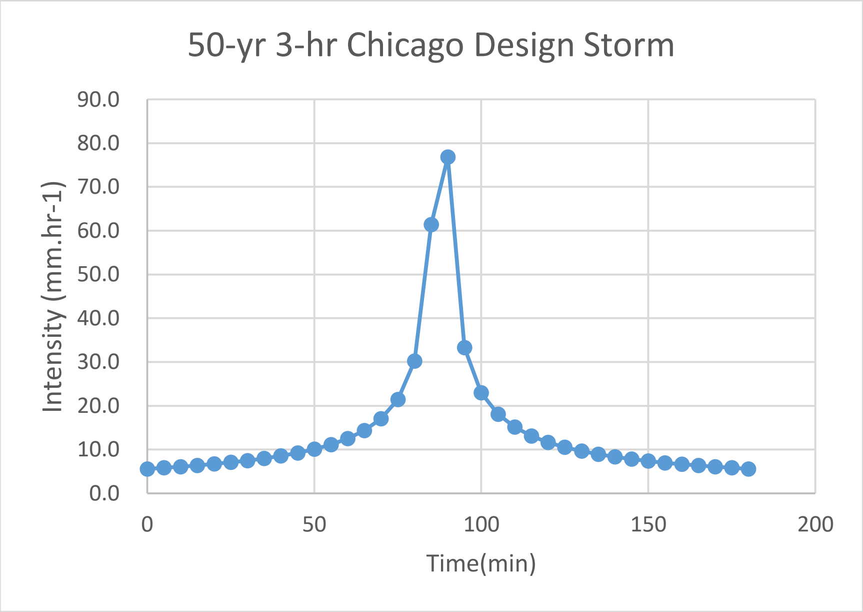

Figure C2: 50-yr 3-hr Chicago Design Storm

Appendix D: Sensitivity Indexes for Test Cases

Table D1: Sensitivity Indexes for Case 3 in Framework 2

Node	Sensitivity Index
J2	8.4
J3	10.6
J4	10.6
J6	11.3
J7	10.7
J8	9.8
J9	10.3
J10	10.6
J11	11.0
J12	9.0
J13	10.3
J14	12.8
J15	10.4
J16	11.2
J17	9.4
J18	10.025
J19	12.4
J20	7.0
J21	7.03
J22	9.1
J23	8.3
J24	10.1
J25	8.7
J26	8.1
J27	11.1
J28	5.1
J29	9.3
J30	4.8
J31	6.2
J32	9.6
J33	10.1
J34	11.1
J35	8.3
J36	8.2
J37	8.4
J38	12.4
J39	15.8
J39 J14 J19 J38 J6 J16	

Table D2: Node criticality indexes for Case 3 in Framework 3

Node	Total Flood volume(10^6 ltr)
J2	0.000
J3	0.002
J4	0.000
J6	0.012
J7	0.791
J8	0.000
J9	0.002
J10	0.000
J11	0.014
J12	0.000
J13	0.000
J14	0.804
J15	0.084
J16	0.010
J17	0.197
J18	0.079
J19	0.000
J20	0.010
J21	0.042
J22	0.005
J23	0.000
J24	0.000
J25	0.000
J26	0.061
J27	0.012
J28	0.057
J29	0.001
J30	0.001
J31	0.000
J32	0.003
J33	0.000
J34	0.001
J35	0.000
J36	0.001
J37	0.003
J38	0.000
J39	21.414
J39 J14 J7 J17 J15 J18	

Table D3: Node criticality indexes for Case with Future climate condition under SSP1.26 in Framework 3

Node	Total Flood volume(10^6 ltr)
J14	2.132
J18	0.346
J11	0.313
J6	0.239
J15	0.237
J23	0.170
J17	0.099
J26	0.099
J28	0.098
J19	0.058
J35	0.049
J9	0.043
J31	0.035
J34	0.035
J22	0.034
J37	0.027
J21	0.024
J7	0.017
J16	0.014
J12	0.010
J27	0.010
J32	0.009
J8	0.008
J3	0.007
J20	0.004
J24	0.004
J10	0.003
J25	0.002
J38	0.001
J29	0.001
J36	0.000
J14 J18 J11	

Table D4: Node criticality indexes for Case with Future climate condition under SSP5.85 in Framework 3

Node	Total Flood volume(10^6 ltr)
J14	2.990
J11	0.451
J6	0.387
J15	0.376
J17	0.367
J18	0.201
J34	0.189
J23	0.179
J28	0.175
J19	0.167
J26	0.155
J7	0.133
J35	0.110
J9	0.077
J37	0.053
J31	0.051
J22	0.049
J21	0.038
J32	0.036
J3	0.015
J12	0.015
J8	0.014
J27	0.013
J20	0.012
J25	0.009
J10	0.007
J30	0.002
J36	0.000
J14 J11 J6	