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A Multi-criteria Risk-based Approach for Optimal Planning of SuDS Solutions in Urban Flood Management

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Abstract

This paper presents a multi-criteria risk-based approach for managing urban flood hazards by using a combination of conventional measures and contemporary Sustainable Drainage Systems (SuDS). A multi-objective optimisation model coupled with a simulation model of UDS in the SWMM software is developed with the three objectives of minimising total costs, the risk of flooding and pollution discharged into receiving waters. *K*-means clustering technique is used to group the optimal solutions. A few optimal solutions and individual SuDS solutions are then ranked together by using the compromise programming (CP) method. The methodology is demonstrated on a case study of the Golestan city UDS in Iran. The results obtained show there are indirect correlations between non-dominated solutions that minimise the risk of either flooding or pollution. The results also show the selected optimal solutions can provide cost-effective strategies that reduce both flood and pollution risks by at least 27% and 50%, respectively.

Keywords: Compromise programming; flood risk management; multi-criteria decision making;

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urban drainage systems

1 Introduction

Ever-growing urbanisation involving replacing vegetative and open areas with buildings, pavements and roads over the recent decades has increased impervious surface areas in urban catchments. All this has resulted in the alteration of natural water systems by dramatically increasing surface runoff volume and peak flow, decreasing the groundwater resources due to decreasing infiltration and percolation rates (Ahiablame and Shakya 2016; Brun and Band 2000; Brandes et al. 2005; Wang et al. 2003), increasing flood risks (Konrad 2003) and decreasing water quality by increasing the pollution of receiving water bodies (Ahiablame and Shakya 2016). The excessive runoff in urban areas collects contaminants from impervious surface areas and discharges them into receiving water bodies such as lakes, rivers and wetlands. Hence, the conversion of permeable surfaces of open land to impervious surfaces and the loss of the water-retaining function of soil in urban areas would change the hydrologic cycle (Booth and Leavitt 1999). Kim et al. (2016) developed a model to evaluate these changes using a Soil and Water Assessment Tool (SWAT) model. The traditional approach for flood risk management in urban areas is to collect and dispose of the flood runoff as soon as possible. This approach conveys the surface runoff out of the urban areas using structural methods and diversion channels, which generally results in the increase of the pollution loads discharged into the receiving water bodies as well as high construction costs and emission of greenhouse gases (Mikulincer and Shaver 2007).

To overcome both urban flooding and water quality issues, Best Management Practices (BMPs) based on the Sustainable Drainage Systems (SuDS), Nature Based Solutions (NBS) or Low Impact

Development (LID) have been well developed in recent decades for urban catchments to reduce runoff volume and flood risk by increasing the permeability of surface areas and storage capacity in the catchments. The concept of SuDS embraces a broad range of technologies and activities that minimise the impacts of urban development on flow patterns (Mustaffa et al. 2016). Recent research works have shown SuDS can improve the performance of drainage systems in both rural and urban areas (Azari and Tabesh 2018). Abi Aad et al. (2010) proposed a new method to model rain gardens and rain barrels using Storm Water Management Model (SWMM) and the cumulative effects of utilising SuDS in urban catchments. SuDS are basically strategies to control the runoff volume and eliminate certain pollutants from stormwater. In fact, SuDS not only decrease total flow and peak runoff, but also improve runoff water quality by decreasing pollution of water bodies receiving from surface runoff. This is achieved due to eliminating pollutants by evaporation, treatment or infiltration using a combination of a series of physical, chemical, and biological processes that include detention/retention, settling, absorption, infiltration, flocculation, and biological uptake (Jia et al. 2013). One of the advantages of this modern management method compared to conventional water management methods is its flexibility. SuDS can also mitigate the urban flood and remove the pollutants from the surface runoff before discharging into urban drainage systems (UDS). Due to the wide range of SuDS and their performance in various conditions, a combination of SuDS may be suitable for the UDS. This combination can be selected based on a few assessment criteria to identify the best design of SuDS. The assessment criteria can be evaluated by using simulation models and can be used in optimisation algorithms to identify the optimal parameters of the SuDS (e.g. site location and technical design parameters such as area, size, permeability, type of filtering media, roughness of materials and etc.) based on the multiple objectives defined in the UDS.

Some research works have developed optimisation algorithms for planning and design of SuDS in the UDS (Alves et al. 2018). The common objective functions used in these studies in the recent decade include minimisation of flood volume (Oraei Zare et al. 2012 and De Paola et al. 2018), minimisation of costs (Dong et al. 2020) and maximisation of the system reliability (Karamouz and Nazif 2013). Various decision variables were also used for the SuDS optimisation problem in the UDS. For example, Azari and Tabesh (2018) proposed the optimal design of SuDS for their area and site location in the UDS. Some studies developed specific objective functions for SuDS optimisation in the UDS. For example, Dong et al. (2020) optimised the size and number of LIDs using a multi-scale decision-making framework to identify cost-effective LID combinations that comply with water quality standards in the UDS. McClymont et al (2020) also developed a resilience-driven multi-objective model to find the trade-off between flood resilience and water quality resilience through SuDS solutions based on the SuDS capital costs applied to a case study in Brazil. They also used a Quality of Life index to analyse identified solutions for day-to-day social impacts. The combination of an optimisation model and a UDS simulation model is also common in this field. For example, Saniei et al (2021) coupled SWMM model with NSGA-II optimisation algorithm to obtain the optimal size, type and location of LIDs considering the long-term condition of rainfalls. Note that LIDs is a general term for SuDS that is mainly applied in the North America for a number of techniques such as swale, bioretention system, permeable pavement and detention pond. As shown above, many studies examined the impact of SuDS for runoff and pollution controls for designing SuDS.

Risk assessment is one of the key factors in disaster management of urban flood that should also be considered when evaluating SuDS in the UDS (Battiston et al. 2021). The risk of a flood event is basically calculated by multiplying the probability of the event by the severity of its consequence e.g. financial or human losses. The probability of a flood event is a non-zero random variable which depends on the rainfall probability but the severity of its effects can be minimised through better flood management (Kundzewicz and Stoffel 2016). There are also several studies that investigated urban flood risk minimisation such as Jiang et al. (2009) that explored effective methods for mitigating flood risks in the UDS, especially reduction of economic losses.

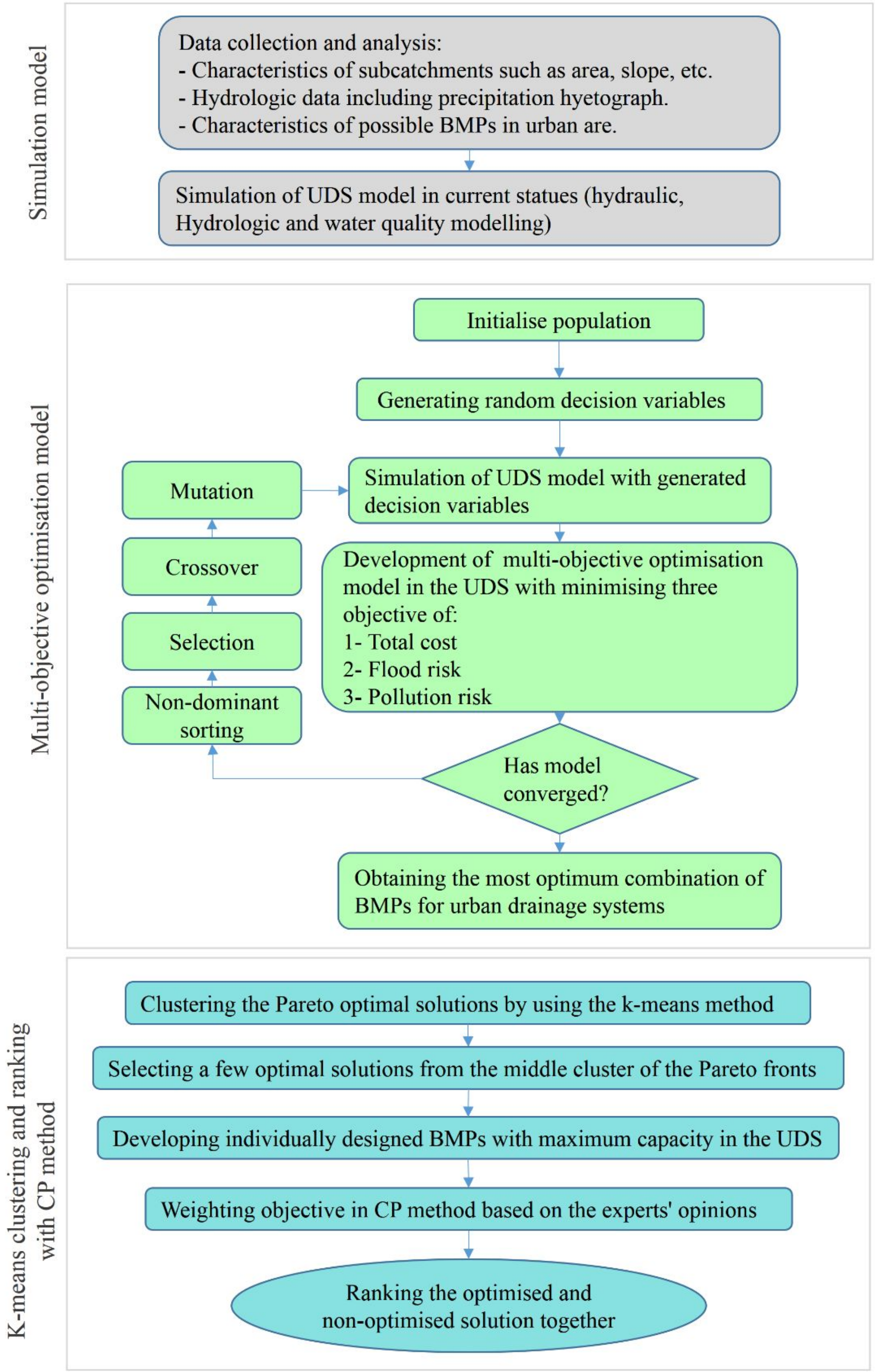
Potential solutions generated by either experts or optimisation models may also need to be ranked or prioritised by using a multi-criteria decision analyses (MCDA) method. In the water industry, these solutions have been ranked by using a few well-known MCDA methods such as AHP (Analytical Hierarchy Process) e.g. Ardeshir et al. (2014), TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution) Afshar et al. (2011) and CP (Compromise Programming) e.g. Zarghami et al. (2008) and other tools such as UWOT (Urban Water Optioneering Tool) Makropoulos et al. (2008). Among these three methods, the CP method is an accurate and simple group decision making method that can be easily used for ranking a number of strategies based on multiple assessment criteria in urban water systems (Morley et al. 2016a). More specifically, Zarghami et al. (2008) used the CP method as a multi-objective decision-making model for optimal long-term planning of conjunctive use of surface and ground water resources. The objectives analysed in their CP method were minimisation of costs and social hazards and maximisation of water supply. Fattahi and Fayyaz (2010) proposed the CP method for the integrated urban water management covering water supply systems with three objectives of minimising water distribution cost and leakage and maximising social satisfaction level.

Behzadian and Kapelan (2015) used the CP model with multiple quantitative and qualitative criteria for ranking several intervention strategies for long-term planning of integrated urban water systems including the urban water supply and drainage systems. Other

As outlined above, multi-objective optimisation methods have been broadly used in recent research works for identifying optimal parameters of SuDS such as size, location, settings, or their composition in the UDS. Various objectives used for optimising SuDS mainly include minimisation of costs, flood volume, peak flow and pollution in the UDS. However, to the best of authors' knowledge, none of the above optimisation models has considered a risk-based approach in the multi-objective optimisation model combined with ranking-based multi-criteria decision analysis for prioritising optimal SuDS in the UDS. The current research aims to develop a risk-based multi-objective optimisation models for long-term planning and optimal design of SuDS and prioritise a few optimal solutions based on the CP model. The risk-based approach used in the paper also aims to minimise the risk of inundation and pollution hazards in urban floods using optimal SuDS and conventional measures. The paper is structured as follows: The flowchart of the methodology followed by the development of simulation and optimisation models are first explained. The next section presents the case study and model development in a real-world application. Then, the results of Pareto optimal front obtained from the multi-objective optimisation algorithm is presented and discussed followed by ranking several optimal solutions based on the CP model. Final remarks and conclusions are drawn with some recommendations for future works.

2 Methodology

This study adopts a methodology for planning and management of urban flood in three main parts as shown in Fig. 1. The first part involves developing simulation model for the UDS which includes data collection for physical components of the UDS and hyetograph of rainfall data with specific return periods to build the UDS model using the SWMM software. The second part entails developing a multi-objective optimisation model by choosing objective functions and decision variables to obtain Pareto-optimal solutions by using multi-objective evolutionary algorithms coupled with the UDS simulation model written in the MATLAB software. The final part includes clustering Pareto-optimal solutions by using *k*-means clustering technique proposed by Hartigan and Wong (1979) in the SPSS software and then selecting a few optimal solutions with proposed strategies and finally ranking them using the CP multi-criteria decision analysis (MCDA) method in Excel platform (Behzadian and Kapelan 2015). Details of the models used in this paper are described in the following.



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155 Fig. 1 The flowchart of the study for planning optimal SuDS solutions in the UDS

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2.1 Simulation model

Hydrological processes and hydraulic performance of the UDS are simulated here by using a model developed in the SWMM software. The following input data are required for the hydraulic and water quality simulation in the UDS: Characteristics of the area considered for the case study including climate information (e.g., precipitation data), land use (residential, commercial, industrial, and undeveloped), physical characteristics of the catchment (e.g., slope, area, width, percent of impervious area, and depression storage), conduits (e.g., offset height or elevation above the inlet and outlet node inverts, conduit length, Manning's roughness, cross-sectional geometry, inlet geometry code number), outfalls, SuDS controls and water quality parameters including TP (Total Phosphorous), TN (Total Nitrogen) and TSS (Total Suspended Solids) and pollutant build-up and wash-off.

A variety of SuDS are available to control flooding and pollutant loads in a catchment although some specific SuDS may be fitted in the catchment to have the performance of interest. Features such as local land use, catchments properties, environmental considerations and catchment slope are crucial factors when selecting SuDS (Behroozi et al. 2018). Here, based on the conditions of the area (being residential area, the soil type, the amount of space for BMPs implementation and the available equipment and etc.), four different types of SuDS are analysed including detention ponds, porous pavements, infiltration trenches, and bioretention tanks.

2.2 Multi-objective optimisation model

A multi-objective optimisation model is developed here to identify to the best combination of SuDS and traditional measure to improve the UDS performance by reducing the risk of both urban flooding and surface runoff pollution discharging into receiving water bodies. The optimisation model considers the following three objective functions: (1) minimisation of the risk of flooding in urban areas; (2) minimisation of the risk of pollution discharged into receiving water bodies; (3) minimisation of total construction cost for traditional measures and new SuDS.

2.2.1 Flood risk in urban areas

The risk of urban flood is defined based on the hazard of urban flooding caused by rainfall, which can lead to the disruption of urban services and economic losses or even human losses. To calculate the risk, the occurrence probability of different rainfalls is multiplied by the severity of consequence of the associated flooding which is considered here as the overflow of the conduits in the UDS. Hence, the risk of flooding (RF) can be calculated as below:

$$RF = \sum_{i=1}^{m}\sum_{j=1}^{n} C_{ij}P_i \qquad (1)$$

where C_{ij} = the severity of consequence of the flood event in node j due to rainfall i; P_i = the probability of rainfall event i; m = the number of analysed rainfalls covering various return periods and n = the total number of monitoring nodes in the UDS.

The focus of the urban flood management is usually on extreme hydrological events with high return periods that cause significant economic and human losses while the discharge of the urban surface pollution into the UDS can happen more frequently during rainfall events with low return periods. Therefore, this study considers the rainfalls with return periods of 2, 10, and 100 years to include both extreme and small flood events. Considering the rainfall return period of T, the occurrence probability of each event (P) can be calculated as:

$$P = \frac{1}{T} \tag{2}$$

The severity of consequences caused by a flood evens can be represented as the magnitude of financial and human losses due to the flood occurrence. The flood damage is typically proportional with the peak flow rate (or volume) and velocity of runoff in urban areas. We can assume that for the cases with almost flat area or slight slopes, the effects of runoff velocity can be neglected. Hence in this study, we consider the volume of flooding caused by overflow in the nodes of the UDS as a surrogate for flood damage (Karamouz and Nazif 2013). This volume can be obtained through the results of the SWMM simulation model.

2.2.2 Pollution risk discharged into receiving water bodies

The consequence of runoff pollutants from urban surfaces such as pavements and roads after a rainfall event can be quantified by the amount of their loads discharging into the UDS. Hence, the pollution risk of urban floods can be calculated as the risk of pollution loads discharging into the UDS. Similarly, the risk of pollution (*RP*) can be calculated by multiplying occurrence probability of rainfall events by the pollution loads, as below:

$$RP = \sum_{i=1}^{m} \sum_{k=1}^{n} A_{ik} P_i \tag{3}$$

where A_{ik} = the total load of pollutants discharged into outlet *k* and rainfall *i*; P_i = the probability of occurrence of rainfall/pollution event *i; m* = the total number of rainfall events covering various return periods; and *n*= the total number of outlets in the UDS. Note that the severity of consequence for the pollution risk is usually calculated by the amount of damage caused by pollution in a flood event. The damage here is referred to the pollution loads entering the UDS and finally the receiving water bodies such as rivers, lakes and wetlands. The loads of pollutants can be monitored as kilograms per event and are calculated by using the results obtained by the SWMM software.

2.2.3 Total construction costs

One of the main barriers to the development of SuDS in urban flood management is usually related to the high cost for their investment and maintenance. On the other hand, the level of investment for construction of flood control techniques has a significant effect on the risk of flooding and pollution. Hence, finding the optimal SuDS costs with the best performance are crucial for a sustainable and viable urban flood management. Here, the total capital investment and operational costs is considered as the third objective of the optimisation model. In this study, the costs associated with traditional measure and new SuDS are taken from the data in the literature (Strecker et al. 2010; Karamouz and Nazif 2013). Cost estimation is often difficult in the design stage due to the lack of valid and accurate construction data, diversification of construction locations, and urban and regional differences. The cost for runoff control structures includes design, construction, probable operation, and maintenance costs. The capital investment used for the lifetime of the structure can also be an assessment indicator. The capital investment (*C*) can be estimated by the following empirical equation based on the size of the structure (EPA 2004):

$$C = aD^b \tag{4}$$

where *D* = decision variables (e.g. volume, area or flow), *a* and *b* = the coefficient and exponent , respectively, determined by a regression analysis. Table 1 shows the cost equations for capital investment of all types of structure used in this study. The table also includes the annual maintenance costs as a percentage of the construction cost. Note that these costs are calculated as per annual costs with respect to a complete lifetime of the structure.

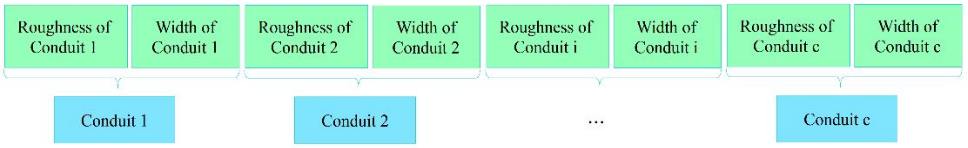
2.2.4 Decision variables

Decision variables forming the solutions of the optimisation model include the design parameters of UDS infrastructure related to SuDS and traditional measures for expansion of the UDS. More specifically, traditional measures analysed here include increasing the capacity of existing conduits through either (1) increasing the cross-sectional area of conduits or (2) improving the roughness of conduits (i.e. decreasing the Manning roughness coefficients of conduits). The SuDS analysed here include (1) detention ponds, (2) porous pavements, (3) infiltration trenches, and (4) bioretention tanks. Fig. 2 shows the structure of the decision variables covering three main components of the UDS: subcatchments, conduits, and junctions. The total number of decision variables (NDV) in a solution is calculated as below:

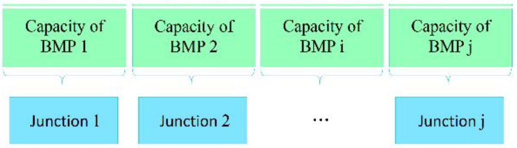
$$NDV = n_s \times SuDS_s + n_c \times SuDS_c + n_j \times SuDS_j \tag{5}$$

where n_s, n_c, and n_j = the number of subcatchments, conduits, and junctions, respectively; and $SuDS_s$, $SuDS_c$ and $SuDS_j$ = the number of decision variables for subcatchments, conduits and junctions. The detail of decision variables for each type is given in Table 2. More specifically, each subcatchment has two decision variables including the type and the total area of SuDS. Three types of SuDS are considered for subcatchments including porous pavements, infiltration trenches and bioretention tanks. Each conduit has two decision variables including the new width and the new Manning roughness coefficient. Finally, each junction has one decision variable which is the surface area of a detention pond. The SWMM hydraulic model is used as the basis of simulation in the simulation-optimisation scheme which is connected to the optimisation model in the MATLAB software. The decision variables are used as the input of the simulation model and the outputs (results) of the simulation model are used as the input for the optimisation model. This procedure is iteratively repeated until the final stopping criteria of the optimisation model are met and Pareto optimal solutions are obtained as a set of optimal solutions.

(a) Subcatchments



(b) Conduits



(c) Junctions

Fig. 2 Decision variables of solutions for (a) subcatchments (b) conduits (c) junctions in the optimisation model

Table 2. Main features of the solutions and decision variables in the UDS

UDS components	**Conceptual solution**	**Decision variable**	**Range/ type of decision variables**
Subcatchments	Decreasing the volume of surface runoff discharged into UDS by increasing infiltration/ storage capacity of subcatchments through adding SuDS	Selection of SuDS: porous pavements, infiltration trenches and bioretention tanks The total area of SuDS	Integer value between 0^* and 3 for the three SuDS Real value between 10% and 20% of the subcatchment area
Conduits	Increasing the existing capacity of conduits	A new width for conduits Decreasing Manning roughness coefficient of conduits	Real value for increasing the existing widths by 0^*, 60, 65, 70, 75, 80, 85, 90 cm Real value for decreasing the existing Manning roughness coefficients by 0^*, 20, 40, 60, 80 percent
Junctions	Increasing the storage capacity at junctions	Construction of new detention ponds at junctions	Real value for the surface area of the detention pond equal to 0^*, 10, 12, 14, 16, 18, 20m^2 and 2m height

* Note that 0 in all cases indicates "do nothing" for the existing component or no new SuDS

2.2.5 Optimisation Method

The above optimisation problem is solved here using the multi-objective optimisation algorithm of NSGA-II (Deb et al. 2002). This optimisation method has been widely used for solving multi-objective optimisation problems especially in similar research works in urban water systems such as water supply systems (Behzadian et al. 2009) and urban drainage systems (Karamouz and Nazif 2013). NSGA-II has a few optimisation parameters such as probability of crossover, probability of mutation and population size that will be adjusted within several trial runs before the main runs.

2.3 *K*-means clustering and the CP Method

Once a set of optimal solutions is obtained by the multi-objective optimisation model, the multiple optimal solutions are narrowed down by using *k*-means clustering method such that a few optimal solutions can be selected by decision makers for comparing and ranking with other available solutions by using the CP method.

The *k*-means method is a clustering algorithm used to create a small set of groups from relatively entities based on subset of variables. This algorithm categorises data sets as a certain number of pre-defined clusters, i.e. *k*, and attempts to estimate the following items: (1) determining cluster centre points as the mean value for the set of points in each cluster; (2) assigning each data sample to a cluster in which its centre point is the nearest one to the data value (Meyers et al. 2013). Generally, the analysis is conducted to make a small number of clusters (e.g., between three and five). This algorithm has been previously applied to research works in the water industry such as pipeline failure predictions in water distribution networks (Kakoudakis et al. 2017) and peak outflow predictions in dam failure analysis (Eghbali et al. 2017).

This paper adopts the compromise programming (CP) as a MCDA technique for ranking the selected solutions based on a few assessment criteria. This method was chosen here due to its simple application for group decision making when a number of assessment criteria are analysed for ranking a list of alternative options in urban water systems (Morley et al. 2016b). The basic idea of the CP method is to determine a set of efficient solutions nearest to an ideal point, for which all the solutions are optimised. The corresponding distance functions are defined by *p*-metrics. The basic equation of the CP model is given as below:

$$\min L_P \equiv \left[\sum_{i=1}^{q} \left(\frac{w_i(f_i^* - f_i(x))}{f_i^* - f_{i^*}}\right)^P\right]^{\frac{1}{P}} \equiv \left[\sum_{i=1}^{q} (w_i d_i)^P\right]^{\frac{1}{P}} \qquad (6)$$

$$d_i \equiv \frac{w_i(f_i^* - f_i(x))}{f_i^* - f_{i^*}} \qquad x \in X$$

where x is the vector of decision variables; X indicates the possible set. $f_i(x)$ is the mathematical expression for the ith criterion ($i \in \{1, \ldots, q\}$); $f^* \equiv f_1^*(x), \ldots, f_i^*(x), \ldots, f_q^*(x)$ indicates the vector of ideal point; $f^* \equiv f_{1^*}(x), \ldots, f_{i^*}(x), \ldots, f_{q^*}(x)$ indicates the vector of anti-ideal point; d_i stands for the degree of discrepancy for the ith criterion; w_i is the weight attached to the ith criterion ($i \in \{1, \ldots, q\}$) and p, the real number in the closed interval $[1,\infty]$, is the topological (André and Romero 2008). Parameter p can be reflective of decision makers' concern based on the maximum deviation (Fattahi and Fayyaz 2010). This paper used an excel-based platform of the CP method that has been applied to urban water systems (Behzadian et al. 2014; Behzadian & Kapelan 2015).

3 Case study

The proposed methodology is demonstrated here on the real-world case study of the UDS for the Golestan city located in the southern part of the Tehran province in Iran as shown in Fig. 3. The average altitude of the city is 1046m above sea level and the height difference between the highest and lowest points of the city is 27.2m. The general direction of the slope is from northern regions to south boundaries and the average value for the slope in urban areas is in the range of 0.5 to 3 percent.

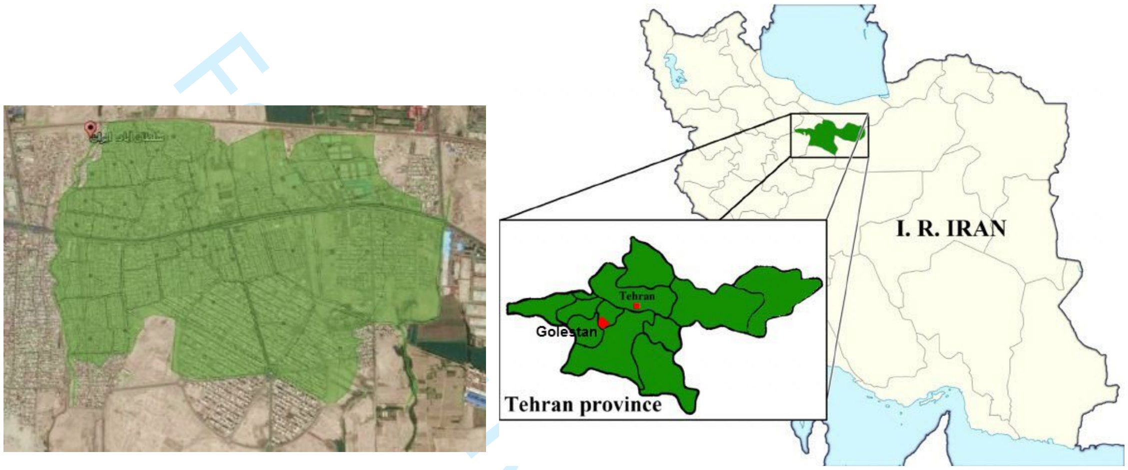


Fig. 3. Overall layout of the case-study for (a) area of the Golestan city and (b) Tehran province in Iran

This study used synthetic design storms for the rainfall simulation in the UDS. Note that continuous simulation by using actual historic data of long-term rainfall record can provide more accurate and robust comparison of the long-term water balance and hydrologic performance of alternative stormwater management options. However, synthetic design storms were selected here as they are typically used for designing the UDS and use of actual historic rainfall requires a long-term rainfall record (e.g. 30-50 years) with high time resolution (e.g. 5-10 minutes) that access to this level of data was not impossible for the case study. Hence, the Intensity-Duration-Frequency (IDF) curves of the rainfall of the closest weather station (i.e. the Mehrabad station) to the project site were selected. Each IDF curve represents the relationship between rainfall intensity and duration for specific frequency (i.e. inverse of return period) of the rainfall. The analysis of rainfalls with various intensities and durations in the IDF curves shows rainfalls with a 6-hour duration are the most critical condition corresponding to the maximum surface runoff in the UDS (Karami et al. 2016). Therefore, rainfalls with return periods of 2, 10 and 100 years (that are typical return periods for the UDS design in the local standards) and a duration of 6 hours are considered here to evaluate risk assessment of flooding and surface runoff pollution. The corresponding average intensity of rainfall obtained from the IDF curves of the case study are 1.94 mm/hr for 2 years, 3.04 mm/hr for 10 years and 5.94 mm/hr for 100 years. Moreover, the basic hyetograph suggested by Yen and Chow (1980) is used here for temporal distribution of rainfall due to its simplicity. This hyetograph is represented by a triangular shape with the time to peak intensity approximately 0.375 times rainfall duration and the peak intensity estimated as a function of total rainfall depth, duration and peak intensity.

To build a SWMM model, a digital elevation map of the case study with scale of 1:2,000 was provided and subcatchments were created based on topography, the slope of streets, the routes for runoff movement, layout of the UDS, and the outlets of surface runoff. The surface runoff of all subcatchments is discharged into two rivers, i.e. Shadchay and Siah-Ab (Fig. 4). The outlet of these rivers is considered as the point of discharge into receiving water bodies. As a result, the SWMM model was built using 33 subcatchments as shown in Fig. 4.

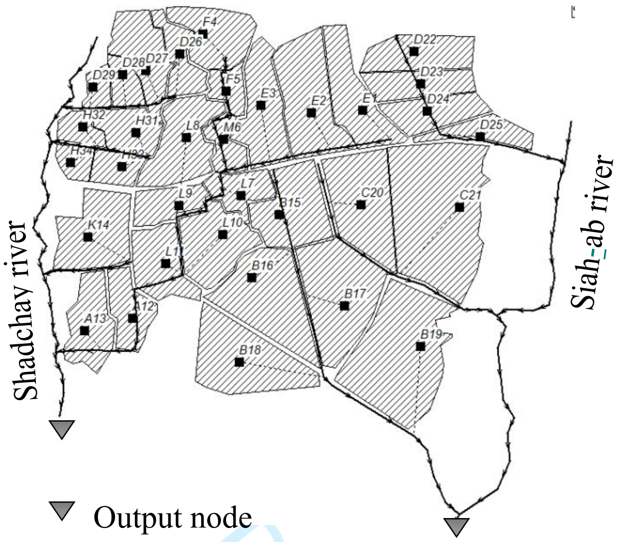


Fig. 4. The SWMM model built for subcatchments and conduits of the UDS

Based on the Manning coefficients recommended by the SWMM, they are considered 0.1 for permeable surfaces and 0.014 for impermeable surfaces including concrete conduits (Rossman 2015). The model simulates the rainfall-runoff conversion in the UDS catchments as a hydrological process as well as flow routing in the UDS conduits as hydraulic modelling by using the kinematic wave method. The dynamic wave and one-dimensional Saint-Venant equation are chosen in the flow routing due to their high accuracy. The Horton method with the parameters recommended by the SWMM user's manual (Rossman 2015) is used for infiltration modelling due to its simplicity and the fact that it requires fewer data and acceptable accuracy. In the case study area, the hydraulic conductivity of the soil is 44 mm/hr. The pollutants modelled here include TSS, TP, and TN. The saturation function is also used in the model to calculate the pollutant build-up which is a function of the number of preceding dry weather days (Rossman 2015). Similarly, the experimental function is also considered for the pollution wash-off which occurs during wet weather periods. The type of build-up and wash-off equations and their coefficients are also selected based on the previous calibration results for the hydraulic and water quality model of the

UDS (Karami et al. 2016; soleimani et al. 2016). Note that the calibration parameters that are also the main sources of uncertainty in the UDS modelling are the roughness coefficients of conduits and perviousness of subcatchments for the hydraulic model and the coefficients of built-up and wash-off equations for the water quality model.

3.1 Optimisation model configuration

The UDS comprises 33 subcatchments and 94 conduits and hence the 33 possible sites for SuDS and 94 locations for conduit rehabilitation including increase in the width or change in the roughness. The UDS also considers 6 potential sites for detention ponds at the UDS junctions based on the pre-defined locations for detention ponds in this study. According to Eq. (5), the total number of decision variables in a solution is equal to: $33\times2+94\times2+6\times1=260$.

The parameters of the multi-objective evolutionary algorithm were determined after a number of trials with randomly generated seeds to achieve the fastest convergence rate for optimal solutions. As a result, these parameters include a population size of 50, a mutation probability of 0.1 with a two-point crossover operator, the probability of incidence of 0.8 and the maximum number of generations equal to 4,000 as stopping criterion of the optimisation algorithm. After adjusting the optimisation parameters, the model was run several times each with a different initial generation to make sure the Pareto-optimal solutions are robust. The size of the search space in the optimisation model can also be calculated as below:

$$\left[33\times\binom{12}{1}\right]\times\left[33\times\binom{4}{1}\right]\times\left[94\times\binom{4}{1}\right]\times\left[94\times\binom{5}{1}\right]\times\left[6\times\binom{6}{1}\right]\cong 3\times10^{11}$$

Given such a large search space for the optimisation problem, the achievement of global optimal solutions cannot be guaranteed, and hence all the solutions are considered as near-optimal solutions. Moreover, comparing the large search space of solutions with the total number of solutions simulated in the optimisation model (i.e. 50 population size × 4,000 generations = 200,000) can reveal the high capability of the optimisation technique in obtaining the near-optimal solutions. The optimisation runs were carried out on a computer with the following specifications: Intel core i7-3610QM @2.30GHz with 6GB of installed memory (RAM). Each loop of the optimisation run including the model simulation took almost 2 to 5 second. The whole time for one optimisation run took around 3 hours.

4 Results and discussion

Fig. 5 shows the projections of the Pareto front of optimal solutions with respect to the three objectives of the urban flood management. As can be seen, for any solution on the Pareto front, there are a set of optimal SuDS and traditional measures for subcatchments, conduits and junctions in the UDS. Each of these optimal solutions is non-dominated, i.e. there is no other solution that can inferior that solution with respect to all objective functions. Hence, the decision maker can choose any of these optimal solutions based on the preferences for the above objectives or limitations due to either pollution standards, regulations for flood risk management or finance for construction. The range of objectives for the optimal solutions in the Pareto front obtained in Fig. 5 are: (1) the flood risk between 220 and 9,100 m^3 of total overflow of the conduits per year, (2) the pollution risk between 5.7 to 13.8 tonnes of total pollutants discharged into receiving water bodies per year; and 3) total costs of SuDS construction between 195×10^3 and 307×10^3 US$. These figures can be compared to the Business As Usual (BAU) i.e. "do nothing", i.e. the flood risk of 7,060 m^3 of total overflow of the conduits per year and the pollution risk of 8.5 tonnes per year. The BAU strategy would be dominated by any optimal solution selected from the Pareto front. For example, if the purpose is to minimise the flood risk while the pollution risk being constant, it is possible to reduce the flood risk to 500 m^3 per year. Alternatively, if the purpose is to minimise pollution risk while flood risk is being constant, a solution with pollution risk equal to as minimum as 6.5 tonnes per year can also be suggested.

As can be seen in the Fig. 5, there is a relatively indirect correlation between the flood risk and pollution risk in the optimal solutions, i.e. the more flood risk is reduced, the more pollution risk is increased. In other words, when selecting an optimal solution with minimum flood risk, it can have a high risk of pollution discharged into receiving water bodies. This can be attributed to the fact that the solutions containing the traditional rehabilitation convey any flood to the downstream of the UDS and hence no blockage/ flooding can happen in the UDS but instead pollutants are more transferred to the receiving water bodies which results in a high risk of pollution. On the other hand, solutions containing SuDS in subcatchments can maintain and treat pollutants in the urban areas instead of discharging them into receiving water bodies but this can increase the flood risk due to their limited capacity. Therefore, the best approach is to select solutions that have a combination of both types of SuDS and traditional measures.

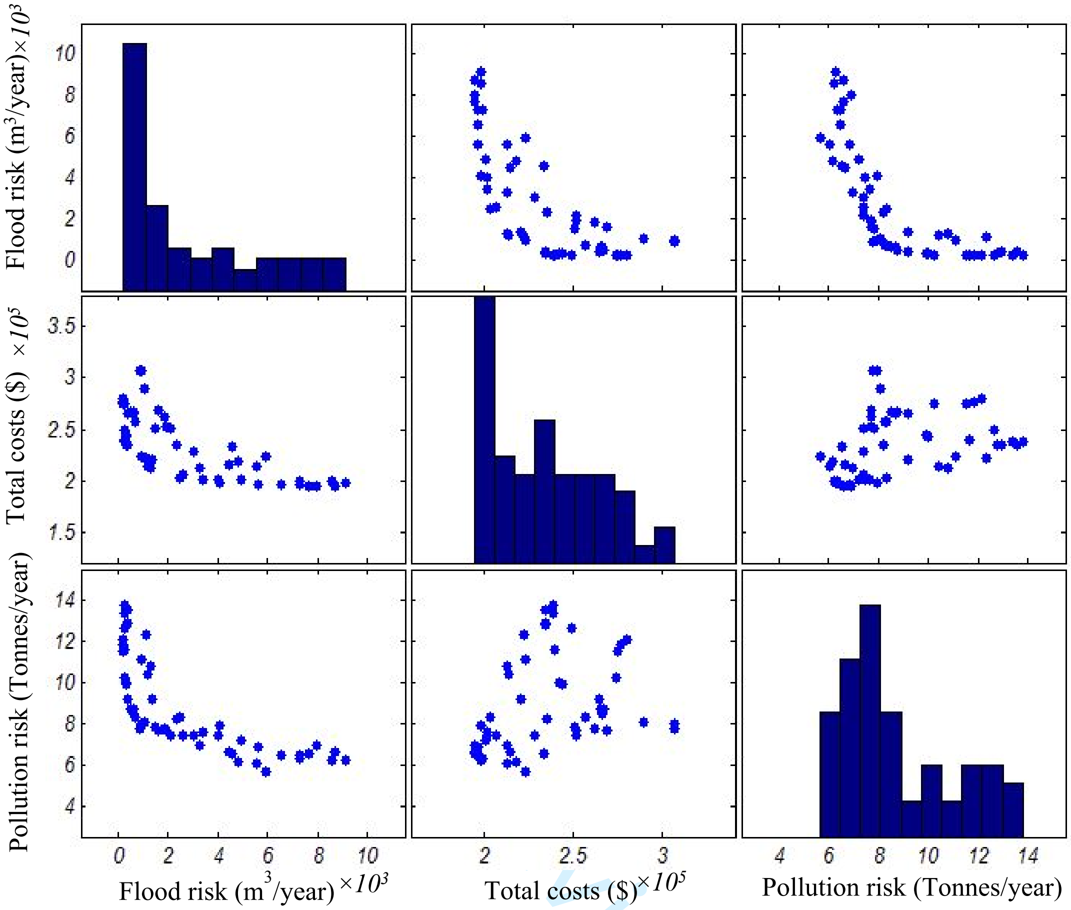


Fig. 5. The projections of the Pareto front of optimal solutions for the three objective functions

In addition, the same correlation can apply between total costs and flood risks which indicates the more investment in optimal solutions, the more flood risk is reduced in the UDS. However, no apparent direct correlation can be observed between total costs and pollution risks. This can be attributed to the traditional measures with the largest sizes that need more capital investment to transfer or retain more flood but there is no guarantee that pollution is minimised simultaneously. For further investigation of the Pareto front, the optimal solutions are clustered around a few groups to better classify the solutions based on their specifications and hence streamline the process of decision making. As a result of applying *k*-means clustering technique, the Pareto-optimal front are divided here into 3 clusters in Fig. 6, as denoted in circle, star and square. The first cluster (i.e. circle) denotes the optimal solutions with the low flood risk but high costs and a high risk of pollution. On the other hand, the third cluster (i.e. square) are those optimal solutions with low costs and a low risk of pollution but a high risk of flooding. The second cluster (i.e. star) includes the optimal solutions in which all three objectives (costs, risks of flooding and pollution) are spread between the above clusters. In other words, the solutions in this cluster mainly cover the middle of the Pareto optimal front. These clusters can help decision makers to pick up an optimal solution from a cluster that is generally closer to objectives and limitations of the urban planning.

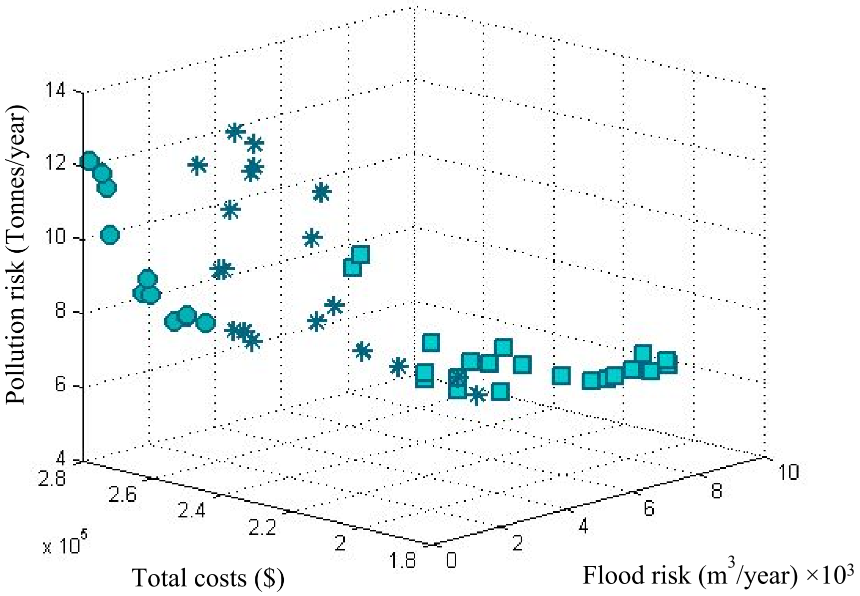


Fig. 6. The 3-D Pareto optimal solutions with *k*-means clustering in three groups (circle, star and square)

The optimal solutions obtained from the Pareto front represent a combination of different SuDS and traditional measures with optimal sizes. For further assessment of optimal solutions, they are compared with individual SuDS with a size equal to the maximum allowable in the optimisation model. Hence, six optimal solutions selected from the second cluster (which is the compromise of the optimal solutions) along with five individual SuDS/traditional measures and the BAU strategy (i.e. "do nothing") are ranked by using the CP method based on the three assessment criteria of the multi-objective optimisation model. The five individual SuDS /traditional measures are defined as below:

1. Strategy #1 (detention ponds): six detention ponds are assumed to be spread in the subcatchments. The total area of each pond is 20m^2.
2. Strategy #2 (increasing the size and reducing the Manning coefficients of the conduits): the width of all existing conduits is increased by 80% and the Manning coefficients is decreased by 80%.
3. Strategy #3 (permeable pavements): 20% of all subcatchments are assumed to be covered by permeable pavements.
4. Strategy #4 (bioretention tanks): it is assumed that 20% of all subcatchment is used for bioretention tanks.
5. Strategy #5 (infiltration trenches): this approach similarly assumes infiltration trenches are used in 20% of all subcatchments.

Moreover, the remaining six strategies (#6-11) are basically non-dominated optimal solutions taken from the second cluster of the Pareto front as described above. The 12 strategies including the BAU are simulated in the SWMM model for the same three assessment criteria used in the optimisation model (i.e. flood risk, pollution risk and total costs). As there are no specific preferences for the assessment criteria, equal weights are used here for the three criteria and hence the distance of each criterion and the overall distance of the CP method for each strategy can be calculated based on Eq. (6) as shown in Fig. 9. Note that if there are specific preferences for the criteria or for the case of group decision making in which various stakeholders with their own viewpoints are involved, different weights of stakeholders can be used in the CP method (Morley et al. 2016a). As it can be seen in the figure, strategy #6 which is one of the optimal solutions is ranked the first. This strategy is a compromise for both risks of flooding and pollution. In addition, the top six ranked strategies are those belonging to the optimal solutions.

The configuration of the highest ranked solution (i.e. strategy #6) is as follows for the main categories of decision variables: (1) 6 detention ponds (i.e. all potential locations) are proposed with a capacity between 20 and 36 m^3; (2) conduit rehabilitation (i.e. width change) out of 94 as "no change" for 27 conduits, increase by 50% for 44 conduits and between 50-100% for remaining conduits; (3) conduit roughness reduction as "no change" for 23 conduits, by 20% for 21 conduits, by 40% for 18 conduits, by 60% for 16 conduits and by 80% for remaining conduits; (4) Addition of SuDS out of 33 subcatchments as no SuDS for 10 subcatchments, bioretention tanks for 6 subcatchments, infiltration trenches for 9 subcatchments and permeable pavements for 8 subcatchments. Fig. 7 shows the location of the detention ponds and the area percentage of subcatchments covered by SuDS that varies between 0 and 20. As can be seen in the figure, although most of the subcatchments with no SuDS seem to be located at the upstream of the UDS, this may not be the case for all upstream catchments. This can be due to different conditions of subcatchments and shows no specific rule and recommendation can be generalised for the allocation of SuDS in the UDS but the suggested framework through multi-objective optimisation model coupled with a MCDA method for prioritising the best strategies can be an efficient approach for achieving this.

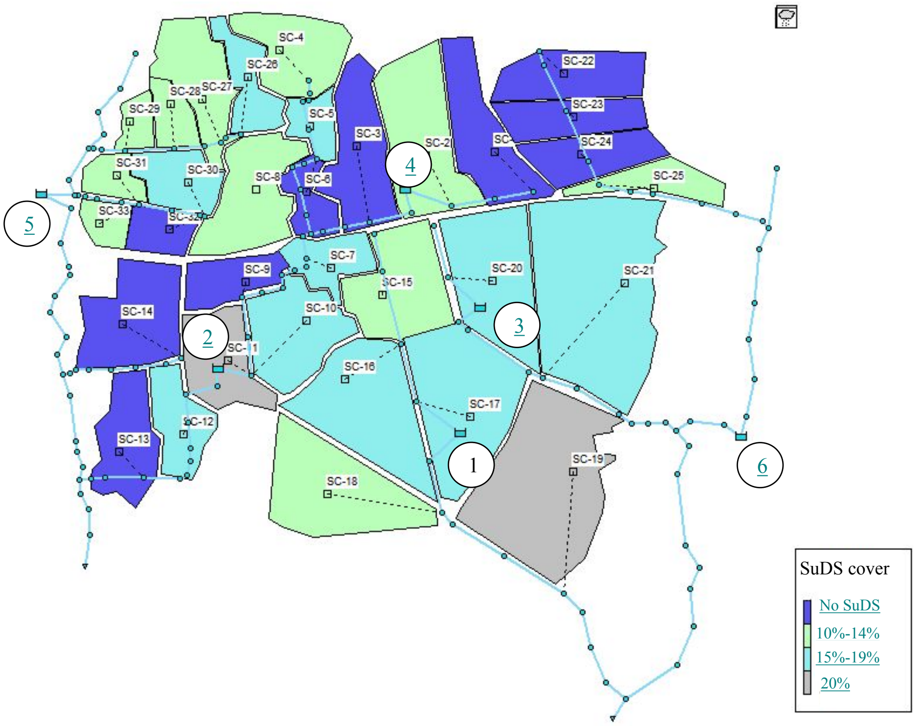


Fig. 7.The area percentage of subcatchments covered by SuDS and the location of detention ponds in strategy#6

Fig. 8 shows the percentage of solutions of the Pareto optimal front for allocating various optimal sizes of the six detention ponds. As can be seen, some detention ponds e.g. #3 and #4 were only picked up one optimal size in various optimal solutions. This can facilitate the decision of the size for those ponds if they are selected in any planning. In addition, the size for remaining ponds are relatively predominant by one specific size in other sites that can streamline the decision making.

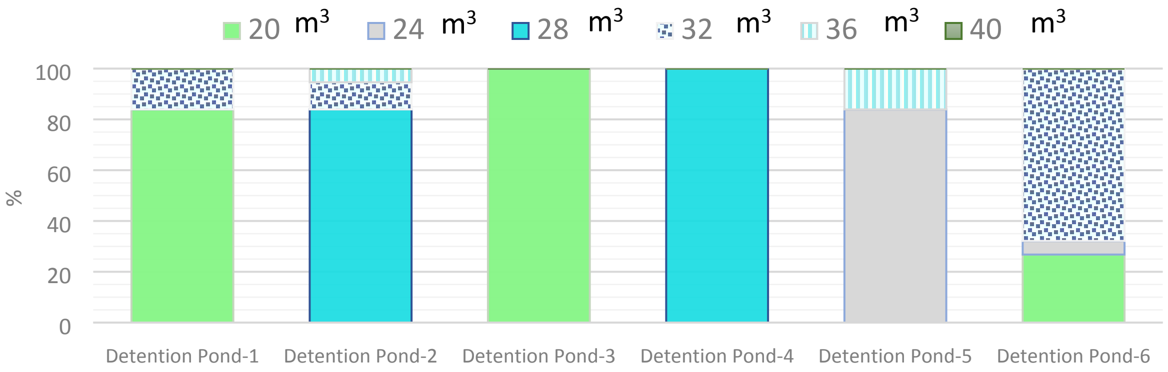
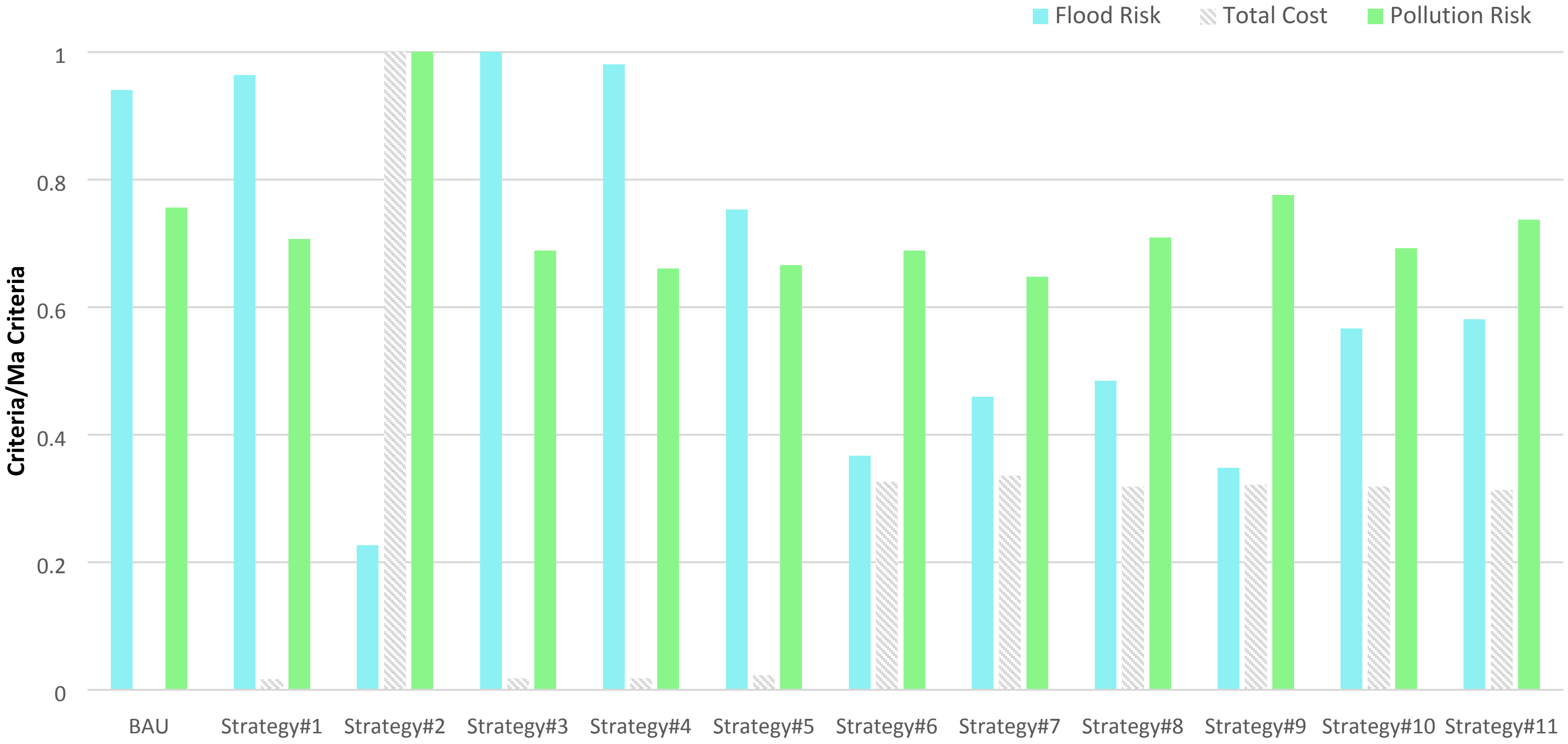


Fig. 8. % of all solutions of the Pareto optimal front for optimal volumes of detention ponds

Although the total costs for most of the individual solutions (#1-#5) are far smaller than the optimal solutions, the associated risks especially flood risks are far low in the optimal solutions. It should be noted that if the cost is a limiting factor for decision making, strategy#6 could be crossed out from the list of eligible solutions and thus only those solutions satisfying the minimum allowable costs could be considered to be analysed by the CP method. Despite a low pollution risk for some individual strategies such as #4 and #5, the associated flood risks in these strategies are much higher than any optimal strategies. The high risk of flooding can be seen in all individual strategies except for strategy #2 in which the performance of conduits has been improved significantly. However, that strategy cause a high risk of pollution and incur the highest capital investment and was also ranked the worst among all strategies. Interestingly, two individual strategies (i.e. #2 and #3) are ranked worse than the BAU. More specifically, strategy #2 (i.e. improving the conduits size and roughness) is a conventional method for increasing the conduits capacity leading to major flood risk reduction but it is the most expensive strategy and would likely results in the highest pollution loads discharged into receiving water bodies. Strategy #3 (i.e. permeable pavement) also has only slight reduction in the pollution risk to receiving water bodies while increasing the flood risk compared to the BAU and there is a cost incurred for this strategy. Therefore, the strategies with optimal solutions have the best combination of conventional and SuDS techniques with optimal size that result in the best trade-off for both risks of flooding and pollution and hence are recommended for the UDS of the case study.



Rank	**10**	**9**	**12**	**11**	**8**	**7**	**1**	**2**	**3**	**4**	**5**	**6**
Distance	0.402	0.398	0.477	0.405	0.394	0.335	0.282	0.287	0.305	0.303	0.316	0.33

Fig. 9. The relative distance of the analysed strategies for the three assessment criteria (flood risk, pollution risk and total costs) by using the CP method and evaluation of strategies by using CP method; note that values of flood risk, pollution risk and cost are normalised

According to what was analysed in this study, infiltration trenches have the significant effect on decreasing pollution loads. McClymont et al (2020) also analysed inclusion of various types of SuDS including rain barrels, green roofs, bioretention tanks, vegetation grass swales and permeable pavements and finally showed bioretention tanks and grass swales were more effective for improving water quality resilience despite increasing considerably the costs. Saniei et al (2021) showed the permeable pavement had the most reduction in flooding and swale on pollutants reduction. However, the result of the current study showed the combination of SuDS in subcatchments are the most effective approach for reducing pollution loads while there is no need for SuDS in all subcatchments.

5 Conclusions

This study presented a risk-based approach to determine the optimal combination of both SuDS and traditional measures with their optimal size for urban flood management. The methodology was based on hydrological-hydraulic simulation modelling of UDS in SWMM coupled with a multi-objective optimisation model to minimise the risk of flood and pollution while minimising the total costs of new SuDS and traditional measures. It also used the *k*-means clustering method to divide the Pareto front into a few clusters sharing the same features of objectives and combinations of SuDS and traditional measures. Selection of several optimal solutions from the trade-off (i.e. medium) cluster were also compared with individually designed SuDS and ranked by using the CP method. The methodology was also demonstrated on a real-world case study of the Golestan UDS in Iran.

According to the analysis conducted in this study, the following can be noted:

- Risk-based approach suggested here can provide cost-effective solutions that are able to concurrently minimise both risks of flood in the UDS and pollution discharged into receiving water bodies due to the rainfalls with large and small return periods, respectively.
- The optimal solutions in the Pareto front show that there are indirect correlations between non-dominated solutions that minimise the risk of either flooding or pollution (i.e. those minimising the flood risk have a high pollution risk and vice versa). This is due to selecting the solutions which mainly convey the flood to downstream in addition to pollution to receiving water bodies and vice versa.
- *K*-means clustering and CP methods can be efficient tools to select the most appropriate solutions amongst a large number of optimal solutions in the Pareto front.
- The ranking of the selected solutions by the CP method shows that all optimal solutions are ranked higher than the non-optimal (engineering-based design) solutions. Even, non-optimal solutions are ranked lower than the BAU due to low impact on reducing either the pollution risk in the traditional measures or the flood risk in SuDS solutions despite the total costs incurred for their construction. For example, applying either porous pavements or detention ponds separately can increase the flood risk by 4% but bioretention tanks can increase it by 20% while infiltration trenches can only reduce the flood risk by 20% which is still less than optimal solutions. These solutions can also reduce the pollution risk by 20%. However, the selected optimal solutions can decrease both flood and pollution risks by 27% and 50%, respectively.

The proposed approach can be used by decision makers for long-term planning of the most effective combination of both traditional and contemporary solutions with optimal sizes which can lead to the best performance of the UDS and simultaneously reducing the risk of flooding and pollution to an acceptable level. While this is an efficient approach to minimise the available risks, the most reliable design for these optimal solutions should also rely on the further analyse carried out to see their robustness against other factors such as climate changes and sensitivity of their design parameters under those conditions in urban stormwater management.

The flood risk analysed in this study was defined as probability of occurrence × severity of consequence. Other risk formulas can be considered in the future works. One example for this is to define risk = hazard (i.e. probability) × exposure × vulnerability. The current study had no inclusion of socio-economic factors but vulnerability in the suggested formula can examine these characteristics such as losses due to financial, human and other social impacts of the community. The exposure can also refer to flood overflow and pollution loads entering the UDS.

5 Acknowledgement

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Table 1. Capital investment for SuDS and UDS rehabilitation used in the study

Type of measure	**Construction cost (US$)**	**Annual operating and maintenance cost (% of construction cost)**	**References**	**Note**
Detention pond	$C = 24.5V^{0.71}$	3%-6%	(Strecker et al. 2010)	The values excluding the land cost estimated in December 2002 V =volume (cubic ft) and A = area (square ft)
Infiltration trench	$C = 173V^{0.63}$	5%-20%	(Strecker et al. 2010)	
Bioretention tank	$C = (2-3)A$	5%-7%	(Strecker et al. 2010)	
Porous pavement	$C = (3-4)A$	0	(Strecker et al. 2010)	
Change of Manning roughness coefficient	$C = 27\Delta n * L$	5%	(Karamouz and Nazif 2013)	Δn = change of Manning coefficient of conduits, ΔA= change of conduit cross-section area (m^2) L=Conduit length (m)
Change of conduit dimensions	$C = 270\Delta A * L$	0.5%	(Karamouz and Nazif 2013)	